The Spatial Expansion of Environmental Policies: Local Pollutant Cap-and-Trade Systems in Korea*

Cheolhwan Kim†

Yale University

First Version: May 2024
This Version: January 30, 2025

Abstract

After decades of implementing several local air pollutant cap-and-trade systems in Seoul Capital Area, South Korea expanded its target regions in 2020. Using district- and plant-level data, I analyze the impact of the expansion on the geographic distribution of emissions and industrial output, focusing on abatement and leakage. The policy decreased its key target, TSP emissions by 13% in target districts. This reduction was driven by cleaner fuel mix represented by electrification − with potential leakage to power plants − and leakage between firms. Also, the firm network played an important role since affiliated plants that were not directly targeted by the policy shared the electrification, and there was leakage within firms. Further, the fact that there was no significant loss in value added in target districts imply that within- and between-firm leakage were mostly within districts. I embed these findings in a spatial general equilibrium model of trade, multiregional production, and emissions. The model addresses identification limitations, provides an interpretation of the empirical findings,

*I am grateful for the support of the Economic Growth Center at Yale. Seunghak Lee and Soeun Park provided outstanding research assistance. I am deeply grateful to Costas Arkolakis, Amit Khandelwal, and Samuel Kortum for their encouragement and guidance. I thank Nicholas Ryan, Kenneth Gillingham, Niclas Moneke, Rohini Pande, and Mayara Felixfor their invaluable feedback and participants at seminars for their helpful comments. All errors are mine. The statistical analysis of firm and plant level data in Korea reported in this study was conducted at a Statistics Data Center of Statistics Korea under arrangements that maintained legal confidentiality requirements (Project Number 5495). Any views expressed are those of the author and not those of Ministry of Environment and Statistics Korea. Statistics Korea's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. The author declares that no relevant or material financial interests are related to the research described in this paper.

†Email: cheolhwan.kim@yale.edu

and allows several counterfactual policy analyses. I quantify the effect of the policy expansion. Then, I study the effect of different spatial policy variations to evaluate the aggregate and regional implications and the effect of an electricity use regulation to consider the emissions from power generation.

JEL Codes: D58, F12, F14, F18, F23, O31, O32
Keywords: Local cap-and-trade system, Abatement, Leakage, Multiplant

1 Introduction

In recent decades, the emissions of local and global air pollutants have been a key policy issue worldwide.[1] A central theme has been reducing emissions, ideally through abatement or clean innovation, such that sustainable growth can be achieved. Abatement comes in the form of fuel intensity improvement, cleaner fuel composition, or emission control devices (e.g., filters and scrubbers). Clean innovation is different from abatement as it is about new products or new production technology (e.g., bill of material) with less emissions. However, these policies can have unintended effects, creating many types of emissions relocation, a phenomenon referred to as leakage in the literature. Broadly, I consider three contexts in which leakage can happen. First, there might be within-firm leakage such that targeted plants shift their emissions and production to non-targeted ones within firms (affiliated plants). Second, there might be between-firm leakage such that targeted plants become less competitive in the market or outsource polluting activities, allowing non-affiliated and non-targeted plants to capture a greater share of production and pollution. Third, there might be leakage to the power generation sector as targeted plants increase their electricity use decreasing fossil fuel consumption (electrification).[2] Depending on the capacities of power plants with different energy sources, the excess demand in electricity can result in greater pollution by the power generation sector. Furthermore, due to administrative burden, most environmental policies in reality prioritize some areas. This locality tends to strengthen the types of leakage between targeted and non-targeted regions. For example, the excess demand in electricity can result in greater pollution by the power generation sector in regions with polluting power plants. In light of these considerations, a set of questions emerge: what is the effect of local environmental policy on the geographic distribution of emissions and industrial output? how is abatement achieved? what are the types of leakage that arise?

To address these questions, this paper focuses on the spatial expansion of local air pollutant cap-and-trade systems in Korea in 2020 and studies the policy effect on the geographic distribution of emissions and output. In evaluating the policy effect, it investigates the

[1] Local air pollutants studied in this paper are NO_x, SO_x, and TSP, which have geographically limited impacts. Global air pollutants are greenhouse gases that affect everywhere no matter where they originate from. This paper studies both, with more weight on the former to be consistent with the policy of interest.

[2] This type of emissions is referred to as Scope 2 emissions, which are indirect emissions from the consumption of purchased electricity, steam, heating, and cooling. These emissions occur as a result of the generation of electricity or other energy sources that a company purchases for its own operations. Even though the emissions occur at the power plant level (not directly at the company), they are attributed to the company based on its energy use. In contrast, Scope 1 emissions refer to direct emissions that come from sources owned or controlled by a company. Environmental policies, in general, have targeted Scope 1 emissions only. Exceptions are the Korean Emissions-Trading-System and the European Union's Carbon Border Adjustment Mechanism.

abatement and leakage mechanisms explained above, using the data of real-time and computed emissions as well as production. Empirically, I find that the policy decreased target emissions by 13% without hurting value added in a significant way. Such results came from the combination of within- and between-firm leakage as well as industrial electrification and the use of emission control device shared within firms. Based on these findings, I build a spatial general equilibrium model of trade, multiregional production (MP), and emissions to address empirical identifying limitations and conduct counterfactual policy analyses.[3] After estimating the model, I start by quantifying the aggregate and regional effects of the policy expansion to evaluate the policy, adding emissions from power plants. This exercise can convey an important policy implication. Industrial electrification can provide a potential pathway to a sustainable growth if paired with clean power generation.[4] This is especially the case for developing countries that are in the process of building these infrastructures. In line with this margin, I analyze the effect of an electricity use regulation to see the importance of electrification and leakage to power plants. Lastly, I investigate the effect of different regional policy variations to study the spatial implications further, which can have another important policy implication. The spatial implication of local environmental policy can deliver a lesson to rising cross-country conflicts on pollution controls and externalities. Although the policy itself is domestic, there are spatial variations in environmental policies and rich micro data that allows me to see the response of firms and plants in the universe − whether they became cleaner or shifted pollution somewhere else.

In Section 2, I provide the policy background. Initially, there was a concentration regulation on local air pollutants for a few large emitters, but the Korean Ministry of Environment changed the policy regime because the previous regulation could not control the total amount of emissions. As a result, the cap-and-trade system was first introduced in Seoul Capital Area, an area surrounding the capital of South Korea, in 2008. In other areas, the previous concentration regulation remained. Later, in 2020, the cap-and-trade was suddenly expanded to other three areas, Central, Southern, and Southeastern areas, still leaving non-targeted areas. These areas are an aggregate of districts in Korea.[5] Priority has been given to these areas because of their large populations and emissions. Each area had own pollution market where targeted plants could trade their emission allowances, but trading across markets was not allowed. Each system had own total emission allowance through which the Ko-

[3]Throughout the analysis, trade denotes within-country cross-region trade.

[4]I classify hydro, nuclear, solar, or wind as a source of clean power generation and fossil fuel as a source of dirty power generation.

[5]In the period of analysis, Korea had around 230 districts. They are the smallest administrative units with self-governing authorities, which is smaller than metropolitan cities and provinces. The latter is a larger administrative unit, which amounts to 17. For example, Seoul Metropolitan City and Gyeonggi Province.

rean Ministry of Environment changed the pollution prices and hence total emissions in the area. In each market, plants in mining and manufacturing and power generation sectors are extensively targeted as they accounted a significant portion of emissions. More specifically, plants that emitted NO_x, SO_x, or TSP more than a certain threshold became subject to the policy and were given emission allowances. Target plants had to buy emissions allowances for excess emissions, or they could sell or save the residual. The policy was designed to be binding under business as usual (BAU) because initial allowances were set to the pre-policy emissions levels and they decreased linearly every year.

In Section 3, I describe the datasets used in the analysis. Note that the questions require micro data and foundation because, as noted above, there are many channels that matter quantitatively. Also, firm heterogeneity matters for better mapping between policy and analysis. Environmental policy, in practice, targets large polluters who are cleaner in terms of emissions intensity. This is because it is hard to regulate pollution across all firms and plants. But such a policy design can encourage leakage to non-targeted polluters who are dirtier. If they are in the same regions, the policy effect might be mitigated. If they are not, emissions are leaked. Hence, I combine several rich datasets about mining and manufacturing sectors that have the information about location, sector, id, revenue, employment, financial and detailed operation information, fuel use, and emissions at the plant, firm, and district levels. They include several policy-related data and census data, which constitute the basis of analysis. Additionally, I merge a power plant database that tracks the fuel use, capacity, electricity generated, and location of each power plant.

In Section 4, I use the data and conduct several empirical analyses to see the policy effect: did the policy decrease target emissions? was there any abatement? was there any types of leakage? which one was larger? In order to answer these questions, I compare the emissions and valued added of targeted districts to those of non-targeted ones and find that the policy decreased target emissions by 13% without hurting value added in a significant way. Motivated by this result, I compare the emissions and output of (1) targeted plants with those of non-targeted ones and (2) affiliated plants with those of non-targeted ones to see the mechanism behind. I find that the policy induced cleaner fuel mix (electrification) and leakage within and outside firm boundary. Interestingly, electrification was shared within firm boundary. The result implies the subtlety of firms' responses: the non-rivalry of clean technology and the relocation of output and pollution. Further analysis on power plants is in progress to capture how power plants responded to the policy and how electrification affected power plants.

In Section 5, I develop a spatial general equilibrium model of trade, MP, and emissions, based on the empirical findings above. The goal of the structural approach is to interpret the

empirical evidence, address several identifying limitations in it, and conduct counterfactual policy analyses. I introduce fuel use, emissions, and firm-level abatement into a model of trade and MP. The former is the novelty of the model that captures emissions and diverse abatement mechanisms that are shared are the firm level. Fuel use, along with power plants, also help to evaluate leakage to power plants. Trade and MP help to capture within and between firm leakage. In Section 6, I calibrate and estimate the parameters of this model. In Section 7, I conduct several counterfactual exercises. First, I investigate the policy effect on the geographic distribution of pollution and economic activities and its aggregate impact. Second, I regulate industrial electricity use. This analysis enables firms and plants to internalize potential pollution externality that originates from electrification. The first two exercises give an important lesson that sustainable growth can be achieved with industrial electrification and clean power generation. It resonates more with developing countries that are building their infrastructure. Third, I study the importance of spatial variations in the policy by imposing unilateral pollution tax or more asymmetric one. This analysis provides a lesson on growing regional disputes over emissions control and corresponding externalities.

Related literature. This paper builds on three strands of literature, bridging the gap between two strands of literature that study the impact of environmental policies on leakage and abatement and clean innovation and introducing them in space to analyze the geographic distribution of emissions and output. The first literature examines how environmental policies influence abatement or clean innovation. Abatement has been studied in a reduce form (Copeland and Taylor (2004)), with emission control devices (Greenstone et al. (2022)), and with changes in sets of fuel types used in production (Murray Leclair (2024)). The literature on clean innovation complements it as clean innovation is conceptually different from abatement (Acemoglu et al. (2012) − see Hémous and Olsen (2021) for a review). In general, it has been accompanied with the study of clean and dirty patents (Aghion et al. (2016)). Furthermore, there is a burgeoning literature that evaluates the effect of a cap-and-trade system on pollution and output with the growing popularity of cap-and-trade system (Fowlie, Holland, and Mansur (2012); Wagner and Petrick (2014); Wagner et al. (2014); Greenstone et al. (2022); Kim (forthcoming)). Such market-based regulations are known to be effective as they provide not only compliance flexibility but also cost effectiveness. I will explore the importance of this mechanism in quantification. However, these papers do not consider any relocation of emissions from regulated to non-regulated units. The second literature fills this gap by investigating the effect of environmental policy on the relocation of pollution and production (Eskeland and Harrison (2003); Levinson and Taylor (2008); Hanna (2010); Broner, Bustos, and Carvalho (2012); Chen et al. (2021); Tanaka, Teshima, and Verhoogen (2022); Yang et al. (2024)). However, this literature ignores abatement and clean innovation

that can arise from environmental policy.

This paper combines the insights of both and studies how environmental policy lead to abatement and leakage and hence emissions and output. Such a balance is necessary because, although both types of responses reduce emissions, their welfare implications can be significantly different. This paper provide more concrete channels of each. For abatement, fuel intensity, fuel substitution, and emission control devices are studied, which have been rarely studied in the literature. For leakage, I extend the literature by considering various forms of leakage. The leakage literature focuses on within- or between- firm leakage where firms and plants shift their dirty production inside or outside firm boundary. This paper additionally considers leakage to power plants because firms and plants can attribute emissions to the power generation sector through electrification. In this context, how clean power generation is another important aspect in evaluating environmental policy (Arkolakis and Walsh (2023)). However, there is still a missing puzzle, space. Considering space is important because different regions are exposed to environmental policy to different degrees, creating different spatial distribution of emissions and output. This margin becomes more significant when the effect of emissions is local.

The third literature relates to this gap by examining the effect of environmental policy or climate shocks in space (Golosov et al. (2014); Desmet, Rossi-Hansberg (2015); Shapiro and Walker (2018); Conte et al. (2021); Farrokhi and Lashkaripour (2024); Kortum and Weisbach (2021); Cruz and Rossi-Hansberg (2022); Krusell and Smith JR (2022); Desmet, Rossi-Hansberg (2023); Weisbach et al. (2023); Cruz (2024); Cruz and Rossi-Hansberg (2024) – see Cherniwchan, Copeland, and Taylor (2017) and Copeland, Shapiro, and Taylor (2021) for a review). This paper contributes to this literature by providing more concrete and diverse channels of abatement and leakage. It is one of the first papers that examine abatement from fuel technology and emission control devices as well as leakage within- and between-firms and to power plants in space. Furthermore, MP and firm heterogeneity are borrowed from an expanding body of literature on trade and MP (Ramondo and Rodríguez-Clare (2013); Tintelnot (2017); Arkolakis et al. (2018); Sun (2020)). This choice is made because they not only match the data and policy better but also have critical policy implications. In practice, large polluting plants are targeted by environmental policy, whose firms have many other plants, and are cleaner in terms of emissions intensity. Then, their response can be more nuanced. For example, leakage within and between firms are one of the easiest ways plants can respond, which can pose a quantitative question. If there is leakage in target areas, the policy effect might be mitigated. Or if there is leakage between targeted and untargeted areas, emissions might be relocated. Note that such microfoundation is possible because of the micro data that contain the universe of mining and manufacturing plants and firms in

Korea.

Lastly, there is a set of closely related papers. Arkolakis, Kim, and Murray Leclair (2025) studies the effect of environmental policy on emissions and output across regions with trade and dynamic changes in sets of fuel types used in production. Garcia-Lembergman et al. (2023) set up a seminal model where trade, MP, energy use, and emissions are combined. They account for the role of MP emissions and output across regions, but without environmental policy, leakage, and abatement and clean innovation. Xiang (2023) extends Garcia-Lembergman et al. (2023) and studies the role of environmental policy on emissions and output with trade, MP, and dynamic clean innovation. The key difference of this paper to them is that it analyzes leakage within firms and to power plants and diverse abatement mechanisms − fuel intensity, fuel composition, and emission control devices − non-rival at the firm level, abstracting from dynamic fuel set changes and clean innovation. This set of new mechanisms fits better the empirical evidence this paper presents, reflects that emissions are local, and, most importantly, provides different policy implications. Leakage to power plants is an important consideration when assessing the policy effect. For example, the excess demand in electricity from electrification can turn on dirty power plants, creating new emissions in different regions. Diverse abatement mechanisms reflect that fuel technology and emission control devices are effective tools in curbing emissions coming from fossil fuel use and production process. The fact that they tend to be shared within firms has an important policy implication because of the policy spillover. In particular, when we focus on emissions that are local, the effect of such mechanisms become more critical. However, they are mostly about the short run responses. For changes in the long run, Arkolakis, Kim, and Murray Leclair (2025) and Xiang (2023) can explain better because changes in fuel sets and clean innovation are costly and take time to realize.

The remainder of the paper is organized as follows. Section 2 provides the policy background. Section 3 describes the data. Section 4 provides empirical evidence. Section 5 presents a theory. Section 6 describes model calibration and estimation, and Section 7 reports the quantitative result. Section 8 concludes.

2 Policy background

This section explains the policy background using several policy documents published by the Korean Ministry of Environment. The ministry has adopted two policies, a concentration regulation and a cap-and-trade system, to lessen the emissions of local air pollutants (NO_x, SO_x, and TSP) of large polluters. In both policies, the targeted emissions are confined to Scope 1 emissions that occur inside the plant boundary, which is the policy unit.

Several large polluting power plants were also targeted by the policy, making Scope 2 regulations redundant. However, there are also differences. The concentration regulation was a command-and-control regime that set the concentration criteria of pollutants for emission facility types and imposed fines for any violations since 1995.[6] But the government felt the need to control the amount of emissions because the amount itself could be large despite the low concentration of emissions. For this reason, a cap-and-trade system was introduced in 2008 and expanded in 2020 where the amount of each local air pollutant emissions were capped in targeted regions, and emissions allowances were freely traded. For TSP, the first adoption was in 2018.

Figures A.1 and A.2 well summarize the spatial expansion of the policy and the policy goal for each pollutant. This is because the government price emissions by controlling emissions allowances in each area $\times$ pollutant market. This price is directly related to the cost of emitting different local air pollutants. High and stable permit price is a credible signal of regulatory stringency. Whether these prices were sufficient to deliver meaningful reductions in regulated emissions, and whether these reductions were offset by increases in unregulated emissions, are empirical questions that I answer in Section 4.Ultimately, the policy aims to decrease total emissions to around 40% of 2019 emissions by 2024. This number was calculated based on a scenario where plants would adopt the best abatement technology available. The technology was designed to be renewed every three years through discussion between the government and targeted plants. Table A.2 summarizes the concrete goals of the policy for each local air pollutant.

How emissions allowances were allocated also matters to understand the policy goal better. The general pattern is a linear decrease over time, which reflects how emissions allowances were allocated to plants. Once being subject to the policy, targeted plants were freely allocated emission allowances according to their latest emissions and the feasible reduction scenario. Although the initial allowance was set to the emission level of 2019 for adjustment, the allowance has decreased linearly over time to satisfy the policy goal above considering feasible abatement technology. This design makes the policy binding under business as usual (BAU), which is a common design in cap-and-trade system.

There are two notable patterns we can observe from the figures. One is that the system was not decreasing in Seoul Capital Area before the expansion. For this reason, I keep plants treated by the initial adoption in the baseline empirical analysis later. The other is that TSP has been more strictly regulated than the other pollutants. This difference originates from

[6]Note that a command-and-control system is the simplest and the most general form of environmental policy. It can be found in developed countries such as European Union countries and developing countries such as India.

the fact that the emissions of TSP and PM from plants have played a critical in expanding the policy. They have accounted for the lion's share of such emissions. For example, a government briefing in 2020 highlighted that the PM emissions of plants accounted for 39% in 2019, which dominated the shares of the other sources. Lastly, there are other policy details. To avoid any harms to early adopters, plants that decreased emissions early have been subject to the five-year average emissions level. Emission allowances could be carried over one year, but borrowing was not permitted.[7]

Throughout the analysis, the treatment is being subject to the cap-and-trade system in 2020. The pretreatment is being absent of any policies. The pretreatment state or the status quo can be being subject to the concentration regulation, but not necessarily. The treated plants were subject to the concentration regulation, but the controlled plants might not have been subject to the same policy as the target was differently selected. For example, the policy unit has changed. The concentration regulation targeted specific polluting facilities while the cap-and-trade system targeted a plant. Also, the concentration regulation has been maintained, but it has been relaxed for targeted plants. So it is less likely for this past regulation to have affected the policy effect.[8]

Monitoring and Punishment

Measuring, reporting, and verifying (MRV) was monthly. Targeted plants were evaluated through their monthly emissions reports and 3rd party verification.However, the evaluation was once a year. Plants that emitted more than their emissions allowances − allocated or traded − were subject to fine proportional to excess emissions and reduction in its allowance proportional to excess emissions. In the worst case, they faced the suspension of business. In general, the penalty was based on excess emissions, regulated areas, the number of violations, and more.

2.1 Policy target

This section explains the target of the policy in three steps. The policy targeted (3) major polluters in high-emissions (2) sectors and (1) regions. I begin with the last criterion first.

[7]The policy design was to meet the annual cap. For example, firms anticipating higher costs in the future are likely to save.

[8]Although the prices and circulations of allowances have increased over time, the main analysis of this paper abstracts from permit allocation for two reasons. First, by a Coasian argument, permit allocation should not affect firm behavior at the margin (Coase (1960)). Second, I lack a credible strategy to test for a causal effect. For such an analysis, see Fowlie and Perloff (2013).

2.1.1 Regions

The policy initially targeted Seoul Capital Area, an aggregate of districts surrounding the capital of Korea, Seoul. Later, it expanded its scope to Central Area, Southern Area, and Southern-East Area. These districts were chosen based on their severe air conditions through expert reviews, discussions among local administrative units and stakeholders, and public information sessions. According to several government officials in charge, the priority of these areas came from the welfare consideration of the policy, given an administrative budget, because they accounted for more than 80% of PM concentration and emissions as well as 88% of the population and 38% of the land area. It is well known that the more plants are regulated, the more costly the regulation becomes. In other words, leakage from target regions to non-target regions was not intentional because there was a concern for it and local air pollutants still could travel although their effects decrease in distance. However, this leakage is still a concern that I investigate it empirically in Section 4.

Figure A.3 summarizes the policy history in a map of Korea that is divided into districts. Note that each area has a separate cap-and-trade system for each local air pollutant. Furthermore, the area does not align with the province boundary and the local jurisdiction of the Ministry of Environment. This gap makes the empirical analysis in Section 4 free from other confounding policy effects whether they are environmental ones or not. In terms of the geographic distribution of the targeted plants, see Table A.3.

2.1.2 Sectors

This paper focuses on the mining, manufacturing, and power generation sectors for the following reasons. First, as the first panel of Figure A.4 shows, the number of treated plants tripled with the expansion, and at the same time, 75% of targeted plants were in these sectors. Second, as the second panel of Figure A.4 shows, emissions from these sectors decreased after the expansion, which accounted for a significant portion of target emissions. In TSP, it was 55%. As indicated by the first point, emissions from these sectors decreased faster (29%) than the rest (36%).

Power plant

The power generation sector, however, deserves careful approach. This is because, power plants are subject to the direct effect of the policy through the regulation and the indirect effect of the policy arising from industrial electrification that was one of the key responses by targeted industrial plants. From the former, Scope 2 regulation such as one on electricity use was not necessary. In the latter, whether there was enough clean power generation to avoid

leakage to power plants matters to evaluate the policy. If clean power generation capacity satisfied the extra demand from the industrial electrification, it was the best scenario. In addition, the geographic distribution of clean and dirty power plants with different capacities is critical, especially when pollutants are local.[9]

The reality needs to be understood with the data. However, in order to understand the data, the electricity market needs to be understood first. The electricity market was managed by the government buying electricity at different prices from power plants and selling at a uniform price to final users − household, industry, and more. There have been two systems that governed the market. One is the system marginal price (SMP) that determines the price of electricity by the marginal cost of the last generating unit required to meet demand at a specific point in time. As Figure A.5, the increased power generation cost is reflected in the wholesale (the auction price of fossil fuel generated electricity) and retail (the price of electricity in industrial use) electricity prices. This increase originates from both changes in fuel prices and environmental regulation. This increase implies that electrification was not a free lunch to industry. The other is the merit order dispatch (MOD) where the lowest marginal cost power stations are dispatched first to supply the grid, and then power is scheduled in the increasing order of marginal cost. Thus, the availability of renewable energy source is important as they have zero marginal costs and emit nothing into the atmosphere. Figure A.6 shows the power generation capacity by source, and the share of clean power generation increased from 36% in 2012 to 43% in 2024.

Whether the growth in power generation was enough is empirical and quantitative questions that this paper will answer later. However, note that the geographic distribution of clean and dirty power plants also matters. Indeed, figure A.7 shows that the distribution of dirty power generation does not overlap with that of clean power generation. How the extra demand in electricity from the industrial electrification can be supplied matters more when we consider such a difference. The issue becomes more serious when pollutants are local because unregulated (or less regulated) districts with dirty power generation can suffer.

2.1.3 Emitters

To be precise, the cap-and-trade system targeted plants in targeted regions.[10] The policy targeted large emitters: (1) emitted NO_x, SO_x, and TSP more than 10t per year in the last

[9] I abstract from grids because, according to Korea Electric Power Corporation and Ministry of Trade, Industry, and Energy, the electricity supply rate has been around 100% in a recent decade.

[10] In general, this policy design works better than the ones targeting firms. If it targeted firms, M&As and splits would have been easier, making it hard to track the targets and calculate emissions and allowances.

two years (2018 and 2019)[11]; and (2) emitted more than 4t of NO_x, 4t of SO_x, or 0.2t of TSP at least once in the past two years (2018 and 2019). Ideally, abatement should dominate leakage within- and between-firms, which I will examine later empirically and theoretically.

2.2 Policy Effect Preview

This project is the first attempt to evaluate the expansion of the policy.[12] So I briefly preview an interview summary before starting main analyses. Several public officials in charge of the two policies (the initial adoption, and the later expansion) were interviewed. According to the one in charge of the initial adoption, the policy decreased the amount of local pollutants emissions, but there has been a concern about leakage, which has not investigated yet. The need for the corresponding data has deterred any further analyses. As noted before, the effect of the second policy has not been analyzed. However, I was able to discuss the policy effect. According to the one in charge of the second wave, the policy seems to have worked effectively because, for example, many targeted plants installed emission control devices despite high costs of such installations. The same leakage concern existed in the second wave, but the one in charge refused to answer related questions.

3 Data

This section explains different datasets used in the analysis. The empirical analysis in Section 4 and the model quantification in Section 6 build on these rich datasets that describe production, energy use and air pollutant emissions by fuel type at various levels − plant, firm, district×industry, and district levels. They cover several years prior to the expansion, which helps the causal inference of Section 4 and the model identification of Section 6.

3.1 Policy Data

I use several pieces of policy-related information acquired from the Korean Ministry of Environment through a formal data request. First, I use a piece of information that has a list of targeted plants and their targeted pollutants, locations, sectors, and names to identify

[11]Let total emissions be the sum of NO_x, SO_x, and TSP emissions of a plant. According to the Ministry of Environment, type 1 is the type of plants that emit more than $80t$ in total, type 2 is the type of plants that emit more than $20t$ but less than $80t$, and type 3 is the type of plants that emit more than $10t$, but less than $20t$. Then this first condition is being classified as either type 1, type 2, or type 3.

[12]There were several attempts to evaluate the initial implementation in 2008. But there is no consensus. Im (2023) shows the effect of the initial adoption with potential leakage, while the Korean National Assembly Research Service reports that it was ineffective.

targeted plants and firms. There is also a separate dataset that has emissions and emissions allowances over time at the policy area levels, which helps understand the policy background, policy variations across districts, and pollution tax. In addition, I use four datasets related to the policy for analysis: tele-monitoring emissions records, district and industry emissions records, measuring station reports, and emissions factors. First, the tele-monitoring records come from the monitoring devices that were applied to a few large emitters. The list of its target includes a subset of both targeted and non-targeted plants before and after the policy expansion. After the policy expansion, they were expanded to all targeted plants.[13] The records show the real-time emissions and concentrations of TSP, SO_x, NO_x, HCI, HF, NH_3, or CO. But the coverage is limited since only large emitters are monitored. Second, the district and industry emissions records include similar air pollutant emissions measured for various activities at the district level. This is one of the datasets that the government used to design the expansion. The most detailed activity classification corresponds to the 3-digit Korea Standard Industry Classification (KSIC). Emissions in this dataset are computed using real-time emissions, input types, emissions factors, the use of emission control devices, and activity types. A strength of this dataset is that it is close to real-time emissions and the policy was grounded on it. Third, the measuring-station-level data are the collection of the real-time concentrations of local air pollutants in each measuring station spread across districts in Korea. These stations have records of SO_2 (ppm), NO_2 (ppm), PM 2.5 $(\mu g/m^3)$, and PM $2.5-10$ $(\mu g/m^3)$.[14] Lastly, the emissions factors are a set of emissions factors the policy used before installing sensors or to find its targets. Since the sensor coverage was around 30%, it was used extensively.[15] They are differentiated across fossil fuels, production processes of different products, and sectors. Without loss of generality, among fossil fuels, coal is the most polluting fuel, oil takes the second place, and then gas.

3.2 Industry Data

The key dataset is Statistical Business Registers (SBR) provided by Statistics Korea. This dataset contains the universe of firms and plants in Korea with the information about revenue, employment, fuel use and greenhouse gas emissions by fuel type, industry classification, and location. It defines a firm in two ways. Both treat corporations as firms. The difference is

[13] A few exceptions have been allowed based on the characteristic of outlets, cost-efficiency, and more.

[14] SO_2 is a part of SO_x as NO_2 is a part of NO_x. PM 2.5 captures particulate matters whose diameters are less than 2.5 micrometers, PM $2.5-10$ captures particulate matters whose diameters are between 2.5 and 10 micrometers, and TSP captures particulate matters whose diameters are more than 10 micrometers in addition to PM 2.5 and PM $2.5-10$. In measuring stations, PM 10 includes PM 2.5, but not the other way around.

[15] For brevity, this information is omitted but is available upon request.

in the way each treats non-corporations. One ties non-corporations as firms if they share at least one owner registered for their tax document while the other does not. I use the former in my analysis, but the result is robust to a change. Further, in 2021, the Survey on Energy Use and Greenhouse Gas Emissions in the Industrial Sector conducted by the Korea Energy Agency has been merged to the SBR, covering years since 2016. Although the survey has served as the basis of industrial environmental policies, misreporting is unlikely because the agency cross-checks other relevant data (e.g., real-time monitored data) to scrutinize the survey answer. Fuel use and greenhouse gas emissions by fuel type are only available for plants with non-zero sales in the mining or manufacturing sectors. This is another reason why I limit the sectors of interest. Fuel uses are measured in ton of oil equivalent (toe) and are categorized as coal, gas, oil, electricity, heat, and others. The category, others, captures the use of waste energy, bio energy, and more, which is not used in the analysis because only a small portion of plants use it and such an in-house energy source is hard to price. Heat is heat energy produced from fossil fuel or renewable so I drop it to avoid double-counting.[16] Then, I use emissions factors to calculate local air pollutant emissions by fuel type and industry-specific production process emissions without any overlaps between the two.[17][18] This is one of the datasets that the government used to design the policy expansion. There are emissions from electricity use, but I do not use them because they do not factor into the spatial distribution of power plants and their energy sources. Another key dataset is Mining and Manufacturing Survey (MMS) provided by Statistics Korea. It has detailed information related to production and finance such as the type of capital, fuel cost, electricity bill, material expense, and wage bill in the mining and manufacturing sectors.

3.3 Power generation Data

I also use the SBR to see how sales changed in targeted power plants within 4-digit KSIC. Given the electricity market mechanism in Korea, this design helps infer how power gener-

[16] Electricity use also include electricity generated by plants themselves. But I treat electricity use as bought without loss of generality. Targeted plants have no incentive to generate electricity by themselves because they can avoid emitting pollutants by buying electricity from outside. Also, it is known that electricity generated by non-power-plants takes around 3.8% of total electricity generation capacity, and there are only 32 manufacturing firms generating electricity by themselves (Survey on Independent Power Producers, 2022). This result is consistent with the finding in France (Colmer et al. (2024)).

[17] For example, producing paper-related products leads to TSP emissions in the production process.

[18] One caveat is that when calculating emissions from production process, I use output that deflates plant-level sales with the corresponding an industry level price without regional consideration. Ideally, I should use plant level unit price and unit output, but such information is not available. For this reason, I use the industry level price. However, since Korea is a small country, the lack of regional consideration is unlikely to change the result significantly. Also, sales is a good proxy of output. As will be shown in estimation (Section 6), sales has a log linear relationship with output, conditional on market variables.

ation changed from a change in sales. In addition, I use a power plant database acquired from Korean Electric Power Corporation which has information about the fuel use, capacity, electricity generated, and location of each power plant in the country. One caveat is that it only captures large power plants. Overall, the power plant data are useful to see how excess demand in electricity, such as industrial electrification, can affect emissions in aggregate and in other regions since different regions have power plants with different fuel types and capacities. I do not look into grids because, according to Korea Electric Power Corporation and Ministry of Trade, Industry, and Energy, the electricity supply rate has been around 100% in a recent decade. As for industrial plants, I use emissions factors for power plants if necessary.

3.4 Others

I use satellite data from Sentinel and Edgar to track real-time emissions across regions. This approach has been proved to be useful to capture the emissions of local air pollutants because they are local and last shortly. This characteristic is beneficial to the measurement as spillovers from the different regions or from the past are unlikely. Also, the unit is granular as it can go as far as 1km $\times$ 1km. I use various social costs of emissions borrowed from the literature for calibration. I use the rent and price of housing to proxy district-level prices of consumption and capital structure, which are rarely available at the fine grid.

3.5 Final Data

For the main dataset, I merge the policy target information, the SBR, and the MMS, using firm and plant tax codes and keep only mining and manufacturing and power plants. There are more details about the matching and cleaning process in Appendix A. Before starting the main analysis, note that this analysis requires micro data because how plants and firms react to the policy can matter quantitatively and provide different policy implications. First, in practice, large polluters are targeted by environmental policies due to administrative burden. But these large polluters are, in most cases, large plants of large firms that have many plants and are cleaner in terms of emissions intensity. So an environmental policy that can shift production within and outside firm boundary can mitigate the effect in targeted areas or worsen the pollution in non-targeted areas. For example, Chen et al. (2021) and Yang et al. (2024) empirically show that the relocation of emissions and output was large in response to environmental policies in China. Or abatement can dominate leakage within firms as clean innovation does in Xiang (2023)'s theory. Thus, it is critical to observe the universe of industrial plants before and after the policy to evaluate the policy. Second, there might

be leakage into the power generation sector. The policy has not included emissions from electricity use, and a significant portion of local air pollutant emissions originate from fossil fuel use. So in response to the policy, targeted plants might have switched from fossil fuels to electricity. In this case, if electricity was produced cleanly in specific regions matters. This locality becomes more important for local air pollutants. For these reasons, I analyze using the micro data to see how plants and firms responded to the policy.

Lastly, there is an important caveat in measuring emissions. As noted in Section 2, the policy used emissions factors before the policy and real-time emissions after the policy to track emissions at the plant level. Although both methods are the ones the policy used, there is a gap between the two. As shown in Greenstone et al. (2022), the role of emission control devices is powerful in reducing the emissions of local air pollutants. This finding implies that emissions computed with emissions factors can capture too much emissions. As will be shown below, using emissions factors is one of common ways to compute emissions. Because of the administrative burden, many government institutions follows a similar way, sometimes with more detailed information about fuels. Also, it is common in the literature (e.g., Wagner et al. (2014); Garcia-Lembergman et al. (2023); Colmer et al. (2024); Murray Leclair (2024)). Further, this approach helps to construct a tractable model. What matters is the role of emission control devices in decreasing emissions. I address this measurement issue by complementing the two approaches together. I use real-time emissions data if possible. However, one issue is that sometimes the data do not have enough information. For example, the district×industry data cannot differentiate emissions from targeted plants from the rest. Similarly, the satellite data and the monitoring station data cannot differentiate industrial emissions from other sources, let alone those from targeted plants. The tele-monitoring records only contain a subset of treated and non-treated plants. Thus, I use computed emissions to guide the microfoundation at the plant level behind any changes in real-time emissions. In addition, I exploit variations across treated plants because they were subject to different policy variations if they were in different policy areas or had different regulated pollutants. Different pollutants have different emissions factors.

4 Empirical analysis

The goal of this section is to estimate the policy effect empirically: did the policy decrease emissions? was there any abatement in energy use? were there any types of leakage? which one was larger if both happened at the same time? what happened to affiliated plants? The answers to these questions will not only show the policy effect but also guide a full-

fledged model analysis in Section B. Here I use difference-in-differences for causal inference.[19] I first evaluate the policy effect using real-time emissions, emissions alerts, and medical expenses at the district (or district×industry) level to see if the policy achieved its intended goal. I compare targeted regions and non-targeted ones and find that the policy decreased emissions in the targeted regions without hurting industrial output significantly. In other words, there was a significant emissions intensity improvement in targeted areas. This finding is interesting because it implies that there has been actual emissions intensity gains, which is different from those of other leakage focused papers (Chen et al. (2021); Tanaka, Teshima, and Verhoogen (2022); Yang et al. (2024)). Then, I evaluate the policy effect at the mining and manufacturing plant level to see the mechanism behind. Here I construct a partial equilibrium model of production and pollution. Guided by the model proposition, I answer the questions by comparing (1) targeted and non-targeted plants and (2) affiliated and non-targeted plants. Affiliated plants are defined to be the ones that belong to the same firm ownership as targeted ones. Non-targeted one are neither targeted nor affiliated ones. The result indicates that both targeted and affiliated plants decreased emissions, which came from decreases in emissions from production process and fossil fuel use. They adopted cleaner fuel mix through electrification and leaked pollution within and across firm boundary and to power plants. The corresponding analysis at the power plant level is in progress.

4.1 District level Policy effect

4.1.1 Empirical Strategy

The ultimate goal of the policy was to decrease emissions in targeted districts. To see the policy effect on emissions and industrial output on the treated and controlled districts, I start by comparing the trends of the targeted districts to those of the untargeted ones. Since the policy targeted plants in specific districts, the evidence can also be interpreted as market spillover. For the outcome variables, I look into real-time emissions from the district×industry data, the measuring station records, the satellite data, emissions alerts, and medical expenses as well as value added from the MMS. Logarithms are taken for all outcome variables. In the baseline specification, I implement this analysis with a semi-parametric difference-in-differences approach, following Heckman et al. (1997) and Heckman et al. (1998)

$$y_{dst} = \sum_{\tau \neq 2019} \beta_\tau \times Treat_{ds} \times Year_\tau + \epsilon_{dst}$$

[19] Note that despite the concern for SUTVA violation, difference-in-differences are the only way to conduct a causal inference. Regression discontinuity and instrument variable approaches require real-time emissions data, which are not available for all plants of interest.

where standard errors are clustered at the district×sector level, d denotes districts, s denotes 3-digit KSIC, and t denotes calendar years. The base period is 2019. Only for the district×industry data, there is s, and I exactly match on it. I only keep sectors where there is at least one targeted plants to focus of the sectors of policy interest. For the others, I add covariates X_{dst} to consider the corresponding information. The coefficients of interest are β_τ, which captures the policy effect on the regulated units in period τ compared to the matched control units over time. $Treat$ is applied differently. For emissions concentrations, it only differentiates districts while, for the rest, it differentiates both districts and sectors. I focus on the district×industry data as they are close to real-time emissions and the policy was based on them.

The identifying assumptions for this causal inference are as follows. First, the SUTVA should be satisfied, which means that there should not be any spillovers (e.g., leakage) between the two groups. I construct a spatial general equilibrium model to handle this limitation. In addition, in the plant level analysis, I address this issue more carefully. Second, the policy should not be anticipated. The policy was suddenly announced with a short gap between the announcement and the implementation. More specifically, the policy was announced in April 2019, but the details came later in December 2019, and the policy was implemented in April 2020. One of the policy requirements has been emissions in the past two years, which were hard to manipulate at the time of announcement. Third, there should be parallel trends between targeted and non-targeted plants and affiliated and non-targeted plants. Although a parallel trend is a prerequisite for a difference-in-differences regression, I exactly match on 3-digit KSIC in 2019 to address sectoral changes over time and to balance the treatment and control groups, which helps the plausibility of the parallel trend. Figure A.8 and Table A.4 summarize the distributions of emissions and output in the targeted and controlled units in 2019 (one year before the policy expansion), showing the balance between the treatment groups and the control groups before and after the match. On average, districts in the treatment group are larger but cleaner than those in the control group. Although several post-match differences are significant, the match helps to justify a parallel trend assumption and hence a difference-in-differences analysis. As a result, the parallel trends of Figure A.9 become more convincing.

4.1.2 Results: targeted districts

The regression result is summarized in Figure A.10 and Table A.5. All emissions decreased, reversing their pretreatment trends. TSP, PM 10, and PM 2.5 decreased by 13, 13, and 12%, and SO_x and NO_x decreased by 10 and 14%. Interestingly, leakage turned out to be not overwhelming as indicated by no significant changes in value added. There was an

insignificant 5% decrease. For robustness, I drop observations in Seoul Capital Area that were targeted from the first wave. The result is robust to the inclusion of this area. To summarize, the policy successfully decreased emissions without hurting industrial output significantly. Although this district-level comparison can help capture the overall policy effect, it is not enough to capture the mechanism behind. Note that the treatment is in three dimensions: districts, sectors, and emissions sizes. Thus, the precise mechanism can be better understood given the plant and firm responses to the policy, and this will change or enrich the policy implication. In the following section, I conduct similar exercises but using at the plant level to see how this effect can be explained by plant and firm behaviors.

4.1.3 Robustness checks: in progress

In this section, I check the sensitivity of the difference-in-differences analysis at the district level.

4.2 Plant level Policy effect

In this section, I complement the district level evidence of the policy effect with the plant and firm level evidence. First, I provide a model guide for this analysis, which provides a tractable solution. Then, based on the proposition of this model, I analyze the policy effect.

4.2.1 Model guide

I provide a partial equilibrium model of production and emissions to guide the empirical analysis and embed it into a full-fledged model. The model is based on the following stylized fact about fuel use and emissions in the the status quo, 2019, before the policy implementation in 2020. Using ln $(Sales/Employment)$ as a measure of plant productivity and computed emissions, Figure A.11 shows that more productive plants have lower emissions intensities and hence are cleaner.[20] I use electricity instead of energy because energy is unobservable while electricity is observable and always used everywhere.

Production and Pollution

Let us consider a single plant firm ω in mining or manufacturing sectors. Firm ω is characterized by its productivity χ. This firm produces using a constant elasticity of substitution (CES) production function of labor, intermediate good, and capital-energy aggregate. Again,

[20]These facts are robust to using other emissions measures, other productivity measures such as TFP, or using different years. They are available upon request.

the aggregate combines fuel-specific capital and fuel use across different fuel types in a CES function.

$$q = \chi \left(\alpha_L \ell^{\frac{\rho-1}{\rho}} + \alpha_M m^{\frac{\rho-1}{\rho}} + \alpha_E e^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

$$e = \left(\sum_{f \in \mathbb{F}} (k_f e_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}$$

where $\alpha_L + \alpha_M + \alpha_E = 1$ and $\lambda > \rho > 0$. ℓ denotes labor, m denotes material (intermediate goods), and e denotes capital-energy aggregate. k_f denotes fuel-specific capital, e_f denotes heating potentials of fuel f use, and $\mathbb{F} = \{Coal, Oil, Gas, Electricity\}$ denotes a set of fuel types that consists of fossil fuels and electricity. Capital-energy aggregate is modeled based on the fact that there is high complementarity between capital and energy compared to the other inputs. For example, almost all capital structures require electricity. Although, this term is named fuel-specific capital, what this fuel-specific capital represent is fuel technology in essence. That explains why fuel-specific capital and fuel use are multiplicative. Also, this choice matches data better because each fuel and each firm have a different fuel intensity and each firm uses different fuel composition. Although fuel types can be aggregated in a different way, I choose to pool them together because electricity is the one and only energy source used by all plants anytime, and this matters when deriving model-based empirical specifications as will be shown later. In other words, if there is any other fuel used by every plant anytime, different CES nests can be considered. There are two elasticities of interest. ρ and λ are the substitution elasticity of production factors and of fuel types, respectively. They are key parameters in environmental economics that will be estimated in Section 6.[21] They capture how an environmental policy affects firm-level input and hence regional and aggregate output and emissions. For example, λ captures how easily fuel composition can change to fuel price changes.

The policy is simplified as pollution tax τ. Then, given its productivity χ and fuel-specific capital $\{k_f\}$, the firm minimizes its production cost, choosing labor ℓ, material m, and fuel use $\{e_f\}_f$

[21] They have been rarely estimated. For example, Murray Leclair (2024) is one of the few that rigorously estimate both in India. However, India is a developing country that has started implementing significant environmental policies recently. For example, the same author finds that fossil fuel, especially coal, is extensively used, which is the opposite of Korea. The lack of those estimates, in particular in an advanced economy, necessitates the corresponding estimation results.

$$\min_{\ell,m,\{e_f\}} \tilde{\tau} \left(\underbrace{w\ell}_{\text{Labor expense}} + \underbrace{p_M m}_{\text{Material expense}} + \underbrace{\sum_{f\in\mathbb{F}} \tilde{p}_f e_f}_{\text{Fuel expense inclusive of pollution tax on fossil fuel}} \right)$$

$$\text{s.t. } q = \chi \left(\alpha_L \ell^{\frac{\rho-1}{\rho}} + \alpha_M m^{\frac{\rho-1}{\rho}} + \alpha_E \left(\sum_{f\in\mathbb{F}} (k_f e_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

where pollution tax on production process is included in every input such that $\tilde{\tau} = 1 + \tau\kappa$ and pollution tax on fossil fuel use is included in energy use such that$\tilde{p}_f = \tau\kappa_f + p_f$.[22] κ denotes emissions factors for production process, w denotes wages, p_M denotes the prices of intermediate goods, κ_f denotes emissions factors for fossil fuel f, p_f denotes fuel prices. More precisely, κ depends on products or sectors, which is considered in the following empirical analysis, but not in the model analysis for simplicity. The four cost terms are standard production factor expenses. Note that the policy does not apply to electricity use, making it as a clean fuel from the perspective of an industrial plant. In this partial equilibrium model, I assume $\{k_f\}$ to be exogenous, but it will be made endogenous later in a full-fledged model. The choice was made to keep similar functional forms throughout the analysis.

The first order conditions with respect to $\{e_f\}$, ℓ, and m are

$$\tilde{\tau}\tilde{p}_f = \frac{\mu q \alpha_E \left(\sum_{f\in\mathbb{F}} (k_f e_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}\frac{\rho-1}{\rho}-1} k_f^{\frac{\lambda-1}{\lambda}} e_f^{\frac{\lambda-1}{\lambda}-1}}{\alpha_L \ell^{\frac{\rho-1}{\rho}} + \alpha_M m^{\frac{\rho-1}{\rho}} + \alpha_E \left(\sum_{f\in\mathbb{F}} (k_f e_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}\frac{\rho-1}{\rho}}} \tag{1}$$

$$\tilde{\tau}w = \frac{\mu q \alpha_L \ell^{-\frac{1}{\rho}}}{\alpha_L \ell^{\frac{\rho-1}{\rho}} + \alpha_M m^{\frac{\rho-1}{\rho}} + \alpha_E \left(\sum_{f\in\mathbb{F}} (k_f e_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}\frac{\rho-1}{\rho}}} \tag{2}$$

$$\tilde{\tau}P = \frac{\mu q \alpha_M m^{-\frac{1}{\rho}}}{\alpha_L \ell^{\frac{\rho-1}{\rho}} + \alpha_M m^{\frac{\rho-1}{\rho}} + \alpha_E \left(\sum_{f\in\mathbb{F}} (k_f e_f)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}\frac{\rho-1}{\rho}}} \tag{3}$$

Using Equation 1 for fuel f and electricity, the ratio of fossil fuel f use to electricity use

[22]Pollution tax on emissions on fossil fuel is isomorphic to fuel specific pollution tax as $\tau_f = \tau k_f$. Further, binding quotas or bans on certain fuel types can be constructed similarly.

can be derived.

$$\frac{e_f}{e_e} = \underbrace{\left(\frac{\tilde{p}_f}{\tilde{p}_e}\right)^{-\lambda}\left(\frac{k_f}{k_e}\right)^{\lambda-1}}_{\equiv A_f} \tag{4}$$

A_f is defined as a ratio such that $A_e = 1$. A_f consists of fuel prices, pollution tax, and fuel-specific capital prices, which are taken as given from the perspective of firms. If we multiply the use of each fuel by its emissions factor, the ratio between fuel-specific emissions can be derived

$$\frac{\kappa_f e_f}{\kappa_e e_e} = \underbrace{\frac{\kappa_f}{\kappa_e}}_{\text{Constant}}\ \underbrace{\left(\frac{\tilde{p}_f}{\tilde{p}_e}\right)^{-\lambda}}_{\text{Price effect}}\ \underbrace{\left(\frac{k_f}{k_e}\right)^{\lambda-1}}_{\text{Intensity effect}}$$

Let us ignore the first term as it is a constant. Then, the first term in the ratio captures the price effect coming from the relative effective price. The use of fossil fuel f decreases in pollution tax related to the use of electricity. This is the channel where pollution tax τ matters. The second term captures the fuel intensity effect through fuel-specific capital.

Now the unit production cost can be derived from the first order conditions above

$$\mu = \underbrace{\frac{1}{\chi}}_{\text{Productivity}} \times \underbrace{\frac{\tilde{\tau}}{\left(\alpha_L^{\rho} w^{1-\rho} + \alpha_M^{\rho} p_M^{1-\rho} + \alpha_E^{\rho}\left(\sum_{f\in\mathbb{F}}\left(\frac{\tilde{p}_f}{k_f}\right)^{1-\lambda}\right)^{\frac{1-\rho}{1-\lambda}}\right)^{\frac{1}{\rho-1}}}}_{\text{Effective factor cost inclusive of pollution tax}} \tag{5}$$

The cost depends on productivity and effective factor cost inclusive of pollution tax. An increase in pollution tax increases the latter and, hence, the unit production cost. Further, based on these findings, a testable proposition can be derived.

Proposition 1.

Assume $\lambda > \rho > 0$.
Result

- Emissions decrease in pollution tax τ.

Mechanism

- The unit production cost increases in pollution tax τ.
- The use of fossil fuel f to electricity decreases in pollution tax τ.

- Fossil fuel emissions intensity of electricity $\frac{\sum_f \kappa_f e_f}{e_e}$, production process emissions intensity of electricity $\frac{\kappa q}{e_e}$, emissions intensity of electricity $\frac{\sum_f \kappa_f e_f + \kappa q}{e_e}$ decrease in pollution tax τ.

- Electricity intensity $\frac{e_e}{q}$ increases in pollution tax τ.

Proof

- See Appendix C

Proposition 1 has several notable aspects. First, the parametric assumptions are not restrictive. $\lambda > \rho > 0$ should hold for CES nests to be well defined. Fuel types are likely to be substitutable ($\lambda > 1$). Many studies including Arkolakis and Walsh (2023) assume a similar parameter to be larger than 1 without loss of generality. Recently, Murray Leclair (2024) empirically finds a similar parameter to be 2.224 in India. Second, in the next section, I use this proposition to guide an empirical analysis. If I take logarithms on the following fuel ratio,

$$\ln \frac{\kappa_f e_f}{\kappa_e e_e} = \ln\left(\frac{\kappa_f}{\kappa_e}\right) + \ln\left(\frac{\tilde{p}_f}{\tilde{p}_e}\right)^{-\lambda} + \ln\left(\frac{k_f}{k_e}\right)^{\lambda-1}$$

Again, the ratio of emissions factors is a constant. One caveat is that the intensity channel is likely to move in the same direction as the price channel. Later, in a full-fledged model, endogenous fuel-specific capital $\{k_f\}$ will depend on productivity and the policy shock. Thus, the treatment effect will contain both channels. After estimating parameters, I study each channel in Section 6. Third, as will be shown later, the policy effect is consistent with the empirical findings in Section 4.2.3 where the policy increased pollution tax τ. This consistency holds even after fuel-specific capital $\{k_f\}$ becomes endogenous and the treatment effect includes the intensity channel.

4.2.2 Empirical Strategy

The purpose of this analysis is to see the policy effect on emissions and industrial output by comparing the trend of (1) treated and untreated plants and (2) affiliated and untreated plants. I focus on TSP as it is a key local air pollutant that motivated this policy expansion. As a robustness check, I also provide results with all local pollutants and greenhouse gases in Section 4.4. Let me denote TSP emissions by TSP, TSP emissions from fossil fuel use by $TSPF$, and TSP emissions from production process by $TSPP$. Then, the outcome variables are ln TSP, ln $(TSPF/TSP)$, ln $(TSPP/TSP)$, ln $Sales$, ln $Electricity$, ln

($Electricity/Sales$), ln ($TSPF/Electricity$), and ln ($TSPF/Sales$). The last two are the measures of emissions intensity where I only consider emissions from fossil fuel use to focus on cleaner emissions intensities. The former is electricity intensity, the latter is emissions intensity of electricity, and they make emissions intensity, ln ($TSPF/Sales$) together. Consistent with Proposition 1, I use electricity, not capital-energy aggregate.[23] As a methodology of casual inference, I use the same semi-parametric difference-in-differences approach, following Heckman et al. (1997, 1998). The baseline specification is

$$y_{pt} = \sum_{\tau \neq 2019} \beta_\tau \times Treat_p \times Year_\tau + \alpha_p + \alpha_{st} + X_{p,2019} \times \alpha_t + \epsilon_{pt}$$

where p denotes plants, t denotes calendar years, s denotes 4-digit KSIC, and $X_{p,2019}$ includes ln $Electricity_{p,2019}$, , ln $Gas_{p,2019}$, and ln $Oil_{p,2019}$. The base period is 2019. The coefficients of interest are β_τ, which captures the effect of the policy on regulated plants in period τ compared to the matched control plants over time. Here I focus on computed emissions. The corresponding analysis on real-time emissions is in progress.

The identifying assumptions for this causal inference are as follows. First, the SUTVA should be satisfied, which means that there should not be any spillovers between the two groups. Since the policy targeted plants and the data are at the plant level, I can address this concern. When analyzing the effect on targeted plants, I only use untreated ones without affiliated ones as the control group. I drop targeted plants from the control group when analyzing the effect on affiliated ones. However, although this process addresses within-firm spillovers, the SUTVA is still likely to be violated because there might have been spillovers between targeted plants and non-targeted ones. For instance, outsourcing or losing market shares could have happened because of the policy. Later, I construct a spatial general equilibrium model to handle this limitation. Second, the policy should not be anticipated. The same argument as in the district level analysis (Section 4.1) holds here. The policy announcement was sudden, the gap between the announcement and the implementation was short, and it was difficult to be un-targeted as the policy was based on past emissions. More precisely, the policy was initially adopted in Seoul Capital Area in 2008. Several stakeholder consultations have been in place since 2017. But the announcement and implementation of its expansion was sudden in 2019 and 2020. Third, there should be parallel trends between targeted and non-targeted plants and affiliated and non-targeted plants.

[23] Technically, I use inverse hyperbolic sine transformation on fuel-related variables because they are subject to a sparsity issue: ln $\left(y + \sqrt{y^2+1}\right)$. For example, there are plants that use only coal, or only gas. Plants that use coal and gas can switch to use only gas next year. This is one of the most sophisticated methods to deal with zeros in the literature (e.g., Colmer et al. (2024)).

Although a parallel trend, not a balance, is a prerequisite for a difference-in-differences regression, the balance helps the plausibility of the parallel trend. For this reason, I use several matching techniques to balance the treatment and control groups. I refine the treatment groups to have at least non-zero emissions in 2018 and 2019 since the policy chose its target plants in this way. Then, I match them with untreated plants in the following ways. First, I drop plants in the control groups whose sales are too small compared to those of the treatment groups in each 4-digit industry classification. Note that sales can be a proxy of emissions as it reflects both output produced and total amount of fuels used. This trimming is necessary because, in the census data, there are too many small plants in the control groups that are likely to have been treated differently by environmental policies. Second, I only keep plants that are observed in 2019 and 2020 together for pairwise balance. Third, in 2019, a year prior to the policy implementation, I exactly match on 4-digit KSIC and propensity score match on electricity, gas, and oil uses in 2019, using a kernel match (Heckman et al. (1998); Imbens (2004); Abadie (2005); Caliendo and Kopeinig (2008); Frondel and Vance (2013); Busso, DiNardo, and McCrary (2014)). This match is to control for the price channel that cannot be fully explained by the treatment. For example, different industries use different sets of fuels and different firms use fuels differently. Also, the portion of firm productivity in the intensity channel needs to be controlled. As noted before, the policy affects both effective fuel prices and fuel-specific capital. However, the latter also depends on firm productivity. For robustness, I also consider the number of plants to control this channel in Section 4.4.[24] Figures A.12 and A.15 and Tables A.6 and A.7 summarize the final data, showing the balance between the treatment groups and the control groups before and after the match in 2019 (a year before the policy implementation). On average, plants in the treatment groups are larger but cleaner than those in the control groups. Although several post-match differences are still significant, we can see that the match decreases the significance or the magnitude of the pre-match differences. In order to account for any residual confounders and improve the efficiency, I further use doubly robust estimators by adding the same covariates used for matching (Robins, Rotnitzky, and Zhao (1994); Robins and Rotnitzky (1995)). Both imply that the chosen matching approach, while not perfect, substantially improves the balance and common support between the treatment groups and the control groups.

[24]In the literature, both kernel and nearest-neighbor matches have been used extensively. I choose the former because it allows to use all the plants in the control groups, which can help to deal with the sparsity issue common at the plant level and avoid a potential bias of picking "nearest" neighbors in the nearest-neighbor matching. Also, I choose the propensity score match because the control groups are much larger than the control groups. Also, as a robustness check, I add regional dummies, and more, which increases the number of covariates used for a match. In Section 4.4, I experiment with other matching methods for robustness.

4.2.3 Results: targeted plants

The main result is summarized in Table A.8 and Figures A.16−A.19. I first show the policy-relevant outcome, emissions, and then the mechanism behind, following Proposition 1. The emissions decreased by around 13%. Then, I decompose such an emissions change to see the mechanism behind. The change in emissions was the combination of output decrease and cleaner fuel mix. The share of production process emissions decreased insignificantly by around 1% while the share of fossil fuel emissions increased by approximately 10%. This implies that the emissions from fossil fuel use decreased by around 3%. However, this emissions reduction was not only driven by leakage. Sales decreased by around 9%, which can be related to leakage within or between firms or abatement cost. As the price of emissions allowances increased over time, sales decreased over time in the targeted plants. But electricity use increased by around 15%, making the fuel mix much cleaner from the perspective of targeted plants. This is because electricity use was not included in the policy. The policy also affected the emissions intensities. Electricity intensity increased by approximately 30%. But fossil fuel emissions intensity of electricity decreased by around 24%. This implies that, although fuel mixes became cleaner, more fuel quantities were used to make up for the power loss related to the decrease in fossil fuel use. The results so far are well in line with Proposition 1.

4.2.4 Results: affiliated plants

I investigate the affiliated plants of targeted plants because the number of affiliated plants is around 69% of that of targeted plants. Given the significant share, this investigation will give a hint on if there might have been firm-level abatement or leakage or both. Thus, I follow the same step as above and find several meaningful responses. The main result is summarized in Table A.9 and Figures A.20−A.23. I first show the policy-relevant outcome, emissions, and then the mechanism behind, following Proposition 1. Although affiliated plants were not directly affected by the policy, Proposition 1 seems to hold to some degree. This result shows that emissions decreased by approximately 5%. Then, I decompose such a change in emissions to see the mechanism behind. The change in emissions was the combination of output decrease and cleaner fuel mix. The share of production process emissions decreased significantly by around 10% while the share of fossil fuel emissions increased by approximately 4% insignificantly. This implies that the fossil fuel emissions decreased by around 1%. Again, this change was not solely driven by leakage. Sales decreased by around 14%. However, electricity use increased significantly by around 23%, making the fuel mix much cleaner from the perspective of targeted plants.

The policy also affected the sales and emissions intensities. As the price of emissions allowances increased over time, sales decreased over time in the targeted plants. Sales also dropped in the affiliated plants initially but recovered over time, implying leakage within firm boundary. On average, sales decreased in every period, implying leakage outside firm boundary or abatement cost. A question could arise about the initial drop in affiliated plants. This drop can be understood as abatement cost as abatement technology was decided at the firm level. So the response of sales can be understood as the combination of abatement cost and leakage within firms. If there have been no dip, abatement would have been unlikely as leakage within firms would have been enough. Further, the leakage over time can be understood as the firm response to the increase in the emissions allowance price, especially when output also creates emissions. Note that fuel responses were, in general, once and for all, while sales decreased over time, which implies abatement is qualitatively different from leakage. In terms of emissions intensities, electricity intensity increased by approximately 42%. But fossil fuel emissions intensity of electricity decreased by around 29%. This implies that, although fuel mixes became cleaner, more fuel quantities were used to make up for some power loss. Again, the results are well in line with Proposition 1.

4.3 Taking stock

All together, the policy decreased emissions − emissions from production process and fossil fuel use both decreased. However, this reduction was not solely driven by leakage. Sales decreased, but electricity increased more. So there were leakage within and outside firm boundary as well as electrification. Furthermore, most of these changes have been shared within firms. Both targeted and affiliated plants showed similar patterns qualitatively despite within-firm leakage.[25] The responses of both are consistent with Proposition 1. Importantly, note that the productivity portion of the policy effect is unlikely to be dominant. For example, if firm productivity has increased, emissions intensity should have decreased. However, the empirical evidence in Section 4.2.3 is against this possibility.

Overall, this finding motivates a multiplant framework with the firm-level decision of abatement technology on fuel use and leakage within firms. Indeed, Table A.10 shows that most of the variations in energy abatement technology across plants comes from those across firms, not within firms. In 2019, the former is around five times larger than the latter. This fact indicates the non-rivalry of clean technology within the firm boundary. In this analysis, I use (computed) emissions intensities because they are the most representative measure of cleanness, but the result is robust to using other measures of energy and emissions −

[25] I argue that it is not a technology spillover but a firm-level decision because of the timeline of the response.

e.g., the adoption of a fuel or a fuel set or a transition of a fuel or a fuel set. It will be interesting to study why abatement is made at the firm level. There are many factors that could have affected such firm-level technology decisions. I explain some of them, which are neither exhaustive nor mutually exhaustive. Factors that can promote firm-level decisions are coordination or synergy among plants within firms, firm reputation (e.g., Corporate Social Responsibility), and increasing returns to scale from fixed costs of adopting new technologies. In contrast, factors that can promote plant-specific decisions are comparative advantage, cost minimization, and pilot test. In Section 5, I make energy abatement technology chosen at the firm level following the MP literature without taking a specific stance.

4.4 Robustness checks

In this section, I check the sensitivity of the difference-in-differences analysis at the plant level. Among others, I focus on ln $(TSPF/Electricity)$ because this is the key variable of abatement technology. But any other outcome variables also show robust patterns. For summary, see Table A.11 and Figure A.24. The baseline is taken from Section 4.2.3 for comparison. First, I add districts for exact match and control for district×time fixed effects. The rationale is that there might have been other policies that confounded the inference and that districts are the smallest administrative units that such policies are designed and implemented. Second, I aggregate all local pollutants to see if other local pollutants show different patterns. This is because different emissions factors are applied to different pollutants. Third, instead of using propensity score match, I use Mahalanobis distance match to check if matching methods affect the result. Fourth, I consider the initial policy implementation in Seoul Capital Area in 2008 by adding the corresponding indicator for exact match and control. In the baseline, I do not consider these early-treated plants because the policy was implemented long time ago and the effect is known to be unclear. Fifth, I add the number of affiliated plants to control for the productivity effect on the intensity channel. From the result, I confirm that they are not a first order effect.

I also look into unexplored outcome variables. I check if other fuel types helped abatement than electricity. Since gas is another clean energy source, along with electricity, I investigate how emissions from gas relative to emissions from electricity changed. The ratio decreased by approximately 16% and 23% in targeted and affiliated plants, respectively. In levels, gas decreased by 1% and barely changed. This implies that the changes in gas use were not a major response.

There are more robustness checks on the way along with the corresponding analysis at the plant level with real-time emissions.

4.5 Connecting dots

4.5.1 Connecting district level and plant level results

Given the policy effect at the district and the plant levels, it is important to connect the dots between the two to understand the policy effect fully. Judging from the no response of value added at the district level, the plant level leakage between targeted and non-targeted districts was not significant enough. It is more likely that this leakage happened within targeted districts whether it was within-firm or between-firm. However, this leakage was not large enough to offset emissions reduction, although untargeted plants within targeted districts were more likely to be dirtier. These findings suggest that either abatement was effective or untargeted plants within targeted districts were not dirty enough to offset emissions reduction. This is a quantitative question where I will use a full-fledged model to answer.

4.5.2 Connecting with previous literature

I briefly discuss how these results relate to those in the literature. First, these findings are consistent with those that study the cap-and-trade effect (Fowlie, Holland, and Mansur (2012); Wagner and Petrick (2014); Colmer et al. (2024)). They find that a cap-and-trade system decreases emissions and improves emissions intensity. However, the evidence of leakage within and outside firm boundary is closer to those that study the leakage effect (Tanaka, Teshima, and Verhoogen (2022); Chen et al. (2021); Yang et al. (2024)). Shifting production and emissions in response to environmental regulations seems to be one of the common firm responses. Still, the fact that there has been abatement is inspiring given that many environmental policies caused significant leakage. I believe this difference came from the difference across policy details. Unlike a command-and-control regime, a cap-and-trade system is market-based and provides compliance flexibility and cost effectiveness by allowing the trade of emissions allowances (Fowlie, Holland, and Mansur (2012)). So, even in the short run, firms on average are likely to go through abatement, even leaking a certain amount of pollution. Lastly, the fact that the evidence is in the middle of the two is well in line with the short run response of the theory in Xiang (2023).

5 Model

The empirical findings show the effectiveness of the policy. Emissions in targeted regions decreased. Cleaner fuel mix, represented by electrification, began to be used by both targeted and affiliated industrial plants. Whether it increased emissions from power plants depended on the marginal power plants that satisfied this new demand from the industry. In addition,

there were two types of leakage in the industry: between-firm and within-firm. Based on these facts, I develop a spatial general equilibrium model of trade, MP, and emissions. The purpose of the model is trifold. First, the model allows an interpretation of the empirical results and addresses several identification threats previously presented. For example, the difference-in-differences results above might have violated the SUTVA assumption because of potential between-firm leakage. Also, the productivity channel might not have been fully controlled. Second, the model allows to quantify the aggregate and regional policy effects. Furthermore, with power generation sectors, the model can capture how electrification affects power plant emissions across regions. Such a change is difficult to study empirically because finding a plausible control group for large polluting power plants is challenging, given that there are only a few of them in the sector. Third, the model allows several counterfactual policy analyses where I study different regional policy variations and electricity use regulation. For these reasons, I use a structural model to address these issues.

The model introduces three features into an otherwise standard quantitative MP framework (Tintelnot (2017); Arkolakis et al. (2018); Sun (2020)). First, I consider energy use and emissions by fuel type. The key mechanism of the model is where industrial and power plants invest in fuel-specific capital, which helps to abate emissions. As a result, the model will generate industrial electrification in response to an environmental policy as shown in the empirical evidence. Further, this innovation allows me to consider emissions coming from power plants. Together, the race between the growth of clean power generation and the velocity of abatement (including industrial electrification) will determine total emissions. Furthermore, the geographic distribution of clean and dirty power plants with different capacities will determine the geographic distribution of emissions. If the excess demand dominates the additional provision of clean power generation capacity, leakage to power plants can happen, especially in regions with high concentrations of dirty power generation. In this context, second, power generation sectors and their emissions are considered. Third, I model heterogeneous firms and plants. This choice better maps the policy to the model because only large polluters were targeted. In addition, this heterogeneity is important because policy implications can change. For example, targeted large polluters were cleaner in terms of emissions intensity. If there was leakage from them to untargeted plants who were dirtier, the policy effect might have been mitigated. Lastly, the trade and MP framework is necessary to capture between-firm leakage and firm-level abatement and within-firm leakage.

Throughout the model analysis, I use subscripts to denote location and fuel type and superscripts to differentiate power plants from industrial plants. I use bold notation to denote vectors and bold notation with bars to denote matrices. I start with the description of households, power generation, and production in a spatial economy setup.

5.1 Environment

The economy consists of N discrete regions with two sectors, manufacturing and power generation. Each region can be the location of power generation, production, and consumption. In region l, there are two sets of capital structures for clean ($K_{l,\mathcal{C}}$) and dirty ($K_{l,\mathcal{D}}$) power generation. The former uses hydro, nuclear, solar, or wind as a source of energy, and the latter uses coal, oil, or gas. Also, there is one set of production capital ($K_{l,\mathcal{P}}$). The source of energy is slightly different: electricity, coal, oil, and gas. Electricity produced by power plants is used as an input in industrial plants, but not directly consumed by consumers. For consumption, there is a mass L_l of agents. They inelastically provide one unit of labor to firms at wage w_l and derive utility from consumption and disutility from emissions. Final good varieties are aggregated into a final good under Dixit–Stiglitz preferences (Dixit and Stiglitz (1977)). Emissions arise either from industrial or power plants. Without loss of generality, I normalize $\sum_l L_l = 1$ and assume no population changes. However, I do not normalize the amount of capital structures as I will allow them to change endogenously across steady states.

In terms of mobility, labor is immobile, fossil fuels are freely mobile, and final good varieties are subject to iceberg trade cost. Hence, there is one price for each fossil fuel, but an environmental policy creates a wedge that makes regional variations in the price. Factor markets are perfectly competitive except the one for electricity. In particular, the supplies of fossil fuels are perfectly elastic.[26] Furthermore, the electricity demand is rationed in the increasing order of marginal power generation cost. This mechanism captures power plants that are marginally turned on in response to a positive demand shock, which is important in considering the amount and distribution of emissions. More details will follow in Section 5.3. Final good varieties in the manufacturing sector are subject to monopolistic competition. Lastly, the environment is static. In other words, the model captures the race between the abatement (including electrification) in the manufacturing sector and clean power generation across steady states. The difference in the velocities of the two across steady states will lead to different policy implications.

5.2 Households

All consumers have identical preferences over final good consumption and emissions. The preferences bear the Armington assumption (Armington (1969)) such that each establishment of a firm produces a unique variety and that there is at most one establishment in a region

[26] This simplification is consistent with the fact that Korea has imported around 95% of its energy source – coal, oil, and gas – every year and that oil and gas have been fully imported.

for a firm. Varieties available in market n are combined under Dixit-Stiglitz preferences for consumption. The parameter σ represents the elasticity of substitution across varieties. It is assumed to be the same between firms and within firms for simplicity. Hence, the demand in n for variety ω_l produced by the establishment of firm ω in location l can be presented as

$$q_{ln}(\omega_l) = \left(\frac{p_{ln}(\omega_l)}{P_n}\right)^{-\sigma} Q_n \tag{6}$$

where $\sigma > 1$ and $Q_n = \left(\sum_l \int_{\omega_l \in \Omega_{ln}} q_{ln}^{\frac{\sigma-1}{\sigma}}(\omega_l)\, d\omega_l\right)^{\frac{\sigma}{\sigma-1}}$. $q_{ln}(\omega_l)$ and $p_{ln}(\omega_l)$ denote the quantity and the price of variety ω_l, P_n denotes the ideal price index, and Q_n denotes total quantity consumed in n. The ideal price index can be expressed as

$$P_n = \left(\sum_l \int_{\omega_l \in \Omega_{ln}} p_{ln}^{1-\sigma}(\omega_l)\, d\omega_l\right)^{\frac{1}{1-\sigma}} \tag{7}$$

where Ω_{ln} denotes the set of varieties produced in location l available in location n.

In addition, emissions affect utility. I use a damage function, $f(SC, \{dist_{ln}, S_l\}_l)$ where SC dictates the social cost of emissions and $dist_{ln}$ denotes the distance between l and n. This function incorporates utility loss from pollution in a reduced form way (Nordhaus (2015); Shapiro (2016); Krusell and Smith JR (2022)). Emissions include local and global air pollutants. This social cost of emissions capture how emissions affect the social welfare in diverse ways. For quantification, I impose a functional form such that $f(SC, \{dist_{ln}, S_l\}_l) = 1/\left(1 + \left(SC \times \sum_l \frac{S_l}{dist_{ln}^2}\right)^2\right)$. Without loss of generality, only for local air pollutants, I assume that emissions within a district have their full effect, but the effect decreases in distance in a quadratic way.[27] There is no distance discount for global air pollutants. All together, the representative household in region n has the following utility

$$u_n = \underbrace{Q_n}_{\text{Utility from consumption}} \times \underbrace{f(SC, \{dist_{ln}, S_l\}_l)}_{\text{Disutility from emissions}} \tag{8}$$

Finally, the budget constraint of this household who owns both power plants and firms is given by

$$\underbrace{P_n C_n}_{\text{Consumption}} = \underbrace{w_n L_n}_{\text{Labor income}} + \underbrace{\Pi_n^{\mathcal{E}}}_{\text{Power generation firm income}} + \underbrace{\Pi_n}_{\text{Manufacturing firm income}} \tag{9}$$

[27] This quadratic form considers the geographic scope of the pollutants and the policy. It is also founded upon the physics (e.g., the inverse square law). More rigorous approaches should consider the direction of wind, the altitude, and more, which is beyond the scope of this paper.

$\Pi_n^{\mathcal{E}}$ is the profit from power plants that have headquarters in location n, and Π_n is the income from manufacturing firms that have headquarters in location n. Each profit will be explained further later.

5.3 Power Generation

Power generation sectors are necessary because the electricity demand of manufacturing plants can create emissions in power plants in different regions when they generate with different energy sources in different regions. In other words, the geographic distribution of power plants with different energy sources implies an additional externality if there is industrial electrification. This is leakage into the power generation sector. For example, more use of electricity in targeted plants can lead to more fossil fuel electricity generation in untargeted areas. This is more critical for local air pollutants because the effect of emissions is concentrated around the source of emissions. In this context, the marginal power plants affected by industrial electrification matter. To identify those power plants, the merit order dispatch (MOD) needs to be understood. This is a system that many countries including Korea uses where the lowest marginal cost power stations are dispatched first to supply the grid, and then power is scheduled in the increasing order of marginal cost. Thus, the availability of renewable energy source is important as they have zero marginal costs and emit nothing into the atmosphere.[28]

For this reason, I model power plants and capture the corresponding emissions. Electricity is generated by power plants and transferred to the final user, or manufacturing plants. The system marginal price (SMP), another key concept in the electricity market, determines the price of electricity by the marginal cost of the last generating unit of x in region m required to meet demand at a specific point in time. As a result, there is a uniform electricity price p_e. I allow firm heterogeneity in the sector because this is in line with the policy and has an important policy implication as explained above. However, I do not consider MP so that firms and plants are the same. This is because firm-level fuel composition change is hard to be considered in this sector while the growth of clean power generation matters. Power plants of different types differ in their energy source to a greater extent than that in the manufacturing sector.[29]

[28] I do not model fuel extraction or mining sectors because the energy dependence of Korean on foreign import has been around 95%.

[29] The power generation sector is simplified. For a more realistic version, see Arkolakis and Walsh (2023).

Electricity Production

Each firm uses constant-returns-to-scale (CRS) technology in the power generation sector. Power plant ν in location l is defined by $z^{\mathcal{E}}$ that denotes productivity. It generates electricity with fossil fuel $f \in \mathcal{D} = \{\text{Coal, Oil, Gas}\}$

$$y_{l,f}(\nu) = z^{\mathcal{E}}(\nu)\, k^{\mathcal{E}}_{l,f}(\nu)\, e^{\mathcal{E}}_{l,f}(\nu) \tag{10}$$

where $k^{\mathcal{E}}_{l,f}$ denotes fuel-specific capital and $e^{\mathcal{E}}_{l,f}$ denotes fuel f use in ton of oil equivalent (toe). Dropping ν for simplicity, I can write the cost minimization problem as

$$\min_{k^{\mathcal{E}}_{l,f}, e_{l,f}} P^{\mathcal{E}}_{l,f} k^{\mathcal{E}}_{l,f} + \tilde{p}_{l,f}\left(\hat{s}^{\mathcal{E}}_{l,f}\right) e^{\mathcal{E}}_{l,f} + \eta_l\left(y - z^{\mathcal{E}} k^{\mathcal{E}}_{l,f} e^{\mathcal{E}}_{l,f}\right)$$

where $\tilde{p}_{l,f}(\nu) = \tau_l\left(\hat{s}^{\mathcal{E}}_{l,f} > \bar{T}\right)\kappa^{\mathcal{E}}_f + p_f$. $\kappa^{\mathcal{E}}_f$ denotes emissions factors and p_f denotes fuel price of fuel f, respectively. $\tau_l\left(\hat{s}^{\mathcal{E}}_{l,f} > \bar{T}\right)$ denotes pollution tax in location l. In fact, pollution tax is binary as some plants become subject to the same pollution tax while the others are not. Consistent with the policy, I capture those by finding power plants whose emissions are above threshold $\bar{T}$ in the absence of pollution tax $\boldsymbol{\tau}$. Since the identity of a power plant is defined with $z^{\mathcal{E}}$ and the emissions of this firm is $s^{\mathcal{E}}\left(z^{\mathcal{E}}\right) = \kappa^{\mathcal{E}}_f e^{\mathcal{E}}_{l,f}\left(z^{\mathcal{E}}\right)$, $\hat{s}^{\mathcal{E}}_{l,f}$ can be replaced accordingly.

The first order conditions with respect to $k^{\mathcal{E}}_{l,f}$ and $e^{\mathcal{E}}_{l,f}$ are

$$P^{\mathcal{E}}_{l,f} = \eta_l z^{\mathcal{E}} e^{\mathcal{E}}_{l,f} \tag{11}$$

$$\tilde{p}_{l,f}\left(z^{\mathcal{E}}\right) = \eta_l z^{\mathcal{E}} k^{\mathcal{E}}_{l,f} \tag{12}$$

Then, the unit power generation cost becomes

$$\eta\left(z^{\mathcal{E}}\right) = \underbrace{\frac{\sqrt{P^{\mathcal{E}}_{l,f}\tilde{p}_{l,f}\left(z^{\mathcal{E}}\right)}}{z^{\mathcal{E}}}}_{\text{Effective energy price}}$$

which does not depend on $y_{l,f}$. The pollution tax only applies to power plants that use fossil fuels and emit emissions beyond threshold $\bar{T}$. It increases the unit cost. Also, Equation 12 and the unit cost shows that fuel-specific capital increases in pollution tax

$$k^{\mathcal{E}}_{l,f}\left(z^{\mathcal{E}}\right) = \sqrt{\frac{\tilde{p}_{l,f}\left(z^{\mathcal{E}}\right)}{P^{\mathcal{E}}_{l,f}}}$$

Clean energy source $\mathcal{C}$ is an aggregate of {Hydro, Nuclear, Solar, Wind}with perfect substitutability. Here ν denotes a power plant that generates with $\mathcal{C}$. A unit of electricity produced in region l is subject to a CRS technology

$$y_{l,\mathcal{C}}(\nu) = z^{\mathcal{E}}(\nu)\, k^{\mathcal{E}}_{l,\mathcal{C}}(\nu)$$

The unit cost is

$$\eta\left(z^{\mathcal{E}}\right) = \frac{P^{\mathcal{E}}_{l,\mathcal{C}}}{z^{\mathcal{E}}}$$

The cost does not depend on $y_{l,\mathcal{C}}$. The electricity generated from fossil fuels and that generated from clean energy are perfect substitutes. Additionally, electricity is assumed to be freely mobile as Korea is one of the countries that have a well-connected grid. For example, according to Korea Electric Power Corporation and Ministry of Trade, Industry and Energy, the electricity supply rate has been around 100% in a recent decade.

Power Generation Problem

According to the SMP, the price of electricity is determined by the marginal cost of the last generating unit of x (in region l) required to meet demand at a specific point in time

$$p_e = \eta(x) \tag{13}$$

The MOD implies that clean power generation is used first as they have close to zero unit power generation cost. Together, they imply that $y\left(z^{\mathcal{E}}_{l,f}\right)$ will be assigned in the increasing order of power generation cost, clearing the electricity market

$$\sum_{l}\sum_{f}\int y\left(z^{\mathcal{E}}\right) dF\left(z^{\mathcal{E}}\right) = e_e \tag{14}$$

where e_e is the total electricity demand from the industry. For example, dirty power generation is used in the increasing order of power generation cost when electricity demand exceeds the capacity of clean power generation. As noted before, these two systemic characteristics have an important policy implication. When there is an increase in electricity demand (for example, industrial electrification), what types of power plants begin to be used (the types of marginal power plants) matters. If the excess demand turns a dirty power plant on, there might be new emissions from this power plant. Hence, the race between the two matters.

After being rationed, the firm profit is

$$\pi^{\mathcal{E}}_{l,f}\left(z^{\mathcal{E}}\right) = \left(p_e - \eta\left(z^{\mathcal{E}}\right)\right) y\left(z^{\mathcal{E}}\right)$$

Firms of different types enter the market and draw productivity paying the corresponding entry cost $f_{l,e}^{\mathcal{E},f}$ of final goods where $f \in \{\text{coal, oil, gas, } \mathcal{C}\}$. Hence, the free entry condition is defined to close the model in a general equilibrium

$$\mathbb{E}_{z_{l,f}^{\mathcal{E}}}\left[\pi_{l,f}^{\mathcal{E}}\left(z^{\mathcal{E}}\right)\right] \leq P_l f_{l,e}^{\mathcal{E},f} \tag{15}$$

which is equal to 0 when the number of active firms in location l, $M_l^{\mathcal{E},f} > 0$. This condition provides the minimum firm productivity needed to establish at least one profitable production plant $\bar{z}_{l,f}^{\mathcal{E}}$, and hence $M_l^{\mathcal{E},f}$. I assume that $z^{\mathcal{E}}$ is drawn from an i.i.d Fréchet distribution with shape parameter $\zeta^{\mathcal{E}} > 1$. The corresponding income from power plants can be expressed as the sum of firm entry costs

$$\Pi_l^{\mathcal{E}} = P_l \sum_f f_{l,e}^{\mathcal{E},f} M_l^{\mathcal{E},f} \tag{16}$$

To summarize, the power generation sector can become clean as dirty power plants invest in fuel-specific capital or as the entry of clean power plants increases.

5.4 Production

Firms can produce and sell different final good varieties in different regions. I introduce firm heterogeneity for a better mapping of the policy and its quantitative implication. MP is also allowed where firms can set up establishments in different places and sell not only to the host regions but also to other neighboring markets. This is because of the empirical evidence on firm-level abatement and within-firm leakage. I index the location of firm headquarters by i, the location of production by l, and the location of consumption by n. In this case, the establishments of the same firms exist in different regions because they sell different varieties. In line with this Armington assumption, there is at most one establishment for one region. The Armington assumption makes the model solution tractable and parameters easy to estimate as the multi-plant firm location decision becomes separable across locations.[30]

The timing of firm ω's activities is as follows. Upon entry, firm ω draws core productivity ϕ and sets up headquarters in location i, paying entry cost $f_{i,e}$ units of the composite final good. Core productivity ϕ drawn from a distribution $F(\phi)$ is common within firms and determines firm ω's overall efficiency no matter where it produces. Then, firm ω chooses its fuel-specific capital $\{k_{l,f}\}_{l,f}$ across all establishments within firms. Hence, firm ω is characterized by ϕ. Conditional on entry and abatement choice, each establishment maximizes its profits.

[30]Indeed, in 2019, out of 791 treated plants, 230 had affiliates with the same 3-digit KSIC while 561 did not. It was 204 and 587 in 4-digit KSIC.

Plant-level Production Decision

Firm ω produces a unique differentiated variety in each establishment under a CRS technology. Establishment ω_l, that of firm ω in location l, produce using a CES production function of labor, intermediate good, and capital-energy aggregate (Equation 17). Again, the aggregate combines fuel-specific capital and fuel use across different fuel types in a CES function (Equation 18).

$$q_l(\omega_l) = \chi_{il}(\omega_l)\left(\alpha_L \ell_l^{\frac{\rho-1}{\rho}}(\omega_l) + \alpha_M m_l^{\frac{\rho-1}{\rho}}(\omega_l) + \alpha_E e_l^{\frac{\rho-1}{\rho}}(\omega_l)\right)^{\frac{\rho}{\rho-1}} \tag{17}$$

$$e_l(\omega_l) = \left(\sum_{f\in\mathbb{F}} \left(k_f(\omega_l)\, e_{l,f}(\omega_l)\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}} \tag{18}$$

There are several key differences between this function and the one given in Section 4.2.1. First, a multiplant framework will be introduced where fuel technology $\{k_{l,f}\}_{l,f}$ is chosen at the firm level. Now the production function will capture the fact that the variation of cleanness is smaller within firms than across firms as indicated in Section 4. Second, more detailed productivities and locations are considered such that $\chi_{il}(\omega_l) = A_{il}\phi z_l$. In addition to core productivity ϕ, there are two additional productivity shifters. On the one hand, A_{il}, also known as MP productivity, denotes productivity shifters common to all firms that are headquartered in location i and have production in location l. On the other hand, z_l denotes establishment specific shocks, reflecting all factors that make location l a particularly successful establishment for the firm. The log-linearity between ϕ and z_l will be important in characterizing the model analytically relaxing the way pollution tax chooses its target.

Given the timing, firm ω's problem needs to be solved backward. I impose two additional assumptions to facilitate a tractable aggregation of the model. First, I assume that firms choose their fuel-specific technology before a set of plant productivity $\boldsymbol{z}$ is observed, and that they make plant-level decisions after $\boldsymbol{z}$ are observed. Therefore, firms decide on $\{k_{l,f}\}$ by forming expectations about which markets they will serve. Second, I assume the plant-level shocks $\boldsymbol{z}$ are drawn independently from a common Pareto distribution with shape parameter θ such that $Pr(z \geq c) = c^{-\theta}$.

As a first step, the cost minimization problem needs to be solved, which can be rewritten because of the CRS technology. Establishment ω_l minimizes its production factor cost

inclusive of pollution tax by choosing labor, intermediate good, and each fuel use

$$\min_{\ell_l, m_l, \{e_{l.f}\}_f} \underbrace{\tilde{\tau}_l\left(\hat{s}_{l,f}\right) w_l \ell_l\left(\phi, z_l\right)}_{\text{Labor expense}} + \underbrace{\tilde{\tau}_l\left(\hat{s}_{l,f}\right) p_{l,M} m_l\left(\phi, z_l\right)}_{\text{Material expense}} + \underbrace{\tilde{\tau}_l\left(\hat{s}_{l,f}\right) \sum_{f \in \mathbb{F}} \tilde{p}_{l,f}\left(\hat{s}_{l,f}\right) e_{l,f}\left(\phi, z_l\right)}_{\text{Energy expense}}$$

$$\text{s.t. } q_l\left(\phi, z_l\right) = A_{il} \phi z_l \left(\alpha_L \ell_l^{\frac{\rho-1}{\rho}}\left(\omega_l\right) + \alpha_M m_l^{\frac{\rho-1}{\rho}}\left(\omega_l\right) + \alpha_E e_l^{\frac{\rho-1}{\rho}}\left(\omega_l\right)\right)^{\frac{\rho}{\rho-1}}$$

where $\tau_l\left(\hat{s}_{l,f}\right) = \tau_l 1\left\{\hat{s}_{l,f} > \bar{T}\right\}$, $\tilde{\tau}_l\left(\hat{s}_{l,f}\right) = 1 + \tau_l\left(\hat{s}_{l,f}\right)\kappa$, and $\tilde{p}_{l,f}\left(\hat{s}_{l,f}\right) = \tau_l\left(\hat{s}_{l,f}\right)\kappa_f + p_{l,f}$. κ denotes emissions factors for production process specific to products or sectors, κ_f denotes emissions factors for fossil fuel f, w_l denotes wage, and $p_{l,M}$ denotes the price of an intermediate good. As before, $\hat{s}_{l,f}$ can be replaced with ϕz_l because the term that multiplies core productivity ϕ and plant productivity z_l, both of which define the identity of the plant, determines its emissions $s^{\mathcal{P}}\left(\phi, z_l\right) = \kappa q\left(\phi, z_l\right) + \kappa_f^{\mathcal{E}} e_{l,f}\left(\phi, z_l\right)$.[31]

I abstract from pollution markets because the idea is isomorphic. In pollution markets, a government adjusts the supply of emissions allowances affecting the price of them. So the exogenous policy tool is the supply. I use pollution tax which is taken as exogenous through the analysis to capture such features without loss of generality.[32] The strength of such a market-based policy is that it gives compliance flexibility and cost effectiveness to targeted plants or firms. Also, the policy mechanism is general enough to capture a command-and-control regime, which is another type of environmental policies commonly adopted in practice.

The unit production cost $\mu_{il}\left(\phi, z; \{k_{l,f}\}_f\right)$ can be derived as

$$\mu_{il}\left(\phi, z; \{k_{l,f}\}_f\right) = \underbrace{\frac{1}{A_{il}\phi z}}_{\text{Productivity}} \times \underbrace{\frac{\tilde{\tau}_l\left(\phi, z\right)}{G_l\left(\phi, z; \{k_{l,f}\}_f\right)}}_{\text{Effective factor cost inclusive of pollution tax}}$$

where $\tilde{\tau}_l\left(\phi, z\right) = 1 + \tau_l\left(\phi, z\right)\kappa$, $\tau_l\left(\phi, z\right) = \tau_l 1\left\{\phi z > \bar{T}\right\}$, $\tilde{p}_{l,f}\left(\phi, z\right) = \tau_l\left(\phi, z\right)\kappa_f + p_{l,f}$, and $G_l\left(\phi, z; \{k_{l,f}\}_f\right) = \left(\alpha_L^\rho w_l^{1-\rho} + \alpha_M^\rho p_{l,M}^{1-\rho} + \alpha_E^\rho \left(\sum_{f \in \mathbb{F}} \left(\frac{\tilde{p}_{l,f}(\phi,z)}{k_{l,f}}\right)^{1-\lambda}\right)^{\frac{1-\rho}{1-\lambda}}\right)^{\frac{1}{\rho-1}}$. The effective

[31] The design of pollution tax target can only depend on ϕ as in Chen et al. (2021), consistent with the data as around 69% of targeted plants have affiliated plants in 2019 (one year before the policy implementation). Or it can also depend on z to capture the remaining 31%. An important caveat is that it can change the corresponding policy implications. For example, Murray Leclair (2024) finds negative correlations between variables similar to ϕ and $\{k_{l,f}\}$ implying that the target choice can have different policy implications. The way the policy finds its target above is closest to that in reality. In quantification, I will explore more on this choice.

[32] The allocation of emissions allowances, in principle, does not matter because of the so-called independence property (Coase (1960)). It is also verified empirically in several studies (e.g., Fowlie and Perloff (2013)).

factor cost consists of pollution tax on output, wage, intermediate good price, fuel price inclusive of pollution tax on fossil fuels, and fuel-specific technology. The unit production cost depends on the core and establishment productivities and effective factor cost, but not on the quantity produced.

Since firms engage in monopolistic competition, the variety price can be determined under the demand (Equation 6) with the unit production cost (Equation 5)

$$\begin{aligned} p_{iln}\left(\phi, z; \{k_{l,f}\}_f\right) &= \mathcal{M}\mu_{il}\left(\phi, z; \{k_{l,f}\}_f\right) d_{ln} \\ &= \mathcal{M}\frac{1}{A_{il}\phi z}\frac{\tilde{\tau}_l\left(\phi, z\right)}{G_l\left(\phi, z; \{k_{l,f}\}_f\right)} d_{ln} \end{aligned} \tag{19}$$

where $\mathcal{M} = \frac{\sigma}{\sigma-1}$ and d_{ln} denotes iceberg trade costs between l and n. Given z, the gross profit (sales net of factor costs) of establishment ω in market l can be expressed as

$$\begin{aligned} \pi_{il}\left(\phi, z; \{k_{l,f}\}_f\right) &= \frac{R_{il}\left(\phi, z; \{k_{l,f}\}_f\right)}{\sigma} \\ &= \frac{1}{\sigma}\sum_n \left(\frac{\mathcal{M}\mu_{il}\left(\phi, z; \{k_{l,f}\}_f\right) d_{ln}}{P_n}\right)^{1-\sigma} X_n \end{aligned}$$

The resulting expected establishment revenue is

$$R_{il}\left(\phi; \{k_{l,f}\}_f\right) = \int \sum_n \left(\frac{\mathcal{M}\mu_{il}\left(\phi, z; \{k_{l,f}\}_f\right) d_{ln}}{P_n}\right)^{1-\sigma} X_n dF\left(z\right) \tag{20}$$

where $1 + \theta - \sigma > 0$. In the second line, I use the fact that ϕ is given at this stage. $B_l\left(\phi; \{k_{l,f}\}_f\right)$ is the market potential of l of firm with core productivity ϕ. Abusing the notation again, the expected gross profit of firm ω in region l can be expressed as

$$\begin{aligned} \pi_{il}\left(\phi; \{k_{l,f}\}_f\right) &= \frac{R_{il}\left(\phi; \{k_{l,f}\}_f\right)}{\sigma} \\ &= \frac{\theta}{\sigma\left(1+\theta-\sigma\right)}\left(\frac{\mathcal{M}}{\phi A_{il}}\right)^{1-\sigma} B_l\left(\phi; \{k_{l,f}\}_f\right) \end{aligned} \tag{21}$$

The expected output is

$$q_{il}\left(\phi;\{k_{l,f}\}_f\right)=\int_1^{\infty}\sum_n\left(\frac{\mathcal{M}\mu_{il}\left(\phi,z;\{k_{l,f}\}_f\right)d_{ln}}{P_n}\right)^{-\sigma}\frac{X_n}{P_n}dF\left(z\right)$$

where $\theta>\sigma$. Note that the corresponding tax revenue needs to be considered as it is not a part of consumption. Tax revenue is assumed to be lost. The tax revenue from this affiliate of firm ω in l can be calculated

$$\begin{aligned}TR_{il}\left(\phi;\{k_{l,f}\}_f\right)=&\int_1^{\infty}\tau_l\left(\phi,z\right)\kappa w_l\ell_l\left(\phi,z\right)+\tau_l\left(\phi,z\right)\kappa p_{l,M}m_l\left(\phi,z\right)\\&+\sum_{f\in\mathbb{F}}\left(\tau_l\left(\phi,z\right)\kappa_f+\tau_l\left(\phi,z\right)\kappa\tilde{p}_{l,f}\left(\phi,z\right)\right)e_{l,f}\left(\phi,z\right)dF\left(z\right)\end{aligned}$$

Finally, the revenue net of pollution tax can be written as

$$\bar{R}_{il}\left(\phi;\{k_{l,f}\}_f\right)=R_{il}\left(\phi;\{k_{l,f}\}_f\right)-TR_{il}\left(\phi;\{k_{l,f}\}_f\right)\tag{22}$$

Firm-level Abatement Choice

In this section, I analyze the fuel-specific capital investment at the firm level. Firms choose fuel-specific technology $\{k_{l,f}\}_f$ at the firm level subject to a constraint that their technology is shared within firms to maximize its global profit. This constraint is based on the set of empirical evidence that abatement is shared within firms, which is in line with the MP literature that technology is non-rivalry within firms. Using the static global profit derived above, firm ω makes a decision on fuel-specific capital with the ratio of fuel-specific capital being the same across its establishments

$$\begin{aligned}\pi_i\left(\phi\right)=\max_{\{k_{l,f}\}_{l,f}}&\sum_l\left(\underbrace{\pi_{il}\left(\phi;\{k_{l,f}\}_f\right)}_{\text{Establishment profit}}-\underbrace{\sum_{f\in\mathbb{F}}P_{i,f}k_{l,f}}_{\text{Fuel technology investment cost}}\right)\\&\text{s.t. }\frac{k_f}{k_e}=\frac{k_{l,f}}{k_{l,e}},\ \forall f\in\mathbb{F}\end{aligned}\tag{23}$$

The problem can be rewritten as

$$\max_{\{k_{l,f}\}_{l,f}}\left\{\Upsilon\left(\phi\right)\sum_l A_{il}^{\sigma-1}B_l\left(\phi;\{k_{l,f}\}_f\right)-\sum_{f\in\mathbb{F}}P_{i,f}\sum_l k_{l,f}\right\}$$

where $\Upsilon(\phi) = \frac{\theta}{\sigma(1+\theta-\sigma)}\left(\frac{\mathcal{M}}{\phi}\right)^{1-\sigma}$ and $B_l\left(\phi;\{k_{l,f}\}_f\right) = \left(\frac{\tilde{\tau}_l^{1-\sigma}\left(\bar{T}/\phi\right)^{\sigma-\theta-1}}{G_l^{1-\sigma}\left(\{k_{l,f}\}_f\right)} + \frac{1-\left(\bar{T}/\phi\right)^{\sigma-\theta-1}}{\tilde{G}_l^{1-\sigma}\left(\{k_{l,f}\}_f\right)}\right)\sum_n\left(\frac{d_{ln}}{P_n}\right)^{1-\sigma}X_n$. $P_{i,f}$ denotes the price of fuel-specific investment in i. Consistent with the empirical evidence, I abstract away from having extensive margin changes or adjustment costs in fuel technology.[33] The investment cost captures how much resources have to be used to increase fuel-specific technology.[34]

The first order condition for k_f for $f \neq e$ gives

$$P_{i,f} = \Upsilon(\phi)\sum_l A_{il}^{\sigma-1}\frac{\partial B_l\left(\phi;\{k_{l,f}\}_f\right)}{\partial k_f} \tag{24}$$

The first order condition for $k_{l,e}$ gives

$$P_{i,e} = \Upsilon(\phi)\sum_l A_{il}^{\sigma-1}\frac{\partial B_l\left(\phi;\{k_{l,f}\}_f\right)}{\partial k_{l,e}} \tag{25}$$

From these two first order condition, we can characterize $\{k_{l,f}\}_f$.

Proposition 2.

Assume $\lambda > 1$

Mechanism

- When pollution tax is close to zero, more productive firms are cleaner. When pollution tax is significantly large, this relationship does not hold because being subject to pollution tax is too much costly.
- The investment of fossil fuel capital $k_{l,f}$ decreases relative to that of electricity capital $k_{l,e}$ when there is pollution tax.
  - This further makes the fuel use ratio cleaner. Thus, fuel substitution is more significant in targeted plants than in affiliated ones because pollution tax directly works on the fuel composition, although fuel technology is shared within firms.
  - This result holds for other fuels than electricity as long as they are different fuels.

[33] Because of the CES structure, firms use all fuel types in their fuel sets at least in small amounts. For fuel set changes and relevant dynamics, see Murray Leclair (2024) and Arkolakis, Kim, and Murray Leclair (2025).

[34] Since they are abatement efforts, they are different from technology menus as in Caselli and Coleman (2006), Oberfield and Raval (2021), and Sun (2020). However, the fact that the choice of capital or emissions technology is made at the firm level is in line with Sun (2020) and Xiang (2023).

Proof

- See Appendix C

As shown above, the marginal gains provide several insights. To summarize, fuel-specific capital $\{k_{l,f}\}$ captures both fuel intensity and fuel composition changes. Despite a potential trade off between the two, they are not necessarily exclusive, but the composition of the capital always increases the share of cleaner fuel types.

Based on the fuel-specific capital choice $\{k_{l,f}\}_{l;f}$, firms decide which market to serve by comparing its establishment profit $\pi_i(\phi)$ and fixed entry cost $P_i f_{i,e}$. Lastly, the free entry condition is defined to close the model in a general equilibrium

$$\mathbb{E}_\phi [\pi_i(\phi)] \leq P_i f_{i,e} \tag{26}$$

which is equal to 0 when the number of active firms headquartered in i, $M_i > 0$. This condition provides the minimum firm productivity needed to profitably establish at least one production plant $\bar{\phi}_i$, and hence M_i. I assume that ϕ is drawn from an i.i.d Fréchet distribution with shape parameter $\zeta > 1$. The corresponding income from manufacturing firms can be expressed as the sum of plant fixed costs and firm entry costs

$$\Pi_{n,\mathcal{P}} = P_n f_{n,e} M_n \tag{27}$$

To summarize, the manufacturing sector can become clean as plants invest in fuel-specific capital or the fuel composition becomes cleaner. The difference between the power generation and manufacturing sectors comes from the difference in sectoral characteristics. In the power generation sector, there is a clean energy source that does not create any leakage. Also, power plants cannot change their fuel composition.

5.5 General Equilibrium

In this section, I define the general equilibrium of the model. To facilitate the definition and calibration, I derive several expressions for aggregate variables. Aggregate variables are expressed in the integrals of firm level variables over the distribution of power generation and industrial firm productivities, $z^{\mathcal{E}}$and ϕ.

First, emissions in location l, s_l originate from industrial plants S_l and power plants $S_l^{\mathcal{E}}$

such that

$$S_l = \underbrace{\int_\omega \left(\sum_{f \in \mathcal{D}} \kappa_f e_{l,f}(\omega) + \kappa q_l(\omega) \right) dF(\omega)}_{S_l^{\mathcal{P}}} + \underbrace{\sum_{f \in \mathcal{D}} \kappa_{l,f}^{\mathcal{E}} e_{l,f}^{\mathcal{E}}}_{S_l^{\mathcal{E}}} \tag{28}$$

Similarly, electricity demand in region l can be written as

$$e_{l,e} = \int_\omega e_{l,e}(\omega)\, dF(\omega) \tag{29}$$

With free mobility, the total electricity demand is the sum of regional ones

$$e_e = \sum_l e_{l,e}$$

Second, as above, we can define the sales of the establishment of firm ϕ in location l to location n

$$R_{iln}\left(\phi; \{k_{l,f}\}_f\right) = \int \left(\frac{\mathcal{M}\mu_{il}\left(\phi, z; \{k_{l,f}\}_f\right) d_{ln}}{P_n} \right)^{1-\sigma} X_n dF(z)$$

Similarly, the tax revenue can be defined as

$$\begin{aligned} TR_{iln}\left(\phi; \{k_{l,f}\}_f\right) = \int_1^\infty & \tau_l(\phi, z)\, \kappa w_l \ell_{ln}(\phi, z) + \tau_l(\phi, z)\, \kappa p_{l,M} m_{ln}(\phi, z) \\ & + \sum_{f \in \mathbb{F}} \left(\tau_l(\phi, z)\, \kappa_f + \tau_l(\phi, z)\, \kappa \tilde{p}_{l,f}(\phi, z) \right) e_{ln,f}(\phi, z)\, dF(z) \end{aligned}$$

Hence, the firm-specific net trade flow can be expressed as

$$\bar{R}_{iln}\left(\phi; \{k_{l,f}\}_f\right) = R_{iln}\left(\phi; \{k_{l,f}\}_f\right) - TR_{iln}\left(\phi; \{k_{l,f}\}_f\right)$$

The aggregate flow can be expressed as

$$\begin{aligned} X_{iln} &= \int \bar{R}_{iln}(\omega)\, dF(\omega) \\ &= M_i \int_{\bar{\phi}_i} \bar{R}_{iln}\left(\phi; \{k_{l,f}\}_f\right) dF(\phi) \end{aligned}$$

Definition

Given a set of labor endowment $\{L_n\}$ and a set of fuel prices $\{p_{l,f,}\}$, an equilibrium is a vector of prices for final goods $\{P_n\}$, a vector of wages $\{w_n\}$, a vector of capital prices $\left\{P_{n,f}, P_{n,f}^{\mathcal{E}}\right\}$, an electricity price p_e, and an allocation $\{k_{n,f}(\phi)\}$, $\{e_{n,f}(\phi,z), \ell_n(\phi,z), m_n(\phi,z)\}$, $\left\{k_{n,f}^{\mathcal{E}}\left(z^{\mathcal{E}}\right), e_{n,f}^{\mathcal{E}}\left(z^{\mathcal{E}}\right)\right\}$, and $\left\{M_n, X_n, \left\{M_n^{\mathcal{E},f}\right\}\right\}$ such that

1. Industrial firms choose optimal fuel-specific capital structures to maximize global profits (Equation 23)
2. The free entry condition is satisfied (Equation 26)
3. The price index satisfies
4. The trade and MP flows satisfy

$$X_n = \sum_{i,l} X_{iln} \tag{30}$$

5. Labor markets clear in each region

$$L_l = \int \ell_l(\omega)\, dF(\omega) \tag{31}$$

The market clearing conditions need two clarifications. First, the product market clearing condition becomes redundant. Here I assume zero current account surplus such that $\Delta_n = 0$. In the model, I use roundabout production so that I assume the price of an intermediate good is identical to that of a final good. But for estimation, I allow them to be different. This choice is made because there is one sector, but outsourcing can be an important response to an environmental policy. Second, fuel income and fuel cost cancel out as non-electricity fuels are traded in a small open economy. In other words, there are no fuel market clearing conditions because fuels are imported at a world price which is taken as given. This part is in a partial equilibrium or it reflects that Korea is a small open economy. This is consistent with the reality as Korea imports more than 95% of its energy source.

Taking stock, this is a spatial general equilibrium model of trade, MP, and emissions. The critical component to the model is fuel-specific technology investment in manufacturing and power generation sectors in response to pollution tax. In the next section, I provide a calibration and estimation strategy. For a solution algorithm, see Appendix D.

6 Quantification

The model will conduct counterfactual policy analyses through comparing steady states. The baseline is one absent any environmental policies such that pollution tax $\tau_l = 0$ for all l and the other with some environmental policies such that pollution tax $\tau_l > 0$ for at least some l. For counterfactual steady states, see Section 7. A transition between these steady states is beyond the scope of this paper.[35] To prepare such analyses, this section explains the calibration and estimation strategy, provides the resulting estimates, and shows the model fit.

6.1 Calibration and Estimation

6.1.1 Calibration

Table A.12 summarizes how parameters are calibrated. In this paragraph, I explain those that need additional explanation. $\bar{T}$, the productivity threshold for pollution tax is set to match the amount of emissions by regulated plants within their industries and regions. For αs on the production side, I take the geometric mean of Equations 32 and 33 and normalize such that $\alpha_L + \alpha_M + \alpha_E = 1$. This is an advantage provided by the geometric mean normalization of the CES function.

6.1.2 Estimation

In this section, I estimate the other parameters that are not calibrated above. I estimate the demand elasticity of substitution and the outer and inner CES elasticities of substitution. Further, I estimate productivity related parameters. Finally, I estimated the industrial and power generation firm entry costs. There are two key differences between the estimation and the model. In estimation, I allow factor costs to be plant-specific. Also, I allow the price of material to be different from that of final good. This relaxation makes the approach closer to that in the production function literature.

CES elasticities The production function of the model is estimated in two steps using a novel combination of methods (Murray Leclair (2024)). First, I adapt the method of Grieco, Li, and Zhang (2016) in order to estimate the demand substitution elasticity in the presence of an unobserved input (inner production function). I then estimate the outer and inner production functions, following recent developments in the production function estimation literature with input-augmenting productivity (Demirer (2020); Zhang (2019)). Lastly, note

[35] See Arkolakis, Kim, and Murray Leclair (2025) for such dynamics.

that, for estimation, I conduct normalization across years and regions, which is important in the estimation of a CES function (León-Ledesma, McAdam, and Willman (2010); Grieco, Li, and Zhang (2016)).

In the outer nest, a unobserved quantity that departs from standard models is the inner production function, capital-energy aggregate, e. The function combines different fuels and fuel-specific capital structures. Using this information and ρ, I can uniquely recover the price and quantity of capital-energy aggregate when other flexible inputs are observed under the assumption that plants are price-takers in the input market.[36] The key to this method relies on using first order conditions to map observed expenditure shares to unobserved input quantity shares. However, since ρ needs to be estimated later, this recovered object is used for later estimation.

After the realization of $\boldsymbol{z}$, the plant-level sales, the sum of revenues across all regions, can be written as

$$\begin{aligned} R_{il}(\phi,z) =& \sum_n p_{iln}\left(q_{ln}(\phi,z)\right) q_{iln}(\phi,z) \\ =& \sum_n P_n Q_n^{\frac{1}{\sigma}} q_{iln}^{\frac{\sigma-1}{\sigma}}(\phi,z) \\ =& q_{il}^{\frac{\sigma-1}{\sigma}}(\phi,z) \sum_n P_n Q_n^{\frac{1}{\sigma}} s_{iln}^{\frac{\sigma-1}{\sigma}}(\phi,z) \end{aligned}$$

where the total quantity manufactured by firm ϕ in l with plant productivity z, $q_{il}(\phi,z) = \sum_n d_{ln} q_{iln}(\phi,z)$, and the plant-level share of output produced in l and sold in region n relative to total output manufactured in region l, $s_{iln}(\phi,z) = \frac{q_{iln}(\phi,z)}{q_{il}(\phi,z)}$. The share can be rewritten as

$$\begin{aligned} s_{iln}(\phi,z) &= \frac{q_{iln}(\phi,z)}{\sum_n d_{ln} q_{iln}(\phi,z)} \\ &= \frac{P_n^{\sigma-1} X_n d_{ln}^{-\sigma}}{\sum_n P_n^{\sigma-1} X_n d_{ln}^{1-\sigma}} \\ &= s_{ln} \end{aligned}$$

where I use the unit production cost and the demand function and the CES demand (Equation 6) in the second line, and I use the definition of the total quantity produced in the third line. This result shows that the share only depends on iceberg trade costs and destination market conditions, making it independent of (ϕ,z). Then, I can rewrite the plant-level

[36] As noted in Grieco, Li, and Zhang (2016), the assumption of price-taking in the input market allows for unobserved variation in input prices, which could be related to plant size, productivity, location, and any other state variables except quantity discounts.

revenue as

$$R_{il}(\phi,z) = q_{il}^{\frac{\sigma-1}{\sigma}}(\phi,z)\,\Gamma_l$$

where $\Gamma_l = \sum_n P_n Q_n^{\frac{1}{\sigma}} s_{ln}^{\frac{\sigma-1}{\sigma}}$. Then, the profit maximization of the plant can be written as follows. Plant of firm ϕ in l maximizes its profit subject to its production technology. Dropping (ϕ, z) and location subscripts for convenience, the problem can be written as

$$\max_{\ell,m,e} q^{\frac{\sigma-1}{\sigma}}\Gamma - \tilde{\tau}\left(w\ell + p_M m + p_E e\right)$$
$$\text{s.t.} \frac{q}{\bar{Q}} = \chi\left(\alpha_L\left(\frac{\ell}{\bar{L}}\right)^{\frac{\rho-1}{\rho}} + \alpha_M\left(\frac{m}{\bar{M}}\right)^{\frac{\rho-1}{\rho}} + \alpha_E\left(\frac{e}{\bar{E}}\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}$$

which can be rewritten as

$$\max_{\ell,m,e}\Gamma\left(\chi\left(\alpha_L\left(\frac{\ell}{\bar{L}}\right)^{\frac{\rho-1}{\rho}} + \alpha_M\left(\frac{m}{\bar{M}}\right)^{\frac{\rho-1}{\rho}} + \alpha_E\left(\frac{e}{\bar{E}}\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}\right)^{\frac{\sigma-1}{\sigma}} - \tilde{\tau}\left(w\ell + p_M m + p_E e\right)$$

Taking ratios across the first order conditions with respect to ℓ, m, and e,

$$\frac{e}{\bar{E}} = \left(\frac{p_E e}{w\ell}\right)^{\frac{\rho}{\rho-1}}\left(\frac{\alpha_L}{\alpha_E}\right)^{\frac{\rho}{\rho-1}}\frac{\ell}{\bar{L}} \tag{32}$$

$$\frac{m}{\bar{M}} = \left(\frac{p_M m}{w\ell}\right)^{\frac{\rho}{\rho-1}}\left(\frac{\alpha_L}{\alpha_M}\right)^{\frac{\rho}{\rho-1}}\frac{\ell}{\bar{L}} \tag{33}$$

From these two ratios, $\frac{e}{\bar{E}}$ and $\frac{m}{\bar{M}}$ can be recovered once ρ is known because the expenditures for labor, fuels, and material and the number of employment are observed. At the plant level, $p_E e = \sum_f p_f e_f$, and I observe fossil fuel expense and electricity bill. Thus, I can identify several production parameters by replacing $\frac{e}{\bar{E}}$ and $\frac{m}{\bar{M}}$ with Equations 32 and 33 and exploiting the first order conditions to control for the transmission bias from unobserved hicks-neutral productivity χ to observed inputs (Doraszelski and Jaumandreu (2013); Doraszelski and Jaumandreu (2018)).

From the first order condition with respect to ℓ, productivity χ can be solved for

$$\chi^{\frac{\sigma-1}{\sigma}} = \frac{\sigma}{\sigma-1}\frac{1}{\Gamma}\frac{\tilde{\tau}w\ell}{\alpha_L\left(\frac{\ell}{\bar{L}}\right)^{\frac{\rho-1}{\rho}}}\left(\alpha_L\left(\frac{\ell}{\bar{L}}\right)^{\frac{\rho-1}{\rho}} + \alpha_M\left(\frac{m}{\bar{M}}\right)^{\frac{\rho-1}{\rho}} + \alpha_E\left(\frac{e}{\bar{E}}\right)^{\frac{\rho-1}{\rho}}\right)^{1-\frac{\rho}{\rho-1}\frac{\sigma-1}{\sigma}} \tag{34}$$

Plugging this productivity into the revenue with a time-varying shock u_t such that $\mathbb{E}[u_t] = 0$

$$R_t = \frac{\sigma}{\sigma-1}\frac{\tilde{\tau}_t w_t \ell_t}{\alpha_L\left(\frac{\ell_t}{\bar{L}}\right)^{\frac{\rho-1}{\rho}}}\left(\alpha_L\left(\frac{\ell_t}{\bar{L}}\right)^{\frac{\rho-1}{\rho}} + \alpha_M\left(\frac{m_t}{\bar{M}}\right)^{\frac{\rho-1}{\rho}} + \alpha_E\left(\frac{e_t}{\bar{E}}\right)^{\frac{\rho-1}{\rho}}\right)e^{u_t}$$

Using Equations 32 and 33, the revenue can be rewritten as

$$R_t = \frac{\sigma}{\sigma-1}\tilde{\tau}_t\left(w_t\ell_t + p_{M,t}m_t + p_{E,t}e_t\right)e^{u_t}$$

Taking logarithms on both sides

$$\ln\frac{R_t}{w_t\ell_t + p_{M,t}m_t + p_{E,t}e_t} = \ln\frac{\sigma}{\sigma-1} + \ln\tilde{\tau}_t + u_t \tag{35}$$

where $\ln\tilde{\tau} = 0$ in the absence of pollution tax τ. The main parameter of interest is the elasticity of substitution in demand, σ. I estimate Equation 35 with non linear least squares (NLLS) for its consistency.[37] I use observations before the policy implementation to remove $\ln\tilde{\tau}$. Further, I apply the delta method to recover the estimate and standard error of σ.

The elasticities of substitution in the outer production function ρ and the inner production function λ are also of interest. To estimate them, I rewrite the profit maximization problem with each fuel specified

$$\max_{\ell,m,\{e_f\}_f}\Gamma\left(\chi\left(\alpha_L\left(\frac{\ell}{\bar{L}}\right)^{\frac{\rho-1}{\rho}} + \alpha_M\left(\frac{m}{\bar{M}}\right)^{\frac{\rho-1}{\rho}} + \alpha_E\left(\left(\sum_{f\in\mathcal{F}}\left(k_f\frac{e_f}{\bar{E}}\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}\right)^{\frac{\sigma-1}{\sigma}}$$
$$-\tilde{\tau}\left(w\ell + p_M m + \sum_f p_f e_f\right)$$

Taking the ratio of the first order conditions with respect to ℓ and e_e

$$\frac{w\ell}{p_e e_e} = \frac{\left(\frac{\alpha_L}{\alpha_E}\right)^{\frac{\rho}{\rho-1}\frac{\lambda-1}{\lambda}}}{\left(\frac{p_E e}{w\ell}\right)^{1-\frac{\rho}{\rho-1}\frac{\lambda-1}{\lambda}}}\left(\frac{\frac{\ell}{\bar{L}}}{k_e\frac{e_e}{\bar{E}}}\right)^{\frac{\lambda-1}{\lambda}}$$

[37] Grieco, Li, and Zhang (2016) use the first order conditions of the non-linear least squares objective function as moment conditions to show the consistency of the parameters.

using Equation 32. Taking logarithms on both sides and rearranging,

$$\begin{aligned}\ln k_e = &\frac{\rho}{\rho-1}\ln\left(\frac{\alpha_L}{\alpha_E}\right) + \ln\left(\frac{\bar{E}}{\bar{L}}\right) + \left(\frac{\rho}{\rho-1} - \frac{\lambda}{\lambda-1}\right)\ln\left(p_E e\right) \\ &- \frac{\rho}{\rho-1}\ln w - \left(\frac{\rho}{\rho-1} - 1\right)\ln l + \frac{\lambda}{\lambda-1}\ln p_e + \left(\frac{\lambda}{\lambda-1} - 1\right)\ln e_e\end{aligned}$$

With a time-varying shock ε_t such that $\mathbb{E}\left[\varepsilon_t\right] = 0$,

$$\begin{aligned}\ln k_{e,t} = &\frac{\rho}{\rho-1}\ln\left(\frac{\alpha_L}{\alpha_E}\right) + \ln\left(\frac{\bar{E}}{\bar{L}}\right) + \left(\frac{\rho}{\rho-1} - \frac{\lambda}{\lambda-1}\right)\ln\left(p_{E,t} e_t\right) \\ &- \frac{\rho}{\rho-1}\ln w_t - \left(\frac{\rho}{\rho-1} - 1\right)\ln l_t + \frac{\lambda}{\lambda-1}\ln p_{e,t} + \left(\frac{\lambda}{\lambda-1} - 1\right)\ln e_{e,t} + \varepsilon_t\end{aligned} \tag{36}$$

From this equation, λ and ρ can be estimated because electricity bill, wage bill, the number of employment, the amount of capital, electricity use, and fuel expense are known. Without loss of generality, I assume k_e is equal to the total amount of capital because electricity is always used in every capital. I use housing prices to proxy district-level capital prices. For plants that use electricity only, λ is not estimable as there is no substitution. I estimate Equation 36 with non linear least squares (NLLS) for its consistency. Lastly, I use the delta method to recover the estimates and standard errors of λ and ρ.

Productivity Productivity can be estimated from Equations 32, 33, and 34

$$\chi = \left(\frac{\sigma}{\sigma-1}\frac{1}{\Gamma}\frac{\tilde{\tau} w \ell}{\alpha_L^{\frac{\rho}{\rho-1}\frac{\sigma-1}{\sigma}}\left(\frac{\ell}{\bar{L}}\right)^{\frac{\sigma-1}{\sigma}}}\left(1 + \frac{p_M m}{w\ell} + \frac{p_E e}{w\ell}\right)^{1-\frac{\rho}{\rho-1}\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

All on the right hand side of the equation are known, except $\left\{\Gamma_l = \sum_n P_n Q_n^{\frac{1}{\sigma}} s_{ln}^{\frac{\sigma-1}{\sigma}}\right\}$. Here Γ_l can be rewritten as $\sum_n P_n^{1-\frac{1}{\sigma}}\left(P_n Q_n\right)^{\frac{1}{\sigma}} s_{ln}^{\frac{\sigma-1}{\sigma}}$. Note that the corresponding district-level information is not readily available. For this reason, I use the following method. I compute $P_n Q_n$ using province-level expenditure redistributed with population and material expense. I use monthly rents to proxy P_n. Then, I compute $s_{ln} = \frac{P_n^{\sigma-1} X_n d_{ln}^{-\sigma}}{\sum_n P_n^{\sigma-1} X_n d_{ln}^{1-\sigma}}$. Here I borrow trade cost d_{ln} from Arkolakis and Walsh (2023). Then, plant productivity χ can be recovered such that $\chi_{il} = A_{il}\phi_i z_l$ where i denotes the locations of headquarters, and l denotes the locations of establishments. I decompose the recovered productivity such that $\ln\chi_{il} = \ln A_{il} + \ln\phi_i + \ln z_l$. I use firm and plant fixed effects to derive the last two productivities and use the residual for the first productivity. Through the decomposition, each specific productivity can be recovered: headquarters-affiliate location productivity between i and l, A_{il}; core productivity, ϕ_i; and

plant-specific productivity,z_l. However, this approach requires normalization for each fixed effect. So I choose the lowest values in 2016 to be the reference points.

Given that z follows Pareto distribution, taking the mean gives the estimate of θ, the Pareto tail parameter that governs the dispersion

$$\mathbb{E}\left[\ln z\right] = \frac{1}{\theta}$$

For the left hand side, I take the average across locations and years and use the law of large numbers. Given that ϕ follows Fréchet distribution with shape parameter $\zeta > 1$, taking the mean gives the estimate of ζ, the shape parameter that governs the dispersion

$$\mathbb{E}\left[\phi\right] = \Gamma\left(1 - \frac{1}{\zeta}\right)$$

where $\Gamma\left(\cdot\right)$ is the Gamma function. Similarly, given that $z^{\mathcal{E}}$ follows Fréchet distribution with shape parameter $\zeta^{\mathcal{E}} > 1$, taking the mean gives the estimate of $\zeta^{\mathcal{E}}$, the shape parameter that governs the dispersion

$$\mathbb{E}\left[z^{\mathcal{E}}\right] = \Gamma\left(1 - \frac{1}{\zeta^{\mathcal{E}}}\right)$$

This concludes the recovery of productivities.[38]

Entry costs The last set of parameters that need to be estimated is the entry costs of industrial and power generation firms, $\left\{f_{i,e}, \left\{f_{i,e}^{\mathcal{E},f}\right\}\right\}$. I estimate them indirectly by matching the numbers of headquarters for each firms in the SBR.

6.1.3 Estimation Result: in progress

The estimated parameters are summarized in Table A.13.

Model fit: in progress This section shows how the model captures the spatial distribution of emissions and output, given the estimated parameters. I compare year 2016 and a steady state where pollution tax $\tau = 0$.

[38] I follow Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015) and do not account for sample selection because the institutional reality in Korea renders an immediate exit in response to a negative productivity shock unlikely. Also, the census data, by construction, contain the information of firms at the end of the year, that will exist or exit in the next year. Moreover, entry often implies large sunk cost that makes an (immediate) exit more unlikely, thus further mitigating the potential for sample selection.

7 Counterfactual experiments: in progress

In this section, I conduct several counterfactual experiments. First, I quantify the effect of the cap-and-trade expansion by increasing or decreasing pollution tax across regions. The former case maps into a case where the policy is not binding while the latter is the goal of this policy. Second, I analyze how uniform pollution tax can change the policy implications to see how regional policy variations work. Third, I consider alternative policies. The most important one is Scope 2 regulations which regulates the use of electricity, incorporating emissions related to power generation to prevent leakage into power plants and the regions with high concentrations of dirty power plants. In addition, I explore how the design of pollution tax target or how the MP framework can change the policy implications. Lastly, I explore how important it is that the policy is market-based by studying command-and-control regime.

8 Conclusion: in progress

References

Abadie, A. (2005). Semiparametric difference-in-differences estimators. The Review of Economic Studies, 72(1), 1–19.

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. American Economic Review, 102(1), 131–166.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. Econometrica, 83, 2411–2451.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. Journal of Political Economy, 124(1), 1–51.

Arkolakis, C., Kim, C., & Leclair Emmanuel, M. (forthcoming). Deep industrial decarbonization: Theory and evidence from South Korea. Mimeo.

Arkolakis, C., Ramondo, N., Clare, A. R., & Yeaple, S. (2018). Innovation and production in the global economy. American Economic Review, 108(8), 2128–2174.

Arkolakis, C., & Walsh, C. (2023). Clean growth. NBER Working Paper No. w31615.

Armington, P. S. (1969). A theory of demand for products distinguished by place of production (Une théorie de la demande de produits différenciés d'après leur origine) (Una teoría de la demanda de productos distinguiéndolos según el lugar de producción). Staff Papers (International Monetary Fund), 16(1), 159–178.

Broner, F., Bustos, P., & Carvalho, V. M. (2012). Sources of comparative advantage in polluting industries. Working Paper, 44, December.

Busso, M., DiNardo, J., & McCrary, J. (2014). New evidence on the finite sample properties of propensity score reweighting and matching estimators. The Review of Economics and Statistics, 96(5), 885-897.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22(1), 31-72.

Caselli, F., & Coleman II, W. J. (2006). The world technology frontier. American Economic Review, 96(3), 499–522.

Chen, Q., Chen, Z., Liu, Z., Suárez Serrato, J. C., & Xu, D. (2021). Regulating conglomerates in China: Evidence from an energy conservation program. NBER Working Papers 29066, National Bureau of Economic Research, Inc.

Cherniwchan, J., Copeland, B. R., & Taylor, M. S. (2017). Trade and the environment: New methods, measurements, and results. Annual Review of Economics, 9, 59–85.

Coase, R. H. (1960). The problem of social cost. The Journal of Law and Economics, 3.

Colmer, J., Martin, R., Muûls, M., & Wagner, U. J. (2024). Does pricing carbon mitigate climate change? Firm-level evidence from the European Union Emissions Trading System. The Review of Economic Studies, rdae055.

Conte, B., Desmet, K., Nagy, D. K., & Rossi-Hansberg, E. (2021). Local sectoral specialization in a warming world. Journal of Economic Geography, 21, 493–530.

Copeland, B. R., & Taylor, M. S. (2004). Trade, growth, and the environment. Journal of Economic Literature, 42(1), 7–71.

Copeland, B., Shapiro, J. S., & Taylor, M. S. (2021). Globalization and the environment. SSRN Electronic Journal.

Cruz, J.-L. (2024). Global warming and labor market reallocation. September 04.

Cruz, J.-L., & Rossi-Hansberg, E. (2022). Local carbon policy. NBER Working Paper No. w30027.

Cruz, J.-L., & Rossi-Hansberg, E. (2024). The economic geography of global warming. The Review of Economic Studies, 91(2), 899–939.

Demirer, M. (2020). Production function estimation with factor-augmenting technology: An application to markups. Working Paper.

Desmet, K., & Rossi-Hansberg, E. (2015). On the spatial economic impact of global warming. Journal of Urban Economics, 88, 16–37.

Desmet, K., & Rossi-Hansberg, E. (2024). Climate change economics over time and space. Annual Review of Economics. DOI: 10.3386/w32197.

Dixit, A. K., & Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. The American Economic Review, 67(3), 297–308.

Doraszelski, U., & Jordi, S. (2013). R and D and productivity: Estimating endogenous productivity. Review of Economic Studies, 80(4), 1338–1383.

Doraszelski, U., & Jaumandreu, J. (2018). Measuring the bias of technological change. Journal of Political Economy, 126.

Eskeland, G. S., & Harrison, A. E. (2003). Moving to greener pastures? Multinationals and the pollution haven hypothesis. Journal of Development Economics, 70(1).

Farrokhi, F., & Lashkaripour, A. (2024). Can trade policy mitigate climate change. Working Paper.

Fowlie, M., Holland, S., & Mansur, E. (2012). What do emissions markets deliver and to whom? American Economic Review, 102(1), 374–402.

Fowlie, M., & Perloff, J. M. (2013). Distributing pollution rights in cap-and-trade programs: Are outcomes independent of allocation? The Review of Economics and Statistics, 95(5), 1640–1652.

Frondel, M., & Vance, C. (2013). Re-identification of treatment effects using matching estimators. Journal of Environmental Economics and Management, 66(1), 1-13.

Garcia-Lembergman, E., Ramondo, N., Rodriguez-Clare, A., & Shapiro, J. S. (2023). The carbon footprint of multinational production. Mimeo.

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. Econometrica, 82, 41–88.

Greenstone, M., Pande, R., Sudarshan, A., & Ryan, N. (2023). Can pollution markets work in developing countries? Experimental evidence from India. The Warwick Economics Research Paper Series (TWERPS) 1453, University of Warwick, Department of Economics.

Grieco, P. L. E., Li, S., & Zhang, H. (2016). Production function estimation with unobserved input price dispersion. International Economic Review, 57(2), 665–690.

Hanna, R. (2010). US environmental regulation and FDI: Evidence from a panel of US-based multinational firms. American Economic Journal: Applied Economics, 2(3).

Hanson, G. H. (2023). Local labor market impacts of the energy transition. Working Paper, National Bureau of Economic Research, W30871.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The Review of Economic Studies, 64(4), 605–654.

Heckman, J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. The Review of Economic Studies, 65(2), 261–294.

Hémous, D., & Olsen, M. (2021). Directed technical change in labor and environmental economics. Annual Review of Economics, 13.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. The Review of Economics and Statistics, 86(1), 4–29.

Kim, C. (2024). The emergence of greenhouse gas trading: Evidence from Korea. Mimeo.

Kortum, S. S., & Weisbach, D. A. (2021). Optimal unilateral carbon policy. Coase-Sandor Working Paper Series in Law and Economics, No. 943.

Krussell, P., & Smith Jr, A. A. (2022). Climate change around the world. Tech. rep., National Bureau of Economic Research.

León-Ledesma, M. A., McAdam, P., & Willman, A. (2010). Identifying the elasticity of substitution with biased technical change. American Economic Review, 100(4), 1330–1357.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. The Review of Economic Studies, 70(2), 317–341.

Levinson, A., & Taylor, M. S. (2008). Unmasking the pollution haven effect. International Economic Review, 49(1).

Levinson, A. (2009). Technology, international trade, and pollution from US manufacturing. American Economic Review, 99(5).

Leclair, E. (2024). Balancing production and carbon emissions with fuel substitution. Working paper.

Nordhaus, W. (2015). Climate clubs: Overcoming free-riding in international climate policy. American Economic Review, 105(4), 1339–1370.

Oberfield, E., & Raval, D. (2021). Micro data and macro technology. Econometrica, 89, 703–732.

Ramondo, N., & Rodríguez-Clare, A. (2013). Trade, multinational production, and the gains from openness. Journal of Political Economy, 121(2).

Robins, J. M., & A. (1995). Semiparametric efficiency in multivariate regression models with missing data. Journal of the American Statistical Association, 90(429), 122–129.

Robins, J. M., Rotnitzky, A., & Zhao, L. P. (1994). Estimation of regression coefficients when some regressors are not always observed. Journal of the American Statistical Association, 89(427), 846–866.

Shapiro, J. S. (2016). Trade costs, CO2, and the environment. American Economic Journal: Economic Policy, 8(4), 220–254.

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), 3814–3854.

Sun, C. (2020). Multinational production with non-neutral technologies. Journal of International Economics, 123.

Tanaka, S., Teshima, K., & Verhoogen, E. (2022). North-South displacement effects of environmental regulation: The case of battery recycling. American Economic Review: Insights, 4(3), 271–288.

Tintelnot, F. (2017). Global production with export platforms. Quarterly Journal of Economics, 132(1).

Wagner, U., Muûls, M., Martin, R., & Colmer, J. (2014). The causal effects of the European Union emissions trading scheme: Evidence from French manufacturing plants (April 1st, 2014). Working Paper - Universidad Carlos III Madrid.

Wagner, U. J., & Petrick, S. (2014). The impact of carbon trading on industry: Evidence from German manufacturing firms. Kiel Working Papers 1912, Kiel Institute for the World Economy (IfW Kiel).

Weisbach, D. A., Kortum, S., Wang, M., & Yao, Y. (2023). Trade, leakage, and the design of a carbon tax. Environmental and Energy Policy and the Economy, 4, 43–90.

Xiang, W. (2023). Clean growth and environmental policies in the global economy. Working paper.

Yang, L., Lin, Y., Wang, J., & Peng, F. (2024). Achieving air pollution control targets with technology-aided monitoring: Better enforcement or localized efforts? American Economic Journal: Economic Policy, 16(4), 280–315.

Zhang, H. (2019). Non-neutral technology, firm heterogeneity, and labor demand. Journal of Development Economics, 140 (May), 145–168.

A Data Appendix

A.1 District-level Data

A.1.1 Data Cleaning

First, sectoral and district concordances are considered in line with the most recent year available. The name of other fixed equipment of commercial and public institutions in non-industrial combustion is changed to others. Similarly, emissions from fugitive dust and biomass burning are dropped. Second, public and private power generation are classified as power generation sectors. Oil refinery, manufacturing combustion, production process except ammonia consumption, organic solvents used for printing industry, other non-industrial coating processes, other industrial coating processes, wood and furniture manufacturing, ship-building, automobile repair, automobile manufacturing, coil coating, metal cleaning process, other industrial cleaning processes, and electronic components manufacturing are classified as manufacturing.

A.1.2 Treatment Assignment

Treatment is assigned across districts and sectors if there is at least one plant in each bin (district×sector).

A.2 Plant-level Data

A.2.1 Data Cleaning

This paper conducts three data cleaning procedures. First, it fills out missing location if necessary. For example, from smaller location codes, districts are found. In the end, there is only one observation without any location details. Second, sectoral and district concordances are considered in line with the most recent year available. The sector of a plant is readjusted to compute emissions from production process. Sectors in 2016 are emptied because of the change in KSIC in 2017 from KSIC 9th to KSIC 10th. I only use the later one as it covers the all the periods of interest except the very first one. Then, 5-, 4-, 3-, 2-digits are created for each year. Differentiating pre/post-treatment periods, mode (and maxmode as tie-breaking) are used to fill out empty ones only. Manufacturing and polluting manufacturing sectors are created based on this. Polluting manufacturing sectors are those targeted by the policy. Empty ones are filled out by differentiating pre/post-treatment periods through mode (and maxmode as tie-breaking). Empty polluting manufacturing sectors are filled with manufacturing sectors and empty manufacturing sectors are filled with

original sectors if missing. Then, it is fixed to that of 2019. In addition, districts were concordanced with year 2022 being the baseline.

A.2.2 Treatment Assignment

The final dataset used in this paper is organized in this way

1. Create a list of firm tax codes, locations, and sectors of treated plants
2. Merge this list with the SBR to identify treated firms
3. Refine the dataset by keeping plants that have any fuel use information or are in the power generation sectors
    (a) This choice effectively leaves only mining and manufacturing and power plants, the sectors of interest
4. Differentiate treated plants and affiliated plants in the treated firms
5. Merge this dataset with the MMS using the plant tax code

The match in Step 2 is successful. After removing treated plants that closed after the policy was expanded, there are only four unmatched plants in the waste disposal industry whose firms are not in the SBR. The industry is beyond the scope of this paper.

When identifying the treated plants in Step 4, I use all the information available in the policy document: name, sector, location, and year.

- Plants are regarded as targeted if their firms are treated and their description matches that of the list
    - Locations, fossil fuel emissions, and sales are considered in order.
    - I do not use any physical proximity measures to identify treated plants
        * This means that I treat plants in different districts and plants in the same districts differently
        * This is because the SBR contains all mining and manufacturing plants
    - However, if there are more than one plants in a district, they are cleared out further using smaller regional units, emissions, and sales
- Plants are regarded as affiliated if their firms are treated, but they are not targeted
- Plants are regarded as not treated if their firms are not treated

B Theory: in progress

This section contains several derivations omitted in the main text for brevity.

C Proofs

Proposition 1.

Assume $\lambda > \rho > 0$

Result

- Emissions decrease in pollution tax τ.

Mechanism

- The unit production cost increases in pollution tax τ.
- The use of fossil fuel f to electricity decreases in pollution tax τ.
- Fossil fuel emissions intensity of electricity $\frac{\sum_f \kappa_f e_f}{e_e}$, production process emissions intensity of electricity $\frac{\kappa q}{e_e}$, emissions intensity of electricity $\frac{\sum_f \kappa_f e_f + \kappa q}{e_e}$ decrease in pollution tax τ.
- Electricity intensity $\frac{e_e}{q}$ increases in pollution tax τ.

Proof

- Ceteris paribus, as emissions become more costly, emissions decrease.
- See Equation 5. The unit production cost increases in pollution tax τ.
- See Equation 4.
  - An increase in pollution tax τ increases the relative price of fossil fuel f compared to electricity.
  - The power term λ on the relative price term captures the standard price substitution effect related to effective fuel prices.
- See Equation 4. Fossil fuel emissions intensity of electricity $\frac{\sum_f \kappa_f e_f}{e_e}$ decreases in pollution tax τ. Production process emissions intensity of electricity $\frac{\kappa q}{e_e}$ also decreases in pollution tax τ. Together, emissions intensity of electricity $\frac{\sum_f \kappa_f e_f + \kappa q}{e_e}$ decreases in pollution tax τ.
- Electricity intensity $\frac{e_e}{q}$ increases in pollution tax τ.

Proposition 2.

Assume $\lambda > 1$

Mechanism

- When pollution tax is close to zero, more productive firms are cleaner. When pollution tax is significantly large, this relationship does not hold because being subject to pollution tax is too much costly.
- The investment of fossil fuel capital $k_{l,f}$ decreases relative to that of electricity capital $k_{l,e}$ when there is pollution tax.
  - This further makes the fuel use ratio cleaner. Thus, fuel substitution is more significant in targeted plants than in affiliated ones because pollution tax directly works on the fuel composition, although fuel technology is shared within firms.
  - This result holds for other fuels than electricity as long as they are different fuels.

Proof

- When pollution tax is close to zero, the mechanism matches the fact that more productive firms are cleaner as $\Upsilon(\phi)$ and hence the marginal gain of the investment increase in core productivity ϕ. This is consistent with Figure A.11. When pollution tax is significantly large, this relationship does not hold because being subject to pollution tax is too much costly.
- Most importantly, an increase in pollution tax τ_l also affects the marginal gain. Depending on the parameter values, it can increase or decrease. If it increases, it implies that plants improve their fuel intensity for regulated fuels to use those fuels more efficiently. Otherwise, it implies that plants divest since these fuels are too costly to use. The directions of different fuel-specific investments are unknown ex-ante. In the following quantification exercise, I let the data tell how fuel-specific capital investment moves. One notable pattern is that whether it increases or not, the marginal gain of a cleaner fuel becomes larger as pollution tax increases with $\lambda > 1$. This can be shown by taking the ratio of Equation 25 for different fuels

$$\frac{P_{i,f}}{P_{i,e}} = \frac{\sum_l A_{il}^{\sigma-1} \frac{\partial B_l\left(\phi;\left\{k_{l,f}\right\}_f\right)}{\partial k_{l,f}}}{\sum_l A_{il}^{\sigma-1} \frac{\partial B_l\left(\phi;\left\{k_{l,f}\right\}_f\right)}{\partial k_{l,e}}} \propto \frac{\left(\frac{\tilde{p}_{l,f}}{k_{l,f}}\right)^{1-\lambda} \frac{1}{k_{l,f}}}{\left(\frac{\tilde{p}_{l,e}}{k_{l,e}}\right)^{1-\lambda} \frac{1}{k_{l,e}}}$$

In other words, the investment of fossil fuel capital $k_{l,f}$ decreases relative to that of electricity capital $k_{l,e}$ when there is pollution tax.

- See Equation 4. This change further makes the fuel use ratio to become cleaner. Thus, fuel substitution is more significant in targeted plants than in affiliated ones because pollution tax directly works on the fuel composition, although fuel technology is shared within firms.
- This result holds for other fuels than electricity as long as they are different fuels.

D Solution Algorithm

The problem needs to be solved in the following steps.

1. Choose regions considering policy areas, administrative units, and commuting zones
2. Set parameters
3. Guess $\{p_e\}$
4. Guess $\{w_i\}$
   (a) Industrial firm optimization
      i. Guess $\{X_n\}$
      ii. Guess $\{P_n\}$
      iii. Solve for $\{k_{l,f}\}$ (Equations 24 and 25)
      iv. Find $\left\{\bar{\phi}_i\right\}$ and $\{M_i\}$ from free entry (Equation 26)
      v. Derive $\{P_n\}$ (Equation 7)
      vi. If $\{P_n\}$ are similar, move on
      vii. Otherwise, use the derived one as a new guess and repeat until convergence
      viii. Derive $\{X_n\}$ (Equation 30)
      ix. If $\{X_n\}$ are similar, move on
      x. Otherwise, use the derived one as a new guess and repeat until convergence
      xi. If each labor market clears (Equation 31), move on
      xii. Otherwise, update $\{w_l\}_l$ using the gradual adjustment method and repeat until convergence (Equation 31)
      xiii. Derive $\{\Pi_n\}$ (Equation 27), $\left\{S_l^{\mathcal{P}}\right\}$ (Equation 28), and $\{e_{l,e}\}$ (Equation 29) such that $e_e = \sum_l e_{l,e}$
   (b) Power generation firm optimization
      i. Guess $\left\{P_{l,f}^{\mathcal{E}}\right\}$

ii. Guess $\left\{M_l^{\mathcal{E},f}\right\}$

iii. Solve for p_e and $\{y_{l,f}\}$ (Equations 13 and 14)[39]

iv. Find $\left\{\bar{z}_{l,f}^{\mathcal{E}}\right\}$ and $\left\{M_l^{\mathcal{E},f}\right\}$ from free entry (Equation 15)

v. If $\left\{M_l^{\mathcal{E},f}\right\}$ are similar, move on

vi. Otherwise, use the derived one as a new guess and repeat until convergence

vii. Solve for $\left\{e_{l,f}^{\mathcal{E}}\right\}$ (Equation 10)

viii. Derive $\left\{P_{l,f}^{\mathcal{E}}\right\}$ (Equation 11)

ix. If $\left\{P_{l,f}^{\mathcal{E}}\right\}$ are similar, move on

x. Otherwise, use the derived one as a new guess and repeat until convergence

xi. If p_e are similar, move on

xii. Otherwise, use the derived one as a new guess and repeat until convergence

xiii. Derive $\left\{\Pi_n^{\mathcal{E}}\right\}$ (Equation 16) and $\left\{S_l^{\mathcal{E}}\right\}$ (Equation 28)

xiv. If $\left\{\Pi_n^{\mathcal{E}}\right\}$ are similar, move on

xv. Otherwise, use the derived one as a new guess and repeat until convergence

(c) Household optimization

i. Derive $\{u_n\}$ (Equation 8)

E Tables

Table A.1: Connection to the Existing Literature

	Trade	MP	Firm	Clean technology	Leakage	Energy
FP	✓			✓	✓	
CCLSX			✓		✓	
GRRS	✓	✓				✓
CMMW				✓	✓	✓
X	✓	✓		✓	✓	
AKL	✓			✓	✓	✓
This paper	✓	✓	✓	✓	✓	✓

Notes: Clean technology denotes abatement and clean innovation. FP denotes Farrokhi and Lashkaripour (2024), CLLSX Chen et al. (2021), GRRS Garcia-Lembergman et al. (2023), CMMW Colmer et al. (2024), X Xiang (2023), AKL Arkolakis, Kim, and Murray Leclair (2025). The key contribution of this paper is to consider several concrete channels of clean innovation and leakage using energy and find new policy implications.

[39] I equally divide demand in a tie-breaking situation

Table A.2: Policy Goal

Nation	Initial year (2020)	Final year (2024)	2024-2020
Pollutant	Allowances	Allowances	Growth rate
Total	430,372	247,917	-42%
NO_x	296,905	173,954	-41%
SO_x	128,153	70,225	-45%
TSP	5,314	3,738	-30%

SCA	Initial year (2020)	Final year (2024)	2024-2020
Pollutant	Allowances	Allowances	Growth rate
Total	46,228	8,830	-81%
NO_x	34,125	7,274	-79%
SO_x	11,627	1,535	-87%
TSP	476	21	-96%

CA	Initial year (2020)	Final year (2024)	2024-2020
Pollutant	Allowances	Allowances	Growth rate
Total	160,616	98,551	-39%
NO_x	114,678	76,249	-34%
SO_x	43,145	20,103	-53%
TSP	2,793	2,199	-21%

SA	Initial year (2020)	Final year (2024)	2024-2020
Pollutant	Allowances	Allowances	Growth rate
Total	87,899	57,345	-35%
NO_x	57,361	36,891	-36%
SO_x	29,847	19,961	-33%
TSP	691	493	-29%

SEA	Initial year (2020)	Final year (2024)	2024-2020
Pollutant	Allowances	Allowances	Growth rate
Total	135,629	83,191	-39%
NO_x	90,741	53,540	-41%
SO_x	43,534	28,626	-34%
TSP	1,354	1,025	-24%

Notes: Total is the sum of NO_x emissions allowances, SO_x emissions allowances, and TSP emissions allowances in ton. Emissions allowances are for all industrial and power plants. Growth rates are taken between 2020 and 2024 and expressed in percentage. SCA denotes Seoul Capital Area, CA denotes Central Area, SA denotes Southern Area, SEA denotes Southern-East Area.
Sources: Ministry of Environment

Table A.3: Distribution of targeted plants

Area	Seoul Capital	Central	Southern	Southern-East	Total
Total	453	320	87	399	1,259

Notes: The number of each cell denotes the number of targeted plants in each area in 2020. The numbers have been calculated directly from the policy document without any adjustments.
Sources: Ministry of Environment

Table A.4: Summary Statistics: Districts

	Pre-Match (Full Sample)			Post-Match (Matched Sample)
	Treated	Never	Difference	Difference
ln TSP	-0.04	-0.59	0.53***	1.12***
$(s.e.)$	3.98	3.95	0.12	0.13
ln PM 10	-0.10	-0.69	0.54***	1.13***
$(s.e.)$	3.90	3.84	0.12	0.13
ln PM 2.5	-0.25	-0.94	0.65***	1.18***
$(s.e.)$	3.80	3.70	0.12	0.13
ln SO_x	0.99	0.50	0.48***	1.12***
$(s.e.)$	4.16	4.28	0.13	0.14
ln NO_x	6.03	5.00	0.96***	1.33***
$(s.e.)$	3.32	3.20	0.10	0.11
N	5,544	2,051	7,595	7,463
ln VA	10.56	9.85	0.64***	0.73***
$(s.e.)$	1.56	1.20	0.06	0.09
N	4,226	1,465	5,691	5,685

Notes: The observations in 2019 are used. The coefficients and the standard errors are rounded to two decimal points. VA stands for value added. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table A.5: Policy Effect: Districts

Targeted	ln TSP	ln PM 10	ln PM 2.5
β	-0.12	-0.11	-0.11
$(s.e.)$	0.04	0.04	0.04
N	7,463		

Targeted	ln SO_x	ln NO_x	ln VA
β	-0.08	-0.14	-0.02
$(s.e.)$	0.05	0.04	0.02
N	7,463		5,685

Notes: The coefficients and the standard errors are rounded to two decimal points. VA stands for value added.

Table A.6: Summary Statistics: Targeted Plants

	Pre-Match (Full Sample)			Post-Match (Matched Sample)
	Targeted	Never	Difference	Difference
ln TSP	3.67	0.94	2.73***	0.62***
$(s.e.)$	8.05	1.32	0.11	0.16
ln $(TSPF/TSP)$	-2.54	-0.93	-1.61***	0.09
$(s.e.)$	5.24	1.29	0.09	0.14
ln $(TSPP/TSP)$	-1.44	-1.44	0.01	-0.06
$(s.e.)$	2.76	1.67	0.07	0.14
ln $Sales$	11.83	7.78	4.05***	0.65***
$(s.e.)$	3.11	3.81	0.07	0.10
ln $Electricity$	5.39	1.15	4.24***	0.95***
$(s.e.)$	3.93	1.31	0.07	0.14
ln $(Electricity/Sales)$	-3.45	-4.24	0.80***	0.33***
$(s.e.)$	1.83	3.28	0.05	0.09
ln $(TSPF/Electricity)$	-7.25	-3.52	-3.73***	-0.28*
$(s.e.)$	5.68	3.20	0.09	0.16
ln $(TSPF/Sales)$	-10.69	-7.77	-2.93***	0.05
$(s.e.)$	5.43	3.78	0.09	0.14
N	702	44,238	44,940	5,794

Notes: The observations in 2019 are used. The coefficients and the standard errors are rounded to two decimal points. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table A.7: Summary Statistics: Affiliated Plants

	Pre-Match (Full Sample)			Post-Match (Matched Sample)
	Affiliated	Never	Difference	Difference
ln TSP	2.39	0.94	1.44***	0.28**
$(s.e.)$	6.20	1.32	0.13	0.14
ln $(TSPF/TSP)$	-1.99	-0.93	-1.07***	-0.17
$(s.e.)$	4.73	1.29	0.11	0.13
ln $(TSPP/TSP)$	-1.44	-1.45	0.002	0.04
$(s.e.)$	3.41	1.68	0.11	0.16
ln $Sales$	10.94	7.78	1.70436	0.43***
$(s.e.)$	2.41	3.81	0.0990894	0.09
ln $Electricity$	3.86	1.15	1.088378	0.45***
$(s.e.)$	3.58	1.32	0.1167871	0.11
ln $(Electricity/Sales)$	-4.13	-4.24	0.11	0.06
$(s.e.)$	3.16	3.28	0.09	0.10
ln $(TSPF/Electricity)$	-6.42	-3.53	-0.48***	0.01
$(s.e.)$	4.76	3.21	0.03	0.03
ln $(TSPF/Sales)$	-10.55	-7.77	-2.78***	-0.32***
$(s.e.)$	4.28	3.79	0.10	0.11
N	395	44,271	44,666	9,499

Notes: The observations in 2019 are used. The coefficients and the standard errors are rounded to two decimal points. Significance levels are indicated as * 0.10, ** 0.05, *** 0.01.

Table A.8: Policy Effect: Plants

Targeted	ln TSP	ln $(TSPF/TSP)$	ln $(TSPP/TSP)$	ln $Sales$
β	-0.13	0.10	-0.01	-0.09
$(s.e.)$	0.05	0.03	0.05	0.03
N	34,893			

Targeted	ln $Electricity$	ln $(Electricity/Sales)$	ln $(TSPF/Electricity)$	ln $(TSPF/Sales)$
β	0.15	0.30	-0.24	0.06
$(s.e.)$	0.05	0.06	0.07	0.05
N	34,893			

Notes: The coefficients and the standard errors are rounded to two decimal points.

Table A.9: Policy Effect: Plants

Targeted	ln TSP	ln $(TSPF/TSP)$	ln $(TSPP/TSP)$	ln $Sales$
β	-0.05	0.04	-0.10	-0.14
$(s.e.)$	0.03	0.03	0.04	0.04
N	91,300			

Targeted	ln $Electricity$	ln $(Electricity/Sales)$	ln $(TSPF/Electricity)$	ln $(TSPF/Sales)$
β	0.23	0.42	-0.29	0.14
$(s.e.)$	0.06	0.09	0.08	0.05
N	91,300			

Notes: The coefficients and the standard errors are rounded to two decimal points.

Table A.10: Variations within- and between-firms

	Within-firms	Between-firms	N (plants)	N (firms)
ln $(TSP/Sales)$	0.43	2.22	59,444	57,107
ln $(NO_x/Sales)$	0.42	2.25	59,444	57,107
ln $(SO_x/Sales)$	0.56	2.88	59,444	57,107

Notes: Plants in 2019 are used. Only S1 emissions are used because these ratios capture the overall emissions intensity. But the pattern is robust to adding Scope 2 emissions, using other years, and using other energy or emissions related measures. Each number is rounded to two decimal points. This variance decomposition is conditional on 4-digit KSIC.

Table A.11: Robustness check: Plants

Targeted	Baseline	(1)	(2)	(3)	(4)	(5)
β	-0.24	-0.55	-0.16	-0.20	-0.26	-0.09
$(s.e.)$	0.07	0.17	0.08	0.07	0.09	0.03

Affiliated	Baseline	(1)	(2)	(3)	(4)	(5)
β	-0.29	-0.25	-0.10	-0.31	-0.24	-0.09
$(s.e.)$	0.08	0.12	0.08	0.08	0.10	0.09

Notes: The coefficients and the standard errors are rounded to two decimal points. (1) considers districts, (2) aggregates all local pollutants, (3) uses Mahalanobis distance matching, and (4) considers the initial policy adoption. The outcome variable is ln TSP S1/Electricity.

Table A.12: Calibrated parameters

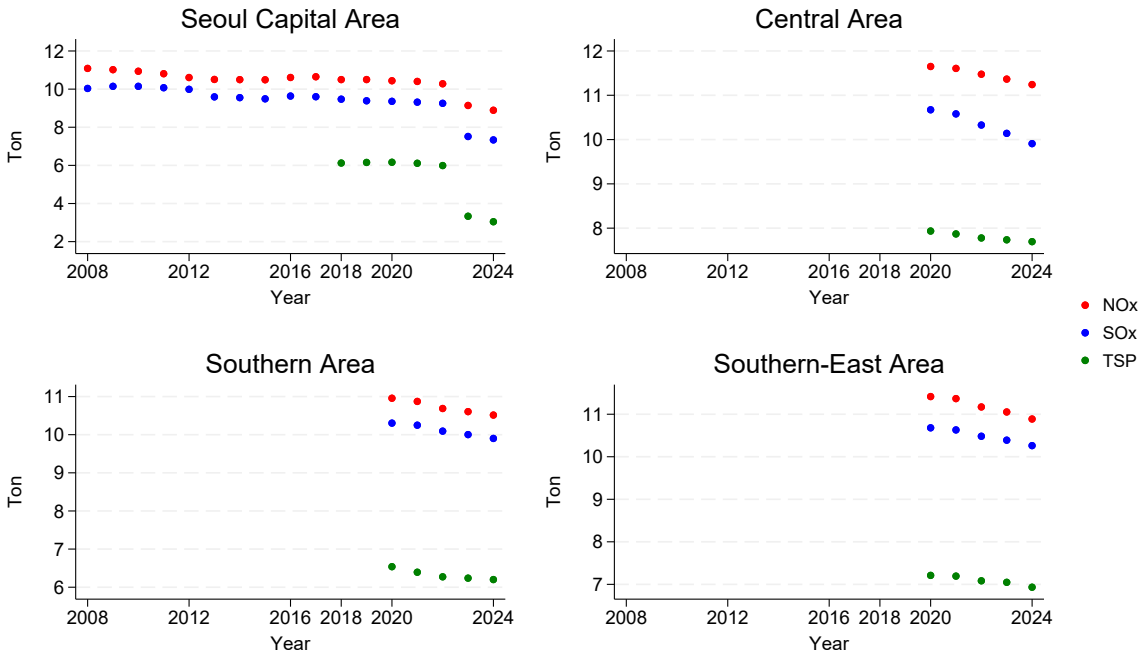
Parameters		Value	Source or method
Policy		Value	Source or method
$\{\tau_l\}$	Pollution tax		Emissions allowance prices
κ	Production process emissions factor (product-specific)		Policy document
$\{\kappa_f\}$	Fossil-fuel-specific emissions factor		Policy document
T	Threshold for pollution tax		See text
Households			
$\{dist_{ln}\}$	Distance between l and n		Plant centroid (km)
$\{L_n\}$	Regional employment		SBR data in 2016
SC	Social cost of emissions	Various	Literature
Power plants			
$\{p_f\}$ (except p_e)	Fuel price		Our World In Data
$\{d_{ln}\}$	Iceberg trade cost		Arkolakis and Walsh (2023)
α_L	CES average labor productivity	0.25	MMS data in 2016
α_M	CES average material productivity	0.71	MMS data in 2016
α_E	CES average capital-energy productivity	0.04	MMS data in 2016

Table A.13: Estimated parameters

Parameters		Value	Observations
Households			
σ	Demand elasticity of substitution	2.59 (0.06)	127,458
Industrial firms			
ρ	Outer production function elasticity of substitution		
λ	Inner production function elasticity of substitution		
θ	Pareto shape parameter		
ζ	Fréchet shape parameter		
$\{A_{il}\}$	MP productivity		
$\{f_{i,e},\}$	Firm entry cost		
Power generation firms			
$\zeta^{\mathcal{E}}$	Fréchet shape parameter		
$\left\{f_{i,e}^{\mathcal{E},f}\right\}$	Plant fixed cost		

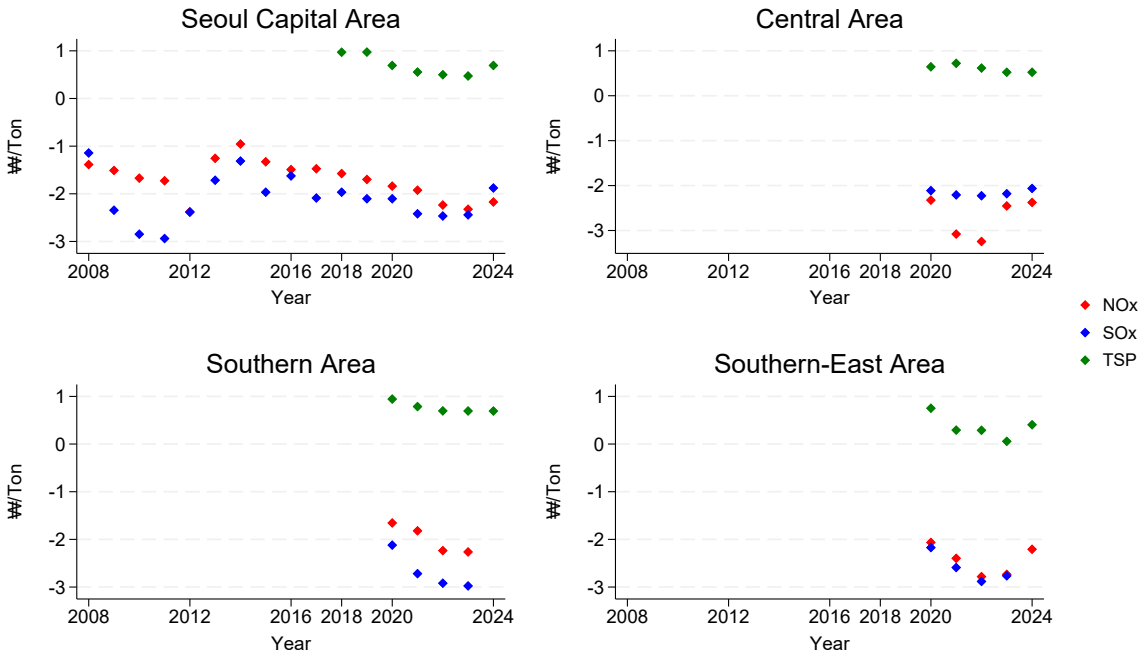
F Figures

Figure A.1: Emissions allowances



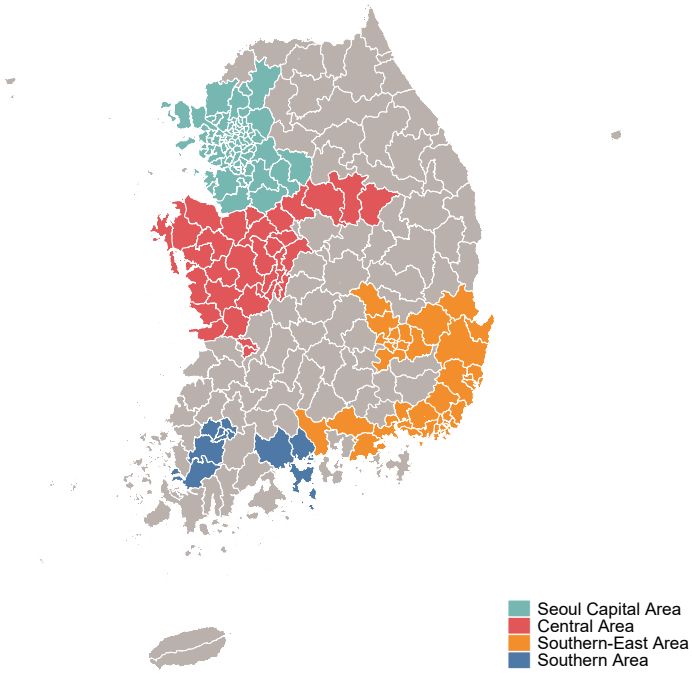
Notes: Emissions allowances are for all targeted establishments in each area.
Sources: Ministry of Environment

Figure A.2: Emissions allowance Prices



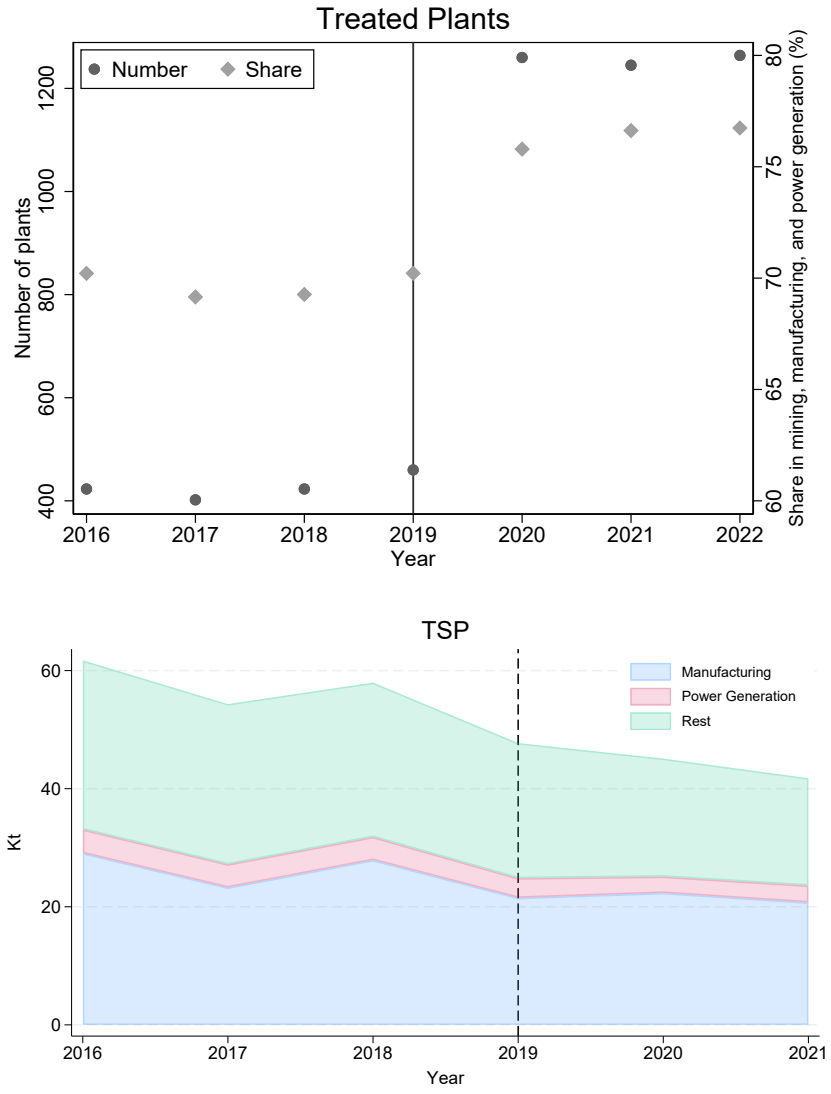
Notes: The average transaction unit price is disclosed as the annual transaction amount divided by the annual transaction volume (excluding free transactions) in each area.
Sources: Ministry of Environment

Figure A.3: Policy variations in Space



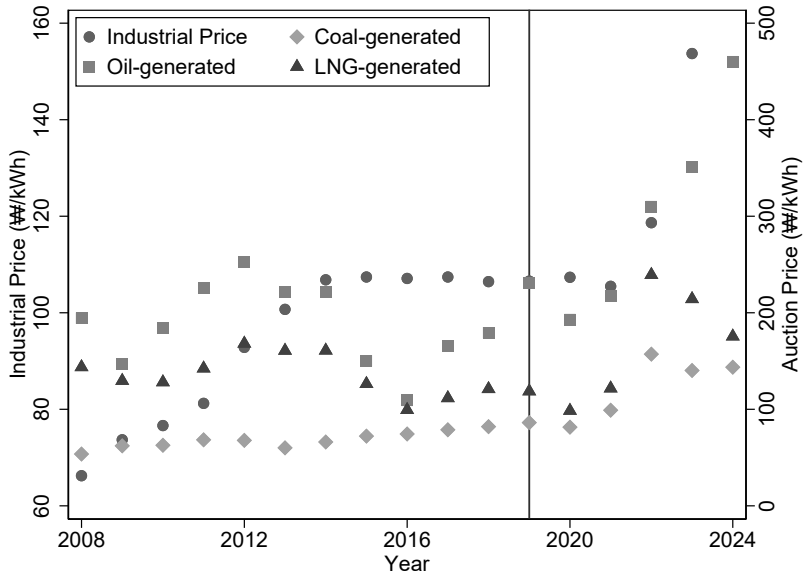
Notes: The figure shows the spatial expansion of local air pollutant cap-and-trade systems. The policy was first implemented in Seoul Capital Area, which has been expanded to other regions (Blue). They are Central Area, Southern Area, and Southern-East Area. The gray area represents non-targeted areas.
Sources: Ministry of Environment

Figure A.4: Mining, Manufacturing, and Power generation



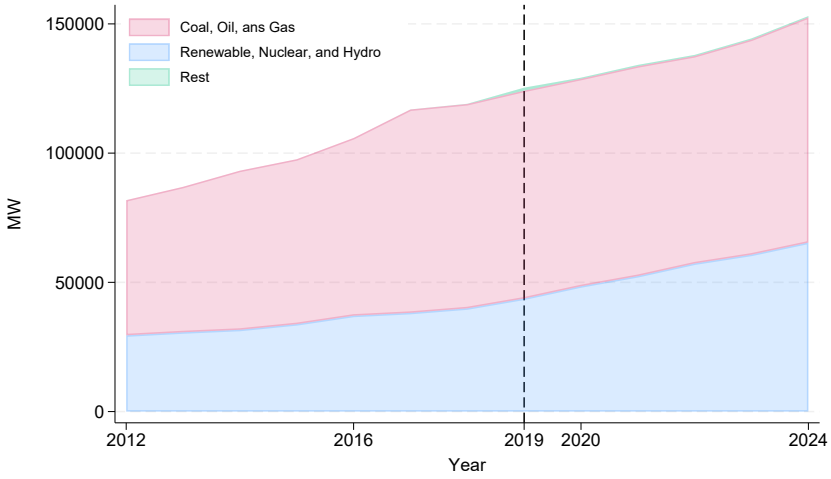
Notes: The upper panel shows the share of treated plants in the mining, manufacturing, and power generation sectors. The lower panel visualizes their shares of TSP emissions.
Sources: Ministry of Environment

Figure A.5: Electricity prices



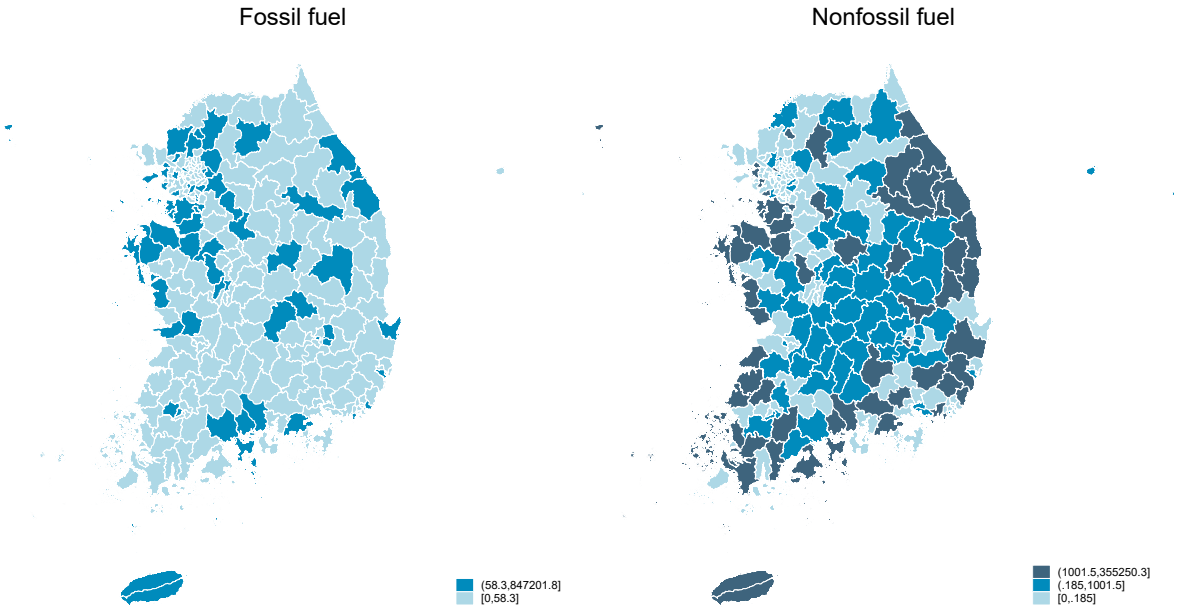
Notes: Industrial price is on the left y-axis and the other prices are on the right y-axis.
Sources: Electric Power Statistics Information System

Figure A.6: Power generation by Source



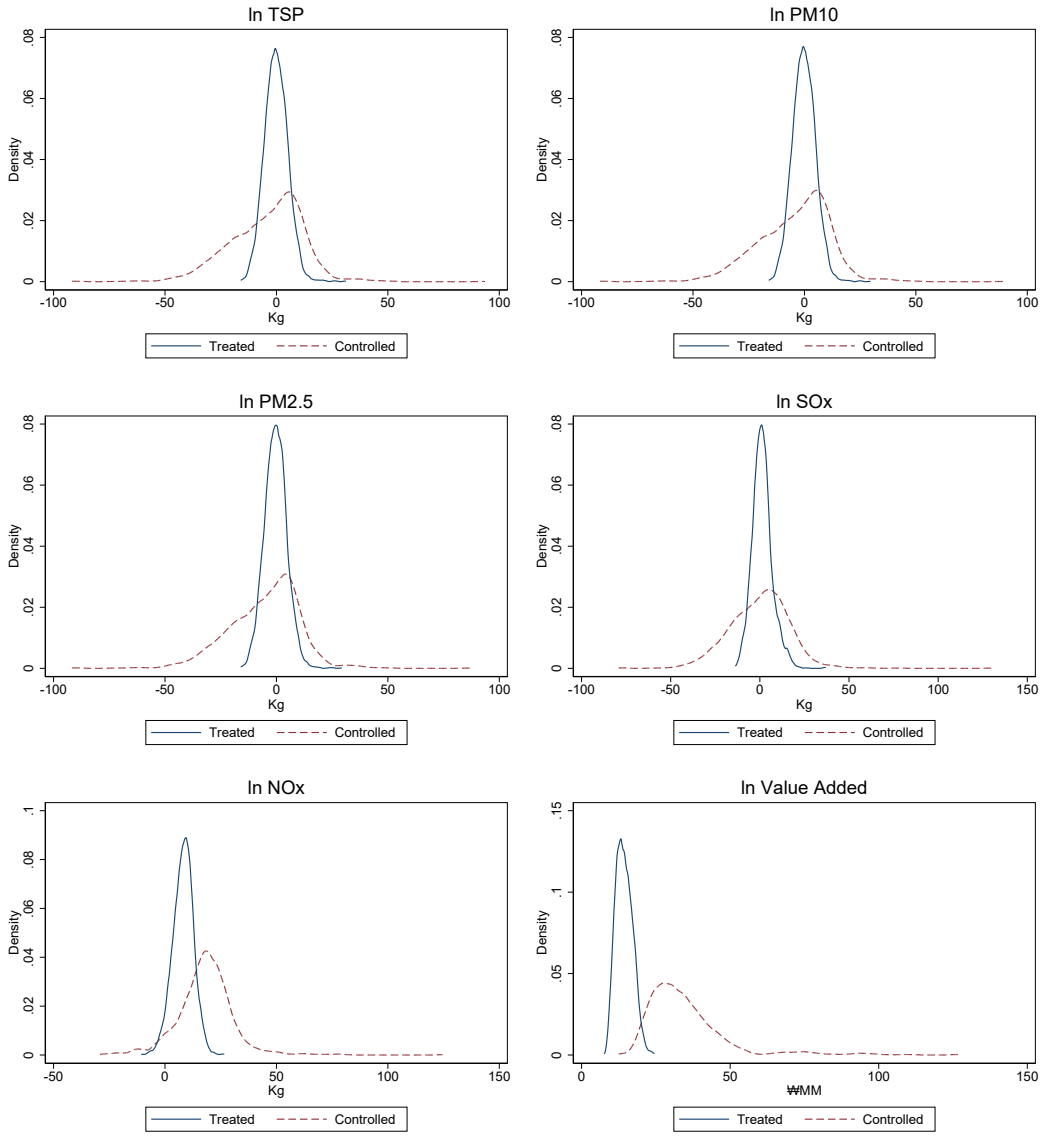
Notes: The unit is Megawatt.
Sources: Electric Power Statistics Information System

Figure A.7: Power generation in Space



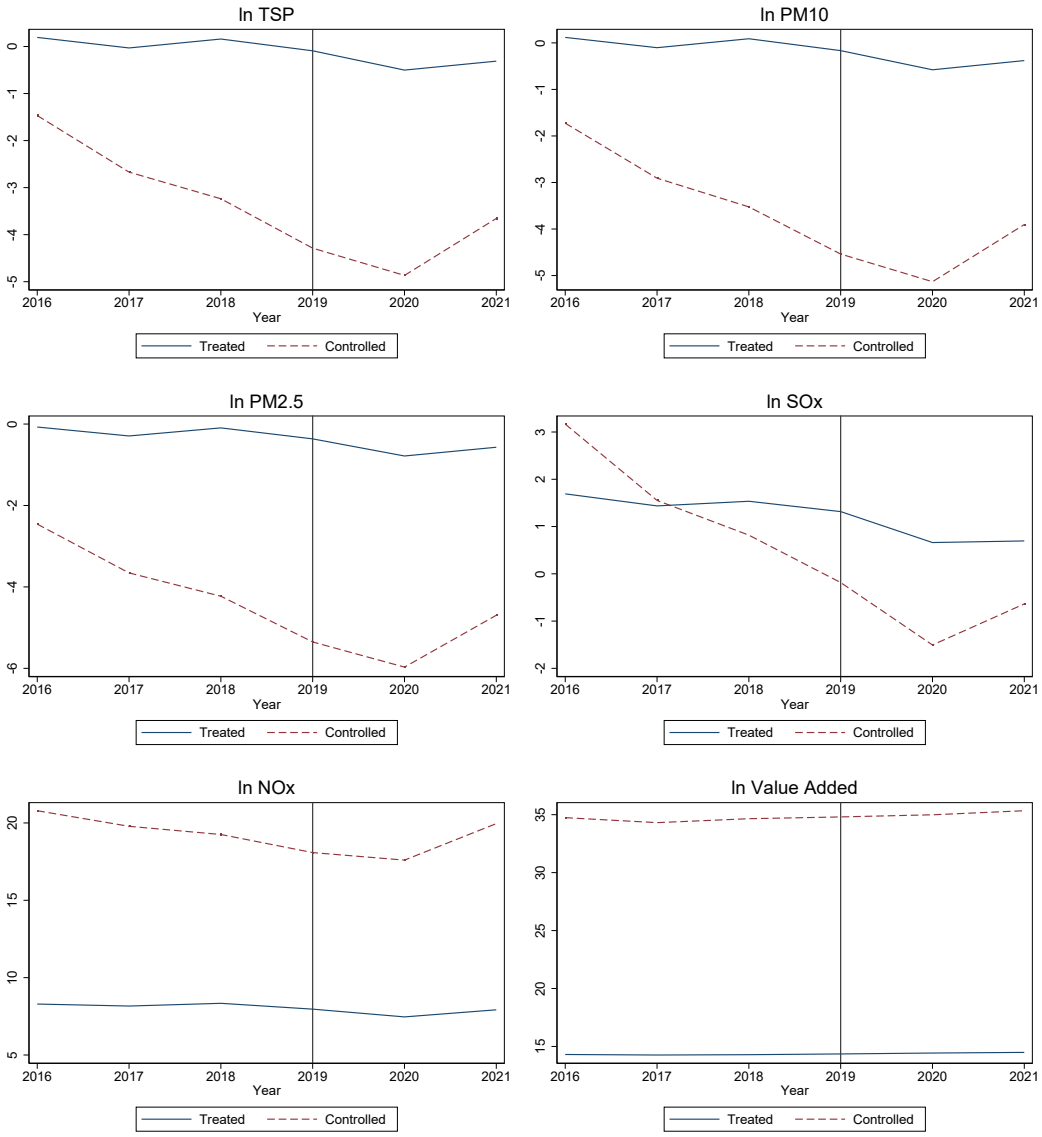
Notes: Fossil fuel includes coal, oil, and gas. Nonfossil fuel denotes the others. The unit is Megawatt. Each threshold represents a quartile if there is any.

Figure A.8: Pretreatment Density: Districts



Notes: Emissions and value added of district×3-digit industry in 2019 are used with the exact match on the 3-digit industry codes.

Figure A.9: Pretreatment Trend: Districts



Notes: Emissions and value added of district×3-digit industry in 2019 are used with the exact match on the 3-digit industry codes.

Figure A.10: Event Dynamics: Districts

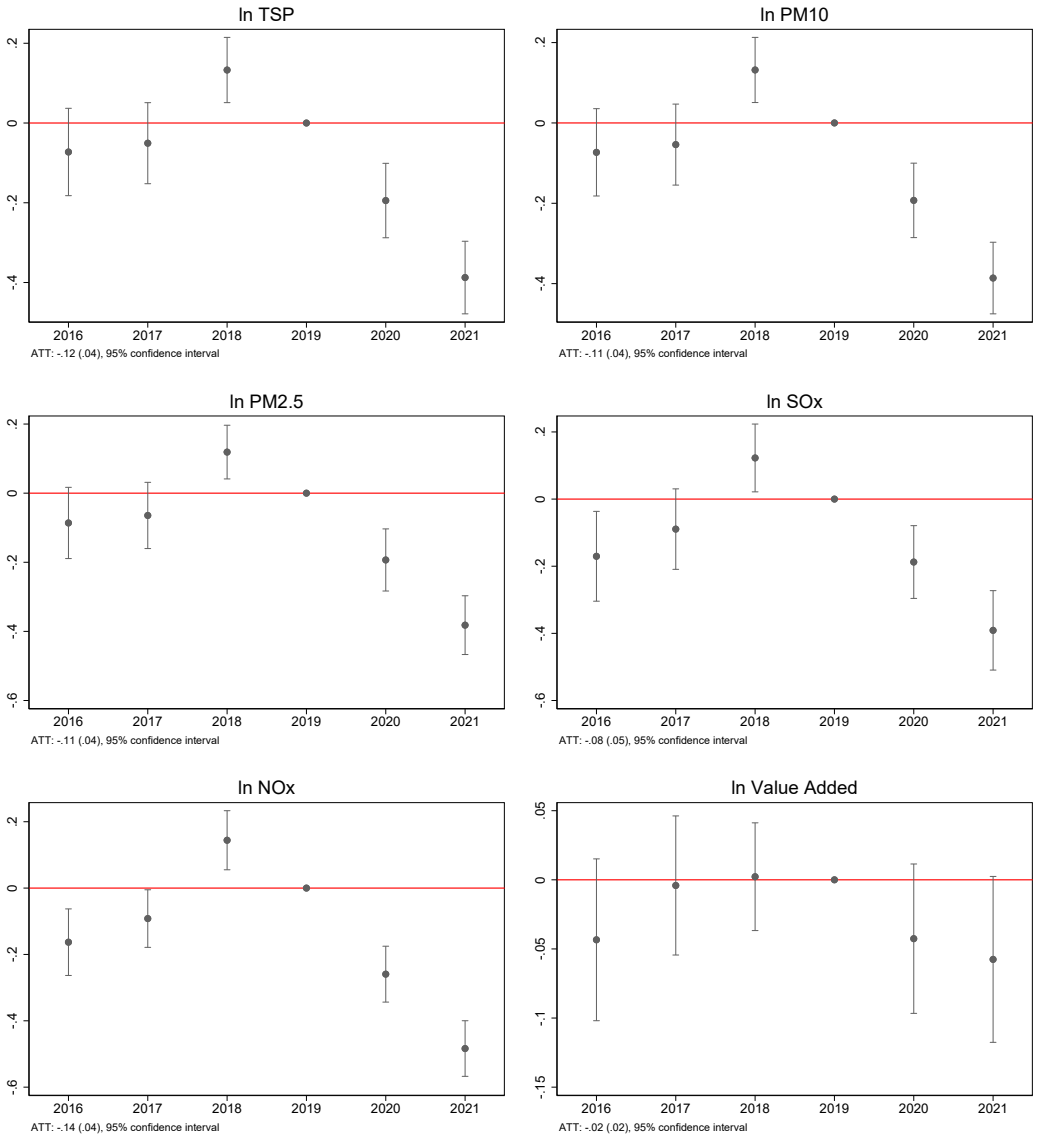
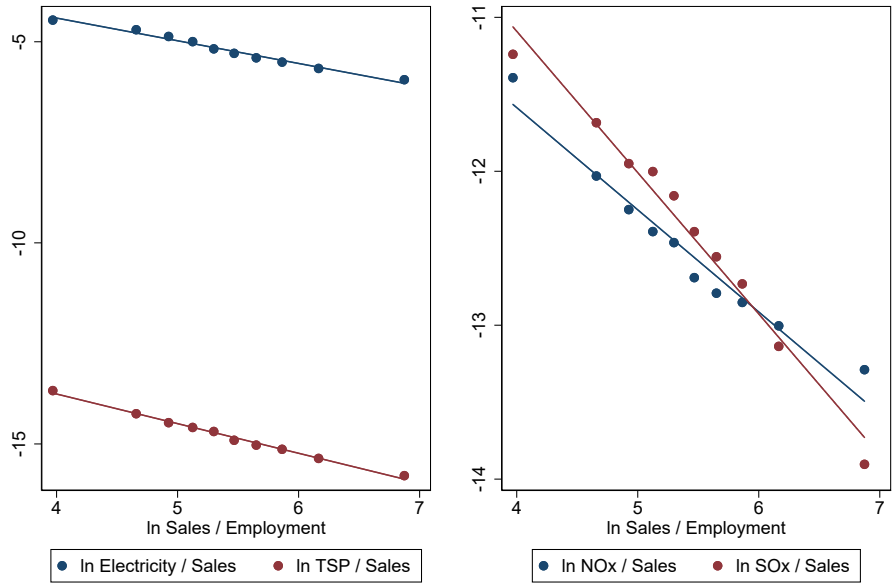


Figure A.11: Productivity and Cleanness



Notes: Plants in 2019 are used. On the x-axis, ln (Sales/Employment) is used as a proxy for productivity, and on the y-axis, several measures of cleanness are used. This binscatter is conditional on 4-digit KSIC.

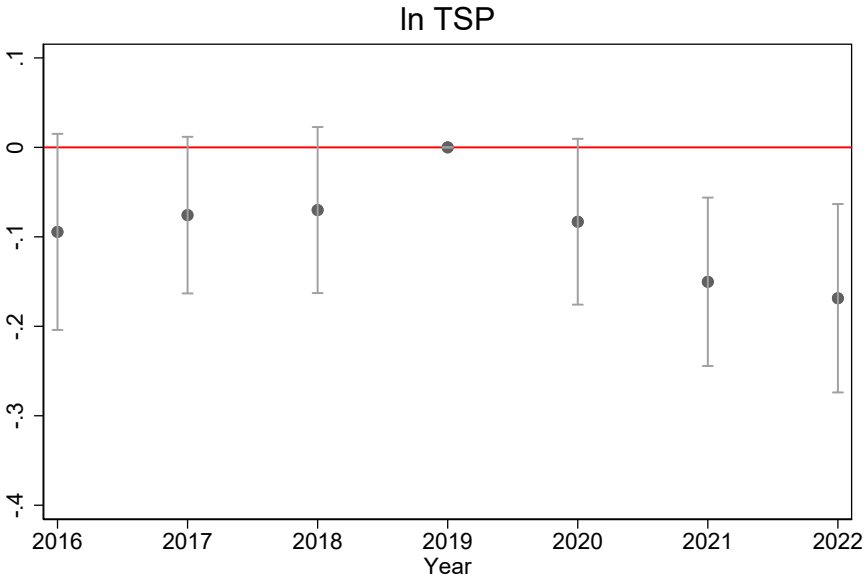
Figure A.12: Pretreatment Density: Targeted Plants
To be uploaded

Figure A.13: Pretreatment Density: Affiliated Plants
To be uploaded

Figure A.14: Pretreatment Trend: Targeted Plants
To be uploaded

Figure A.15: Pretreatment Trend: Affiliated Plants
To be uploaded

Figure A.16: Event Dynamics: Targeted Plants



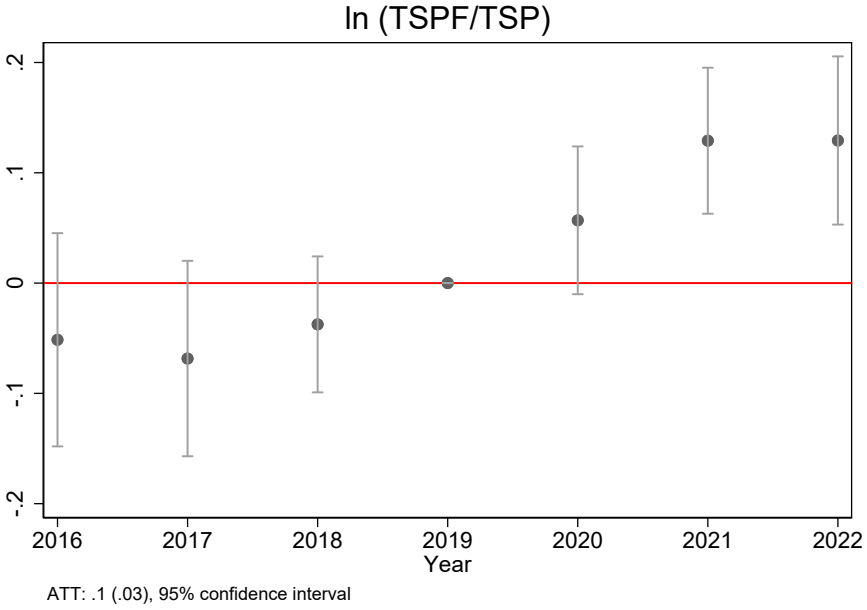
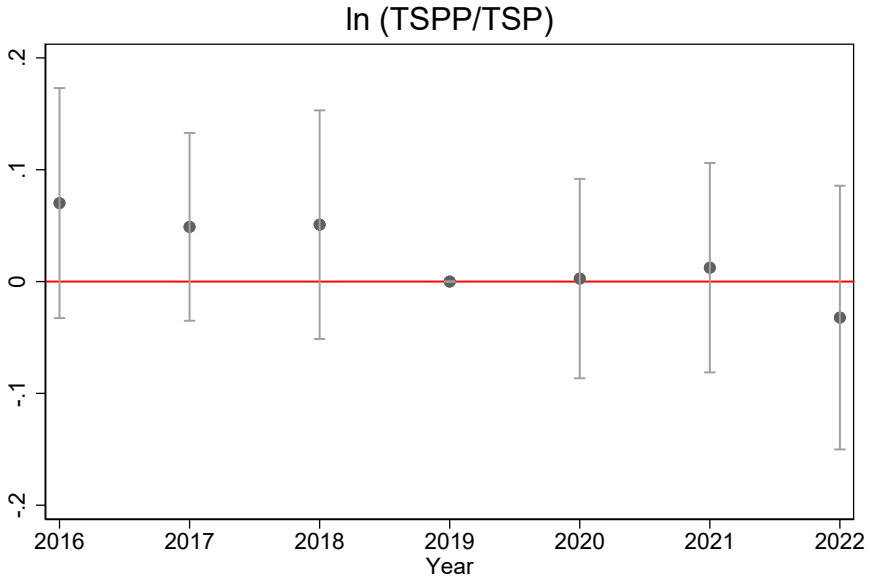


Figure A.17: Event Dynamics: Targeted Plants



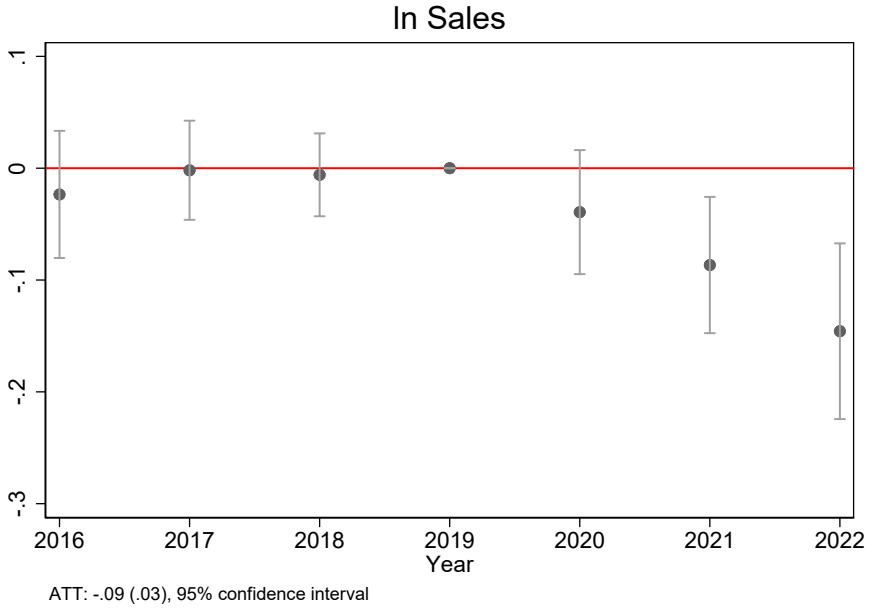
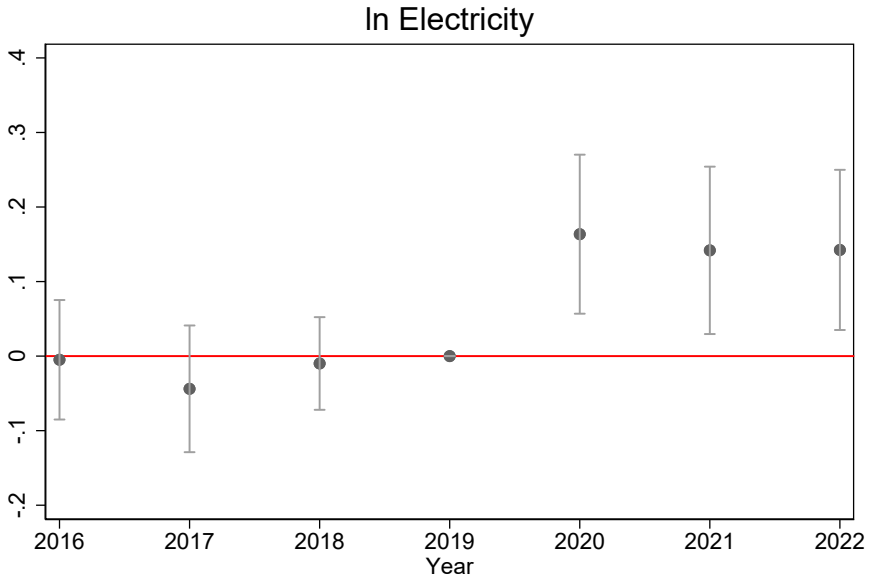


Figure A.18: Event Dynamics: Targeted Plants



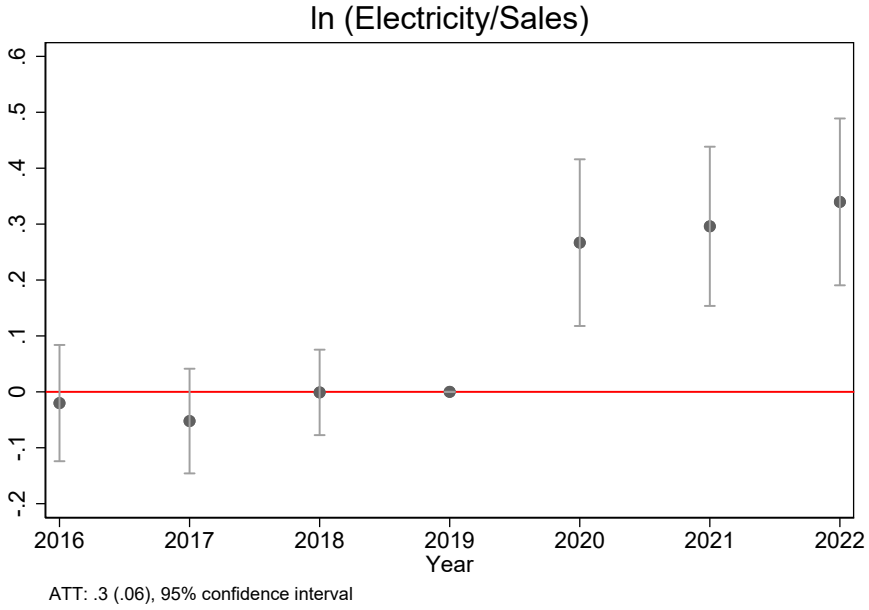
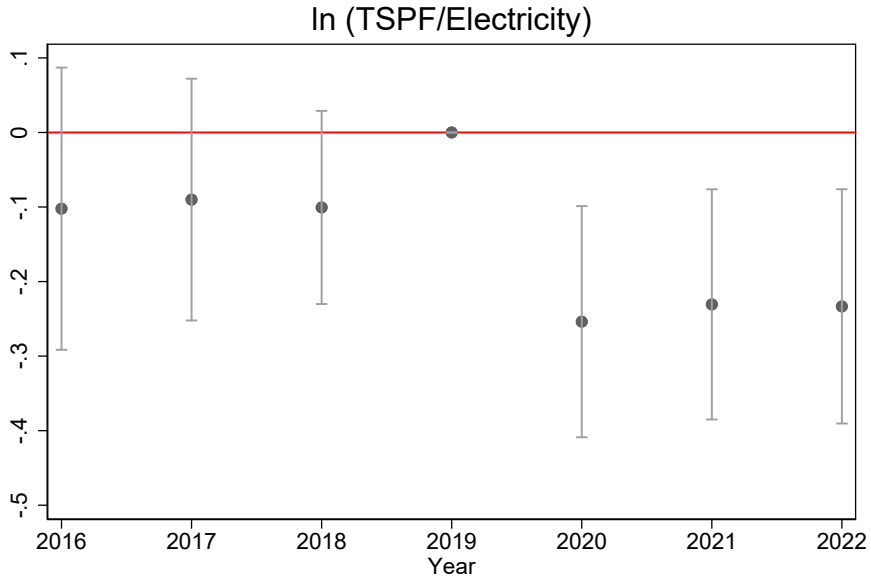


Figure A.19: Event Dynamics: Targeted Plants



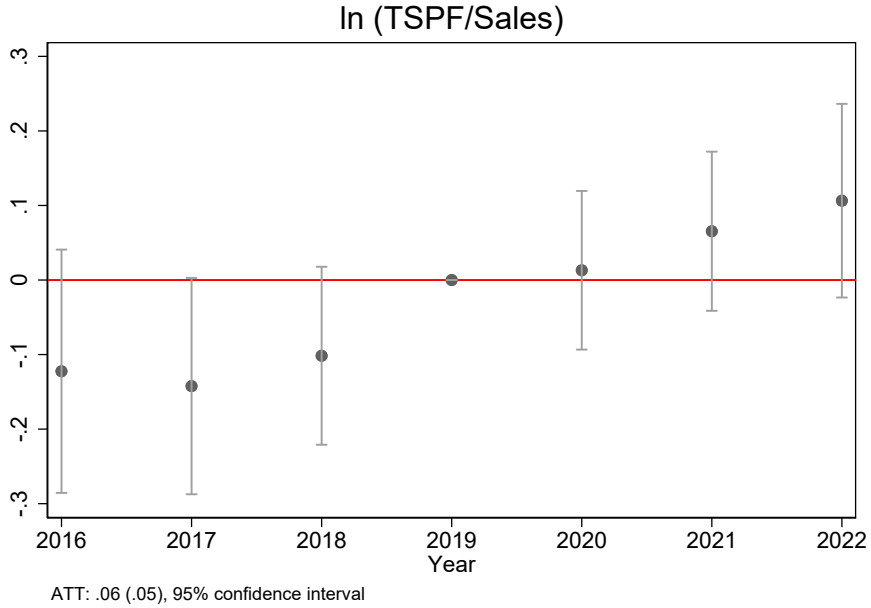
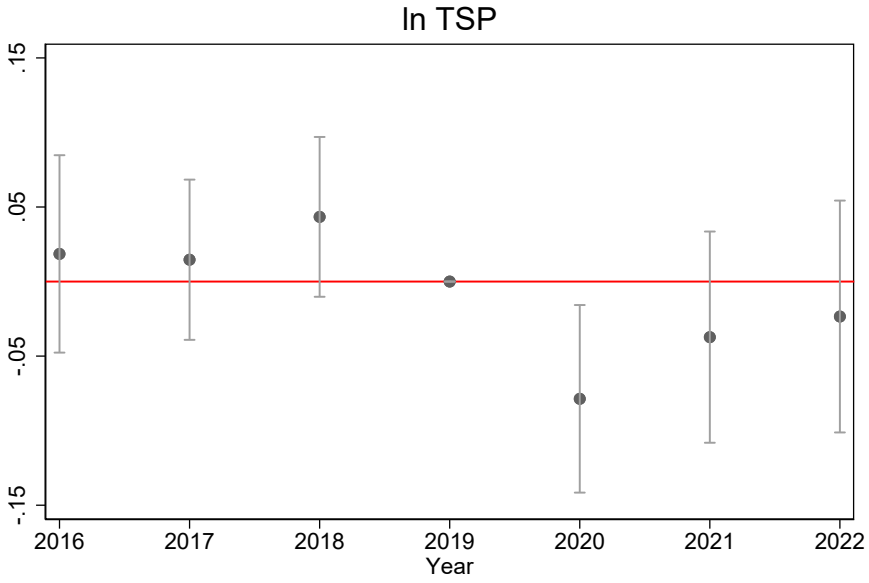


Figure A.20: Event Dynamics: Affiliated Plants



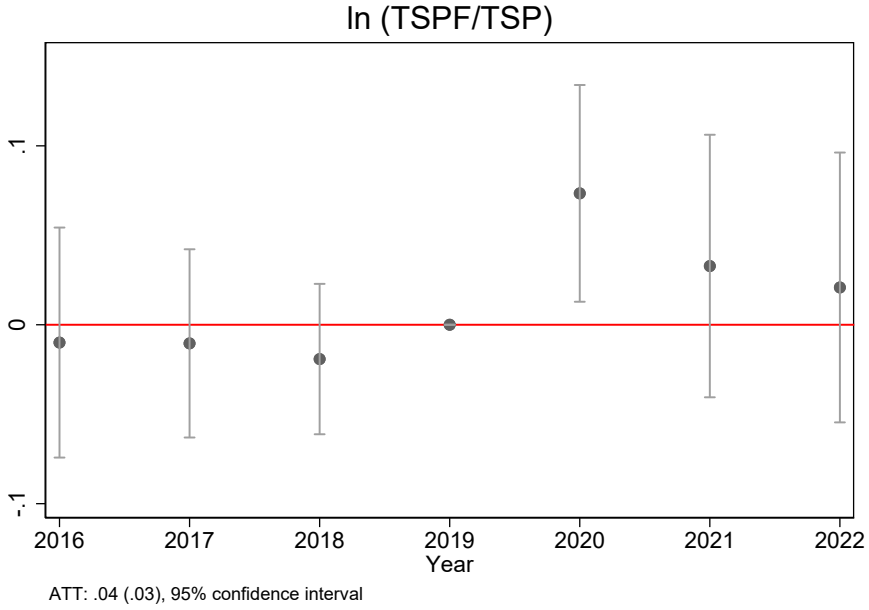
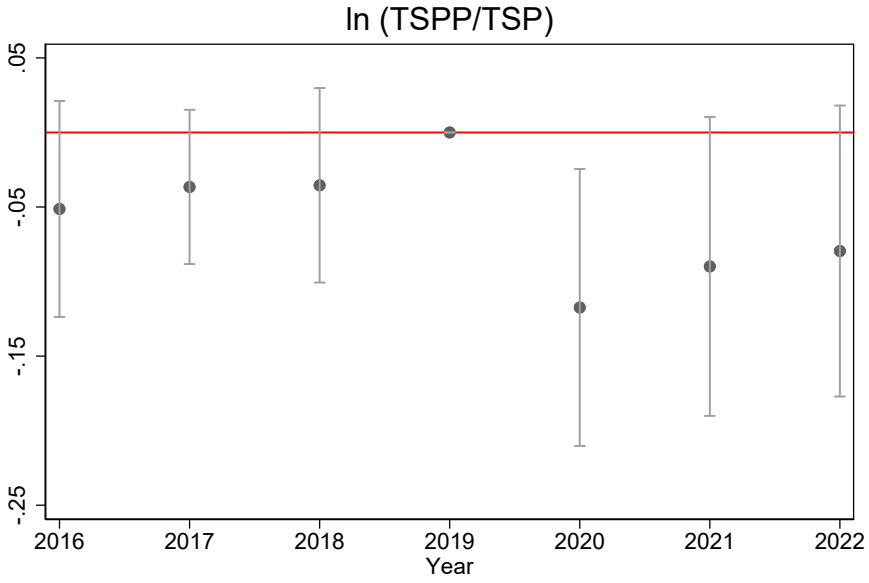


Figure A.21: Event Dynamics: Affiliated Plants



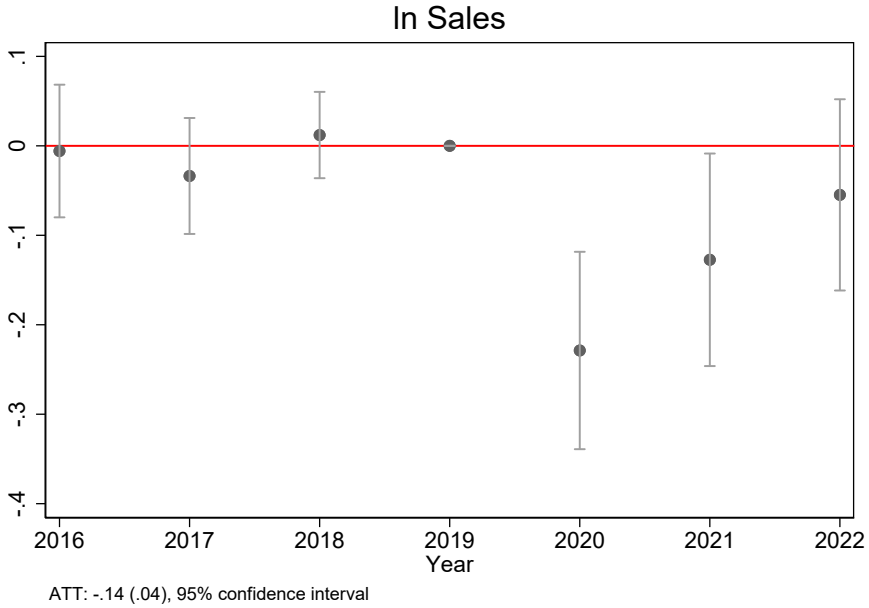
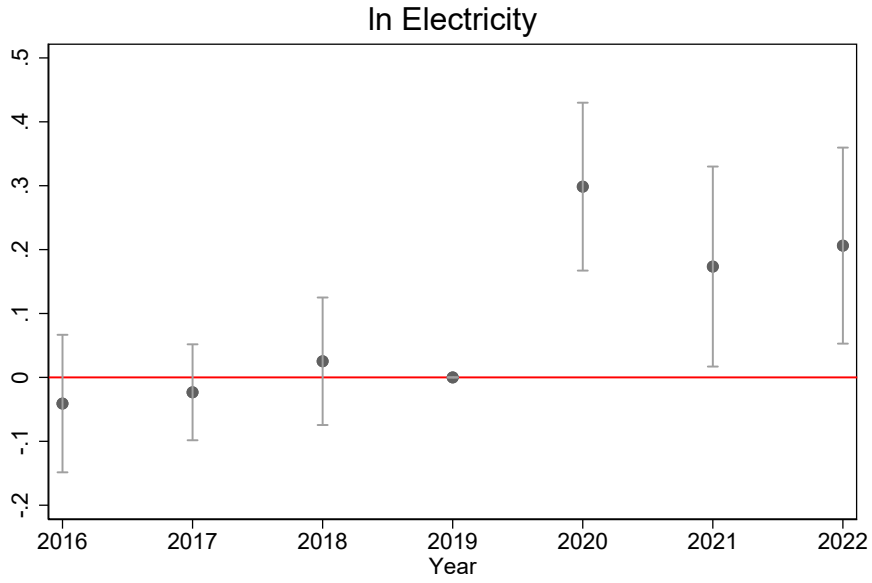


Figure A.22: Event Dynamics: Affiliated Plants



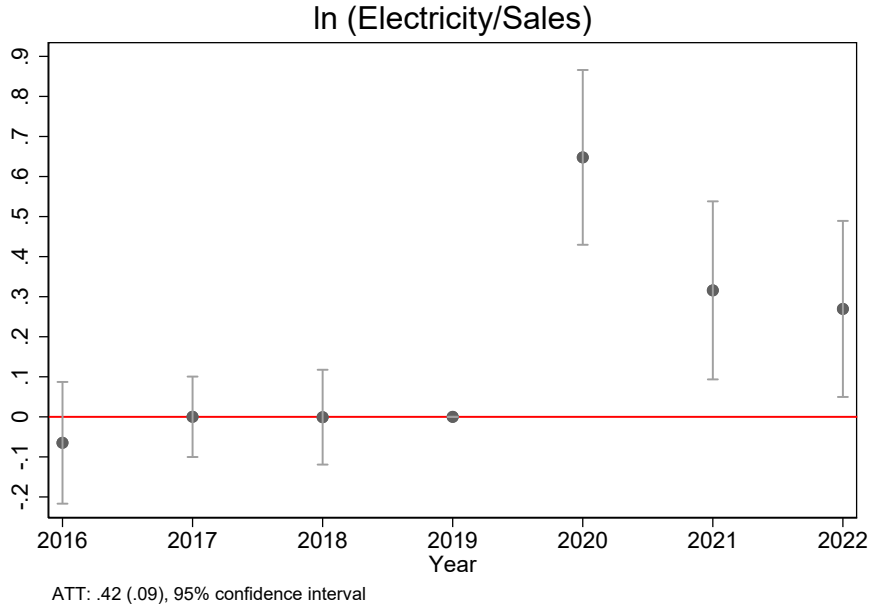
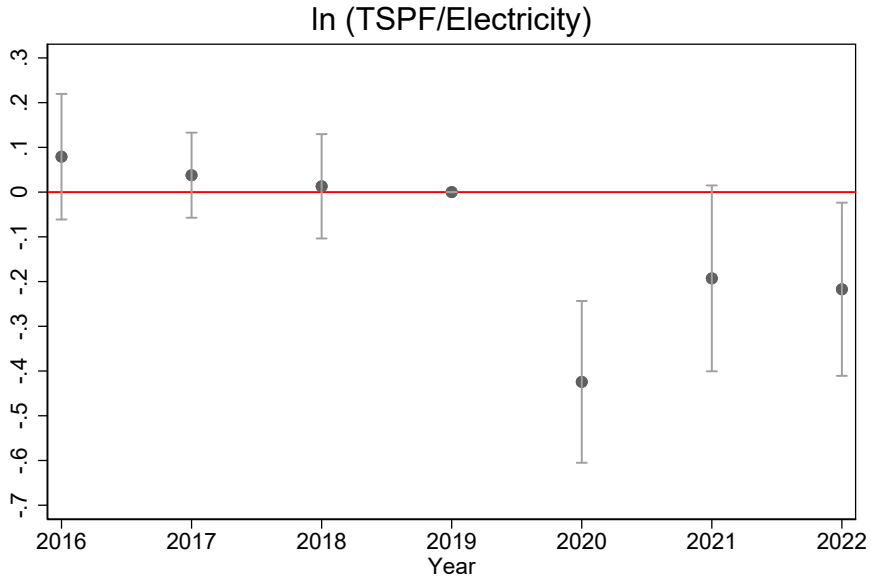
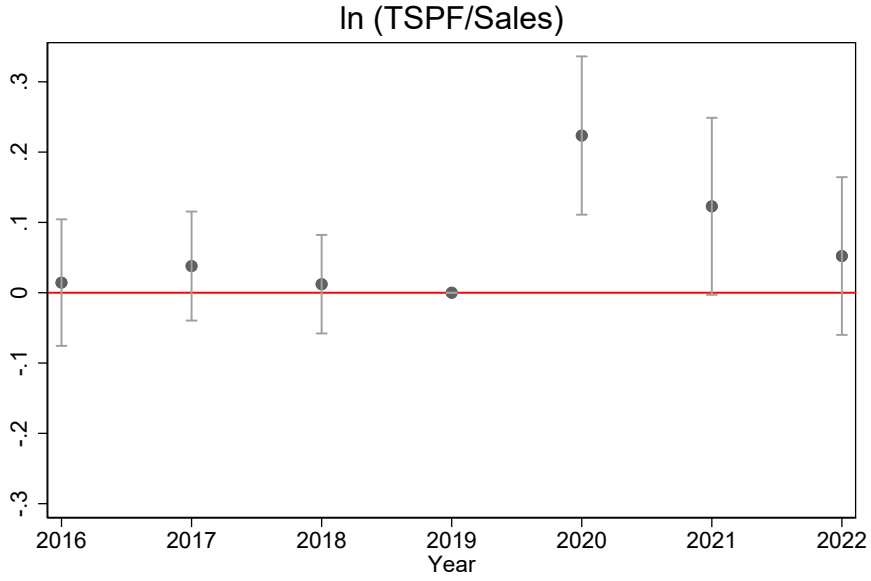


Figure A.23: Event Dynamics: Affiliated Plants

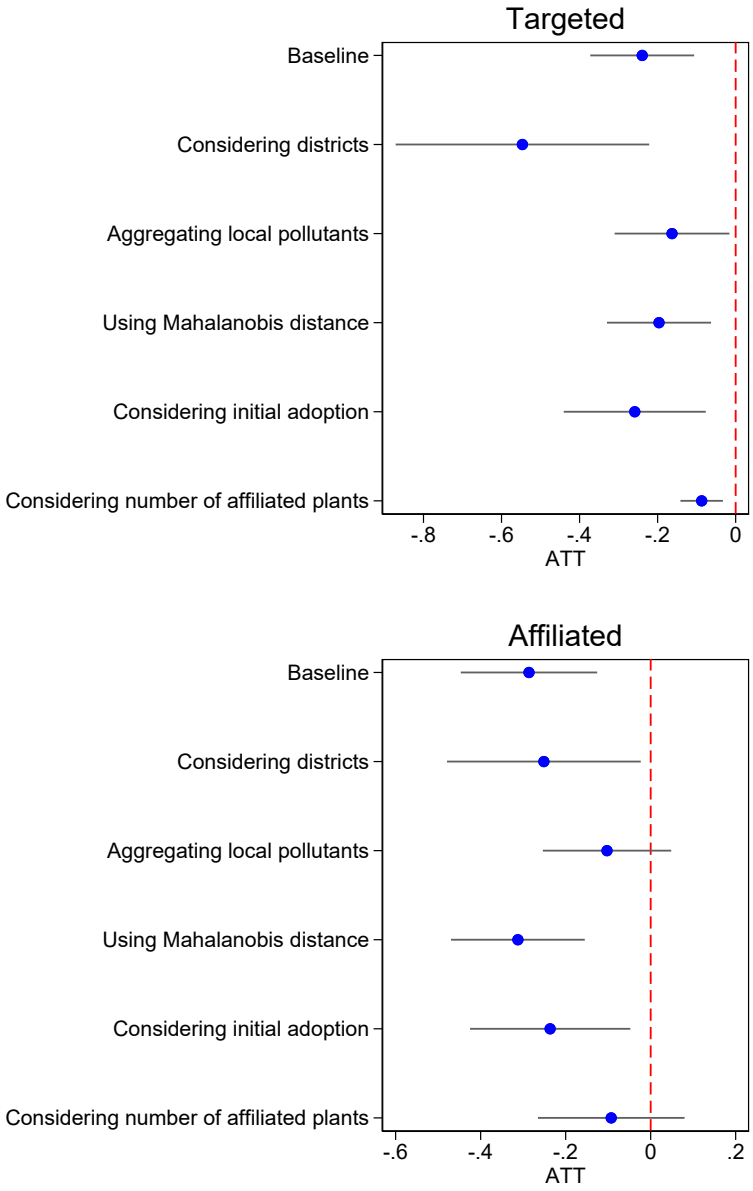


ATT: -.29 (.08), 95% confidence interval



ATT: .14 (.05), 95% confidence interval

Figure A.24: Robustness check: Plants



Notes: The outcome variable is ln $(TSPF/Electricity)$. The upper panel is the response of targeted plants while the lower one is that of affiliated plants.