Pollution Taxes as a Second-Best: Accounting for Multidimensional Firm Heterogeneity in Environmental Regulations

Ruozi Song   Fan Xia   Bing Zhang*

December 2023

Abstract

This paper documents the first-order welfare effects of firm heterogeneity under a homogeneous emission tax regime. Local and firm-level variations in market power, abatement costs, and abatement benefits can create a gap between optimal and realized emission reduction. We examine this question in the context of China's highly concentrated cement industry, which was subjected to multiple emission tax changes across time and location between 2011 and 2018. Using a comprehensive firm-level data set that allows us to estimate firm-level responses to regulation, we find substantial heterogeneity in the compliance behavior of firms — through adjustments in output levels, price, and emission intensity. We then use the structurally estimated firm-level marginal abatement costs to quantify the deviation of local marginal pollution abatement costs from its marginal benefits. The model shows that the gap between observed abatement and production firm responses and the socially optimal responses is explained by two factors: the firm's market power and the correlation between local abatement costs and benefits. By using variation in market power generated by two data-driven approaches and local abatement costs and benefits, we can empirically assess the importance of each of these two drivers of the sub-optimal response to emission taxes. A counterfactual analysis shows that output-based rebates coupled with a homogeneous emission tax can help mitigate the distortion from market power and generate a 4.72 billion RMB (0.67 billion dollars) welfare increase.

Keywords: emissions tax; firm heterogeneity; market power; second-best setting; distributional impacts

JEL Codes: D02, D04, D22, D24, D43, D58, D61, D62, H23, L13, L61, Q52

*Ruozi Song: World Bank (rsong1@worldbank.org); Fan Xia: Nanjing University (xiafan@nju.edu.cn); Bing Zhang: Nanjing University of Finance and Economics (zhangb@nju.edu.cn). We thank Antonio Bento, Paulina Oliva, Matthew Kahn, Robert Metcalfe, and Geert Ridder for valuable comments and suggestions. For helpful discussion, we thank Augustin Bergeron, Islamul Haque, Taraq Khan, Rajat Kochhar, Xiongfei Li, John Matsusaka, Noah Miller, Jeff Nugent, Liying Yang, and participants at LSE Environment Week.

1 Introduction

Large and persistent productivity differences across firms in producing both the intended products and the by-product, i.e. emissions[1], have been documented in many studies (Syverson (2004), Hsieh & Klenow (2009), Lyubich et al. (2018), Shapiro & Walker (2020)). Though firm heterogeneity can be sizeable, it is less problematic when market-based approaches to pollution regulation are employed. For example, Pigouvian taxation enables producers to internalize pollution costs such that firm-specific marginal pollution abatement costs are equalized to the Pigouvian tax. Then, regulators can set the Pigouvian tax to be equal to marginal damage of emissions[2] to achieve the social optimum, without requiring firm-specific information. Though the differential impacts that environmental regulations create across different locations and demographic groups have been covered extensively in recent literature, the focus has been on the ex-post assessment of the distributional impacts of these policies rather than on the optimal design of policy(Fowlie et al. (2012), Grainger & Ruangmas (2018), Hernandez-Cortes & Meng (2020), Shapiro & Walker (2021)). Importantly, local and firm heterogeneity can have first-order welfare effects in the outcome of policy instruments as (1) typical emission taxes are spatially uniform[3], while pollution damage *varies* at the local level, and (2) polluting firms can enjoy *various* degrees of market power and *distinct* cost structures at the same spatial unit. Both factors can alter the efficiency of a policy, and the spatial correlation between them may affect the efficiency of a spatially uniform policy.

This paper studies how and when the differential impacts of environmental regulations can have a first-order effect on designing an efficient policy. More specifically, what are the channels that enable local firm heterogeneity to impact efficiency at an aggregate level, besides affecting the distribution of costs and benefits? When do welfare-seeking regulators need to care about the differences between polluting firms? What is the magnitude of welfare loss, if any, when firm heterogeneity is ignored by regulators? We answer these questions under the framework of a spatially uniform emission tax[4], which has been shown to be feasible in practice.

A growing literature has documented how environmental regulations reshape manufacturing

[1] Emission productivity is defined as output per ton emission.

[2] The marginal damage of emissions is defined as the monetary costs that are imposed on residents from one ton of emissions.

[3] For example, Fuel taxes in the United States vary at the state level.

[4] Spatial uniform emission taxes can still vary across spatial units, e.g. states or provinces, and industries.

sectors through production adjustment, changes in output composition, decreasing pollution per unit of output, and entry and exit of firms (Bovenberg & Goulder (2002), Levinson (2009), Shapiro & Walker (2018)). These environmental regulations also impose unequal abatement costs on firms that possess substantially different market power and cost structures (Shapiro & Walker (2020)). However, less attention has been paid to incorporating these findings into the design of environmental regulations.

To build a theoretical foundation for how local firm heterogeneity can affect efficiency at an aggregate level, in the first part of the paper, I develop a micro-founded quantitative model with heterogeneous polluting firms competing in Cournot fashion, consumers, and a welfare-maximizing regulator. Firms differ in market power and cost functions, both in production and in abating emissions. They can adjust output level and emission intensity which is defined as emission per output when facing the emission tax. This model incorporates four key features from empirical literature that allow emission taxation to impact firms differently: (1) varying degrees of market power across firms within the same market[5]; (2) firm-specific cost structures in both production costs and emissions abatement costs; (3) cross-firm reallocation; and (4) heterogeneous pollution damages across space[6]. Under the restriction that emission tax only varies at an aggregate spatial unit level, local heterogeneity in market power, costs, and pollution damage can create two wedges in the optimal tax rate under this second-best setting. The first wedge stems from the differential market power of firms, and the second stems from the spatial correlation between the marginal cost of abatement of local firms and local marginal damage of pollution. The sum of these two terms provides a statistic that is useful for testing empirically whether firm heterogeneity matters for designing a welfare-maximizing regulation.

Bringing the model with firm heterogeneity to an empirical setting poses several challenges. First, firm-level emission abatement costs, even with detailed firm-level data, can be difficult to measure. Commonly-adopted accounting and engineering estimates are obtained by calculating the installment, operating, and maintenance costs of abatement technologies, such as end-of-pipe

[5]Firms in the context of spatial competition can possess different levels of market power within the same market, depending on their proximity to their consumers. This is especially true for polluting industries, e.g. steel, power, and cement, when transportation costs are substantial. Also, firms' market power can come from non-market factors such as connections with local governments and banks to access cheaper credit.

[6]Spatial variation in pollution damages can come from both pollution dispersion and location-specific characteristics, such as population density, age distribution, etc.

filters. But these estimates can neglect firms' strategic behaviors under emission taxation, which may alter emission abatement costs. For example, firms may choose to reduce output to comply. The corresponding loss in revenue due to emission taxation should be counted as a part of emission abatement costs. Firms who find it optimal to reduce emission intensity can also upgrade production or emission processes[7]. This can alter the operation and maintenance costs of abatement technologies and bias engineer estimates which are based on existing technologies. Second, it is difficult to validate whether firm-level market power is measured properly. Most literature defines market power using market concentration, e.g. Herfindahl–Hirschman index, or firm-level measures based on the number of nearby firms weighted by distance to other firms and their firm sizes (Miller & Osborne (2014), Macchiavello & Morjaria (2021), Allen & Atkin (2022)). However, these measures may fail to capture other important contributors to market power, which can stem from non-market factors like access to cheaper credit, especially in a context with weak institutions.

We tackle these challenges in the context of China's cement industry. The distinctive features of the Chinese cement industry, variation from the multiple adjustments in emission tax rates across time and locations in China, and the comprehensive and novel firm- and market-level data collected make it possible to test the validity of the model, estimate it empirically, and run policy counterfactuals.

The cement industry in China is one of the major emission sources of both carbon and air pollutants and accounts for 58% of global cement production in 2015. The cement market is concentrated in China with the top 25% largest cement firms taking up 50% of total production (Liu et al. (2021)) — a common feature of polluting capital-intensive industries. Also, cement firms compete in local markets that vary in their input markets and local demand. This creates substantial spatial differentiation in cement firms. Due to high transportation and storage costs, spatial location is one critical source of market power. Furthermore, cement products are highly homogeneous and firm-level heterogeneity in market power should not come from different quality of cement products, which is often difficult to observe in practice. These features make it credible to differentiate cement firms only based on market power and cost structures, without taking into account other

[7]There are multiple methods and combinations for firms to reduce emission intensity. For example, during the production process, firms can opt for higher-quality coal with less SO_2 content, re-optimize how to deliver air into the kiln to make combustion more efficient, and reduce overall cement output. Converters and filters installed at the end of the pipe can also reduce most pollutants such as SO_2, NO_x, and dust.

common sources of firm heterogeneity documented in the literature (Syverson (2004), Hottman et al. (2016)).

China launched an environmental taxation regime in 2003, which allows each province to decide its emission tax rates within a range determined by the central government. During our study period, from 2011 to 2018, adjustments in tax rates occurred three times on average across provinces, at different points in time. Tax rates range from 0 RMB per ton emission to 12,000 RMB, or equivalently 1,740 dollars, per ton of emissions[8].

This paper combines several novel data sets, including firm-specific product-level price, firm-level input, output, emission, characteristics such as age and capacity, as well as market-level sales data to study heterogeneous firm decisions when emissions taxation are levied in the same market. Product-level prices allow us to estimate firm-specific market power through two data-driven approaches: deviation of firm-specific price from market-level price and coal cost pass-through. These data-driven approaches require no strong assumptions about the sources of market power. Furthermore, underlying firm-level abatement cost curves can be structurally recovered from observing firms' decisions on output and emission intensity under different emission tax rates.

In the second part of the paper, I document substantial firm heterogeneity in emission intensity and market power, through both deviation of firm-specific price from market-level price and coal cost pass-through, in the same market with similar environmental regulations. The extent of firm heterogeneity is even larger than the US counterparts, as documented in Lyubich et al. (2018). Next we use time variation in emissions tax levels within provinces to identify differential impacts of emissions tax based on observables. We find that all firms increase the price by around 0.52% significantly if emissions tax increases by 10%. But state-owned enterprises (SOEs), larger firms, and cleaner firms tend to increase prices even more. This confirms the hypothesis that there exists differential market power of firms even within the same market and industry. Furthermore, we estimate how firms react to emissions tax through two common methods, adjusting output and emission intensity. The emissions tax reduces the emission intensity of all firms by 0.29%. But SOEs, larger firms, and more-polluting firms reduce their emission intensity by an additional 0.83%, 0.29%, and 0.28%, respectively. The same firms also increase their output relative to their

[8]Detailed information on tax rate adjustments were collected from announcements by each provincial government. Currency is converted based on the exchange rate in 2021.

counterparts. This suggests that firms face a trade-off between decreasing output and decreasing emission intensity under all emission taxes. In summary, all emission taxes further increase market power in the cement industry, as larger firms increase their market share and revenue. These heterogeneous responses can be explained by the underlying market power and cost structure of production and emission abatement, as predicted by the theoretical model.

The third part of the paper estimates the quantitative model with heterogeneous polluting firms. The model is estimated by matching the observed firms' product price, output volume, and emission intensity with the model prediction; assuming the underlying abatement cost function — a one-to-one mapping between emission abatement costs and emission intensity — stays the same for each firm between 2011 to 2018. Two sets of parameters can be estimated. The parameters that govern the curvature and scale of firm-specific abatement cost functions are estimated from adjustments in emission intensity in response to changes in emissions tax rates. The parameters in production cost functions are estimated using the output adjustments. The demand elasticity is estimated using a standard instrument variable approach, where supply-side cost shifters — coal prices and wages — are used as the instruments for market-level prices. The demand elasticity of cement in China is -2.95, which is slightly more elastic than the estimates documented in Fowlie et al. (2016) (-2.26). We find that on average the marginal cost of producing one-ton of cement, including the abatement cost, is 289 RMB (42 dollars). Lastly, I conduct the empirical test derived from the model and find that firm heterogeneity does matter for designing an efficient emission tax in the context of China's cement industry.

In the counterfactual exercise, I simulate the welfare changes across provinces under the emissions tax incorporating firms' market power, and spatial correlation between the cost of abatement and pollution damage. Total welfare increases by 3.4% when emissions tax rates are changed from the ones under the status quo to the ones we derive from the model. If emissions tax revenue is recycled through output subsidies, total welfare increases further by 1.2%, as output subsidies can address market power distortion without distorting firms' emission behavior. Compared to the status quo, a combination of emissions taxation, which accounts for local firm heterogeneity, and output-based rebates from tax revenue recycling can generate a 4.72 billion RMB (0.67 billion dollars) welfare increase in the Chinese cement industry.

The methodology in this paper can be further applied to study the economic costs of various environmental regulations, such as carbon tax and emission standards, in other concentrated polluting industries. This is especially crucial for regulations that tackle carbon emissions as the damage of carbon emission is global while economic costs are local.

Related Literature. This paper contributes to three distinct pieces of literature in environmental and development economics. First, this paper provides a micro-founded model and new empirical evidence for the existing literature in the choice of price instruments and quantity instruments under uncertainty in both costs and benefits (Weitzman (1974), Pizer (2002), Burtraw et al. (2022)). When the compliance cost of regulations and benefits are certain, price instruments (e.g. emission tax) should be equivalent to quantity instruments (e.g. emission trading). However, when there is more uncertainty on the cost side, price instruments are preferred. Firm heterogeneity is one form of cost uncertainty as it is difficult for regulators to observe the private information of an individual firm. Most existing studies in this area are either theoretical, or estimate costs/benefits through simulations. This paper estimates the extent of uncertainty using empirical data and provides new empirical evidence on the choice between price and quantity instruments.

Second, this paper contributes to policy design in second-best settings (Buchanan (1969), Goulder (1998), Bento et al. (2014), Fowlie & Muller (2019)). Although the literature on optimal emissions tax has extended to incorporating practical issues such as market power in polluting industries (Ryan (2012), Fowlie et al. (2016), Cardoso (2020)), less is known about how to design environmental regulations when there is substantial local firm heterogeneity on market power and cost structure. The availability of novel and comprehensive firm-level data, has made it possible for us to extend this analysis from the market level to the local firm level and estimate the local correlation between firms' abatement costs and emissions damage at a granular level. This paper provides a theoretical framework and shows that the local correlation between costs and benefits should be incorporated even when designing spatially uniform emissions taxation.

In addition, our paper further extends the recent growing literature on applying empirical industrial organization techniques (Ericson & Pakes (1995), Bajari et al. (2007)) to study the cost of environmental regulations (Ryan (2012), Fowlie et al. (2016) and Cardoso (2020)). However, due to data limitations, existing literature on estimating the cost of environmental regulations often assumes that firms only adjust output in reaction to environmental regulations, without changing their production and abatement technologies. This can be a fair assumption in the context of developed countries. However, firms in our study demonstrate a tremendous decline in emission intensity. Our paper builds on this empirical finding and proposes a flexible partial equilibrium model, where firms can not only adjust output but can also alter emission intensity. Thus, the cost of environmental regulations includes both economic losses due to output adjustment and the higher marginal cost of abatement to maintain abatement technologies. Data limitations have also led to existing literature examining market power at the market level through market concentration or market-level cost pass-through (Miller & Osborne (2014), Miller et al. (2017), Ganapati et al. (2020)). The detailed firm-level data we use allows us to examine firm-level market power using two different data-driven approaches.

The remainder of the paper is structured as follows. Section 2 describes the cement industry in China, the background of relevant environmental regulations, and data construction. Section 3 presents a model with heterogeneous firms and provides a theoretical foundation for how firm heterogeneity affects the efficiency of emissions tax. Section 4 documents substantial firm heterogeneity in emission intensity and market power within the same market, and identifies differential impacts of emissions tax on various firms classified by observables. Section 5 outlines the estimation strategy of the structural model. Section 6 presents simulations under alternative policy designs. Section 7 concludes the paper and discusses future research.

2 Background and Data

2.1 Environmental Regulations in China

China's GDP grew by 588 percent during the two decades after the Reform and Opening in 1978. One major driving force of the growth was industrial manufacturing, which led to tremendous air and water pollution. Air pollution in China mostly is sourced from industrial coal combustion and transportation. The World Health Organization (WHO) estimates that outdoor air pollution led to 300,000 premature deaths per year in China (Cohen et al. (2005)).

To ease the growing concerns about pollution, the Chinese Ministry of Environmental Protection (MEP) started to collect more detailed monitor-level pollution data and firms' emission data, and release various environmental regulations. By the end of 2019, 1,634 pollution monitors have been placed in all provinces and cities, with 6 monitors in each city on average. The annual

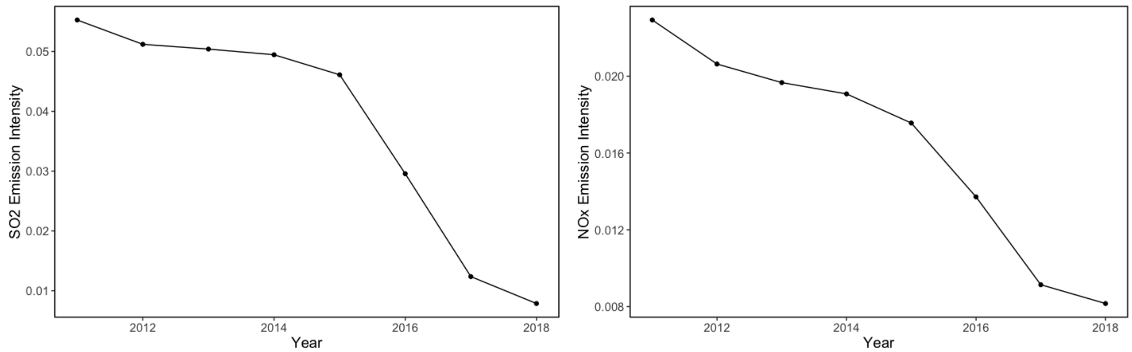
Environmental Statistical Database, which contains both ecological data and firms' self-reported production and emission data, has been collected since 1999. In addition, starting in 2007, the MEP required plants in high-emitting industries to install and operate Continuous Emissions Monitoring Systems (CEMS). By the end of 2013, 14,410 firms had joined the system and kept uploading hourly, automatically recorded pollutant-specific emission data to an online platform for each province. This CEMS data makes it possible to cross-check self-reported emission data.

Emission standards and emission taxation are the two major instruments of environmental regulations in China. The MEP in the central government issues emission standards for each sector and updates them occasionally. Starting in 2013, the MEP issues two separate sets of emission standards each time, general standards and special standards. The special standards are more stringent and apply only to key regions, which are more politically important[9]. Emission taxation was established in 2003 in a form of charges for emission permits before 2018, and emissions tax after 2018[10]. Compared to emission standards, emission taxation leaves local governments more flexibility to adjust the tax rates. Normally, the MEP in the central government set up a price floor (RMB/ton) for each pollutant, SO_2, NO_2, and CO. Provincial governments can adjust the tax rates across time.

There was only one major change in emission standards for the cement industry in the period of interest, from 2011 to 2018, which took effect in July 2015. More detailed information on changes in emission standards for the cement industry in the last two decades is documented in Table B.1. Emission tax rates, however, have been adjusted three times, on average, in each province at different times over the study period. I collected each change in tax rates across provincial governments and time by searching for the announcement on each official website of the provincial government. Figure A.3 documents the detailed changes in tax rates across provinces over time. In Figure 1, I plot the average SO_2 emission intensity of cement plants in China, defined as the amount SO_2 generated to produce one ton of cement, between 2011 and 2018. The change in emission standards in 2015 altered the trend of emission intensities. But there was still a constant decrease in emission intensity over time, which suggests that changes in emission tax rates can be responsible for the decline as well.

[9] Most cities in the key region are either the capital of the province or nearly Beijing, which is the capital of China. A map of cities in the key region is in Figure A.2

[10] The MEP in local governments managed emission permits, while after 2018, the Tax Bureau in local governments collect emissions tax.



(a) SO_2 (b) NO_x

Figure 1: Average Emission Intensity in China's cement industry from 2011 to 2018

Note: This figure demonstrates the trend of average SO_2 and NO_x emission intensity, defined as the amount of emission generated (ton) to produce one ton of cement, in China's cement industry. Data is collected from the Annual Environmental Statistic Database.

2.2 Cement Industry in China

Producing cement involves several key steps. First, the key material, limestone, is transported into a kiln, where it is heated to around 1,400 degrees Celsius. The heating process uses the most energy among all the other key steps. 94.3% of Chinese cement plants relied on only coal in 2018, which makes the heating process generates the most emission. The heated ground limestone becomes cement clinker. Next, after cooling down, clinker is ground into fine powder in a cement mill. This step consumes relatively less energy, and thus, generates fewer emissions. Most cement plants integrate the heating and grinding steps. Finally, the fine powder, which is the final product of cement, is then packed into bags or trucks and delivered to construction sites. There, Cement is mixed with water, sand, and gravel to generate fresh concrete and used for constructing buildings and roads. Figure A.1 documents these steps in detail and their associated energy consumption.

Cement product is very standard. Thus, the extent of quality differentiation is very limited. Also, moisture in the air can be quickly absorbed by cement and makes it unusable. Thus, it is hard to store a large amount of cement and hedge future risk. As a result, cement production can be very responsive to demand.

The concentration in China's cement market has been increasing during the last decade. From 2014 to 2019, the share of the top ten cement firms, based on capacity, increased from less than 40% to more than 50%. Several factors contribute to the increasing concentration. First, as transportation costs rise, cement plants that are close to raw materials or construction sites gain more advantages. Transportation costs can take up around 30% of cement price. Also, anecdotal evidence shows that larger firms can manage to comply with increasingly stringent environmental regulations, while many smaller firms suffer more. This can further expand the market share of larger firms. Figure 2 displays the spatial distribution of cement plants in China.

Demand. Cement firms in China compete in a local market. Due to high transportation costs and a low value-to-weight ratio, more than 80% of cement firms ship cement within 300 kilometers by trucks. In the empirical analysis, we treat each province as a local market for the cement industry. Cement is mostly used in constructing buildings and roads. Thus, demand for cement is highly correlated to local economic conditions and population. In addition, there is a limited capacity for consumers to substitute cement with other materials due to high costs.

International Trade. Imports and exports of cement in China take up a very limited share of overall cement production. In 2018, the total domestic cement production was 1.96 billion tons, while imports and exports of cement only took up 0.05 percent and 0.38 percent respectively. Thus, in the theoretical framework, we do not take into account the effect of environmental regulations on international trade.

Abatement Technologies. Clinker production is the most polluting process in the cement industry. Thus, all the available pollution abatement technologies try to reduce the emission of this heating process. There are five major categories of technologies to abate emissions associated with clinker production: (1) upgrading cement kiln types, (2) increasing energy efficiency, (3) reducing clinker to cement ratio, (4) reducing sulfur content in coal, and (5) employing end-of-pipe abatement technologies(Liu et al. (2021)). Nearly 100 percent of clinker production employs precalciner kilns, which are the most efficient type of kilns available. Thus, there is not much room to further reduce emissions through changes in kiln types. But under the other four categories, there are multiple technologies or a combination of different technologies to reduce emissions. For example, air can be delivered into a kiln in a way such as coal combustion is more efficient, which can increase energy efficiency. Also, a proportion of SO_2 can be absorbed in a kiln through the reaction with calcium oxide. However, it is hard to observe the exact technologies each plant uses to reduce overall emissions.

2.3 Data

In this section, I discuss how several novel data sets are combined to provide comprehensive and detailed information on the regional cement markets in China, plant-level production, emission, and sales (both prices and quantities), and other economic conditions like energy prices and housing prices.

Chinese Environmental Statistical Database. To study firm-level heterogeneity in emission and production, I obtain firm-level information from the Chinese Environmental Statistical Database (CESD) from 2011 to 2018, which is collected and managed by the MEP. The CESD provides the most detailed annual data on plant-level characteristics, such as location and 4-digit industry code, output (value), energy consumption, abatement investment, and emissions across various pollutants. Plants in the CESD are sampled based on the annual accumulated emissions. Since cement plants are capital-intensive and highly polluting, most of the cement plants should exceed the threshold and show up in the CESD data. I verify this by comparing the plants in the CESD and a complete list of cement plants provided by the China Cement Association. I find that 96 percent of cement plants are included in the CESD.

There are two caveats of the CESD. First, all information is collected by the MEP through self-reported surveys. It is reasonable to doubt the accuracy of the data, especially the one on emission information. Thus, emissions information in the CESD is cross-checked with information from Continuous Emissions Monitoring Systems (CEMS), which are placed in the chimneys of plants and automatically record hourly pollutant-specific emission data. I match firms in the CESD with the ones in CEMS based on firm ID and location and cross-check the emissions data after 2014[11]. Emissions in the two data sets are highly correlated. The second caveat is that cement plants can only be filtered through the 4-digit industry code[12]. However, not all these cement plants are involved in highly-polluting clinker production. Some plants may only provide grinding services or transportation, which generate relatively neglectable emissions. I collect information on whether a plant owns kilns from China Cement Association and further filter out irrelevant plants.

China Cement Association. To complement firm-level data in the CESD, I obtain more detailed information from the China Cement Association (CCA), which is critical to study firm-level mar-

[11] CEMS cover a comprehensive list of plants only after 2014.

[12] The 4-digit industry code for cement plants is 3011.

ket power. The CCA, established in 1987, is a non-profit organization that collaborates with cement firms, universities, and research institutions to assist growth and collaboration in the cement industry in China. It surveys a full list of existing cement plants and collects detailed information. First, I obtain a complete survey of all cement plants with functioning kilns and their production capacity. This allows me to filter out other firms in the cement industry that do not engage in highly-polluting clinker production. Also, monthly product-level sales prices[13] of each firm is provided by the CCA. This makes it possible to measure firm-level market power using two data-driven approaches, deviation of firm-specific price from market-level price and coal cost pass-through, without strong assumptions on the sources of market power. Lastly, monthly regional market-level data like sales and final prices, that account for transportation costs, is obtained to estimate market-level demand function. Imports and exports data is used to verify the validity of ignoring international trade in the theoretical framework.

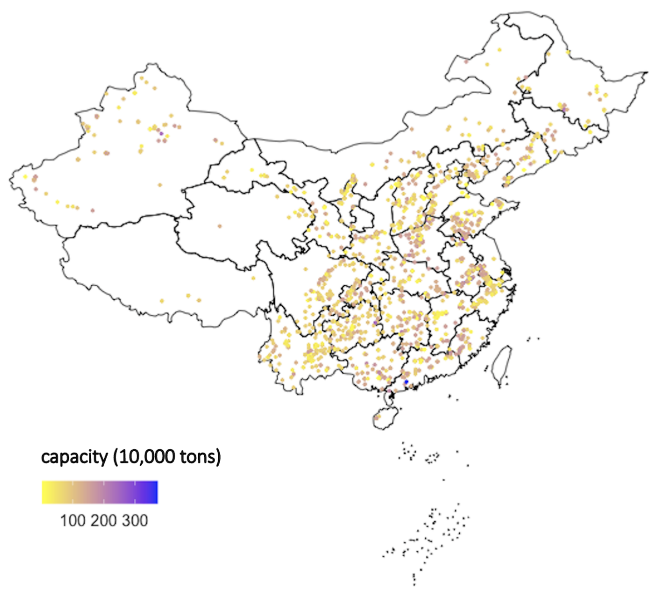


Figure 2: Map of Cement Plants in the Main Data

Note: This figure displays the cement firms and their capacities (in 10,000 tons) in the main data.

Firm Registration Database. Using available data sets, it is hard to confirm the number of firm exits in the Chinese cement industry. When certain firms stop showing up in the database, I can not

[13]Product-level sales prices are the so-called *factory door prices*, which are prices that do not account for transportation costs. Final prices paid by consumers are measured at the regional market level.

distinguish firm exits from missing data entries. Thus, in the main data, I only include firms that survived over the whole study period, from 2011 to 2018. To verify a cement plant was established before 2011, I match the CESD with the Firm Registration Database from Qichacha, which provides firm information upon registration such as time of establishment and registered capital, based on firm name and location.

National Bureau of Statistics of China. To estimate regional market demand, I need to collect information both on supply-side factors and demand-side controls. Monthly housing prices and annual GDP, as well as monthly coal prices, natural gas prices, electricity prices, and manufacturing wages, are obtained from the National Bureau of Statistics of China.

Province	**Number of Firms**	**Average Output** 10,000 tons	**Average Price** RMB/ton of cement	**Average Emission Intensity** kg/ton of cement	**Tax Rate** RMB/ton of emissions
Yunnan	136	137.38	311.29	8.00	1,263.16
Sichuan	117	243.71	287.16	8.38	4,105.26
Shandong	106	171.03	303.83	4.28	6,315.79
Anhui	105	471.48	285.72	4.72	1,263.16
Hebei	105	147.46	293.30	9.14	5,684.21
Xinjiang	96	56.57	347.65	16.67	1,263.16
Guizhou	89	261.50	307.33	9.12	2,526.32
Henan	88	191.41	292.06	5.57	5,052.63
Zhejiang	84	249.56	330.94	4.09	1,263.16
Hunan	83	152.87	284.39	7.43	2,526.32
Guangdong	80	328.38	327.50	6.89	1,894.74
Shanxi	79	106.86	271.59	7.33	1,894.74
Inner Mongolia	77	139.60	296.78	8.20	1,263.16
Guangxi	74	355.38	293.12	3.49	1,894.74
Jiangxi	72	221.15	313.78	6.35	1,263.16
Hubei	70	202.55	329.68	4.91	2,526.32
Shaanxi	64	175.60	270.04	9.10	1,263.16
Liaoning	60	122.49	284.10	4.83	1,263.16
Gansu	59	153.19	301.04	9.44	1,263.16
Jiangsu	54	415.61	296.87	4.76	5,684.21
Chongqing	54	326.81	298.37	15.94	2,526.32
Fujian	49	163.78	311.04	5.41	1,263.16
Ningxia	35	129.26	242.97	6.83	1,263.16
Heilongjiang	33	70.02	361.99	2.50	1,263.16
Jilin	28	173.93	371.69	2.97	1,263.16
Qinghai	18	99.74	302.14	5.92	1,263.16
Hainan	10	248.79	353.79	7.35	2,526.32
Beijing	8	77.13	328.29	2.88	12,631.58
Tianjin	3	80.89	315.79	2.58	10,526.32

Table 1: Summary Statistics for Cement Markets

Note: This table displays the summary statistics for cement markets, which are defined at the provincial level. Emission intensity is measured in kilograms of SO_2 emissions when producing one ton of cement.

3 Model

To build a theoretical foundation for how local firm heterogeneity can affect the efficiency of environmental regulations at an aggregate level, I develop a micro-founded quantitative model with heterogeneous polluting firms in this section. Regulators seek to maximize aggregate welfare in each regional market and address the pollution externality by setting up spatially uniform emissions tax, while pollution damage differs at the local level. Regulators do not have complete information on individual firms' market power and cost structures. Instead, they observe the distribution of market power and cost structures across all firms in the same market.

Under this second-best setting, a key insight from the model is that optimal emission taxation design may not only depend on the industry average of firms' costs and market power, but also the variance and covariance between firms' costs and pollution damage. This theoretical framework provides a statistic so that it can be tested empirically whether local firm heterogeneity and differences in pollution damage matter for efficiency at an aggregate level.

3.1 Setup

I set up a quantitative partial equilibrium model in each market. Firms are assumed to operate independently across different markets. Regulators seek to maximize total welfare within the same market. Thus, the model setup is the same across markets at different times. Throughout the following analysis, I omit the market and time subscript for convenience.

A. Firms

Let N be the number of firms in each market. Firms, that produce homogeneous products, compete in Cournot fashion and generate aggregate output, Q. The resulting market-level price, $P(Q)$, is the price consumers pay after accounting for transportation costs. Since the cement is a homogeneous product, in an equilibrium, consumers pay the same price, $P(Q)$, for cement from different firms. Firm i charges a factory door price, p_i, which is the product price before shipment.

Firms differ in market power, costs, which include production costs and emission abating costs separately, and emission intensity (defined as the amount of emission to produce per unit of output). ϵ_i is a firm-specific and time-invariant parameter that captures the market power of firm i. It is defined as the ratio between firm i's factory door price, p_i, and the market price after accounting for transportation costs, $P(Q)$. The higher the ϵ_i, the higher the market power is. This measure can capture the market power from spatial advantage and other non-market factors. For example, if a firm i is located closer to its customers, transportation costs are lower so that firm i can charge a high factor door price. In addition, if the same firm is preferred by consumers due to personal connections, ϵ_i is higher as well. Firm i's production cost is a function of output, $c_i(q_i)$. To abate emission, it encounters an abatement cost, $c_a^i(e_i)q_i$, where $c_a^i(e_i)$ is a firm-specific marginal cost of emission abatement. $c_a^i(\cdot)$ represents a one-to-one mapping between firm i's emission intensity and the marginal abatement cost to maintain this level of emission intensity. It decreases in emission intensity. e_i represents firm i's emission intensity.

Under an emission tax rate τ_e, firm i can adjust either its output level, q_i, or its emission intensity e_i, which is defined as emission per output. Since firms can choose from a composite of abatement technologies and it is hard to observe the exact technologies firms employ, both of the decisions are treated as continuous variables. The marginal emission abatement cost, $c_a^i(e_i)q_i$, changes as the firm changes emission intensity. But I assume that the underlying marginal abatement cost function, $c_a^i(\cdot)$, stays the same for each firm. Thus, firm i's marginal abatement costs just move along the function $c_a^i(\cdot)$ when the emission tax rate changes.

Firm i's profit maximization problem is:

$$\max_{q_i,e_i}(P(q_i + \sum_{j\neq i} q_j^*))\epsilon_i q_i - c_i(q_i) - \tau_e e_i q_i - c_a^i(e_i)q_i, \tag{1}$$

where q_j^* is the optimal output chosen by other firms in the same market.

The optimal output and emission intensity level under the emission tax rate τ_e from the first-order conditions is:

$$[q_i] : \underbrace{(P(Q) + \frac{\partial P(Q)}{\partial Q} q_i)\epsilon_i}_{\text{marginal revenue}} = \underbrace{(\frac{dc_i(q_i)}{dq_i} + \tau_e e_i + c_a^i(e_i))}_{\text{marginal cost}} \tag{2}$$

$$[e_i] : \quad \underbrace{-\frac{dc_a(e_i)}{de_i}}_{\text{marginal abatement cost}} = \tau_e \tag{3}$$

These two conditions generate conventional firms' optimization rules. When a firm chooses an optimal level of output, its marginal revenue from one more output should be equal to the marginal cost. This can also be interpreted as the firm is indifferent between losing the profit from producing one output and saving the cost related to emissions, emissions tax, and the marginal abatement cost, for producing the same output. Also, the marginal abatement cost should be the same as the emission tax rate. It indicates that the higher the emission tax rate, the lower the emission intensity. But the marginal abatement cost increases simultaneously.

This model incorporates several key features from empirical literature that allow emission taxation to shape firms differently: (1) market power, (2) distinct cost structures in both production and emission abatement, and (3) cross-firm reallocation through different output changes across firms.

B. Demand

Since cement is fairly homogeneous, I assume that customers have a constant price elasticity of demand across markets. The aggregate demand function in each market m is:

$$lnQ_m = \alpha_{0m} + \alpha_1 lnP_m, \tag{4}$$

where Q_m is the aggregate output in market m, and P_m is the market price that accounts for transportation costs. α_1 is the price elasticity of demand. The intercept α_{0m} is market-specific and captures market-specific differences in aggregate demand arising from economic conditions.

3.2 Equilibrium

The following conditions have to be satisfied in an equilibrium: (1) each firm i chooses the level of output and emission intensity such that the profit, defined in Equation 1 is maximized; (2) consumers are indifferent to cement from different cement plants after transportation costs are accounted for; and (3) market is clear. More specifically, the following equations define an equilibrium in each regional market in each period. I omit the subscript for market and time for convenience.

$$q_i = \frac{\frac{dc_i(q_i)}{dq_i} + c_a^i(e_i) + \tau_e e_i - \epsilon_i P}{\epsilon_i P/\alpha_1} Q \tag{5}$$

$$-\frac{dc_a(e_i)}{de_i} = \tau_e \tag{6}$$

$$P = \frac{\sum_i [(\frac{dc_i(q_i)}{dq_i} + c_a^i(e_i) + \tau_e e_i)/\epsilon_i]}{N + 1/\alpha_1} \tag{7}$$

$$Q = exp(\alpha_0) P^{\alpha_1} \tag{8}$$

There are several insights from market equilibrium. First, firms with a lower marginal production cost or a lower marginal abatement cost enjoy a larger market share. This is consistent with the finding that more efficient and cleaner firms tend to have a larger market share, as documented in Weber (2021). Second, firms with higher market power tend to have a larger market share. Third, increasing emissions tax rates decrease firms' emission intensity and increases both market-level prices and firm-level factory door prices. Finally, firms with a lower marginal cost of abatement reduce emission intensity more than those with a higher marginal cost of abatement. These insights will be tested empirically in Section 4.

3.3 Welfare-Seeking Regulators

In each region/market, welfare-seeking environmental regulators address the pollution externality by setting up a spatially uniform emissions tax. The welfare measure at each period in each market is composed of total consumer surplus (CS), producer surplus (Π), emissions tax revenue (T), and total pollution damage (Φ). Here, I assume a conventional utilitarian social welfare function, as in Fowlie et al. (2016) and Ida et al. (2022), with equal weights on different components of the welfare measure:

$$\begin{aligned} W(\tau_e) &= CS(\tau_e) + PS(\tau_e) + T(\tau_e) - \Phi(\tau_e) \\ &= \int_0^{Q^*} P(z)dz - P(Q^*)Q^* + \sum_i \pi_i(\tau_e) + \sum_i \tau_e e_i^* q_i^* - \sum_i \phi_i e_i^* q_i^* \end{aligned}$$

where Q^* is the aggregate output in the equilibrium; q_i^* and e_i^* is firm i's optimal level of output and emission intensity.

Environmental regulators seek to maximize the total welfare in the region:

$$\max_{\tau_e} W(\tau_e)$$

Let μ_i be firm i's operating markup, $\mu_i = p_i - c_i - c_a^i(e_i)$. The marginal benefit of pollution abatement of firm i, ϕ_i, can be decomposed to regional average pollution damage and a firm-specific deviation from the average, $\phi_i = \overline{\phi} + \eta_i$. Under the first-best setting where regulators can design firm-specific emissions tax rates, the optimal taxation design is:

$$\tau_e^* = \phi_i - \underbrace{\frac{\sum_i \mu_i \frac{dq_i}{d\tau_e}}{\sum_i \frac{de_i q_i}{d\tau_e}}}_{\text{market power}} \tag{9}$$

When it is only feasible to design a spatially uniform emissions tax rate in each region, the optimal taxation design under this second-best setting is:

$$\tilde{\tau_e} = \overline{\phi} - \underbrace{\frac{\sum_i \mu_i \frac{dq_i}{d\tau_e}}{\sum_i \frac{de_i q_i}{d\tau_e}}}_{\text{market power}} + \underbrace{\frac{\sum_i \eta_i \frac{de_i q_i}{d\tau_e}}{\sum_i \frac{de_i q_i}{d\tau_e}}}_{\text{correlation between cost and benefit}}. \tag{10}$$

Under the restriction that emission tax only varies at an aggregate spatial unit level, local heterogeneity in market power, costs, and pollution damage can create two wedges in the optimal tax rate under this second-best setting. The first wedge stems from the differential market power of firms, and the second one is from the spatial correlation between the marginal cost of abatement of local firms and local marginal damage of pollution. When firms compete in a form of oligopoly, they are already producing at a level that is below social optimal. Thus, firms' market power creates a negative tax wedge in the optimal design of emissions tax rates. In addition, where there is a spatial correlation between the cost of pollution abatement and marginal pollution damage, the optimal emissions taxation design can depend on the covariance between cost and benefit. Simultaneous high pollution damage and low abatement cost create a positive wedge in the optimal emission tax rate. This provides a micro-founded perspective to explain the importance of understanding the correlation between costs and benefits in policy designs, as proposed in Weitzman (1974).

3.4 Statistics of Welfare Implications and Policy Counterfactuals

When should welfare-seeking environmental regulators care about local firm heterogeneity? The theoretical framework above provides two natural statistics that can be tested empirically to answer this question. First, if the second term in Equation 10, $t_2 = \frac{\sum_i \eta_i \frac{de_i q_i}{d\tau_e}}{\sum_i \frac{de_i q_i}{d\tau_e}}$, is close to zero, then environmental regulators can ignore the heterogeneity in pollution damage and only focus on addressing the distortion from market power. This statistic represents the correlation between the local marginal benefits of pollution abatement and the marginal costs of emissions abatement of the local firms. It can be estimated using the marginal benefits of pollution abatement measures, which is discussed in detail in Section 5.4, and the marginal change in firms' emissions if the emissions tax rate increases by 1 unit, which can be estimated in a reduced-form way. Second, if the sum of the two wedges in Equation 10, defined as $t_1 = \frac{\sum_i \mu_i \frac{dq_i}{d\tau_e}}{\sum_i \frac{de_i q_i}{d\tau_e}} + \frac{\sum_i \eta_i \frac{de_i q_i}{d\tau_e}}{\sum_i \frac{de_i q_i}{d\tau_e}}$, is close to zero, then environmental regulators can just set the emissions tax rate as the average marginal pollution damage in the region. The first term can be estimated using data on firms' markup and the marginal output adjustments of firms if the emissions tax rate increases by 1 unit, which can be obtained using reduced-form estimates.

To assess the welfare gain from the emissions taxation derived from the theoretical framework, I run the following policy counterfactuals.

Alternative emissions tax rates. The first policy counterfactual we investigate uses the optimal emission tax rates derived from the theoretical framework. I will compare the welfare gain in each region by switching the emissions tax rates from the ones under the status quo to the optimal ones.

Output-based rebates. To address the distortion from market concentration, tax revenues from emissions taxation can be recycled to firms in a form of output-based rebates. More specifically, the emissions tax firm i needs to pay becomes:

$$t(s; \tau_e, e_i, q_i) = \tau_e(e_i - \mathbf{s})q_i \tag{11}$$

The output-based rebates are equivalent to production subsidies in theory. The new market equilibrium under the output-based rebates is:

$$q_i = \frac{\frac{dc_i(q_i)}{dq_i} + c_a^i(e_i) + \tau_e(e_i - \mathbf{s}) - \epsilon_i P}{\epsilon_i P/\alpha_1} Q \tag{12}$$

$$-\frac{dc_a(e_i)}{de_i} = \tau_e \tag{13}$$

$$P = \frac{\sum_i [(\frac{dc_i(q_i)}{dq_i} + c_a^i(e_i) + \tau_e(e_i - \mathbf{s}))/\epsilon_i]}{N + 1/\alpha_1} \tag{14}$$

$$Q = exp(\alpha_0) P^{\alpha_1} \tag{15}$$

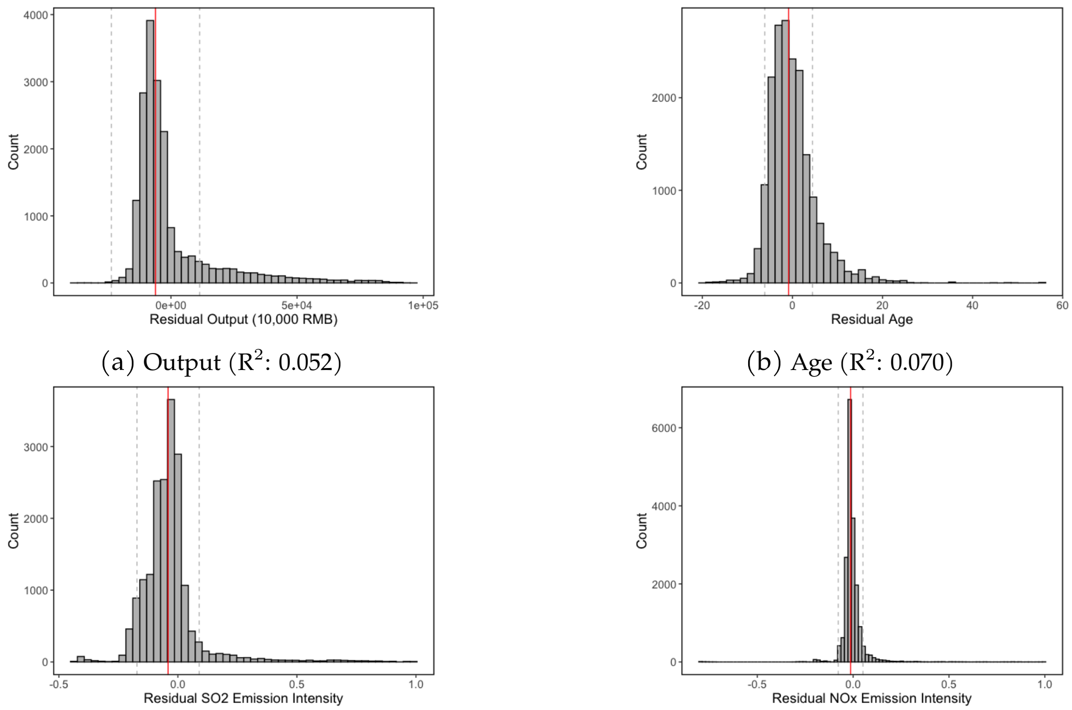
Under this new equilibrium, the aggregate output increases, and the market-level price decreases. The emission intensity decision of firms is not affected by the output-based rebating. Thus, the deadweight loss from market concentration can be mitigated through output-based rebates.

4 Empirical Evidence

In this section, I first document substantial firm heterogeneity in output and emission intensity within the same regional market in the Chinese cement industry. This validates the relevance to study how firm heterogeneity matters for efficient policy designs in the context. Then, the differential impacts of emissions taxation on output, emission intensity, and prices are estimated using two-way fixed effects estimation. The differential impacts can be explained by two key dimensions of firm heterogeneity, market power, and cost structures. The empirical results are consistent with model predictions in Section 3.2.

4.1 Firm Heterogeneity

To measure the local heterogeneity of cement firms in the same market, I regress annual firm-level output, as well as SO_2 and NO_2 emission intensity with province-year fixed effects and firms' ages as the control. Then residuals from these regressions are plotted in Figure 3. The age of a firm can be considered a proxy for technology. But even within this narrowly defined cement industry and regional market and after controlling for ages, there still exists substantial firm heterogeneity. For example, province-year characteristics, such as market conditions and environmental regulations, and firms' ages can only explain 5.2 percent of the variation in firms' output and 13.8 percent of the variation in firms' emission intensity. Thus, similar to cement plants in the U.S, as documented in Lyubich et al. (2018), cement plants in China show a substantial and even larger extent of firm heterogeneity.



(a) Output (R^2: 0.052)

(b) Age (R^2: 0.070)

(c) SO_2 (R^2: 0.138)

(d) NO_2 (R^2:0.051)

Figure 3: Firm Heterogeneity in the Same Market and the Same Year

Note: This figure illustrates firm-level heterogeneity in the same market and the same year. Histograms report the residual output, age, SO_2, and NO_2 emission intensity, after adding province-year fixed effects and controlling for firm ages (except for the age regression). The Red line indicates the median and the dotted black line indicates one standard deviation. Small R^2s suggests that even after controlling for age, there still exists a substantial extent of firm heterogeneity in the same region market in the same year.

In addition to firm size and emission intensity, I employ a data-driven approach to measure firm-level market power. Coal is a major input for clinker production. When the coal price increases, a firm with higher market power can pass through some of the increasing costs to customers, by raising the product price. Thus, coal price pass-through can be used to measure firm-level market power. I estimate coal price pass-through by capturing how much change in monthly product prices is associated with a change in monthly coal prices from 2011 to 2018. More detailed steps are documented in C.2.

Figure 4 illustrates the distribution of coal price pass-through by province. The market power also shows large heterogeneity across locations. On average, if the coal price increases by 1 RMB per ton, the cement price will increase by 0.45 RMB per ton. The cement price of a firm, whose market power is at the 75th quantile, will increase by 0.36 RMB per ton more compared to the one at the 25th quantile.

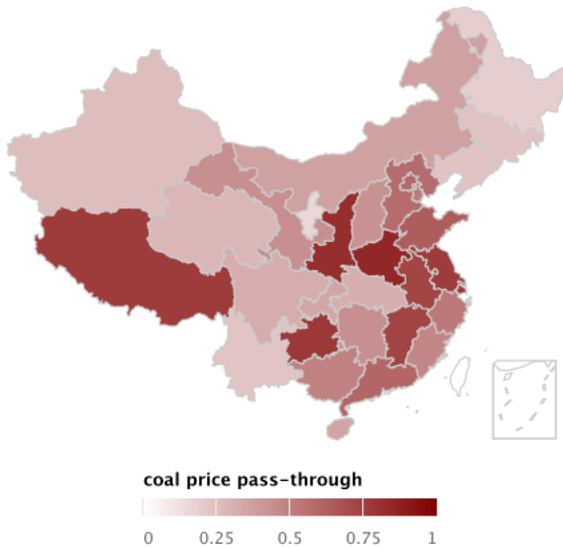


Figure 4: Coal Price Pass-Through by Province

Note: This map displays the average coal price pass-through across firms in each market. Coal price pass-through is defined as the change in product price when the coal price increases by one unit. It suggests that market concentration is different across locations. More detailed information on estimating the coal price pass-through is documented in C.2.

4.2 Differential Impacts of Emissions Taxation

4.2.1 Empirical Strategy

I estimate differential impacts of emission taxation on firms' output, emission intensity, and prices, by exploiting the variation from both the intensity of tax exposure and the timing of tax rate changes. Firms are classified based on four observables in 2011, which is before any changes in emissions tax rates in the study period, to study the differential impacts: (1) ownership (privately-owned or state-owned), (2) size (output is below the median or above the median in the same market), (3) emission intensity (SO_2 emission intensity is below the median or above the median in the same market), and (4) age (ages are below median age or above in the same market).

A conventional two-way fixed effect design is employed to estimate the differential impacts of emission taxation:

$$y_{ist} = \alpha_0 \tau_{st} + \alpha_1 \tau_{st} \times Group_i + X_{it}\beta + \gamma_i + \eta_t + \epsilon_{ist} \quad (16)$$

where y_{ist} is firm i's output/emission intensity/factory door price in market/province s and year t; τ_{st} is emissions tax rates in province s in year t; Group$_i$ indicates which categories firm i falls into; X_{it} is a set of controls which include the stringency of emission standards and provincial characteristics like GDP and housing price; γ_i and η_t are firm fixed effects and year fixed effects respectively.

One major identification assumption is that changes in emissions tax rates are not correlated with unobserved time-varying factors that can affect firms' outcomes. One possible way to violate the identification assumption is through co-existing environmental regulations that can be corrected with emissions taxation. I document detailed information on environmental regulations that involve the cement industry in Section 2. Another major environmental regulation is emission standards, which only changed once during the study period. In the regressions, I control for various emission standards that apply to cement firms in different markets. The second identification assumption is that firms' outcomes should not change if there were no changes in emissions tax rates, after adding various fixed effects and controls in Equation 16. We test this assumption using an event study framework in Section 4.2.3.

4.2.2 Results

Table 2 shows the estimates on differential impacts of emissions taxation. First, these estimates can be interpreted by examining each category separately. When facing higher emissions tax rates, privately-owned firms decrease output and emission intensity significantly. But they can mitigate some of the loss from increasing cement prices. For privately-owned firms, a one percent increase in emission tax rate is associated with a 0.025 percent decrease in output, a 0.027 percent decrease in emission intensity, and a 0.067 percent increase in cement price. From 2011 to 2018, emissions tax rates increase by 412 percent on average, then privately-owned firms decrease their output by 10.3 percent, decrease emission intensity by 11.1 percent, and increase their cement price by 27.6 percent over this period. Compared to privately-owned firms, when facing a one percent increase in tax rates, state-owned enterprises (SOE) increase their output by 0.034 percent relatively, further reduce the emission intensity by 0.083 percent, and further increase the price by 0.018 percent. This suggests that compared to privately-owned firms, state-owned firms can benefit from emissions taxation relatively by expanding it market share.

Similar to privately-owned firms, smaller firms and dirtier firms decrease output and emission intensity, and increase the price, when facing emissions taxation. Compared to smaller firms, larger firms reduce emission intensity more, but also increase price more. Notice that the sign of the effects on output is always opposite to the sign of the effects on emission intensity, for firms falling into group 2. This suggests that firms face a trade-off between reducing output and reducing emission intensity, which is consistent with the theoretical framework in Section 3.2. In Panel B, dirtier plants reduce their emission intensity even more, which shows that it is relatively cheaper for them to reduce emission intensity instead of reducing output. This is also consistent with the practical observation that it normally costs less for dirtier plants to abate emissions, as there are still many available technologies for them to choose from.

4.2.3 Robustness

The second identification assumption we haven't addressed yet requires that firms' outcomes should not change systematically over time in the absence of changes in emissions tax rates, after adding various fixed effects and controls in Equation 16. To address this, I employ an event study framework. An event occurs if the new emissions tax rate exceeds 2,000 RMB per ton of emission, which is the median tax rate and still relatively small compared to the maximum tax rate, 12,000 RMB per ton of emission.

Since different provinces changed their emissions tax rates at a different time, this binary treatment, the event I define, follows a staggered roll-out design. One fast-growing literature in treatment effect raises the issue of potential bias of two-way fixed effect models, especially with heterogeneous treatment effect (Goodman-Bacon (2018), Roth & Sant'Anna (2021)). Thus, I incorporate one of the latest event study estimators, proposed in Callaway & Sant'Anna (2020), that can address this issue. Provinces where emissions tax rates never exceeded 2,000 RMB per ton of emission (16 out of 33 provinces) are set as the control group.

Figure 5 displays the average impact of entering a high tax rate category on the average per-

	Panel A: log(Output)			
	Ownership	Size	SO_2 Intensity	Age
	Private, SOE G1, G2 (1)	Small, Large G1, G2 (2)	Low, High G1, G2 (3)	New, Old G1, G2 (4)
log(Tax)	-0.025^{***}	-0.031^{***}	-0.048^{***}	0.024
	(0.010)	(0.009)	(0.014)	(0.023)
log(Tax)$\times G2$	0.034^{***}	0.015	0.016	-0.071^{**}
	(0.012)	(0.019)	(0.014)	(0.030)
Observations	12,942	12,942	12,942	12,942
R^2	0.923	0.927	0.926	0.960

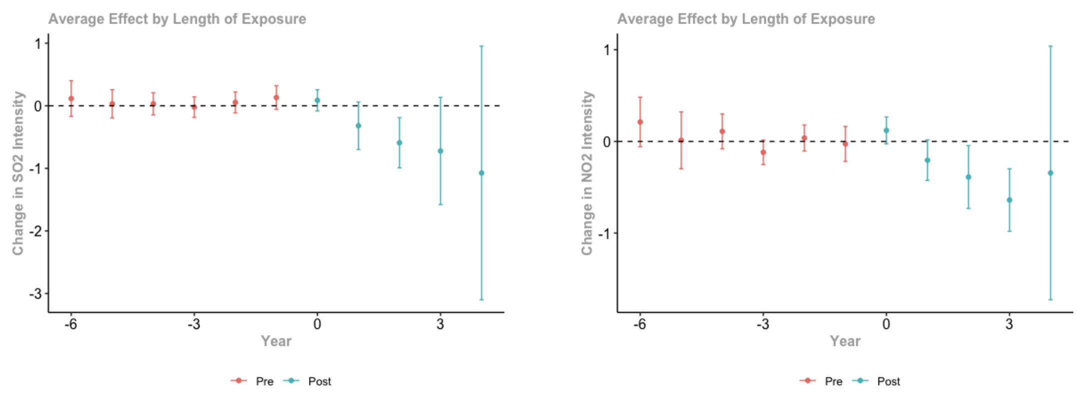
	Panel B: log(SO_2 Emission Intensity)			
	Ownership	Size	SO_2 Intensity	Age
	Private, SOE G1, G2 (1)	Small, Large G1, G2 (2)	Low, High G1, G2 (3)	New, Old G1, G2 (4)
log(Tax)	-0.027^{*}	-0.026^{*}	-0.032^{**}	-0.062^{**}
	(0.015)	(0.014)	(0.013)	(0.026)
log(Tax)$\times G2$	-0.083^{***}	-0.029^{***}	-0.028^{**}	0.039^{*}
	(0.028)	(0.036)	(0.013)	(0.022)
Observations	12,942	12,942	12,942	12,942
R^2	0.789	0.790	0.808	0.854

	Panel C: log(Price)			
	Ownership	Size	SO_2 Intensity	Age
	Private, SOE G1, G2 (1)	Small, Large G1, G2 (2)	Low, High G1, G2 (3)	New, Old G1, G2 (4)
log(Tax)	0.067^{***}	0.062^{***}	0.080^{***}	0.037^{***}
	(0.007)	(0.008)	(0.008)	(0.012)
log(Tax)$\times G2$	0.018^{*}	0.015^{*}	-0.015^{*}	-0.017
	(0.010)	(0.008)	(0.009)	(0.014)
Observations	12,942	12,942	12,942	12,942
R^2	0.734	0.734	0.741	0.754

Table 2: Differential Effects of Emission Taxation on Firm-Level Outcomes

Note: This table estimates the elasticity of output, SO_2 emission intensity, and firms' factory door prices concerning emissions tax rates from different groups of firms. Firms are classified based on four pre-treatment observables, ownership (privately-owned or state-owned), size, emission intensity, and age. Emissions tax rates are continuous. On average, three changes in tax rates occurred in each province between 2011 to 2018. Firm and year fixed effects are included and emission standards are controlled for. Standard errors are clustered at the firm level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

centage change in firms' emission intensity. There is no significant pre-trend before events occur. This suggests that the second identification assumption is likely to be satisfied.



(a) SO_2

(b) NO_2

Figure 5: Event Study: The Effect of Entering a High Tax Rate Category on Percentage Changes in Firm-Level Emission Intensity

Note: This figure shows the effect of entering a high tax rate category, when tax rates are higher than 2,000 RMB/ton, on the average percentage change of a firm's emission intensity. I follow Callaway & Sant'Anna (2020) to estimate the dynamic treatment effect that addresses potential bias in a staggered roll-out design under two-way fixed effects due to heterogeneous treatment effects. This figure suggests that there is no significant pre-trend on firms' emission intensity before emissions tax rates are significantly high. Standard errors are clustered at firm level.

5 Model Estimation

The empirical evidence in the above section suggests that the theoretical model can reflect those empirical findings. In this section, I bring the model to the empirics by structurally estimating key parameters. To do so, I need to make some assumptions about the functional form of firms' underlying cost functions.

5.1 Demand

I estimate the demand function using the following specification:

$$lnQ_{mt} = \alpha_m + \alpha_1 lnP_{mt} + \alpha_2 X_{mt} + \epsilon_{mt}$$

lnQ_{mt} is the natural log of total market demand in market m and time t. A market is defined at the provincial level. α_1 is the constant elasticity of demand. To cope with the endogenous price due to simultaneous equation issues, supply-side cost shifters, coal prices, and wages are applied as instruments for market-level prices. X_{mt} includes demand shifters such as population and housing price, which is a proxy for construction demand, in market m and time t.

Table 3 summarizes the estimation of price elasticity of demand using various specifications. All specifications include market/province fixed effects. No other controls that potentially shift cement demand are included in the first specification. In the subsequent specifications, demand shifters such as housing price, clinker price, and storage-capacity ratio are included. Specification 4 is selected as the preferred one, as it takes into consideration the most comprehensive demand shifters that can bias our estimate for the price elasticity of demand. Thus, the price elasticity of demand is -2.952[14] throughout the rest of the analysis.

	Dependent variable: Log output			
	(1)	(2)	(3)	(4)
Log price	-0.523^{***}	-0.600^{***}	-1.244^{***}	-2.952^{***}
	(0.145)	(0.190)	(0.418)	(0.859)
Log housing price		0.164	0.215	0.206
		(0.149)	(0.199)	(0.266)
Log clinker price				1.445^{***}
				(0.473)
Log capacity ratio			-1.104^{**}	-1.263^{**}
			(0.409)	(0.469)
Observations	1,499	1,461	1,461	1,392
R^2	0.752	0.769	0.766	0.729
First-stage F-test	307.05	251.37	120.17	40.10

Table 3: Demand Elasticity Estimation Using Instrument Variable Approach

Note: The unit of observation is a province-year-month from 2011 to 2018. Province fixed effects are included in all specifications. Standard errors are clustered at the province level. First-stage F-test reports the Kleibergen-Paap statistics. *p<0.1; **p<0.05; ***p<0.01

[14] The estimate is higher in absolute value than the price elasticities of demand estimated in the context of developed countries in the literature. For example, Ryan (2012) estimates a demand elasticity of -2.26 using the U.S. Geological Survey (USGS) for all the Portland cement producers in the United States from 1980 to 1999. Using similar data from USGS over the period 1981–2009, Fowlie et al. (2016) estimate a demand elasticity of -2.03.

5.2 Firm-Level Cost Functions

Firms encounter both production costs and emission abatement costs. I assume firms have constant marginal production costs, and the underlying marginal abatement cost function, a one-to-one mapping between the marginal abatement cost and emission intensity, stays the same over the study period. This is a reasonable assumption as abatement technologies have not had breakthroughs during this period.

More specifically, assume each firm has a linear production cost function, $c_i(q_i) = c_i q_i$, and linear abatement cost function, $c_a^i(e_i)q_i$. The marginal cost of abatement function is $c_a^i(e_i) = A_i e_i^{-\delta} - A_0$. δ governs the curvature of the marginal abatement cost function, while A_i accounts for firm-specific characteristics that can decide the level of the marginal abatement cost function. As emission intensity goes down, it is more expensive to operate and maintain abatement technologies. Also, when there is no environmental regulations, firm i's emission intensity is $e_i^0 = (\frac{A_i}{A_0})^{\frac{1}{\delta}}$, which is firm-specific. This reflects substantial firm heterogeneity in emission intensity documented in Section 4.

Then, the quantitative model is structurally estimated by matching the observed firms' product price, output volume, and emission intensity with the model. Two sets of parameters are supposed to be estimated, the marginal production cost, c_i, and parameters in the marginal abatement cost function, $\{A_i, \delta, A_0\}$.

Abatement costs. The equilibrium condition for optimal emission intensity in Equation 6 can be re-written as:

$$log(e_{it}) = \frac{log(A_i\delta)}{1+\delta} - \frac{log(\tau_{eit})}{1+\delta} + u_{it}, \tag{17}$$

where u_{it} represents mean-zero measurement errors. The parameter that governs the curvature of the marginal abatement cost function, δ can be estimated through the variation in multiple changes in emissions tax rates faced by the same firm. The firm-specific parameter A_i can be estimated through firm fixed effects.

Production costs. The equilibrium condition for optimal output in Equation 5, combined with the market clear condition in Equation 7 and Equation 8, can be re-written as:

$$\frac{q_{it}}{Q_{mt}}\frac{P_{mt}}{\alpha_1} + p_{it} - \tau_{eit}e_{it}(1 + 1/\delta) = c_i - A_0 + v_{it} \tag{18}$$

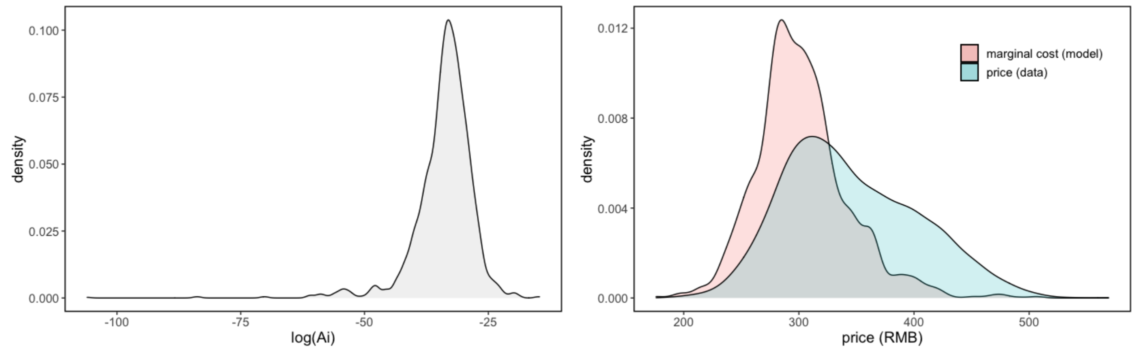
where q_{it} and p_{it} is firm i's output and factory door price respectively; Q_{mt} is aggregate output in the market; v_{it} is the mean-zero measurement errors. $c_i - A_0$ can be identified through fixed effects, but c_i and A_0 can not be identified separately.

Table 4 shows the estimates of market-level parameters. The parameter that governs the convexity of a marginal abatement cost function, δ, is estimated to be 5.150 with a very small standard error. This suggests that the marginal abatement cost function is fairly convex. Since the intercept

	Estimate	Standard Error
Demand elasticity: α_1	-2.952	0.859
Convexity of marginal abatement cost function: δ	5.150	0.964

Table 4: Estimated Structural Parameters

of the marginal abatement cost function, A_0, and the marginal production cost c_i can not be identified separately, I plot the total marginal cost, which is a sum of the marginal production cost and the marginal abatement cost, in Panel (b) in Figure 6. On average, the marginal cost of producing one ton of cement, including both the marginal production cost and the marginal abatement cost, is 289 RMB (42 dollars). The distribution of estimated marginal costs falls in a reasonable range compared to the distribution of product prices in the data. The distribution of the firm-specific parameters that decide firms' emission intensity under no environmental regulations, A_i, is plotted in Panel (a) in Figure 6. This distribution reflects the empirical finding that there exists substantial firm heterogeneity in emission intensity under the status quo.



(a) Log A_i (b) Marginal Cost: $c_i + c_a(e_i)$

Figure 6: Estimated Firm-Level Costs

5.3 Goodness of Fit

I make use of a moment that is not matched when estimating parameters to cross-check the goodness of fit of the model. Recall that the marginal cost of abatement function is assumed to be $c_a^i(e_i) = A_i e_i^{-\delta} - A_0$. Then, under no environmental regulations, firms' emission intensity is $e_i^0 = (\frac{A_i}{A_0})^{\frac{1}{\delta}}$ or $log(e_i^0) = \frac{log(A_i)}{\delta} - \frac{log(A_0)}{\delta}$. The standard error of $log(e_i^0)$ should be very similar to that of $\frac{log(A_i)}{\delta}$. In Figure 7, I plot the distribution of $\frac{log(A_i)}{\delta}$, which is structurally estimated, and the distribution of $log(e_i^0)$ from actual data. e_i^0 is measured using firms' emission intensity in 2011 when stringent environmental regulations had not been implemented. These two distributions have very similar dispersion. The standard error for the distribution from model prediction is 1.279 and is 1.359 for the distribution from actual data.

In addition, in the model, firm-specific market power is measured using the ratio between firms' factory door prices (before shipment) and the market price (after shipment). The higher the ratio, the larger the market power a firm has. To cross-check whether this is a credible measure of market power, we compare it with coal price pass-through, another data-driven measure for market power estimated in Section 4. Figure A.4 shows that these two measures, estimated using different variations, are highly correlated. This suggests that these two market power measures seem to be credible.

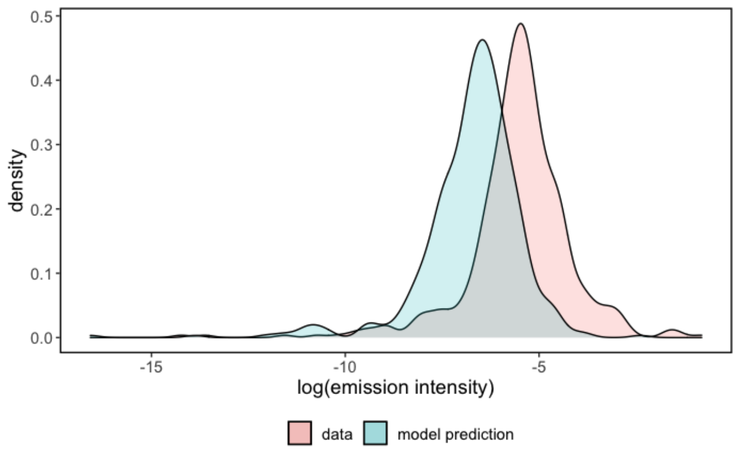


Figure 7: Comparison of Actual and Outside Moments

Note: One moment that has not been used in structural estimation is $\frac{log(A_i)}{\delta} = log(e_i^0) + \frac{log(A_0)}{\delta}$. 'Model prediction' plots the distribution of $\frac{log(A_i)}{\delta}$, and 'data' plots the distribution of actual $log(e_i^0)$. e_i^0 is measured using firms' emission intensity in 2011 when stringent environmental regulations had not been implemented. Since A_0 can not be identified, 'model prediction' should generate a parallel shift of the distribution of the log of emission intensity without regulations. Dispersion of the two distributions is almost identical, with the standard error being 1.279 from model prediction and 1.359 from actual data.

5.4 Environmental Damage

After estimating firm-related costs, the marginal damage of pollution needs to be measured to understand the welfare implications of firm heterogeneity. Emissions create damage not directly from firms' emissions, but through pollution concentration. The challenge here is to measure marginal pollution damage per unit of emission, rather than the commonly-known marginal pollution damage when air quality, e.g. PM_{10} concentration, decreases by one unit. Then, the key step is to link the firm's emission to pollution concentration.

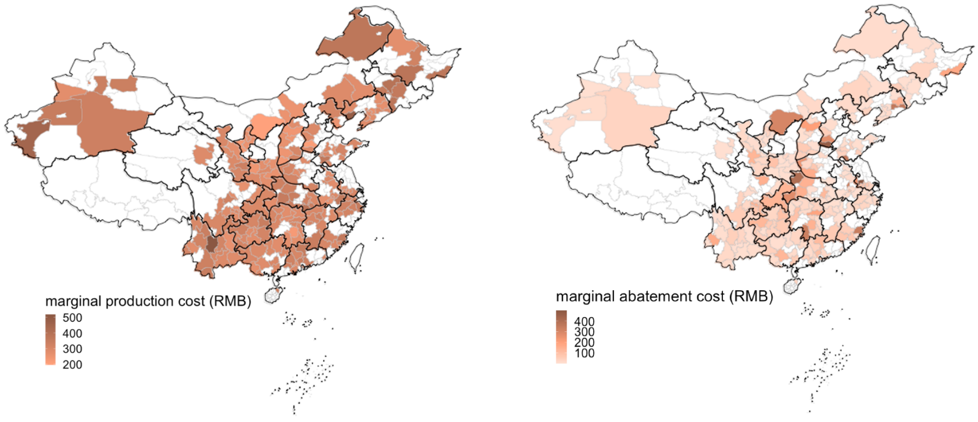
There is a rich literature in environmental science that builds mathematical or statistical procedures for identifying and quantifying the sources of air pollutants at a receptor location[15]. More studies in economics literature start to apply those models to measure pollution damage per unit of emissions and emissions dispersion (Hernandez-Cortes & Meng (2020), Shapiro & Walker (2020)).

For simplicity, I build a simplified version of the conversion model to measure the monetary value of the decline of one ton of emission. First, Annual average PM_{10} is regressed on annual total

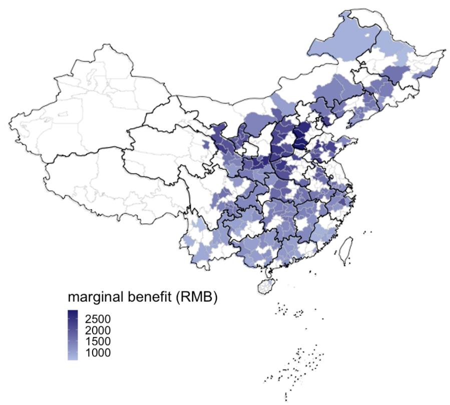
[15] These procedures are called Air Pollutant Receptor Modeling: https://www.epa.gov/scram/air-pollutant-receptor-modeling

emissions from industrial sectors, collected from Chinese Annual Statistical Yearbooks, controlling for weather conditions, elevation, and the number of passengers and the amount of freight transported. Then, I apply the finding in Ito & Zhang (2020) that the willingness to pay for clean air is around \$1.34 annually per household to remove 1 ug/m^3 of PM_{10}.

Panel (a) in Figure 8 shows the average marginal costs per ton of cement, aggregated at the city level, using the structural estimation above. Compared to the variation in the marginal production cost, there is a larger variation in the marginal abatement cost in the Chinese cement industry. This is consistent with what is documented in Lyubich et al. (2018) about US manufacturing firms. Marginal benefits per ton SO_2 abatement are documented in Panel (b) in Figure 8. The average marginal benefit per ton SO_2 abatement is 1,496 RMB (214 dollars). There is a significant local correlation between costs and benefits in the context of the Chinese cement industry. It can be welfare-enhancing if firm heterogeneity is incorporated into designing spatial uniform taxation at the provincial level.



(a) Marginal Costs per Ton of Cement



(b) Marginal Benefits per Ton of Abatement

Figure 8: Estimated City-Level Marginal Costs and Benefits (RMB)

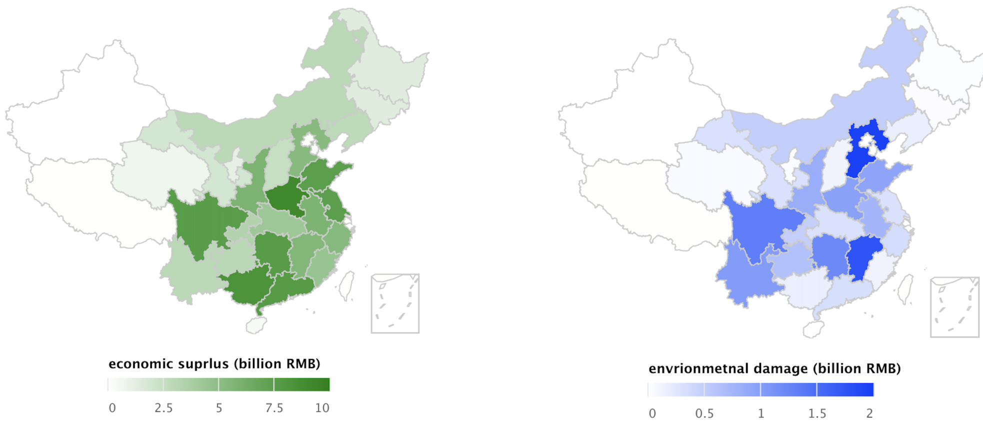
Note: This figure shows the estimated marginal costs of cement production and the marginal benefits of pollution abatement by the city. The left figure in Panel (a) shows the marginal production cost and the right figure shows the marginal abatement cost per ton of cement to maintain the emission intensity level. Notice that the marginal cost of production, c_i, and the constant in the marginal abatement cost function, A_0, can not be separately identified, as documented in Section 5.2. Thus, the left figure shows the distribution of $c_i - A_0$ and the right figure shows the distribution of the marginal abatement cost function without the constant term. These two figures represent the variation, rather than the levels, of marginal cost functions. Panel (b) shows the estimated marginal benefit per ton of SO_2 abatement.

6 Simulation Results

In this section, we discuss results from counterfactual simulations that are based on two policy counterfactuals in Section 3.4. In both of the policy counterfactuals, I stick to the existing tax structure, where emissions tax rates vary at the provincial level.

The baseline welfare is measured under the status quo, cement production, and emissions in

2018 in the Chinese cement industry. Total welfare is composed of *economic surplus*, defined as the summation of consumer surplus, producer surplus, and emissions taxation, and *environmental damage*, which is measured using the marginal benefits of pollution abatement estimated in Section 5.4. Figure 9 displays the spatial distribution of economic surplus and environmental damage across provinces. In total, the Chinese cement industry generated welfare that worthies 101.76 billion RMB in 2018, which is equivalent to 14.54 billion dollars.



(a) Economic Surplus

(b) Environmental Damage

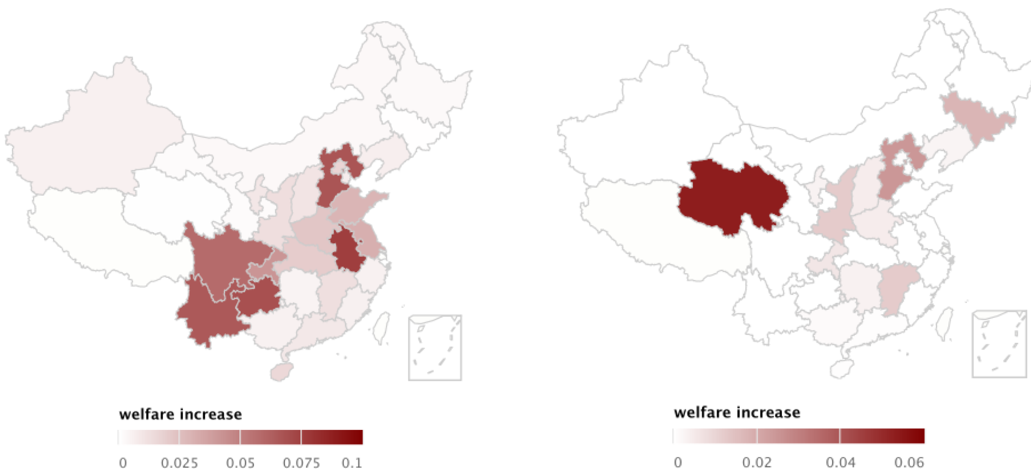
Figure 9: Baseline Welfare (billion RMB)

Note: This figure shows the baseline welfare under the status quo in 2018. Economics surplus is defined as the summation of consumer surplus, producer surplus, and emissions taxation. Environmental damage is the monetary value of pollution damage from cement production.

In the first simulation, the emissions tax rates under the status quo are adjusted to the optimal ones that incorporate firm heterogeneity and spatial differentiation in marginal pollution damage. I find that on average, total welfare increases by 3.4 percent across provinces, which worthies 3.46 billion RMB (0.49 billion dollars). Panel (a) in Figure 10 shows the spatial variation in the welfare gain. Provinces with higher welfare gains are the ones that demonstrate spatial correlation in costs and benefits, as shown in Figure 8.

To further address the distortion due to market concentration, tax revenues from emissions taxation are recycled back to firms in a form of output-based rebates in the second counterfactual. On average, output-based rebates further increase welfare by another 1.2 percent, which is 1.26 billion RMB (0.18 billion dollars). Panel (b) in Figure 10 shows that provinces where the cement industry is more concentrated and thus has a higher coal price pass-through, as shown in Figure

4, tend to gain more from the output-based rebates. Compared to the status quo, a combination of emissions taxation, which accounts for local firm heterogeneity, and output-based rebates from tax revenue recycling can generate a 4.72 billion RMB (0.67 billion dollars) welfare increase in the Chinese cement industry.



(a) New Tax Regime

(b) New Tax Regime + Output-Based Rebates

Figure 10: Simulated Welfare Change by Province

Note: This figure shows the simulated percentage changes in welfare under two policy counterfactuals. The left figure displays the percentage change of welfare by the province under the optimal emissions taxation that accounts for firm heterogeneity, compared to that under the status quo. The right figure shows the additional welfare change if the tax revenue from the optimal emissions taxation is recycled through output-based rebates.

7 Conclusion

This paper studies the importance to account for firm heterogeneity and spatial variation in marginal pollution damage when designing a spatial uniform environmental regulation. I provide a theoretical framework to demonstrate how differential impacts of environmental regulations, commonly treated as a second-order factor, can matter for efficiency under the second-best setting. Two factors enter the optimal emissions taxation design, the extent of market power and covariance between the costs of abatement and the benefits of emission abatement. This theoretical framework provides a natural statistic that can be tested empirically to check whether local heterogeneity matters for efficient policy designs.

Then, I apply the model to the Chinese cement industry, document the extent of heterogeneity, and, test whether heterogeneity matters for efficiency in this context. By switching to the emissions tax rates that incorporate local heterogeneity, total welfare increases by 3.4 percent. If tax revenues are recycled in a form of output-based rebates to address the distortion from market concentration, total welfare further increases by 1.2 percent.

It is important to acknowledge several caveats of the paper. First, I study the short-term effect of environmental regulations, where I assume the underlying abatement technologies remain the same. Second, I build a static partial equilibrium model with heterogeneous firms that only incorporates a single industry. In reality, there can be cross-industry reallocation through consumers' substitution in the short-run and firms' entries and exits in the long run.

This framework can be extended in future research. First, how to design efficient carbon taxation, which takes into account the co-benefits of pollution abatement, can be studied. Carbon taxation involves global collaboration. Firm heterogeneity and spatial variation in pollution damage are more salient when designing carbon taxation. Then, at what level of government should the tax be, and how to deal with the limited information of regulators? Second, future research can be conducted in a more interdisciplinary way. A more complicated pollution dispersion model can be embedded to account for the spatial spillover of emission damage. This is especially critical to design environmental regulations to mitigate carbon.

References

Allen, T. & Atkin, D. (2022), 'Volatility and the gains from trade', Econometrica **90**(5), 2053–2092.

Bajari, P., Benkard, C. L. & Levin, J. (2007), 'Estimating dynamic models of imperfect competition', Econometrica **75**(5), 1331–1370.

Bento, A., Kaffine, D., Roth, K. & Zaragoza-Watkins, M. (2014), 'The effects of regulation in the presence of multiple unpriced externalities: Evidence from the transportation sector', American Economic Journal: Economic Policy **6**(3), 1–29.

Bovenberg, A. L. & Goulder, L. H. (2002), Environmental taxation and regulation, in 'Handbook of public economics', Vol. 3, Elsevier, pp. 1471–1545.

Buchanan, J. M. (1969), 'External diseconomies, corrective taxes, and market structure', The American Economic Review **59**(1), 174–177.

Burtraw, D., Holt, C., Palmer, K. & Shobe, W. (2022), 'Price-responsive allowance supply in emissions markets'.

Callaway, B. & Sant'Anna, P. H. (2020), 'Difference-in-differences with multiple time periods', Journal of Econometrics .

Cardoso, D. S. (2020), 'Optimal carbon taxation under oligopoly: An application to commercial aviation'.

Cohen, A. J., Ross Anderson, H., Ostro, B., Pandey, K. D., Krzyzanowski, M., Künzli, N., Gutschmidt, K., Pope, A., Romieu, I., Samet, J. M. et al. (2005), 'The global burden of disease due to outdoor air pollution', Journal of Toxicology and Environmental Health, Part A **68**(13-14), 1301–1307.

Czigler, T., Reiter, S., Schulze, P. & Somers, K. (2020), 'Laying the foundation for zero-carbon cement', McKinsey & Company **9**.

Ericson, R. & Pakes, A. (1995), 'Markov-perfect industry dynamics: A framework for empirical work', The Review of economic studies **62**(1), 53–82.

Fowlie, M., Holland, S. P. & Mansur, E. T. (2012), 'What do emissions markets deliver and to whom? evidence from southern california's nox trading program', American Economic Review **102**(2), 965–93.

Fowlie, M. & Muller, N. (2019), 'Market-based emissions regulation when damages vary across sources: What are the gains from differentiation?', Journal of the Association of Environmental and Resource Economists **6**(3), 593–632.

Fowlie, M., Reguant, M. & Ryan, S. P. (2016), 'Market-based emissions regulation and industry dynamics', Journal of Political Economy **124**(1), 249–302.

Ganapati, S., Shapiro, J. S. & Walker, R. (2020), 'Energy cost pass-through in us manufacturing: Estimates and implications for carbon taxes', American Economic Journal: Applied Economics **12**(2), 303–42.

Goodman-Bacon, A. (2018), Difference-in-differences with variation in treatment timing, Technical report, National Bureau of Economic Research.

Goulder, L. H. (1998), 'Environmental policy making in a second-best setting', Journal of Applied Economics **1**(2), 279–328.

Grainger, C. & Ruangmas, T. (2018), 'Who wins from emissions trading? evidence from california', Environmental and resource economics **71**(3), 703–727.

Hernandez-Cortes, D. & Meng, K. C. (2020), Do environmental markets cause environmental injustice? evidence from california's carbon market, Technical report, National Bureau of Economic Research.

Hottman, C. J., Redding, S. J. & Weinstein, D. E. (2016), 'Quantifying the sources of firm heterogeneity', The Quarterly Journal of Economics **131**(3), 1291–1364.

Hsieh, C.-T. & Klenow, P. J. (2009), 'Misallocation and manufacturing tfp in china and india', The Quarterly journal of economics **124**(4), 1403–1448.

Ida, T., Ishihara, T., Ito, K., Kido, D., Kitagawa, T., Sakaguchi, S. & Sasaki, S. (2022), Choosing who chooses: Selection-driven targeting in energy rebate programs, Technical report, National Bureau of Economic Research.

Ito, K. & Zhang, S. (2020), 'Willingness to pay for clean air: Evidence from air purifier markets in china', Journal of Political Economy **128**(5), 1627–1672.

Levinson, A. (2009), 'Technology, international trade, and pollution from us manufacturing', American economic review **99**(5), 2177–92.

Liu, J., Tong, D., Zheng, Y., Cheng, J., Qin, X., Shi, Q., Yan, L., Lei, Y. & Zhang, Q. (2021), 'Carbon and air pollutant emissions from china's cement industry 1990–2015: trends, evolution of technologies, and drivers', Atmospheric chemistry and physics **21**(3), 1627–1647.

Lyubich, E., Shapiro, J. & Walker, R. (2018), Regulating mismeasured pollution: Implications of firm heterogeneity for environmental policy, in 'AEA Papers and Proceedings', Vol. 108, pp. 136–42.

Macchiavello, R. & Morjaria, A. (2021), 'Competition and relational contracts in the rwanda coffee chain', The Quarterly Journal of Economics **136**(2), 1089–1143.

Miller, N. H. & Osborne, M. (2014), 'Spatial differentiation and price discrimination in the cement industry: evidence from a structural model', The RAND Journal of Economics **45**(2), 221–247.

Miller, N. H., Osborne, M. & Sheu, G. (2017), 'Pass-through in a concentrated industry: empirical evidence and regulatory implications', The RAND Journal of Economics **48**(1), 69–93.

Pizer, W. A. (2002), 'Combining price and quantity controls to mitigate global climate change', Journal of public economics **85**(3), 409–434.

Roth, J. & Sant'Anna, P. H. (2021), 'Efficient estimation for staggered rollout designs', arXiv preprint arXiv:2102.01291 .

Ryan, S. P. (2012), 'The costs of environmental regulation in a concentrated industry', Econometrica **80**(3), 1019–1061.

Shapiro, J. S. & Walker, R. (2018), 'Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade', American Economic Review **108**(12), 3814–54.

Shapiro, J. S. & Walker, R. (2020), Is air pollution regulation too stringent?, Technical report, National Bureau of Economic Research.

Shapiro, J. S. & Walker, R. (2021), Where is pollution moving? environmental markets and environmental justice, in 'AEA Papers and Proceedings', Vol. 111, pp. 410–14.

Syverson, C. (2004), 'Market structure and productivity: A concrete example', Journal of political Economy **112**(6), 1181–1222.

Weber, P. (2021), Making clean firms cleaner: Targeting environmental regulation to maximize returns, in 'AEA Papers and Proceedings', Vol. 111, pp. 436–39.

Weitzman, M. L. (1974), 'Prices vs. quantities', The review of economic studies **41**(4), 477–491.

Appendices

A Appendix Figures

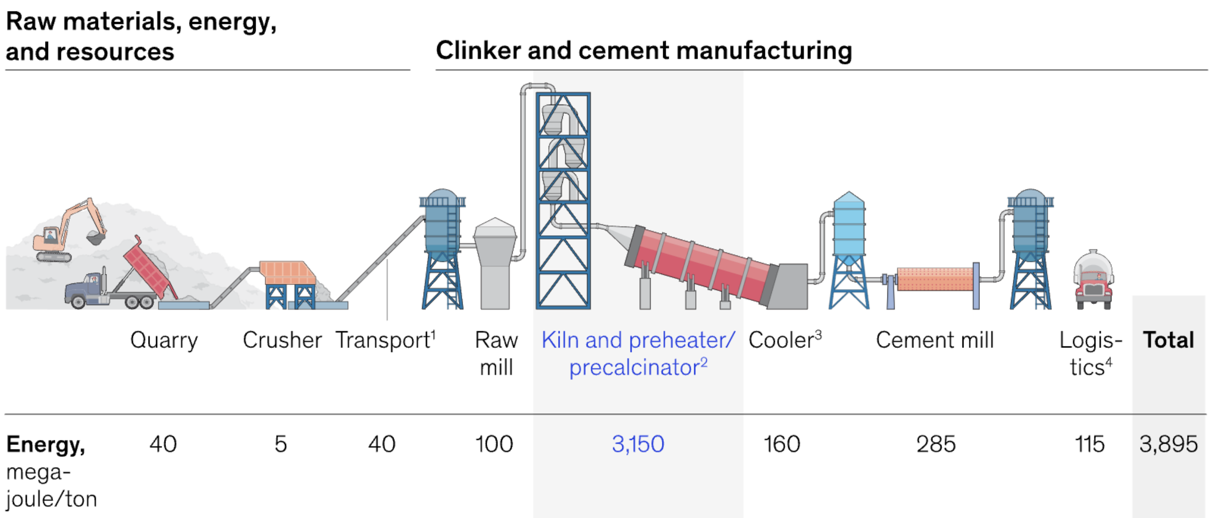


Figure A.1: Cement Production Process

Note: From Czigler et al. (2020)

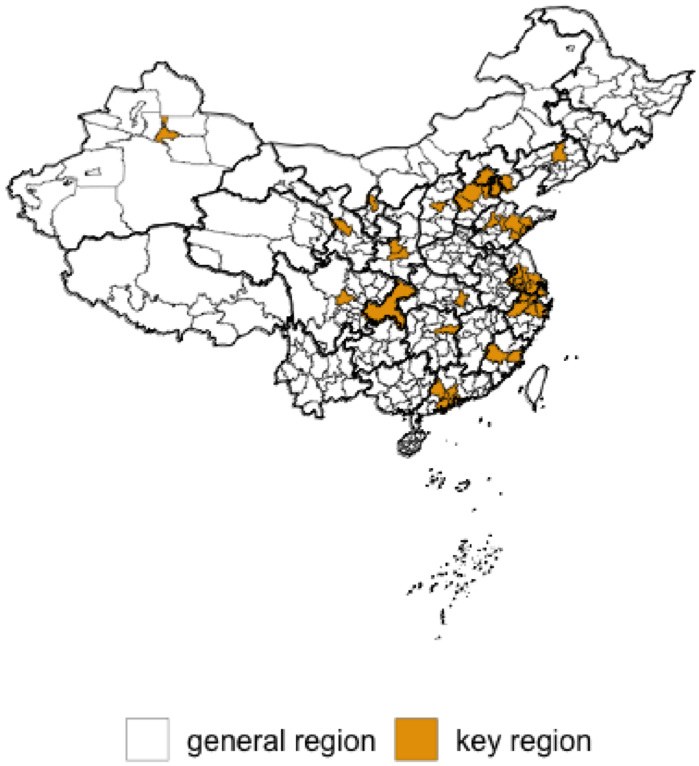
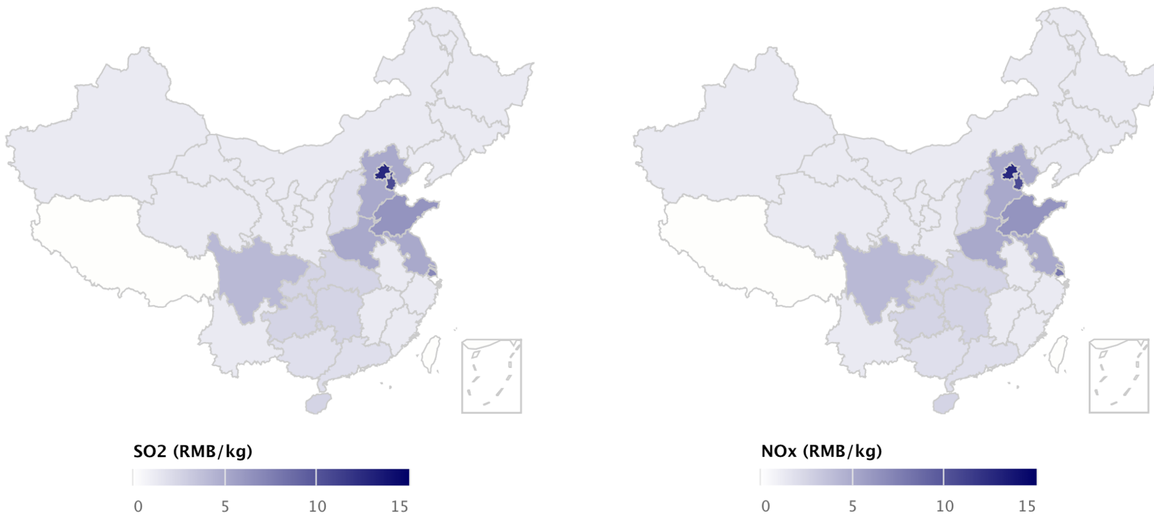
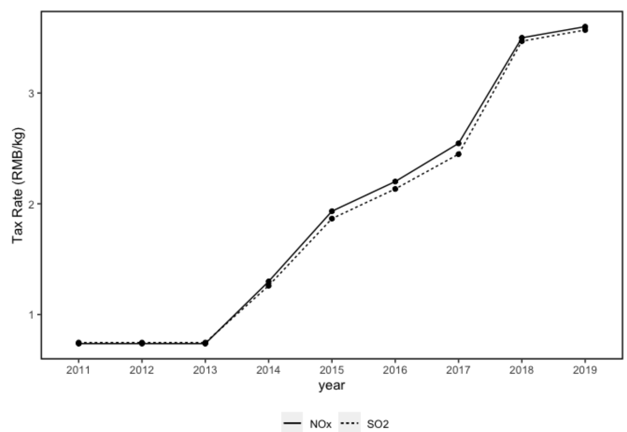


Figure A.2: Key Regions for Emission Standards in China



(a) Emissions Tax Rates by Province in 2018



(b) Average Emissions Tax Rates by Year

Figure A.3: Emissions Tax Rates in China

Note: This figure reports emissions tax rate changes by province across years. Panel (a) shows the spatial variation of the emissions tax rates. Panel (b) shows average emissions tax rate changes over time.

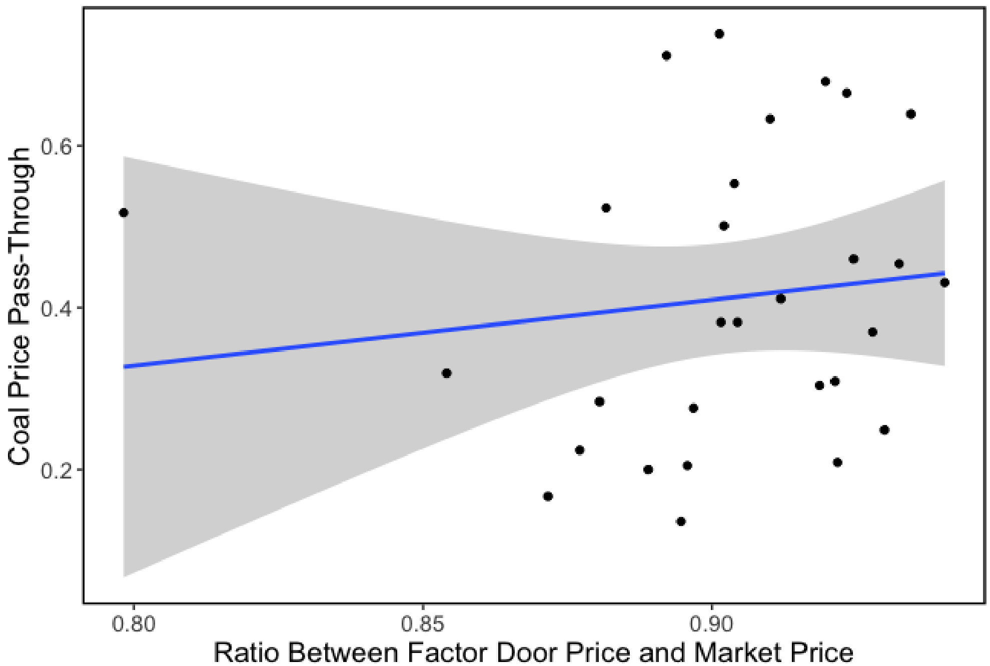


Figure A.4: Correlation Between Two Market Power Measures

Note: This figure reports the correlation between two market power measures. This first one is used in the theoretical model and is defined as the ratio between firms' factor door prices and the market price. The second is firm-level coal price pass-through. The high correlation between these two measures suggests that the market power measures are consistent across different specifications.

B Appendix Tables

Standards ID	Effective Date	Pollutant	General Standards mg/m^3	Special Standards mg/m^3
GB 4915-2004	07-01-2006	Particulate Matter	100	100
		SO_2	400	400
		NO_2	800	800
		Fluoride	10	10
	01-01-2010	Particulate Matter	50	50
		SO_2	200	200
		NO_2	800	800
		Fluoride	5	5
GB 4915-2013	07-01-2015	Particulate Matter	30	20
		SO_2	200	100
		NO_2	400	320
		Fluoride	5	3

Table B.1: Emission Standards in China's Cement Industry

Note: Starting in 2013, the emission standards specify special standards in the key region and general standards everywhere else. The effective dates in the table apply to existing plants. The emission standards for new plants normally occurred one year before the dates for existing plants. Since only cement plants that survived the whole study period are included in the main data, we only focus on existing plants.

C Appendix Derivations

C.1 Comparative Statistics from the Theoretical Framework

$$
\frac{dP_m}{d\tau_e} = \frac{(1+\frac{1}{\delta})\sum_i e_i}{\sum_i \epsilon_i + \frac{1}{\alpha_1}} > 0 \tag{19}
$$

$$
\frac{dp_i}{d\tau_e} = \frac{\epsilon_i(1+\frac{1}{\delta})\sum_i e_i}{\sum_i \epsilon_i + \frac{1}{\alpha_1}} > 0 \tag{20}
$$

$$
\frac{dQ_m}{d\tau_e} = \frac{\alpha_1(1+\frac{1}{\delta})(\sum_i e_i)Q_m}{((\sum_i \epsilon_i + \frac{1}{\alpha_1})P_m} = \frac{(1+\frac{1}{\delta})\sum_i e_i}{\sum_i \epsilon_i + \frac{1}{\alpha_1}}\frac{dQ_m}{dP_m} < 0 \tag{21}
$$

$$
\frac{dc_a(e_i)}{d\tau_e} = \frac{e_i}{\delta} \tag{22}
$$

$$
\frac{de_i}{d\tau_e} = -\frac{(A_i\delta)^{\frac{1}{1+\delta}}}{1+\delta}\tau_e^{-\frac{1}{1+\delta}-1} \tag{23}
$$

where $\mu_i = p_i - \frac{dc_i(q_i)}{dq_i} - c_a(e_i) - \tau_e e_i$.

C.2 Coal Price Pass-Through

$$
\frac{dP}{dMC} = \underbrace{\frac{dP/P}{dMC/MC}}_{\text{pass-through elasticity}} \times \underbrace{\frac{P}{MC}}_{\text{markup}}
$$

Pass-through elasticity:

$$
p_{ist} = \rho mc_{it} + X_{it} + \eta_i + \pi_t + \epsilon_{ist}
$$

- p_{ist}: log of output price of plant i in province s at time t (monthly)
- mc_{it} log of the marginal cost of plant i at time t
- Bartik instrument for marginal cost: product of (lagged) industry fuel input shares and national time-series variation in the prices of these fuels