



Empirical Studies on Japanese Power Sector and the Environment: Market Liberalization, Decarbonization, and Innovation

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博 士 論 文

令和 5 年 12 月

神戸大学大学院経済学研究科

経済学専攻

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Empirical Studies on Japanese Power Sector and the Environment: Market Liberalization, Decarbonization, and Innovation

(日本の電力部門と環境問題に関する
実証研究：
市場自由化、脱炭素、技術革新)

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Xiao Jia

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Chapter 1

Introduction

The power sector is one of the world's largest emitters of carbon dioxide, accounting for over 40 percent of global CO₂ emissions in 2020.¹ Therefore, achieving carbon abatement in the specific sector is a major task of climate mitigation. Despite various efforts made, fossil fuels remain to be a major source for power generation.² This presents a range of tasks. Japan, for example, relies heavily on coal and natural gas for electricity generation, which together account for nearly 70 percent of total power generated,³ resulting in considerable carbon emissions. The shutdown of nuclear power plants following the 2011 Fukushima nuclear incidence exacerbated the problem. Rebalancing the current power mix is therefore indispensable given the 46% target of carbon abatement by 2030 and a long-run target of carbon neutrality by 2050. Another concern is the high electricity prices paid by resident consumers in Japan which has the highest the before-tax electricity price among countries of USA, the UK, France, Germany and Italy,⁴ which is a consequence of high reliance on fossil fuels, low penetration of renewable energy, and the structure of the power sector.

The government of Japan made a number of regulatory efforts aimed at tackling the aforementioned problems, and the outcomes of such efforts have collected great interest. Regulations can be conducted either in a command-and-control manner or in a market-based form. While the former has been criticized in terms of efficiency, views on the latter are also mixed if it offers enough incentives and/or yields favorable results. Therefore, the welfare outcomes of these policy instruments need to be further investigated. Questions are raised, for example, whether consumers

¹<https://www.iea.org/data-and-statistics/charts/global-co2-emissions-by-sector-2019-2022>.

²Coal and natural gas together account for nearly 60 percent of all power sources in 2020.

³https://www.enecho.meti.go.jp/en/category/brochures/pdf/japan_energy_2021.pdf, page13.

⁴Ibid., page 4.

benefit from the liberalized power market and how power utilities respond. If there are beneficial results for the agents, are they realized in the sacrifice of the environment? How do corporates react to regulations? Do they switch to lower-cost production factors (often carbon intensive) thus generating more emissions or turn to new technologies that improve their efficiency?

The objective of this dissertation, therefore, lies in the ex-post examination of two market-based schemes and a voluntary scheme in Japan. First, we investigate the trade-off between power prices and carbon emissions. As power market liberalization lowers electricity prices, it can also cause carbon emissions to rise since firms may switch to fossil fuels that are lower in generation costs. We next turn our focus to innovations in power generation technologies induced by carbon pricing. Besides through energy conservation, carbon abatement can also be achieved by innovations in low-emitting technologies induced by higher costs of carbon. Finally, we examine if innovation can also be induced by environmental regulations in a voluntary form. Given the high policy costs of mandatory schemes, a voluntary regulation may spur innovation in a more cost-efficient manner.

The remainder of the dissertation is organized as follows. Chapter 2 focuses on the liberalization of retail power market in Japan and tests if it lowers power prices while increasing carbon emissions. We analyze the trade-off based on a difference-in-differences (DID) approach and a Synthetic Control Method (SCM) based on quarterly data from 2012 to 2020.⁵ The findings suggest the trade-off between cheaper power bills and increased carbon emissions. Residential consumers pay less due to market entry by competitive fringes, while the incumbent firms switch

⁵Study period is indicated by fiscal years. The 2012 to 2020 period is for the analysis of power prices, while the sample period spans 2012 to 2018 in the analysis for carbon emissions.

to cheaper fossil fuels in order to retain the market share. Regulations on carbon emissions generated by incumbent power firms as well as adoption of efficiency-improving devices are necessary.

Chapter 3 explores the Tokyo-Saitama Emissions Trading System (TSETS), a regional carbon cap-and-trade program, by examining its innovation outcomes. We focus on two types of power generation technologies, the one using fossil fuels and the one using renewable sources; two types of firms, ones that are specialized in renewable power technologies and those innovating in both; two types of firm behaviors, market entry (the extensive margin) and marginal innovation (the intensive margin), and. Using data spanning from 2006 to 2016 and combining DID with a Propensity Score Matching (PSM-DID), we found increases in both types of innovations at the intensive margin. We then focus on Tokyo ETS and Saitama ETS separately. The analysis reveals heterogeneous impact between the two schemes, highlighted by a technological change from fossil-powered generation to the renewable ones under Saitama ETS. Results from firm heterogeneity analysis recommend stronger support for renewable-specialized firms.

Chapter 4 further explores low-carbon innovations and tests if they are induced by a voluntary environmental regulation. We employ the environmental performance scores rated for listed firms in Japan by the carbon disclosure program (CDP). The scores are classified into five rankings (F, D, C, B, A in the ascending order) to measure the firms' willingness to comply with environmental targets. Data span from 2013 to 2018. We address potential endogeneity problem using an instrumental variable (IV) method, from which we found firms rated as A become substantially more innovative in green technologies. However even a slight improvement from F to D ranking is also conducive to additional innova-

tions. Further analysis of high-emitting firms suggests increased innovations at all rankings that are higher than F. Encouraging firms, particularly the high-emitting ones, to voluntarily disclose carbon information thus spurs the growth of green technologies which lead to carbon abatement.

Chapter 5 presents the concluding remarks by summarizing the empirical findings and proposing policy implications.

Chapter 2

Impacts of Retail Liberalization on Power Prices and Carbon Emissions

2.1 Introduction

The reform of electricity market has been implemented in many countries since the early 1980s, mainly in OECD countries. Generally, such market reform consists of several aspects including privatization, unbundling vertically integrated sectors, and introduction of competition to wholesale and/or retail electricity market. The series of reform has been motivated by factors such as rising operational cost, poor quality of service, volatile fuel prices, high retail prices and innovation in generation technology.

Despite the various economic and political motivations for the market restructuring, the key aim of market reform underlies in the improvement of efficiency which could lead to lower and reasonable electricity prices. Numerous previous studies have found negative relationship between competition and electricity prices (Steiner, 2001; Hattori and Tsutsui, 2004; Nagayama, 2009; Erdogdu, 2011), which benefits the consumers. Besides, deregulation in power market could lead to environmental consequences, such as an increase of carbon emissions: Mansur (2007) and Chaton and Guillerminet (2013) suggest higher level of carbon emissions in competitive power markets through simulation; while Asane-Otoo (2016) finds a negative correlation between competition policy and emission intensity. However, few empirical studies have linked the price effect and environmental outcomes together. Furthermore, the most of previous studies examine the impacts of power market reform on electricity prices in multiple countries or regions by using a series of policy dummy as explanatory variables.

This study estimates the price effect and environmental effect of the last phase of retail liberalization in Japan. Through the empirical analysis, we examine

if retail competition leads to lower electricity prices for household consumers in competitive regions compared to other regions in Japan. We further investigate if carbon emissions change as a result of the enhanced competition. Different from most of the previous studies, this study adopts difference-in-differences (DID) approach to capture the policy effect that can address the omitted variable biases. Additionally, because different reform steps generally lead to different outcomes and are much likely to be correlated with one another, it is extremely difficult to assess the overall impact of electric market reform. Hence, isolating the effects of the sub-components may be important (Asane-Otoo, 2016). The phase-by-phase retail liberalization in Japan provides a good opportunity for investigating changes in household electricity price and a potential trade-off between economic benefit and environmental quality. Besides, since the study is confined to Japanese power market, some potential measurement error in cross-country analysis could be avoided to some extent (Erdogdu, 2011). We also employ a synthetic control method (SCM) to test the robustness of the results from the DID framework.

The results of this study indicate that retail prices were reduced and emissions of carbon dioxide increased after the full liberalization, suggesting a likely trade-off between economic welfare and environmental quality. Specifically, we find that electricity prices paid by residential consumers in competitive regions (regions that are higher in the market share of new entrants) dropped nearly by 1.48 JPY/kWh. Regarding to the environmental impact, the power utilities supplying competitive regions see an increase in carbon emissions, which is consistent with our expectation. The result from SCM, however, suggests an effect of smaller magnitude on both power prices and carbon emissions. The price effect is also susceptible to changes in fuel prices and potential confounders. Effectiveness of retail compe-

tition itself thus might be small in terms of reducing electricity prices, and it is necessary to combine competition policy with environmental regulations to attain a carbon-neutral market liberalization.

The rest of the chapter proceeds as follows: Section 2 offers an overview of power market reform in Japan. Section 3 summarizes previous studies and gives hypothesis developments. Section 4 explains the empirical methodology and dataset. Section 5 presents the baseline results. Section 6 demonstrates an alternative inference strategy and corresponding results. Section 7 summarizes and discusses the findings before concluding.

2.2 Power market reform in Japan

Japan has implemented a series of power market reforms since 1995 for the purpose of improving the efficiency of the vertically integrated system with 10 regional monopolies (called the General Electric Utilities) that operate generation, transmission, and distribution. As key components of the market reform, competition has been introduced to both the generation sector and the retail sector: the power generation sector has been open to Independent Power Producer (IPP) since 1995. The retail market for extra-high-voltage consumers has been liberalized since 1999, followed by the high-voltage consumers for both commercial use (over 500kW) and medium-scale factories since April 2004, and other consumers belonging to the high-voltage category since April 2005. The retail market for household consumers who contribute about 30% to total electricity consumption remained regulated.

Although the introduction of competition led to decrease in electricity rates,

the structure of regional monopoly by GEUs is basically unchanged, and competition was insufficient under the partial liberalization. By the end of March 2011, unregulated demand contributed only 3.6% to total demand, and new entry has not even realized in some areas defined as monopoly-supplied regions. The Japan's electricity sector was exposed to another challenge by the Great East Japan Earthquake in 2011. Most nuclear power units shut down and generation from thermal power plants increased sharply to compensate for the lost capacity. As a consequence of higher reliance on imported fossil fuels and relatively high prices of oil and gas in the same period, household electricity prices raised by nearly 25%. Increased input of fossil fuels also hinders carbon abatement.

To cope with the issue of insufficient competition together with a series of problems caused by the earthquake, the Policy on the Electricity System Reform was approved by the cabinet in 2013. The post-earthquake reform is scheduled to pursue stable electricity supply, as well as to promote further competition in the retail market to suppress electricity prices and to increase consumer welfare. As scheduled by the policy, a full retail liberalization was realized in April 2016, and the retail market of the low-voltage segment is open to competitive fringes (referred to as Power Producer and Supplier: PPS) since then.

Distribution of PPS, however, is uneven through the country. Because most of the competitors operating in Tokyo and Kansai region (Goto and Sueyoshi, 2015), it could generate different price outcomes across regions. On the other hand, incumbent utilities facing competitive market condition might increase cheaper thermal generation in the short-run (Burtraw et al., 2000). As a result of firms' profit-oriented behavior, it may cause a further increase in carbon emissions.

2.3 Literature Review

There have been numerous empirical studies on policy effects of electric market reform. The earliest studies focusing on electric power market reform consist of numerous cross-country studies, with various policy instruments and/or competition indicators as explanatory variables and electricity prices as outcome variables.

Among the earliest studies, Steiner (2001) uses panel data for 19 OECD countries from 1986 to 1996 to examine how such market reforms have affected performance in the electricity supply. Regulatory reforms investigated in the study consist of third-party access (TPA) which could be a measure of competition, private ownership, unbundling of transmission from distribution and introduction of the wholesale market. Based on results, the author argues that in the long run, liberalization may reduce electricity prices, while the coefficient for TPA representing consumers' access to new suppliers is not significant, probably due to the limited actual entry. The insignificant coefficient of TPA in the analysis of operational efficiency could also be attributed to the insufficient entry of third-party competitors. Hattori and Tsutsui (2004) reexamine Steiner (2001) by using three-year longer panel data. In contrast to the previous study, they find significant effects of TPA instead and attributed it to the actual expansion of TPA. In other words, the effect of TPA on electricity prices had not been significant until the actual entry of third-party became active enough. Nagayama (2009) uses panel data for 83 countries spanning from 1985 to 2002 to examine how each policy instrument of power market reform could affect industrial and household electricity prices in different country groups. The author claims that among numerous policy instruments, retail competition lower electricity prices in some but not all

regions. Nagayama (2009) and Erdogdu (2011) share a similar results that effects of power market reform containing several reform steps could hardly be estimated at an overall level and that outcomes of a specific instrument may not be uniform across different countries. Literature above reveal a negative correlation between electricity prices and competition in the retail market, though not significant for some periods and some countries or regions.

Different from the above studies in terms of the outcome variable, a study by Erdogdu (2011) investigates the relationship between price-cost margins of electricity and a series of policy instruments of power market reform. By using panel data covering 63 countries for the period between 1982 and 2009, the study finds heterogeneous impacts of different steps of reform and as well discovered difference in policy outcomes between developed and developing countries. Choice of supplier, for instance, is found to be negatively correlated to the price-cost margin for households when pooled data for all countries in the sample are used. As the author investigates non-American developing countries, however, an opposite relationship between choice of supplier and price-cost margin is found. The author, therefore, argues that each step of reform has a different impact on price-cost margins for consumers and country groups. The results suggest that policy makers should be careful when deciding whether to adopt the structure of power market in other countries. Sharabaroff et al. (2009) find negative and statistically significant correlation between efficiency and market restructure activities by using panel data for all states of the United States.

Different from the cross-country approach applied in the earliest studies, Hattori (2009) focuses on Japan and examines market power of the incumbent electric utilities in the electricity retail market after the partial liberalization in 2000.

The author suggests that the markup rate will be greater as the market share of incumbent utilities raises. A higher price, on the other hand, leads to a lower market share of the incumbent, suggesting successful competition when the price is relatively high.

Though consumers are much likely to benefit from competition, the environmental impact of competition policy could be quite ambiguous. Several researchers have estimated an uncertain environmental outcome brought about by deregulation. Burtraw et al. (2000) suggest that determinants of the environmental effect of restructuring lie in the demand side as well as in the supply side. Specifically, as competition leads to lower electricity prices, demand for electricity could increase and consequently incur an increased power generation followed by increases in emissions of pollutants. The extent of change in demand depends on its sensitivity to electricity prices (Burtraw et al., 2000). The supply side, on the other hand, could affect environmental quality through its power mix and generation technology with the level of demand held constant. One possible scenario where restructuring hinders the penetration of zero-emitting technologies suggests an increase in generation at old and inefficient fossil-fired generators. A more optimistic scenario envisions entry of new and clean generators. Swisher and McAlpin (2006) examine emissions by the US electricity sector from 1993 to 2002 and discuss possible explanatory variables including control technologies, changes in energy demand and generation, demand-side management programs, the fuel mix, and regulatory policy. The authors first suggest several possible outcomes of the interaction between regulatory reforms and market factors. Retail competition, for instance, is likely to generate a higher level of emissions along with demand management while an opposite result is found regarding to renewable energy. Moreover, al-

though competition could lead to lower prices, the inelastic demand for electricity limits the effect of electricity prices on demand, generation and emissions. They find that emission of carbon dioxide increased by 19% after deregulation. Burtraw et al. (2000) argues that in the short run, competition encourages low-cost plants to operate while in the long run it encourages efficient generators to enter the market.

Several studies offer empirical evidence on the relationship between the power market reform and emissions of pollutants. Mansur (2007) observes utilities' strategic behaviors within the restructured PJM power market in the US and concludes that monopoly setting leads to less emission of pollutants than a competitive market. Sharabaroff et al. (2009) also investigates the efficiency-effect of restructuring by applying an instrumental variable approach and suggests a potentially positive role for restructuring in air pollutions. Emissions of carbon dioxide, in particular, is significantly related to electric market restructuring when the endogeneity is considered. Chaton and Guillerminet (2013) support the findings by Mansur (2007) in a simulation study that assess the environmental impact of competition policy in electricity sectors of EU countries. They find that competition can increase emissions. Asane-Otoo (2016) investigates the effect of restructuring on GHG emissions and finds that competition policies correlate negatively with emission intensity whereas the environmental effect of reducing market entry barrier is found to be insignificant. Goto et al. (2017) measures the impact of power market reform on the environmental efficiency of incumbent power utilities in Japan and reveals that it is mostly invariant from 2003 to 2015, while differences in efficiency might become larger as liberalization advances. To summarize, the environmental effects of restructuring power markets are generally uncertain due to differences in

demand elasticity, power mix of utilities (both incumbent and competitive fringes), efficiency of incumbent power utilities and environmental policies across countries and/or over time.

Based on previous studies mentioned above, it is expected that competition in electricity retail market will bring a change in Japan, though the impact could be uneven among regions. Carbon emissions, on the other hand, is expected to increase after the full liberalization: First, demand for electricity is not perfectly inelastic, it could thus increase in response to lower prices caused by competition. Generation, followed by emissions, could increase as a consequence, particularly in the context where nuclear power has not yet recovered. Second, despite its rapid growth, renewable power is still not advantageous in terms of generation cost or efficiency measured by capacity factor compared to thermal power plants . For the sake of efficient operation and cost reduction, therefore, it is more profitable for utilities to switch to thermal power generation after liberalization.

Based on the above considerations, the following hypotheses can be proposed regarding the price effect and environmental effect of retail competition in the household segment:

Hypothesis 2.1 *The retail market liberalization leads to lower electricity retail prices paid by household consumers in competitive regions.*

Hypothesis 2.2 *Emissions by utilities facing competitive market condition increase after the full liberalization.*

2.4 Methodology and Data

2.4.1 Empirical Method

We examine changes in retail prices and carbon emissions after the retail liberalization in Japan. Models are constructed and estimated for the two parts, respectively. The former estimates the average treatment effect of the liberalization on treated regions¹ and is given by:

$$P_{it} = \beta_0 + \beta_1 Compete_i * Post_t + \beta_2 Thermalshare_{it} + \sum_j \gamma_j Cost_{jt} + \alpha_i + \theta_t + u_{it} \quad (2.1)$$

where P_{it} refers to adjusted average electricity retail prices for residential consumers in GEU-controlled region i in year-quarter t ; dummy variable $Compete_i$ equals to 1 if region i is under competitive market condition, i.e., if the observation belongs to Tokyo or Kansai, and 0 otherwise; dummy variable $Post_t$ takes the value of 1 if t is observed after the first quarter of FY2016 and 0 otherwise; $Post_t * Compete_i$ is thus the DID estimator, which takes 1 if an observation is in competitive region after April 2016. $Thermalshare_{it}$ indicates the share of electricity generated from thermal power plants in total generation in region i in year t . $Cost_{jt}$ refers to the generation costs by fuel type $j \in \{Coal, LNG, Oil\}$ in year t . α_i , θ_t and u_{it} stand for the firm fixed effect, the time fixed effect and the error term, respectively.

¹The power market liberalization is nationwide. However, since we assume that a higher market share of new entrants leads to larger decrease in power prices, we focus on regions supplied by Tokyo Electric Power Company and Kansai Electric Power Company and define them as the "treated" regions. See Figure 2.1 for the trend of market shares of PPS in Tokyo, Kansai, and other regions.

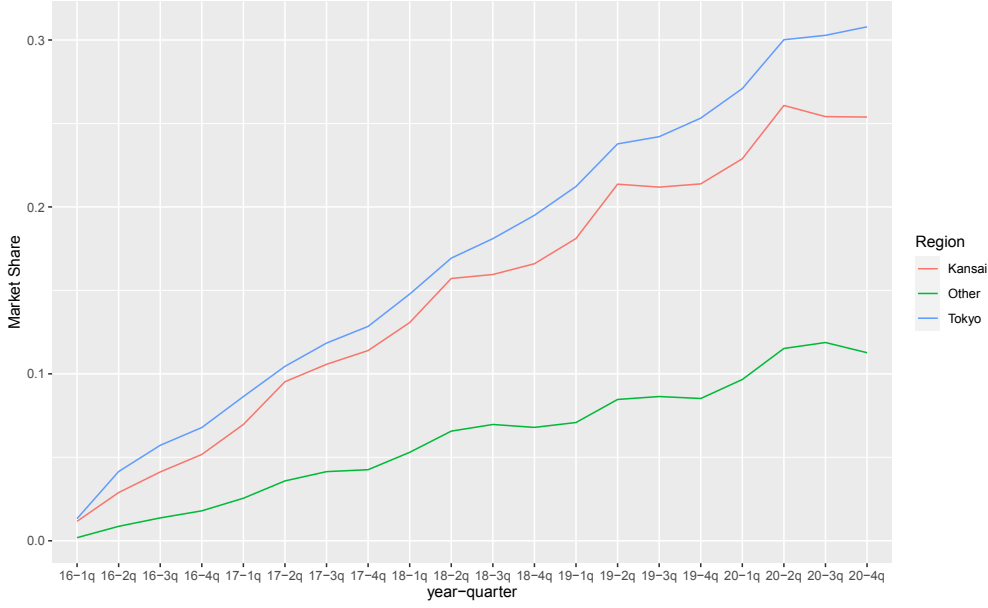


Figure 2.1: Market share of PPS

To test the hypothesis that the utilities facing competitive market condition tend to switch to fossil fuels after liberalization, the third model estimating CO₂ emissions by fuel type is constructed as follows:

$$Emissionon_{it}^j = \sigma_0 + \sigma_1 Compete_i * Post_t + \sum \gamma_j FP_{jt} + \alpha_i + \theta_t + u_{it} \quad (2.2)$$

Dependent variable is the CO₂ emissions from the use of fuel type j (coal or LNG) in region i through year-quarter t ; dummy variables $Compete_i$ and $Post_t$ are defined in the same way to that of the price effect part; control variable FP_{jt} is CIF prices of fossil fuel j in month t . α_i , θ_t and u_{it} are firm fixed effect, year-month fixed effect and error term, respectively. Emission from oil is not estimated since the relatively small portion oil accounts for.²

²According to the Agency of Natural Resources and Energy, oil accounts for less than 10% in terms of total power resources.

2.4.2 Data

The sample period of price analysis spans from the start of FY2012 to the end of FY2020. Because the price data is calculated from quarterly sales data, the dataset for the analysis is at quarterly level. The data for carbon emissions is collected at the month level and aggregated at the quarter level. Since data on power generation from coal is not available for Tokyo Electric Power Company or Chubu Electric Power Company since FY2019, the sample period for emission analysis is limited to FY2018. Quarterly price data are available as early as 2008, while we discard the period from FY2008 to FY2011 since the Great East Japan Earthquake occurred in 2011 caused a systematic change to the power mix. Table 2.1 summarizes the statistics.

Retail prices of residential electricity (electric light, or *dento* in Japanese) are calculated by dividing sales (thousand JPY) by demand (MWh) through each quarter of each monopoly-supplied region. The data is available from GEUs' quarterly reports. In order to remove macro-level impacts on prices, we adopt the 2015-base consumer price index published by the Statistics Bureau of Japan as deflator. Adjusted average retail prices (JPY/kWh) thus are used as dependent variable. Generation cost by fuel type are obtained from the official website of Power Producer and Supplier (PPS); data on generation from thermal power plants and total generation are collected from the Agency of Natural Resources and Energy (ANRE); the variable "Thermal share" is calculated by dividing thermal power generation by total generation. All the data for control variables were collected at the monthly level while then merged into the quarter level. As for the part of environmental impact, while data for CO₂ emissions are not directly

available, they can be calculated by fuel usage, generation by fuel type, and emission factors.³ The amount of fossil fuel consumption for electricity generation and generation by fuel type is published monthly by ANRE; emission factors are published by the Ministry of the Environment and the Federation of Electric Power Companies of Japan. CIF prices of fossil fuels are from the Ministry of Finance.

2.5 Results

2.5.1 Effects on Electricity Prices

Table 2.2 reports the average treatment effect on quarter-level retail power prices in the competitive regions, i.e., Tokyo and Kansai. Retail electricity prices purchased by residential consumers in the post-treatment period decreased by approximately 1.5 JPY/kWh compared to the pre-treatment period, as reported in column (1). Results are similar when removing control variables or replacing the year-quarter FE with year FE and quarter FE or a time trend, as reported through columns (2) to (4). This amounts to a saving of annual power bill of 4,500 JPY for each household in the competitive region, given the annual consumption around 3,000 kWh.⁴

When investigated separately, however, we find heterogeneous effects between regions. As presented in Table 2.3, Tokyo experiences a drop in retail power prices of 2.26 JPY/kWh as the result of liberalization, which is more than 3 times that

³Emissions are calculated as (fossil fuel usage) * (emission factor) until March 2016. Emissions since April 2016 are calculated as (power generation by fuel type) * (emission factor). Specifically, per kilogram of coal generates 2.33 kg of CO₂, while per kilogram of LNG generates 2.70 kg of CO₂. Coal-fired power plants generate 0.864 kg of CO₂ per kWh, while LNG-fired power plants generate 0.476 kg of CO₂ for per kWh electricity generated.

⁴<https://www.fepc.or.jp/smp/enterprise/jigyoku/japan/index.html>.

Table 2.1: Descriptive Statistics

Variable	Unit	Obs	Mean	Std	Min	Max
Treatment group						
Retail prices	Yen/kWh	104	24.364	2.213	19.952	29.023
Thermal share		104	0.691	0.273	0.010	0.967
Coal generation cost	Yen/kWh	104	12.253	1.252	10.606	14.928
LNG generation cost	Yen/kWh	104	10.967	1.995	7.923	15.629
Oil generation cost	Yen/kWh	104	24.815	3.983	17.520	36.045
CO ₂ from coal	million ton	104	2.452	1.453	0.000	5.705
CO ₂ from LNG	million ton	104	9.196	5.993	0.000	21.452
Coal CIF price	thousand JPY/MT	104	10.570	1.756	7.289	15.517
LNG CIF price	thousand JPY/MT	104	58.679	15.560	34.202	93.569
Oil CIF price	thousand JPY/kL	104	48.115	14.557	21.930	87.748
Control group						
Retail prices	Yen/kWh	364	23.301	2.403	17.260	28.545
Thermal share		364	0.749	0.207	0.000	1.290
Coal generation cost	Yen/kWh	364	12.253	1.247	10.606	14.928
LNG generation cost	Yen/kWh	364	10.967	1.988	7.923	15.629
Oil generation cost	Yen/kWh	364	24.815	3.969	17.520	36.045
CO ₂ from coal	million ton	260	3.375	1.603	0.000	7.026
CO ₂ from LNG	million ton	260	2.757	2.743	0.000	10.947
Coal CIF price	thousand JPY/MT	260	10.570	1.751	7.289	15.517
LNG CIF price	thousand JPY/MT	260	58.679	15.515	34.202	93.569
Oil CIF price	thousand JPY/kL	260	48.115	14.515	21.930	87.748

Note: Hokkaido and Hokuriku are excluded from the sample due to their extend period with no generation from LNG. This leads to smaller number of observations in the control group for the analysis on LNG emissions.

in Kansai area. Removing control variables or using different FEs do not change the result qualitatively. The different magnitudes could be explained by the pre-treatment price levels. Higher retail prices in Tokyo through the pre-treatment period can provide stronger incentives for the competitive fringes to enter the market, thus leading to larger reductions in prices as the market liberalization comes into effect. Hypothesis 2.1 is thus justified by the results above. Specifically, regions under competitive market conditions exhibit price reductions which are larger in magnitude in the area with higher market share of new entrants.

An event study of power prices is conducted to examine if the parallel trend assumption is satisfied. The result is demonstrated in Figure 2.2. The quarter prior to the treatment is used as the baseline which is indicated by -1 on the X-axis. While several post-treatment coefficients are negative and statistically significant, none of the pre-treatment coefficients is statistically different from 0, alleviating the concern of anticipatory effects.

2.5.2 Effects on carbon emissions

Event studies on carbon emissions, depicted by Figure 2.3, alleviate the concern for anticipatory effects in the competitive region. The effect on carbon emissions from burning coal in competitive regions is summarized in Table 2.4. As reported in column (1), emissions from coal in the post-treatment period increased by 0.692 million tons compared to the pre-treatment level, which supports Hypothesis 2.2. Intuitively, as market competition is enhanced by new entrants and power prices fall in the treated regions, regional monopolies retain their market share by switching to fossil fuels which are lower in costs. Emissions generated from burning coal

Table 2.2: Effects on retail prices in competing regions

	<i>Dependent variable:</i>			
	Retail prices			
	(1)	(2)	(3)	(4)
Compete*Post	−1.483*** (0.242)	−1.609*** (0.243)	−1.609*** (0.261)	−1.609*** (0.302)
Thermal share	1.027*** (0.301)			
Coal generation cost	−3.260*** (0.879)			
LNG generation cost	−2.167*** (0.350)			
Oil generation cost	−2.838*** (0.405)			
Controls	Y	N	N	N
Company FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	N	N
Year FE	N	N	Y	N
Quarter FE	N	N	Y	N
Year-quarter trend	N	N	N	Y
Observations	324	324	324	324
R ²	0.881	0.876	0.845	0.786
Adjusted R ²	0.861	0.856	0.835	0.778

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 2.3: Effects on retail prices in Tokyo and Kansai

	<i>Dependent variable:</i>			
	Retail prices			
	(1)	(2)	(3)	(4)
Tokyo*post	−2.264*** (0.320)	−2.470*** (0.316)	−2.470*** (0.340)	−2.470*** (0.397)
Kansai*post	−0.749** (0.312)	−0.748** (0.316)	−0.748** (0.340)	−0.748* (0.397)
Thermal share	0.837*** (0.299)			
Coal generation cost	−3.235*** (0.861)			
LNG generation cost	−2.159*** (0.343)			
Oil generation cost	−2.819*** (0.397)			
Controls	Y	N	N	N
Company FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	N	N
Year FE	N	N	Y	N
Quarter FE	N	N	Y	N
Year-quarter trend	N	N	N	Y
Observations	324	324	324	324
R ²	0.886	0.883	0.852	0.793
Adjusted R ²	0.867	0.864	0.842	0.785

Note:

*p<0.1; **p<0.05; ***p<0.01

increased consequently. The increase in emissions from coal-fired power plants, however, seems to be driven only by Tokyo Electric Power Company, which saw an increase of 1.4 million tons of carbon emissions, as suggested by Table 2.5. There is little evidence that Kansai Electric Power Company saw increases in emissions from coal in the post-liberalization period.

The result of emissions from LNG is summarized in Table 2.6. Carbon emissions in the competitive region from LNG increased by nearly 1.825 million tons on average compared to the pre-treatment period. The robustness of the result is confirmed by columns (2) to (4). The increase, as suggested by Table 2.7, is driven mainly by Tokyo region. In particular, Tokyo region saw an increase around 2.782 million tons, which is over treble that in the Kansai region. Hypothesis 2.2, therefore, is confirmed by the findings from Equation 2.2. Specifically, emissions from using either coal or LNG increased by more in Tokyo region where the market share for new entrants is higher.

2.6 Robustness Check

2.6.1 Methodology

To further investigate the causal effect of the power market liberalization, we deviated from a standard DID approach to the Synthetic Control Method (SCM, Abadie and Gardeazabal (2003)). The former assumes a parallel trend across the pre-intervention period, that is, potential confounders that affect the outcome are constant over time thus could be removed by taking difference in the time dimension. The latter, however, relaxes the parallel trend assumption, controls

Table 2.4: Effects on carbon emissions from coal in competitive regions

	<i>Dependent variable:</i>			
	CO ₂ from coal			
	(1)	(2)	(3)	(4)
Compete*Post	0.692*** (0.184)	0.692*** (0.184)	0.692*** (0.178)	0.692*** (0.210)
Coal price	3.227** (1.582)			
LNG price	−0.226 (0.143)			
Oil price	−0.247** (0.121)			
Controls	Y	N	N	N
Company FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	N	N
Year FE	N	N	Y	N
Quarter FE	N	N	Y	N
Year-quarter trend	N	N	N	Y
Observations	252	252	252	252
R ²	0.834	0.834	0.831	0.760
Adjusted R ²	0.807	0.807	0.818	0.749

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 2.5: Effects on emissions from coal in Tokyo and Kansai

	<i>Dependent variable:</i>			
	CO ₂ from coal			
	(1)	(2)	(3)	(4)
Tokyo*post	1.400*** (0.234)	1.400*** (0.234)	1.400*** (0.228)	1.400*** (0.271)
Kansai*post	−0.015 (0.234)	−0.015 (0.234)	−0.015 (0.228)	−0.015 (0.271)
Coal price	3.227** (1.514)			
LNG price	−0.226* (0.137)			
Oil price	−0.247** (0.115)			
Company FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	N	N
Year FE	N	N	Y	N
Quarter FE	N	N	Y	N
Year-quarter trend	N	N	N	Y
Observations	252	252	252	252
R ²	0.849	0.849	0.845	0.774
Adjusted R ²	0.823	0.823	0.833	0.763
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

Table 2.6: Effects on emissions from LNG in competitive regions

	<i>Dependent variable:</i>			
	CO ₂ from LNG			
	(1)	(2)	(3)	(4)
Compete*Post	1.825*** (0.225)	1.825*** (0.225)	1.825*** (0.224)	1.825*** (0.260)
Coal price	6.041*** (2.107)			
LNG price	-0.453** (0.190)			
Oil price	-0.476*** (0.161)			
Controls	Y	N	N	N
Company FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	N	N
Year FE	N	N	Y	N
Quarter FE	N	N	Y	N
Year-quarter trend	N	N	N	Y
Observations	196	196	196	196
R ²	0.986	0.986	0.985	0.978
Adjusted R ²	0.983	0.983	0.983	0.977

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 2.7: Effects on emissions from LNG in Tokyo and Kansai

	<i>Dependent variable:</i>			
	CO ₂ from LNG			
	(1)	(2)	(3)	(4)
Tokyo*post	2.782*** (0.271)	2.782*** (0.271)	2.782*** (0.273)	2.782*** (0.324)
Kansai*post	0.868*** (0.271)	0.868*** (0.271)	0.868*** (0.273)	0.868*** (0.324)
Coal price	6.041*** (1.940)			
LNG price	−0.453** (0.175)			
Oil price	−0.476*** (0.148)			
Company FE	Y	Y	Y	Y
Year-quarter FE	Y	Y	N	N
Year FE	N	N	Y	N
Quarter FE	N	N	Y	N
Year-quarter trend	N	N	N	Y
Observations	196	196	196	196
R ²	0.988	0.988	0.987	0.981
Adjusted R ²	0.986	0.986	0.985	0.979
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

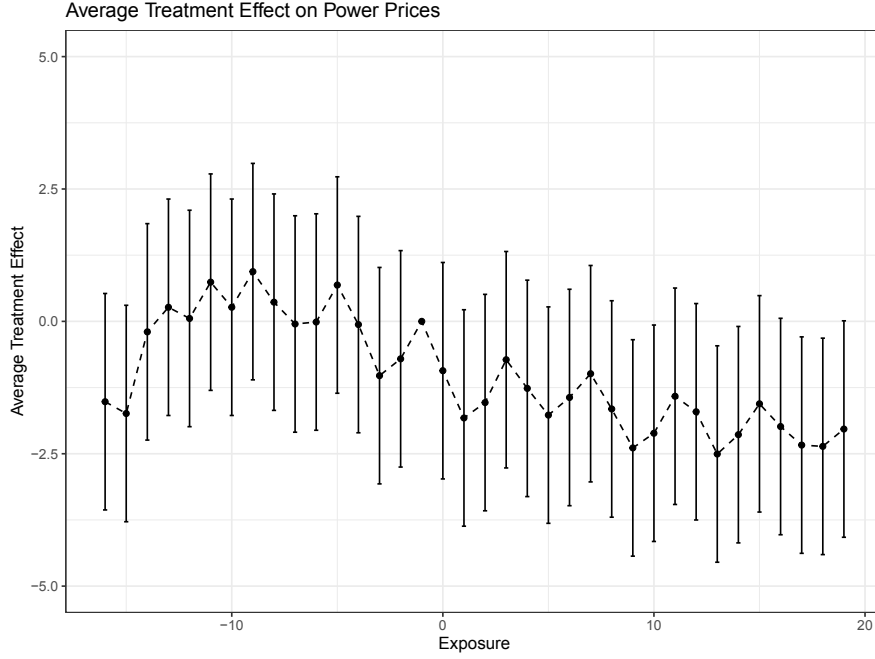
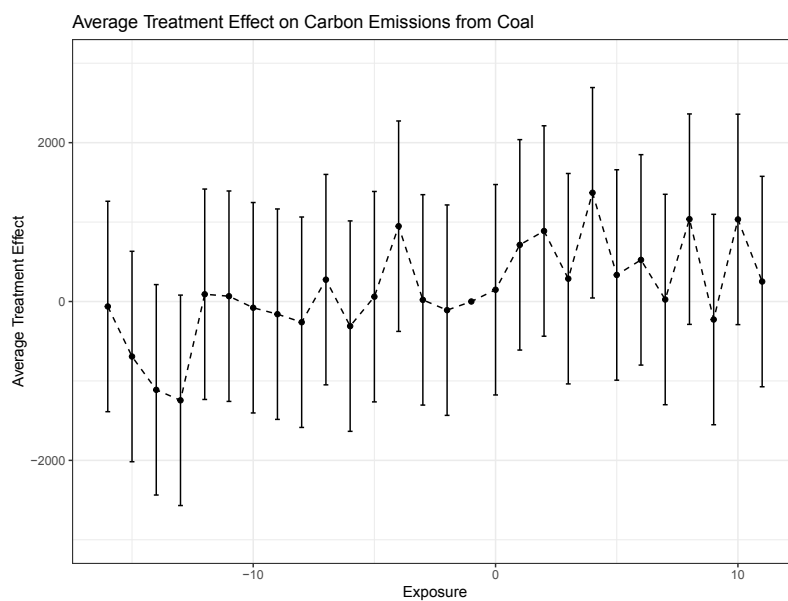
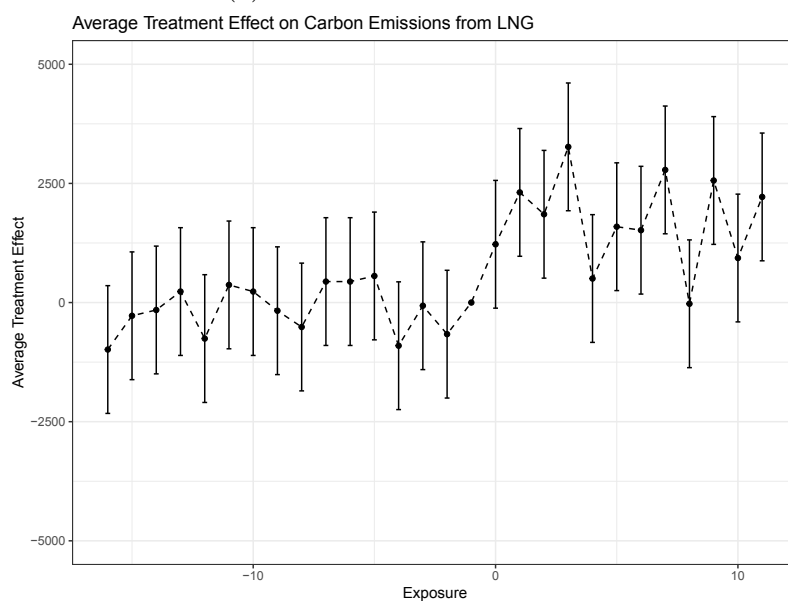


Figure 2.2: Average Treatment Effect on Power Prices

for unobservable confounders, and allows for treatment effect to vary over time. Specifically, the SCM “create” the trajectory of the outcome variable absent the intervention. Based on values of the outcome variable and specific predictors, non-negative weights are assigned to control units in the way that they best resemble the pre-intervention status of the treated unit. The counterfactual is thus a convex weighted average of control units, and the average treatment effect is the difference between the true treated unit and the counterfactual.

The above description can be summarized by following the notation of Abadie et al. (2010). The sample consists of $J + 1$ regions that are observed through $t = 1, \dots, T_0, T_0 + 1, \dots, T$. Region $i = 1$ is the only region that is affected by the intervention, and regions $i = 2, \dots, J + 1$ are control units that are unaffected which make up the donor pool. The intervention occurs at $T_0 + 1$, $[1, T_0]$ is thus

(a) CO₂ emissions from coal(b) CO₂ emissions from LNGFigure 2.3: Average Treatment Effect on CO₂ Emissions

the pre-treatment period and $[T_0 + 1, T]$ is the post-treatment period. Given the outcome variable observed in i at time t Y_{it} , Y_{it}^I denotes the outcome that would be observed if i received the intervention, and Y_{it}^N denotes the outcome absent the intervention. Outcomes of the treated unit at time t are thus Y_{1t} and Y_{1t}^N , respectively. The effect of the intervention, therefore, is $\alpha_{it} = Y_{it}^I - Y_{it}^N$. Let D_{it} be an indicator that takes 1 if i is exposed to the intervention at time t , and 0 otherwise. Then observed outcome can be denoted as $Y_{it} = Y_{it}^N + \alpha_{it}D_{it}$. Only $i = 1$ is exposed to the intervention, thus we have

$$D_{it} = \begin{cases} 1, & \text{if } i = 1 \text{ and } t > T_0, \\ 0, & \text{otherwise.} \end{cases}$$

Our goal is to estimate the vector of α_{1t} for $t > T_0$, which is $\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N$. The task arises that Y_{it}^N for $t > T_0$, which is the trajectory of the treated unit for $t > T_0$ in the absence of intervention, needs to be estimated. The SCM suggests using the mean value of pre-treatment outcomes and other predictors for the outcome variable to predict the trajectory of the treated unit across $t > T_0$ had it not been treated. Specifically, weights w_i ($i = 2, \dots, J + 1$) where $w_i \geq 0$ and $\sum_i w_i = 1$, are assigned to control units in the donor pool in the way that the weighted average closely tracks the trajectory of Y_{it}^N for $t < T_0$.

Specifically, the outcome variables are power prices, CO₂ emissions from coal, and that from LNG. The treated unit is the competitive region.⁵ Pre-treatment means of the outcome variables are used as predictors. The share of thermal power generation serves as another predictor. Moreover, to capture the difference in

⁵We first view the competitive areas as a whole region, then separate it into Tokyo and Kansai.

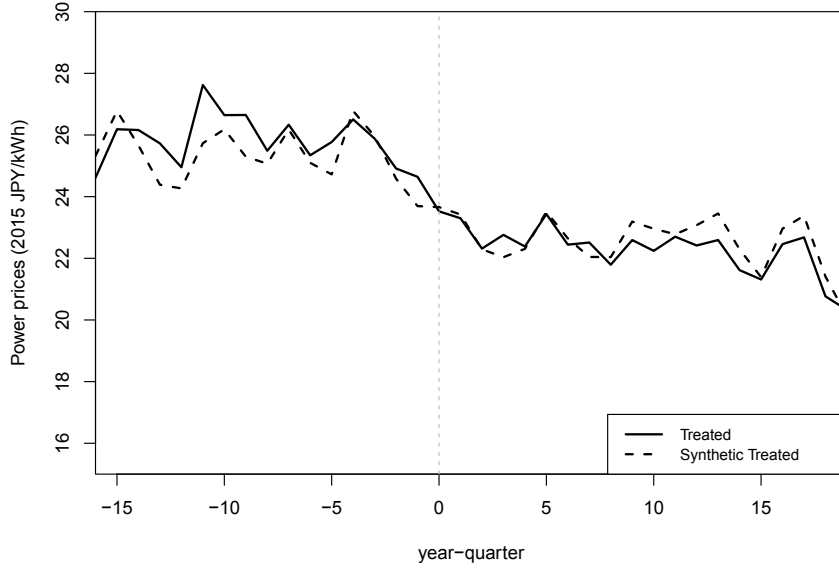


Figure 2.4: Competitive regions versus synthetic control (power prices)

market power of monopolies across regions, we employ the share in total demand of high-voltage electricity supplied by regional GEUs⁶ as a predictor. Weights assigned to each donor unit are based on the pre-treatment means of the predictors described above.

2.6.2 Effects on power prices

Figure 2.4 depicts the quarterly retail power prices for the treatment group, i.e., the competitive regions, and its synthetic from the first quarter of FY2012 to the fourth quarter of FY2020. The horizontal axis indicates the number of quarters to the first quarter of FY2016. The vertical line thus indicates the treatment

⁶This is also known as the specific-scale demand, or “Tokuteikibo-juyou” in Japanese. High-voltage power is already liberalized since April 2004, the variable thus proxies for the market power of regional monopolies.

timing. There are deviations of the two trajectories through the FY2012-FY2014 period, which can be caused by the substantial increase in power prices in the Tokyo region following the 2011 nuclear incidence. Nevertheless, the trajectories track each other closely within the one-year window prior to the treatment. We then observe deviations in the post-treatment period. In particular, retail prices in the competitive region drop below the counterfactual since the end of FY2017 and continue to decrease in the following years.

Table 2.8: Predictor means (competitive region as a whole)

	Treated	Synthetic	Sample Mean
Price & Coal			
Power price	25.840	25.357	23.562
Emissions from coal	2.863	4.357	3.388
Emissions from LNG	10.513	4.826	2.307
Thermal share	0.909	0.891	0.874
High-voltage PPS share	0.610	0.650	0.619
LNG			
Power price	25.840	25.355	23.886
Emissions from coal	2.863	5.624	3.424
Emissions from LNG	10.513	8.551	3.230
Thermal share	0.909	0.932	0.896
High-voltage PPS share	0.610	0.680	0.627

Note: The donor pool for LNG analysis excludes Hokkaido and Hokuriku because they do not use LNG for power generation across the sample period.

Table 2.8 compares the mean values of outcome variables for the treated region, the synthetic of treated region, and the sample mean. The mean of synthetic unit resembles the treated unit better in terms of pretreatment means of power prices, emissions from LNG, and the share of thermal generation. Table 2.9 summa-

rizes the assigned weights to control units in the donor pool. Chubu and Tohoku contribute 34% and 66%, respectively, to the synthetic treated unit, while other regions play subtle roles in reproducing.

Table 2.9: Region weights (competitive region as a whole)

Region	Weight (price)	Weight (coal)	Weight (LNG)
Chubu	0.339	0.112	1.000
Chugoku	0.000	0.000	0.000
Hokkaido	0.000	0.000	-
Hokuriku	0.000	0.000	-
Kyushu	0.000	0.000	0.000
Shikoku	0.000	0.488	0.000
Tohoku	0.661	0.400	0.000

Note: Hokkaido and Hokuriku are dropped in the LNG analysis because they do not generate power from LNG across the sample period.

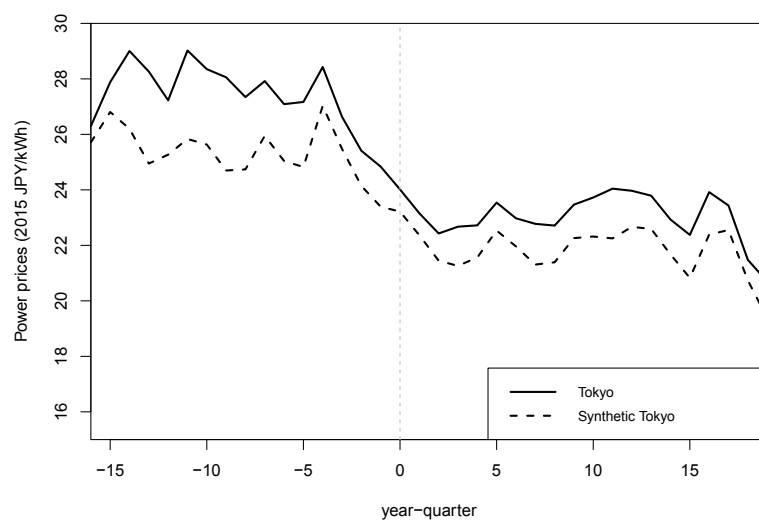
The price effect of power market liberalization is given by the difference between retail prices in the competitive region and its synthetic counterpart. Figure 2.5 highlights that the difference enlarges in later years following the intervention. The mean value of post-treatment power prices in the competitive region is 22.31 JPY/kWh, while the estimated post-treatment counterfactual is 22.55 JPY/kWh. That is, power prices in the competitive region would be 22.55 JPY/kWh in the absence of the intervention. The estimated effect of the intervention on power prices is thus -0.24 JPY/kWh. The estimated effect is smaller compared to what we derived from the DID analysis.

Figure 2.5 illustrates the trajectories of Tokyo and Kansai, respectively, versus their synthetic versions. Part (a) highlights a large deviation even in the pre-treatment period, suggesting a poor fit using current predictors. This can be

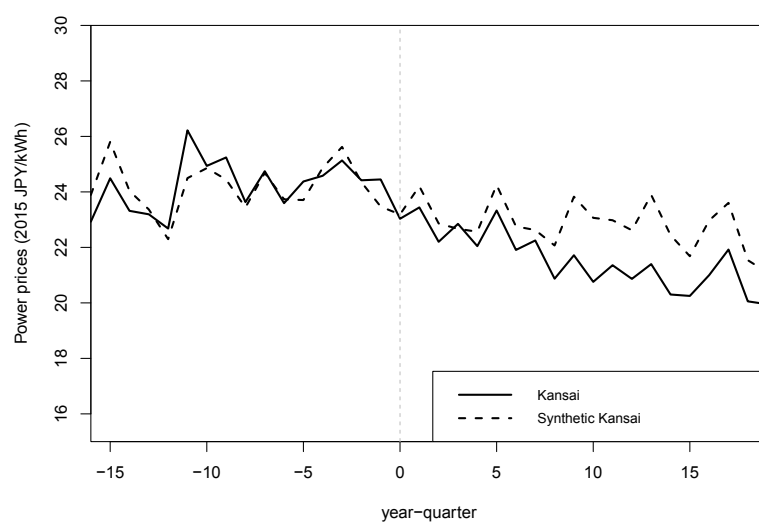
caused by the substantial pre-treatment high power prices⁷ in Tokyo region following nuclear incidence. Consequently, the counterfactual part of Tokyo region cannot be reproduced, making it impossible for inference under an SCM setting in the same region. Nevertheless, part (b) suggests a convincing reproduction for the Kansai region. Specifically, the lines track each other closely across the pre-treatment period while they diverge immediately after the intervention. The observed post-treatment average price is 21.58 JPY/kWh while the counterfactual suggests 22.85 JPY/kWh, implying an effect of -1.27 JPY/kWh on power prices in Kansai area caused by the liberalization. Part (b) of Figure 2.6 illustrates the result. The sign echoes that under the DID setting, while is larger in magnitude.

To examine if the reduction in prices is ascribed to the larger PPS market share, featured by a fiercer competition in the target region, we conduct placebo tests by substituting the competitive regions with control units in the donor pool. Gap plots are depicted in Figures A2.1 and A2.2. Black lines repeat the gap plots of the treated units while gray lines indicate the gaps between donor units and their would-be cases. Figure A2.1 suggests that the competitive region experienced a relatively large price decrease led by the liberalization, even among the well-fitted donor units. The effect is particularly large in the later phase following the intervention. Moreover, part (b) of Figure A2.2 indicates a small probability of observing larger price decreases than in the competitive region, since the placebo gaps are not as large in the post-treatment period. Part (a) of Figure A2.2 suggests higher-than-other power prices in Tokyo across the sample period, due to which a synthetic Tokyo cannot be produced. Other regions exhibit gaps that either deviate

⁷Since the weights assigned to control units are nonnegative and no greater than 1, Tokyo with the highest price level cannot be reproduced by other regions where prices are lower.



(a) Tokyo versus synthetic Tokyo (power prices)



(b) Kansai versus synthetic Kansai (power prices)

Figure 2.5: Retail Prices in Tokyo/Kansai versus synthetics

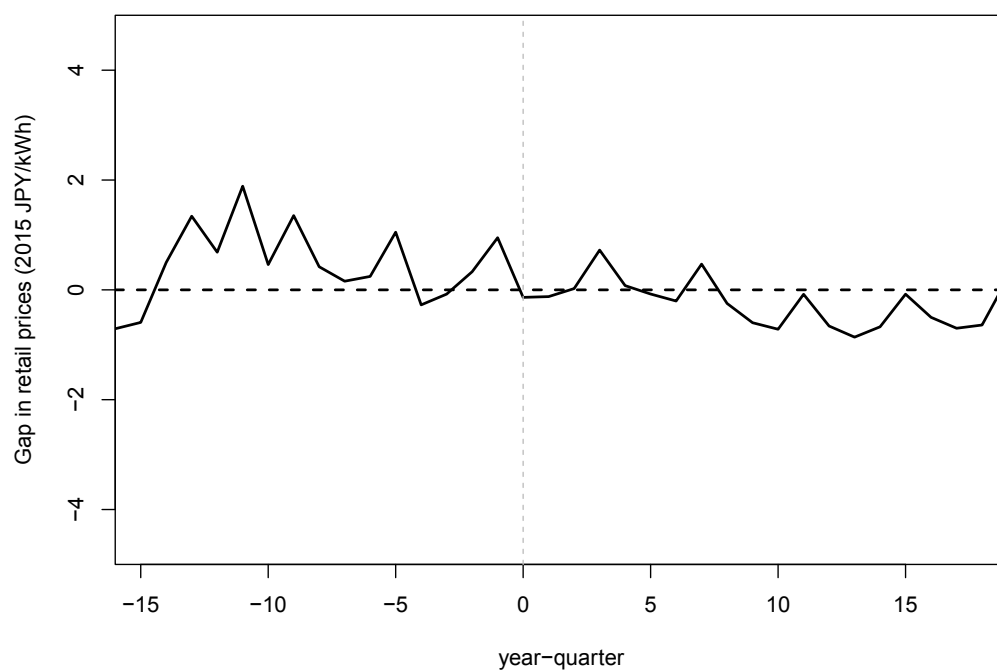


Figure 2.6: Gaps in retail prices in competitive regions

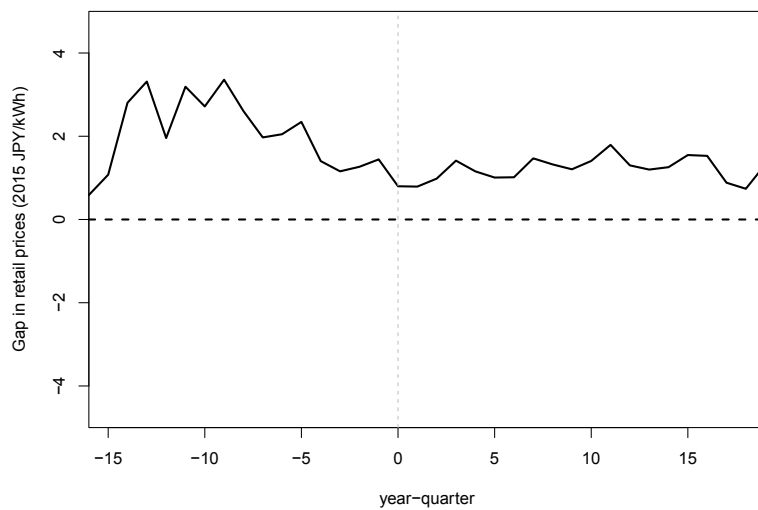
away from 0 before the treatment or fluctuate around 0 after the intervention.

2.6.3 Effects on carbon emissions

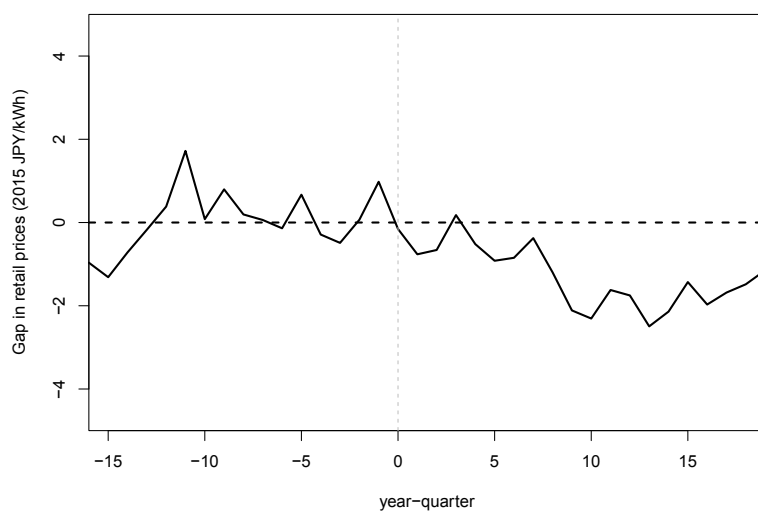
The estimated effect on carbon emissions from burning coal in the competitive region is depicted by Figure 2.7. The pre-treatment trajectories are in close proximity while a large deviation is observed immediately after the intervention. While the counterfactual predicts 3.33 million tons of CO₂, the observed post-treatment mean is 3.89. That is, carbon emissions from coal in the competitive region would be 3.33 million tons had it not been exposed to the intervention. The estimated effect on CO₂ emissions from coal is thus 0.54 million tons, a number smaller than 0.69 million tons from the baseline analysis. The gap between observed and synthetic outcomes is plotted in Figure 2.9. While Figure 2.8 portrays the trajectories of Tokyo and Kansai versus their synthetics, synthetic counterparts are not well produced, particularly that of Tokyo. Estimation by region thus is infeasible under the current SCM framework.

Corresponding placebos are summarized through Figure A2.3 to Figure A2.4. Figure A2.3 suggests larger emission effect on competitive regions than on donor units, implying that increased emissions from coal are caused by the intervention. While the post-treatment counterfactual failed to be reproduced, part (a) of Figure A2.4 suggests a substantially larger increase in emissions from coal in Tokyo region compared to control units. Part (b) implies that the estimated effect on Kansai does not differ much from that on donor regions.

Figures 2.11 and 2.12 portray the trajectories of emissions from LNG. While the DID estimator suggests 1.83 million tons of increase which is driven by Kansai



(a) Gaps in retail prices in Tokyo



(b) Gaps in retail prices in Kansai

Figure 2.7: Gaps between retail prices in Tokyo/Kansai and synthetics

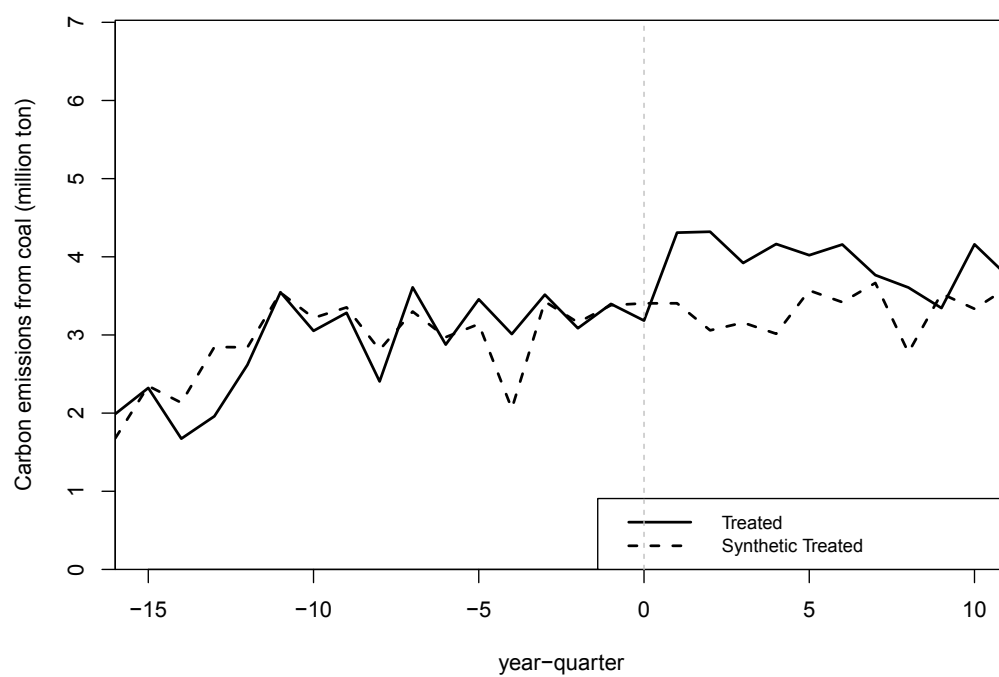
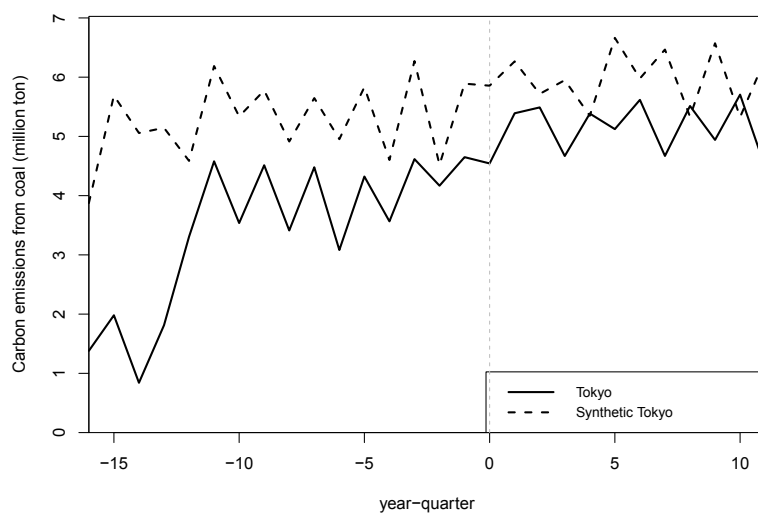
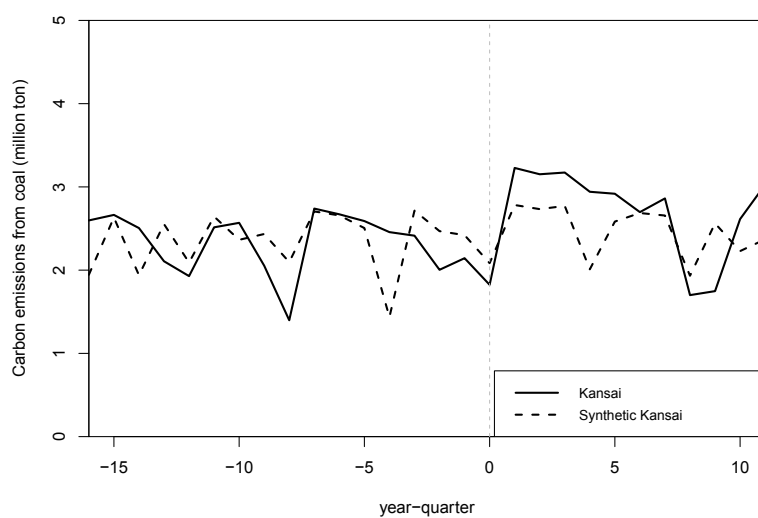


Figure 2.8: Emissions from coal in treated regions versus the synthetic



(a) Emissions from coal in Tokyo versus synthetic Tokyo



(b) Emissions from coal in Kansai versus synthetic Kansai

Figure 2.9: Trajectories of emissions from coal in Tokyo/Kansai versus synthetics

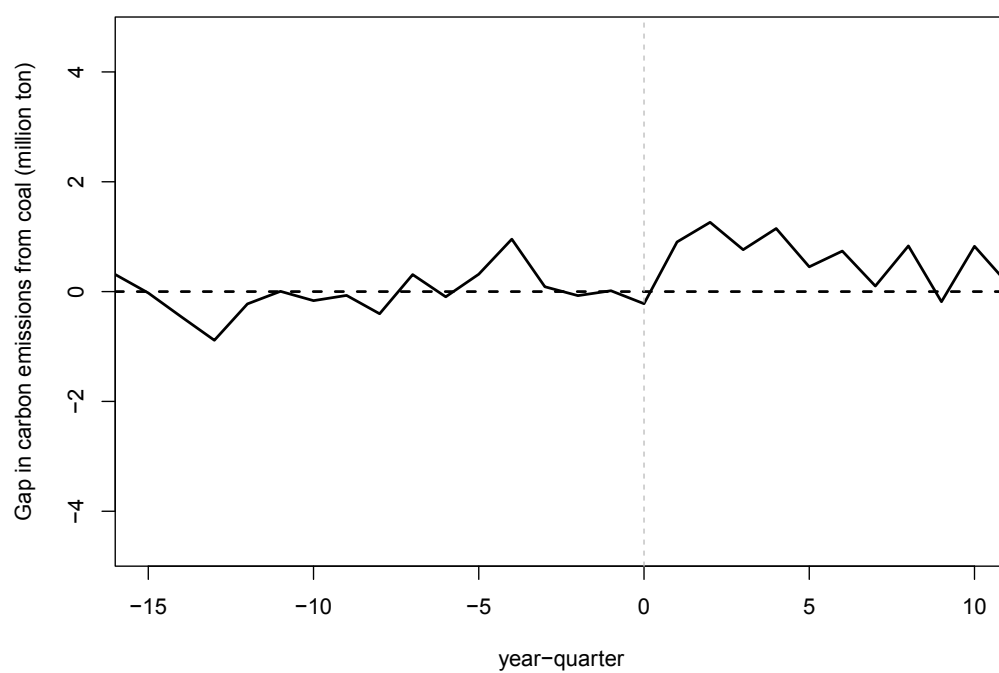
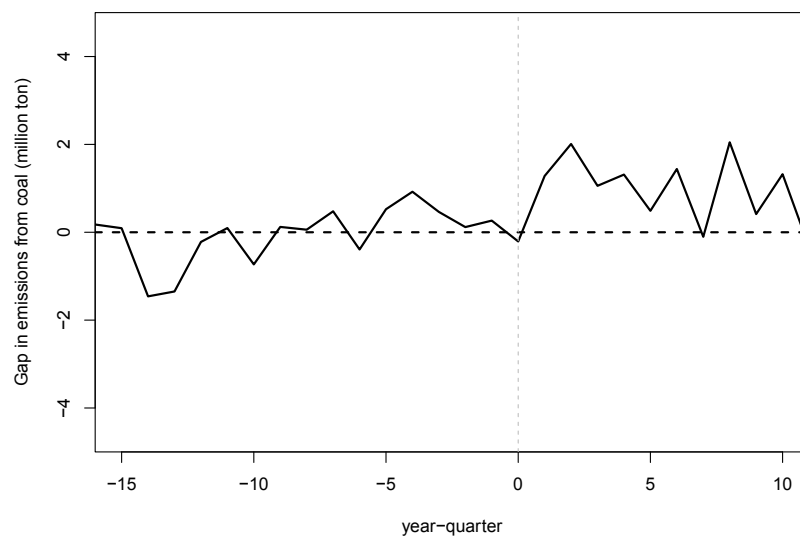
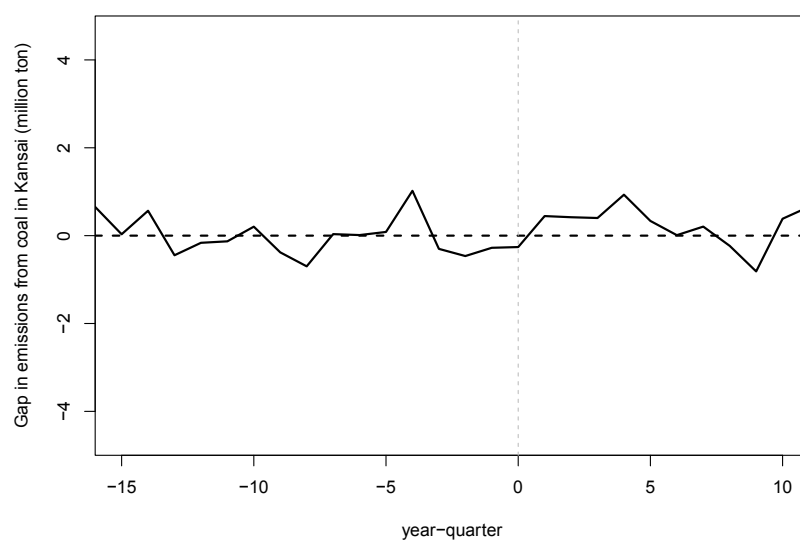


Figure 2.10: Gaps in emissions from coal between competitive regions and the synthetic



(a) Gaps in emissions from coal in Tokyo



(b) Gaps in emissions from coal in Kansai

Figure 2.11: Gaps in emissions from coal between Tokyo/Kansai and synthetics

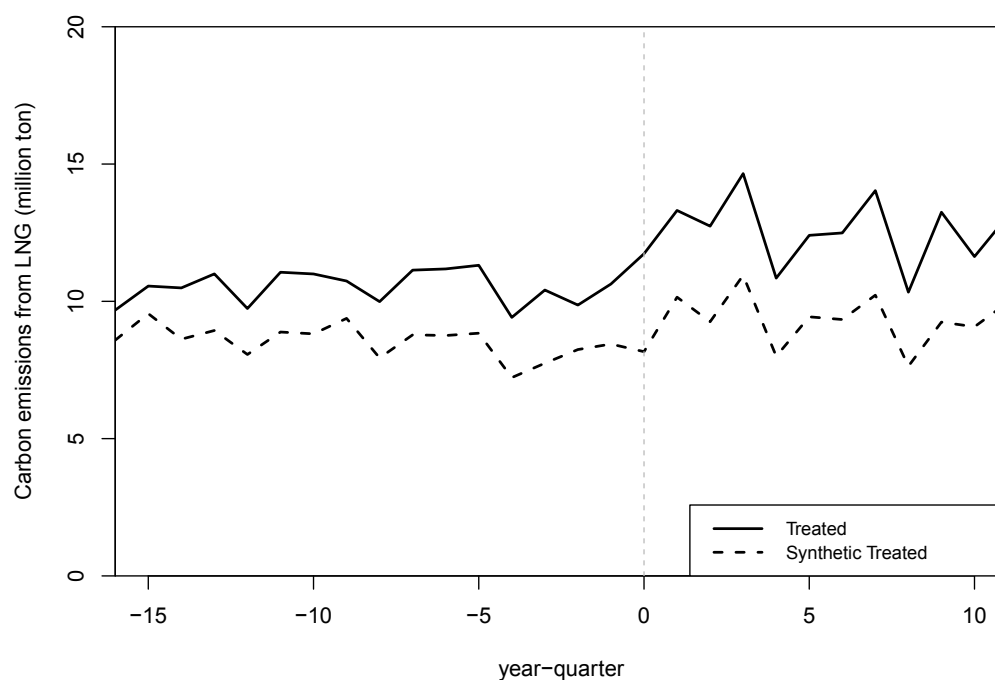
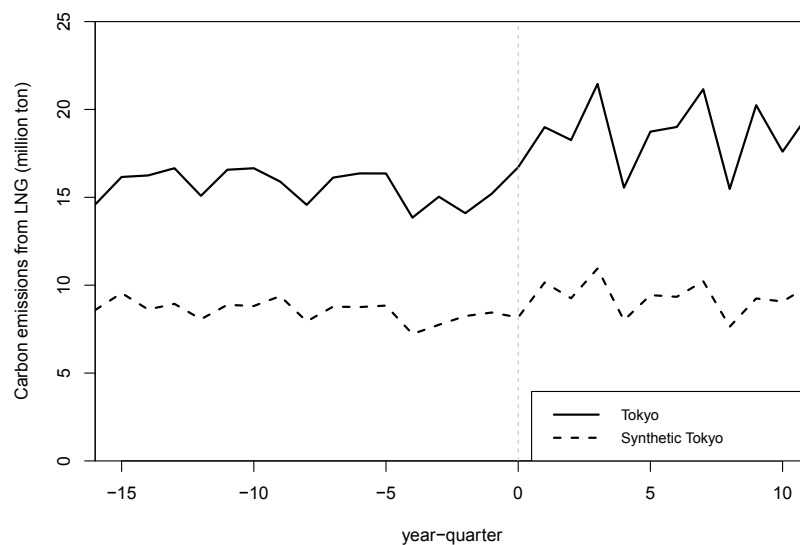
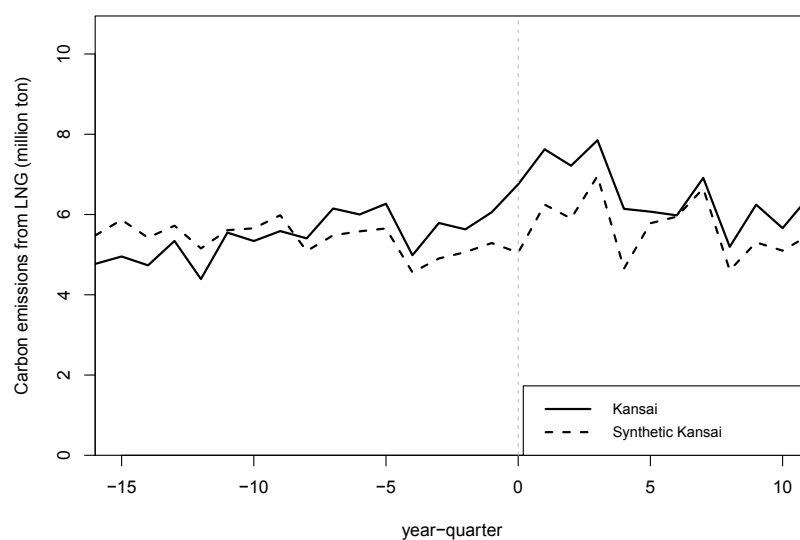


Figure 2.12: Emissions from LNG in competitive regions versus the synthetic

region (2.78 million tons), our SCM framework fails again in reproducing the counterfactual trajectory. In particular, the observed emissions in the competitive region are largely above the weighted outcome of donor units, which could be driven by the substantial LNG emissions in Tokyo, as suggested by part (b) of Figure 2.12. The synthetic mean outperforms the sample mean only in power price and emissions from LNG, as indicated by the lower panel of Table 2.8. A 100% weight is assigned to Chubu in the analysis for emission from LNG. Gap plots (Figures 2.13 and 2.14) and placebo results (Figures A2.5 and A2.6) also render the results in doubt. Estimating the effect on emissions from LNG, therefore, is not feasible under the current framework.



(a) Emissions from LNG in Tokyo versus the synthetic



(b) Emissions from LNG in Kansai versus the synthetic

Figure 2.13: Emissions from LNG in Kansai versus synthetics

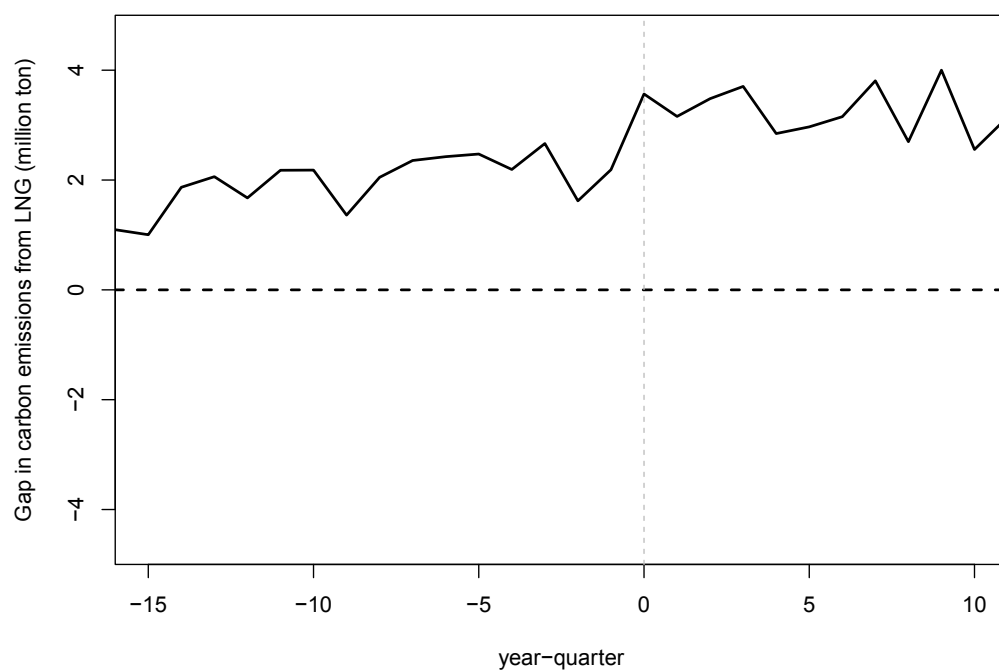
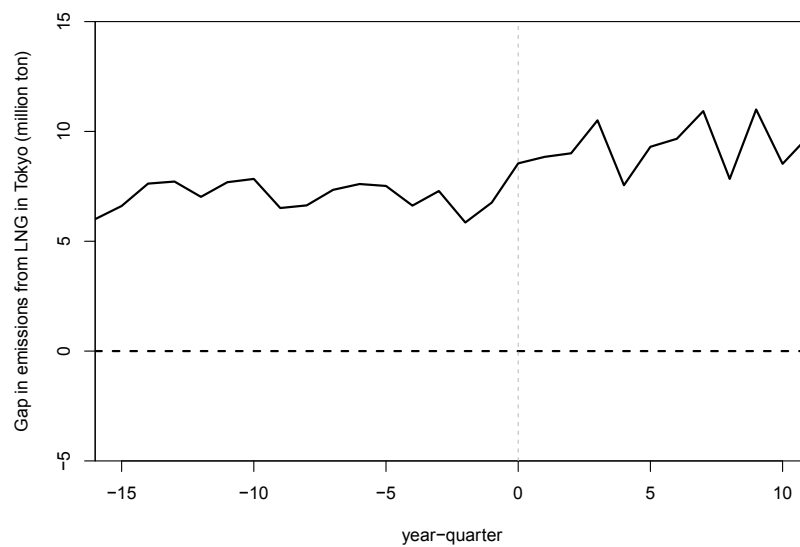
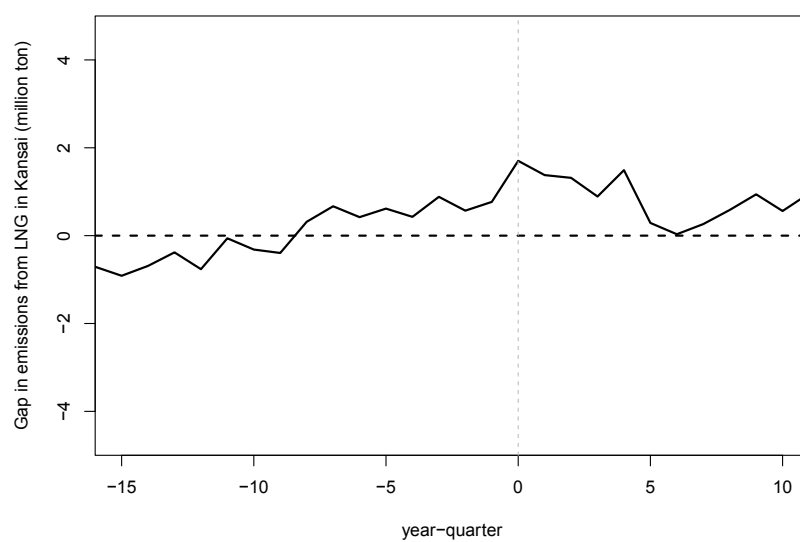


Figure 2.14: Gaps in emissions from LNG in competitive regions



(a) Emissions from LNG in Tokyo versus the synthetic



(b) Emissions from LNG in Kansai versus the synthetic

Figure 2.15: Emissions from LNG in Tokyo/Kansai versus synthetics

2.7 Discussion and Conclusion

This chapter aims to empirically investigate both price effect and environmental effect of the retail liberalization of the power market in Japan. Both a DID and a SCM framework are applied to test the following assumptions: competition following the liberalization leads to lower prices; incumbent power companies facing in competitive regions increase emissions from fossil fuels after the full liberalization.

Table 2.10: Summary of results

	<i>DID</i>			<i>SCM</i>		
	price	coal	LNG	price	coal	LNG
Treat	-1.483	0.692	1.825	-0.24	0.54	-
Tokyo	-2.264	1.400	2.782	-	-	-
Kansai	-0.749	-0.015	0.868	-1.27	-	-

Note: Coefficients estimated by DID are indicated by bold characters if significant at a 5% level. Prices are measured by 2015 JPY/kWh. Emissions are measured by million tons. Spaces are left vacant if the estimation is not feasible under SCM.

Coefficients are summarized in Table 2.10. The DID framework suggests a -1.48 JPY/kWh in electricity prices paid by residential consumers in the competitive region. This suggests an effective competition in the two regions, especially in Tokyo region where retail prices are found to decrease by 2.26 JPY/kWh. The price effect, however, is moderate in Kansai region, which is estimated as -0.75 JPY/kWh. In contrast with the DID framework, SCM suggests moderate decrease in the competitive region (-0.24 JPY/kWh) while a larger decrease in Kansai region (-1.27 JPY/kWh). We attribute this to potential confounders having different trends between groups in the pre-treatment period, which cannot

be differenced out with the DID approach. The issue is likely to be driven by Tokyo⁸. The estimated price effect on Tokyo under DID is also put into doubt by anticipatory effects, as suggested by Figure A2.8.

Environmental effects are also found in the competitive regions. Under a DID setting, the region increased carbon emissions from coal by 0.69 million tons and that from LNG by 1.83 million tons. Increases in either type of emissions are mainly driven by Tokyo. Emissions from coal in Tokyo region, however, suffer from anticipatory effect, as depicted in part (a) of Figure A2.9. This makes the DID-estimated coefficient for Tokyo unconvincing. Fortunately, emissions from LNG seem to share the similar pre-intervention trend in Tokyo versus control regions (illustrated in part (a) of Figure A2.10). As for LNG emissions in Kansai region (part (b) of Figure A2.10), while the trends are similar before the intervention, the difference after treatment seems to be moderate. The synthetic control approach, however, only succeeded in regenerating the trajectory of emissions from coal in the competitive region as a whole. Estimating emission effects by region or that caused by LNG usage is not feasible under SCM.

To summarize, the competitive region as a whole justifies our hypotheses and exhibits a trade-off, i.e., reduced power prices followed by increased carbon emissions from major fossil fuels, whereas the policy effects in each region are not well supported due to potential confounders. Besides the aforementioned cause, firms' strategic behaviors can also cause the outcome variables to change prior to the policy intervention. For instance, incumbent firms conduct limit pricing wherein

⁸As mentioned previously, Tokyo region is affected by the Great East Japan Earthquake and the following shutdown of nuclear power plants. Power prices increased substantially as a consequence. Also, as depicted by Figure A7, parallel trends between two groups may be violated by the increasing trend from FY2012 to FY2013 in the treatment group.

they suppress prices in advance to prevent would-be competitors from entering the market. Additionally, electricity prices are susceptible to price fluctuations of fossil fuels. The policy effect thus could either be exaggerated by cheaper fuels or be offset by increase in fuel prices.

Note that the estimation of regional impact falls short in several ways besides the above one. First, the restart of nuclear power plants may also lead to price reductions. Specifically, KEPCO restarted the Takahama No.3 and No.4 generators in January and February 2016, followed by Ooi No.3 and No.4 in 2018.⁹ Consequently, the price effect may stem from the restart of nuclear units instead of the market competition following retail liberalization. One needs to be careful when explaining the price effect in Kansai region. Second, the context of our study is featured by a nationwide policy. The SCM, however, is designed for causal inference of an intervention applied to a small group, e.g. a province in a country. Therefore, it is possible that regions other than the highly competitive ones are also affected. Reproducing the whole country with countries/regions where the power market is not yet liberalized may be a more appropriate way.

Several implications can be drawn from the findings. First, promoting new entries is conducive to lower power prices, which is associated with increases in consumer welfare. By the end of FY2022, the market share of PPS is around 30% in Tokyo and Kansai region, followed by Hokkaido and Chubu which have over 20%, while the rest is in the 10% - 20% interval.¹⁰ Another fact is that the PPS market share is under a nationwide decrease. One task thus lies in providing market entry incentives for competitive fringes and keeping them staying in the

⁹Information on restart of nuclear power plants can be confirmed on the website of KEPCO: <https://www.kepc.co.jp/corporate/pr/2016/index.html>.

¹⁰Calculated based on power market data from <https://pps-net.org/unit>.

market. Second, cheaper power bills are followed by increased emissions. Therefore, regulations on emissions from power plants are indispensable,¹¹ particularly given the 46% reduction target by 2030. Third, energy transition through development of low-carbon and/or zero-carbon technologies is inevitable. Although several power companies¹² managed to restart nuclear power plants, nuclear capacity is far from full recovery. Consequently, thermal power using fossil fuels is still playing a predominant role in power generation. Innovations in green technologies, such as alternative energy production, carbon capture and storage devices, are powerful tools either for short-term carbon abatement or for achieving climate targets in a longer run. Finally, subsidies for renewable power generation¹³ and the spread of residential solar panels is also favorable for climate mitigation.

¹¹A carbon cap-and-trade program has been introduced in Tokyo and Saitama Prefecture, known as Tokyo-Saitama Emission Trading System. The majority of regulated entities, however, are official buildings and facilities that are not for the use of power generation.

¹²Kansai Electric Power Company, Kyushu Electric Power Company, and Shikoku Power Company are currently operating nuclear power plants.

¹³Feed-in-tariff for solar power generation is currently in effect.

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Chapter 3

Induced Innovation in Power Generation Technologies

3.1 Introduction

Many countries have pledged ambitious climate targets in the Paris Agreement and adopted various policy measures to achieve the goals. Carbon pricing stands at the forefront of such policy measures and is anticipated to reduce carbon emissions in a cost-effective manner. In addition to its direct impact on emission reductions, carbon pricing is expected to foster environmental innovations by promoting investments in novel technologies regarding renewable energy (RE) and more efficient use of fossil fuels (FF). Innovations in RE technologies make a greater contribution than FF in the transition to net zero emissions. Nevertheless, it remains unknown whether an introduction of carbon pricing policy leads to the faster growth in RE technologies than that in FF technologies.

This study provides new insights into the effect of a regional carbon pricing scheme on innovations in power generation technologies, using patent application data on RE and FF technologies. Our primary objective is to examine whether a regional carbon pricing policy, the Tokyo-Saitama Emissions Trading System (TSETS), leads to a transition from FF to RE technologies, which is critical for achieving net zero emissions. To explore the energy transition, we investigate the innovation effect of the TSETS on the number of patent applications (intensive margin) and the entry into the technology market (extensive margin). By distinguishing these two effects, we can identify technological changes existing firms and new entrants make.

In this study, we distinguish innovating firms by their technology mix: specialized and mixed firms. A firm is defined as a specialized firm if it innovates in either RE or FF technology during the study period. A firm is defined as a mixed firm if

it innovates on both technologies across the study period. Specialized firms drive technological change through technology entry decisions and further investments in RE technologies. In contrast, mixed firms can induce the change by reallocating their resources and switching technology from FF to RE. Comparing the responses of these two types of firms to the TSETS, the analysis sheds light on the impact of carbon pricing on innovation in further detail. It also adds empirical evidence to previous studies that have examined innovation and firm-level heterogeneity (Acemoglu and Cao, 2015; Noailly and Smeets, 2015).

Our study contributes to the literature on the innovation impact of environmental regulations. The induced innovation theory suggests that an increase in factor prices incentivizes the usage of technologies that require less input of the more expensive factor (Hicks, 1932). For instance, carbon taxes imposed on firms can lead to technological change by affecting their profits (Milliman and Prince, 1989). Previous studies on the impact of energy prices (Popp, 2002; Aghion et al., 2016; Kruse and Wetzel, 2016) support the induced innovation theory by showing a positive relationship between higher costs of energy-intensive factors and efficiency-improving innovations. Our study adds to this branch of literature by exploring the effect of carbon pricing on technological change measured by the number of patent applications and the firms' technology entry.

The TSETS is a regional cap-and-trade program implemented by the Tokyo metropolitan government and Saitama prefectural government.¹ The program consists of two regulation schemes, the Tokyo ETS and the Saitama ETS, which differ

¹Impacts of the TSETS on energy consumption and carbon emissions have been investigated by Abe and Arimura (2022); Sadayuki and Arimura (2021). Abe and Arimura (2022) focused on the Tokyo ETS and found decreased energy consumption by regulated business establishments. Sadayuki and Arimura (2021) found that the TSETS has reduced carbon emissions from regulated entities.

in enforcement. We focus on this feature to explore whether a stricter regulatory scheme leads to a greater innovation effect.² Moreover, we examine whether a carbon trading system implemented in a region within a country can stimulate low-carbon technologies. The extant literature on the innovation effect of emissions trading systems has mainly focused on the European Union Emissions Trading System (EU ETS) that covers a broad geographical region (Hoffmann, 2007; Anderson et al., 2010; Rogge and Hoffmann, 2010).³ Using a matched difference-in-difference (DID) method, Caeli and Dechezleprêtre (2016) investigated the causal impact of the EUETS on low-carbon innovations. The authors found as much as a 10 % increase in low-carbon patent filing by regulated firms compared to the counterfactual case. The innovation impact was, however, found only in regulated firms. Thus, the system might play a limited role in inducing innovations on a larger scale. Regarding the innovation impact of TSETS, Hamamoto (2021) investigated the technology adoption in the manufacturing sector driven by the Saitama ETS. The study highlighted the adoption of high-efficiency machines within the first three years of the second compliance period. However, this adoption effect was not found in the first compliance period, attributed to the moderate emission target set for the period. The findings indicate some success of the Saitama

²We make the statement based on the “weak” version of the Porter Hypothesis (Jaffe and Palmer, 1997). The hypothesis argues that a stricter environmental regulation stimulates innovations.

³Hoffmann (2007) explored the electricity sector of Germany and investigated corporate technology investment decisions against the launch of the EUETS. The author found that the EUETS induced short-term low-carbon investments but played a limited role in inducing actual technological change. Anderson et al. (2010) explored the system by surveying Irish EUETS firms during the pilot period (2005–2007). They found that 48% of responding Irish firms employed new machinery equipment that contributes to emissions reductions. Rogge and Hoffmann (2010) explored the EUETS and its effect on power generation technologies based on interviews within Germany. The authors found that the EUETS is associated with increased carbon-free technologies.

ETS in encouraging carbon abatement efforts, even though the scheme imposed no penalties. Our study complements these studies by exploring whether an ETS spurs innovations and incurs technological changes even if it is introduced in a geographically limited region within a single country. It also investigates whether the TSETS induces innovations rather than technology adoptions and whether the existence of penalties leads to different innovative responses.

The findings of this study reveal a positive innovation impact of the TSETS, whereas the rate and direction of technologies vary by firms' technology mix and regulatory scheme. FF patents by mixed firms are found to be the most responsive, which aligns with the finding of Noailly and Smeets (2015), followed by RE patents by mixed firms and specialized firms. We further reveal a stronger response by firms under the Tokyo ETS than those under the Saitama ETS, which is attributable to the stricter enforcement mechanism of the former. The Saitama ETS, however, is found to be responsible for a switch of innovation activities from FF to RE. These findings thus offer implications for the effectiveness of a regional cap-and-trade program on potential carbon abatement by inducing green innovations.

The rest of the chapter is organized as follows. Section 2 presents detailed information on the TSETS and states our hypotheses. Section 3 provides an estimation model, data sources, and econometric methods. The baseline results are presented in Section 4, and the robustness of the results is tested in Section 5. Section 6 concludes.

3.2 Background and Hypotheses

In April 2010, the Tokyo Metropolitan Government launched a mandatory carbon abatement program aimed at facilities with an annual energy consumption of over 1,500 kL oil-equivalent CO₂. These facilities are required to report and reduce their GHG emissions by a certain percentage of their base-year emissions. Entities that are above the inclusion threshold since the launch could set the base-year emissions as the average emissions of any consecutive years between FY2002 and FY2007. For new entrants, the baseline is calculated as the average emissions of three consecutive fiscal years within the preceding compliance period⁴ or an emissions intensity standard provided by the government. Non-compliant facilities are subject to a stricter target of 1.3 times the shortfall, as well as fines and publication of their violations. The program encompasses approximately 1,200 commercial or industrial facilities, with total emissions from regulated facilities accounting for around 20% of total emissions from the targeted sectors in Tokyo. Market participants consist of facilities over the inclusion threshold and non-compliance entities which hold trading accounts. Credits are currently tradable at JPY 650 (USD 4.94) per t/CO₂ and banking is permitted between consecutive compliance periods. Additional credits may be earned through emissions reductions from unregulated facilities and the use of RE technology.

The Tokyo ETS is linked to a target-setting program introduced by Saitama Prefecture (Saitama ETS, henceforth) in 2011. Geographical delimitations of the two schemes are demonstrated in Figure 3.1. The program covers 587 commercial buildings or factories and accounts for 17% of total emissions. Allowances under

⁴The program is divided into three compliance periods with incremental abatement targets.

Saitama ETS are tradable at a price of JPY 144 (USD 1.06), and only emitting facilities can attend the program. Although the Saitama ETS shares the same inclusion threshold and identical abatement targets as in the Tokyo ETS in Phase I, there are several major differences between the two systems, as shown in Table 3.1. First, the Tokyo ETS imposes more stringent abatement targets on facilities than the Saitama ETS, except during the first compliance period. Second, in the event of non-compliance, facilities under the Saitama ETS are subject to publication of their violation but are not subject to penalties. By contrast, entities regulated by the Tokyo ETS are subject to a stricter abatement target (1.3 times of the shortfall) or penalties if they fail to comply with the target. These differences can lead to distinct innovation behaviors between the entities regulated by the two schemes.

We expect that the carbon pricing generates a market for RE technologies, thereby promoting innovation in clean technologies and stimulating the transition from RE to FF. Thus, we propose the following hypothesis:

Hypothesis 3.1 *The TSETS promotes technology transition from FF to RE and encourages RE market entry by firms.*

Moreover, a stricter regulation scheme could lead to greater innovation incentives, as discussed in Section 1, whereby firms regulated by the Tokyo ETS are under greater compliance pressure, as the scheme imposes penalties on firms that fail to comply with abatement targets. Thus, we propose the following hypothesis.

Hypothesis 3.2 *Firms under the Tokyo ETS have greater innovation incentives than do those regulated by the Saitama ETS.*

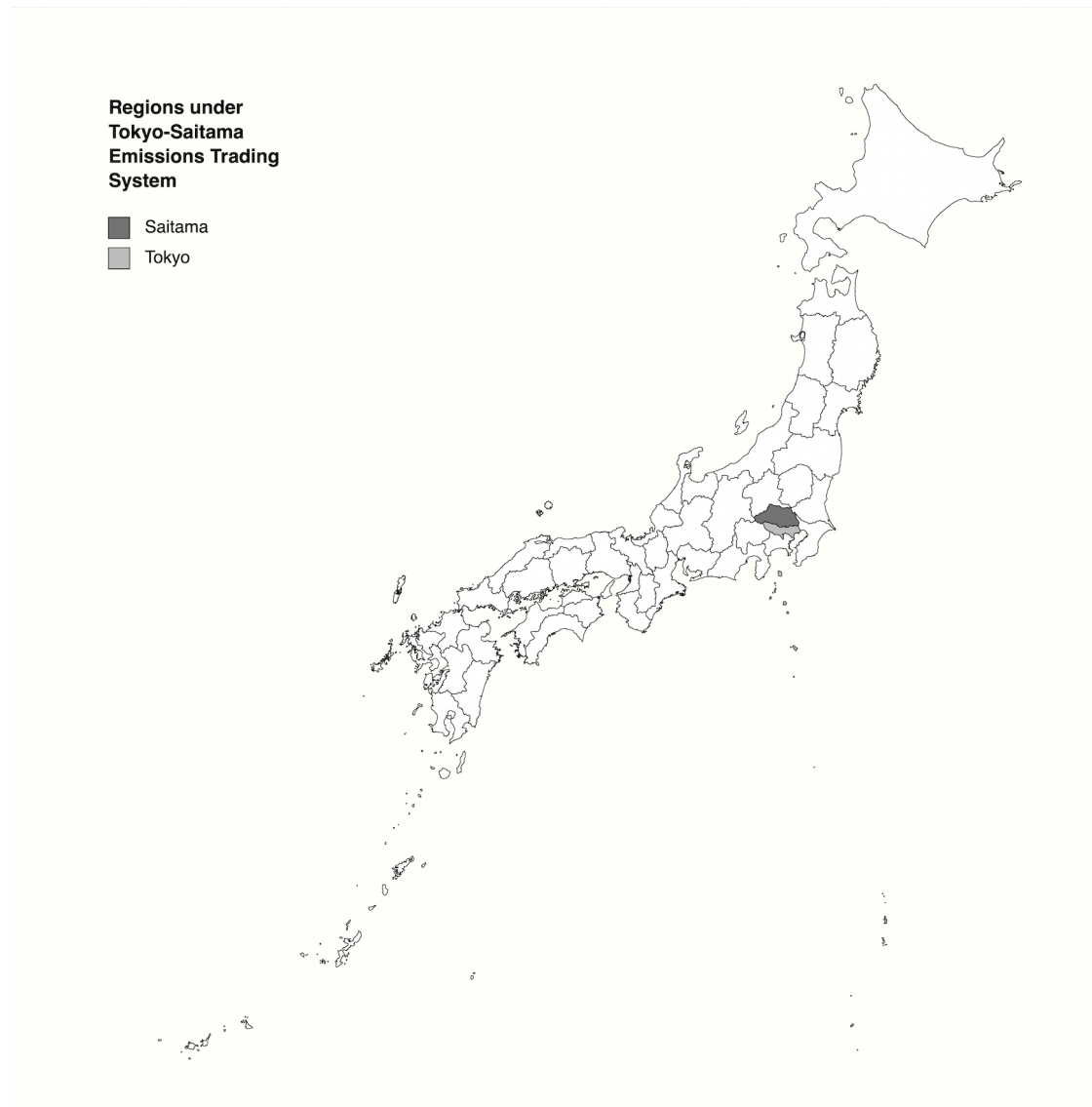


Figure 3.1: Map of Japan

Table 3.1: Comparison between the Tokyo ETS and Saitama ETS

	Tokyo ETS	Saitama ETS
Time of Validation	April 2010	April 2011
Inclusion Threshold	1,500 kL oil-equivalent CO ₂	
Sectors	Consumption of fuels, heat, and electricity in commercial and industrial buildings	
Participants	Compliance facilities and non-compliance entities	Compliance entities
Base-year emissions	Incumbents: average annual emissions of any three consecutive years between FY 2002 and 2007; New entrants: historical emissions or emission intensities provided by the government	
Abatement Target		
Phase I [*] (Apr 2011 - Sep 2016)	6% for factories; 8% for commercial buildings	
Phase II (Apr 2015 - Jan 2022)	15% and 17%	13% and 15%
Phase III (Apr 2020 - Jan 2026)	25% and 27%	20% and 22%
Non-compliance	Stricter abatement target or penalty	Name Published
Offsets and Credits	Emissions reductions achieved by non-regulated facilities; Use of renewable energy	Forest Absorption
Allowance prices	JPY 650 (USD 4.94)	JPY 144 (USD 1.06)

^{*} A phase is defined as a compliance period plus an additional adjustment period of 18 months. Facilities can trade credits to fulfill the abatement target during the adjustment period.

Furthermore, we measure policy stringency by the number of regulated facilities. As enforcement is imposed at the facility level, we expect firms operating a greater number of regulated facilities to have stronger innovation incentives than those with fewer regulated facilities. Thus, the following hypothesis is proposed.

Hypothesis 3.3 *Firms operating a greater number of regulated facilities have greater innovation incentives.*

3.3 Methodology and Data

3.3.1 Estimation Model

We construct a zero-inflated Poisson model to estimate the innovation effect on both the intensive and extensive margins. The model comprises two components. Initially, we explore firms' entry and exit dynamics by estimating a logit model, which indicates whether a firm has successfully introduced innovations in RE/FF, enabling them to enter the market of RE/FF technology, as indicated by

$$Pr(Patent_{it} = 0) = \Gamma(\mu_{it}^c) = \frac{e^{\mu_{it}^c}}{1 + e^{\mu_{it}^c}} \quad (3.1)$$

where $\mu_{it}^c = \log \lambda_{it}^c$. The dependent variable of Equation 3.1 is the likelihood of observing a zero value of patent application. We then investigate the rate of innovation by estimating a log-linear regression in which the dependent variable is Poisson distributed:

$$E(Patent|D_i, DID_{it}, \log A_{it-1}, X_i, \tau_t) = \lambda_{it}^c$$

$$s.t. \quad \lambda_{it}^c = \exp(\beta_0 + \beta_1 D_i + \beta_2 DID_{it} + \beta_3 \log A_{it-1} + X_i + \tau_t) \quad (3.2)$$

where i and t index firm and year, respectively. A_{it} denotes stocks of knowledge, represented by the sum of contemporaneous patent applications and a discounted stock of knowledge, based on the perpetual inventory method. The variable D_i is a treatment dummy variable that takes the values of 1 if firm i operates at least one facility above the regulation threshold in Tokyo or Saitama, and DID_{it} is a variable of interest that equals 1 when a firm operating regulated facilities is observed in the post-treatment period. We address the situation in which a firm owns large facilities (LFs) in both regions by defining the treatment timing as consistent with the year of a firm's initial report of CO₂ emissions. For example, if a firm's initial report of CO₂ emissions after the establishment of ETS is from the LF located in Tokyo, then the firm receives the treatment starting from 2010. If the initial report, however, is from the LF operated in Saitama Prefecture, we define the year of initial treatment as 2011.

We include $A_{it} = Patent_{it} + (1 - 0.15) * A_{it-1}$ as the stock of knowledge available for firms to explain the change in patent applications by technology-push factors. The variable is lagged by one year in the regression to account for the gap between current innovation and past knowledge stocks. We use the count of patent applications to account for path dependency and assume a depreciation rate of 0.15, consistent with the related studies (Hall et al., 2010). Because the knowledge stock variable is based on the realization of past patent applications, which might not be exogenous, firm fixed effects, which require strict exogeneity, might not be appropriate. To address this, we employ pre-sample estimators developed by Blundell et al. (1995), Blundell et al. (2002) to capture firm-level heterogeneity.

Specifically, we include for each firm the average pre-sample patent applications in all technology areas, as indicated by X_{it} .

Following Noailly and Smeets (2015), we distinguish between mixed firms that file patents for both RE and FF over the sample period and specialized firms that file patents for only either of these technologies. We estimate the model separately for each type of firm, including all variables in both models. However, in the regressions on patents by RE-specialized firms, we do not include the stock of the FF technology owing to the lack of FF knowledge stock accumulated by these firms.

To account for the difference in the innovation effect resulting from policy stringency, we conduct a regional heterogeneity analysis by interacting the region dummies with their respective treatment time dummies. Specifically, the interaction term equals 1 since 2010 if the region dummy of Tokyo takes 1, or since 2011 if the Saitama dummy equals 1. The region dummy is defined in terms of the prefecture where the initially reported LF in the post-intervention period is located. We refer to a firm operating LFs in both regions as a Tokyo ETS-regulated firm, because we believe that firms prioritize the Tokyo ETS owing to its stricter obligations placed on facilities. Additionally, we incorporate the number of LFs that each firm operates in Tokyo, Saitama, and other prefectures by interacting with the DID estimator. Thus, the estimated coefficient measures the marginal innovation effect of an additional LF.

To reduce the sample selection bias, the above analysis is carried out using a matched sample. The rationale behind matching is to find control units in the sample that resemble the treated units in terms of observable covariates such that two types of units exhibit similar likelihoods of receiving the treatment. The degree

of similarity between treated and control units is measured by propensity scores, wherein similar pairs exhibit scores that are in close proximity in value. Specifically, we conduct a one-to-one nearest neighbor matching in line with Rosenbaum and Rubin (1985) by regressing the treatment assignment on several covariates to predict the probability for firm i to be treated. The regression corresponds to Equation 3.3.

Since firms receive the treatment only if they own facilities that generate carbon emissions above the threshold, the treatment allocation is regressed on their pre-treatment average carbon emissions. Pre-treatment average patent applications for RE and FF technologies are also employed as covariates of matching to ensure that control units and treatment units are similar in terms of innovation capacity and the likelihood of receiving the treatment in the pre-intervention period. We conduct a one-to-one nearest neighbor matching and use a 0.2 caliper⁵ based on the following equation:⁶

$$Treat_i = \rho_0 + \rho_1 RE_i^{pretreat} + \rho_2 FF_i^{pretreat} + \rho_3 CO2_i^{pretreat} \quad (3.3)$$

where $Treat_i$ is the treatment allocation, which takes 1 if firm i is regulated by the ETS, and 0 if not. $RE_i^{pretreat}$ indicates the pre-treatment average of RE patents, $FF_i^{pretreat}$ is the pre-treatment average of FF patents, and $CO2_i^{pretreat}$ refers to pre-treatment average emissions of carbon dioxide.

The above model gives the estimated probability of a firm being treated, based on which we obtain propensity scores and find a similar control unit for each

⁵We refer to results from Cochran and Rubin (1973) and use the caliper width equal to 0.2 of the pooled standard deviation of the logit of the propensity score.

⁶Further details on the matching procedure are demonstrated by Table A3.1 in the Appendix.

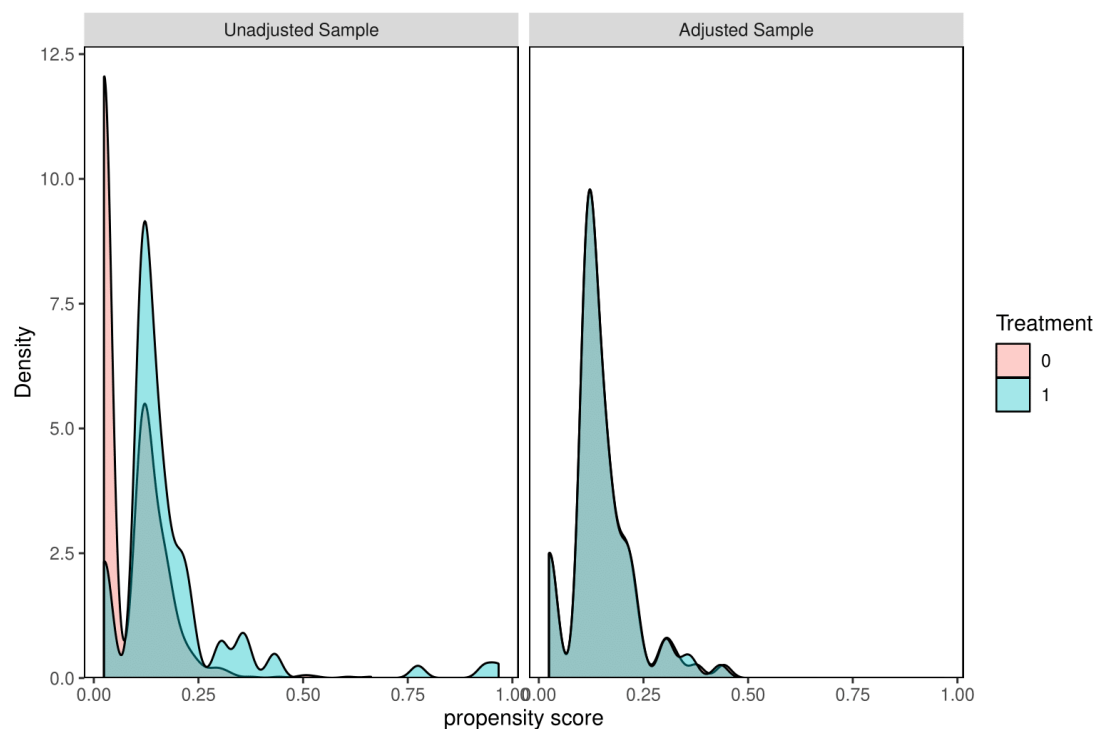


Figure 3.2: Propensity Score Density

treated unit. A total of 87 pairs of control and treated units are obtained. As shown in Figure 3.2, the balance between control and treatment is substantially improved after matching. Statistics shown in Table 3.2 also indicate an improved balance.

3.3.2 Data

Table 3.3 presents the summary statistics of the variables used in this study. The original sample consists of 4,073 observations of 996 firms that engage in RE and/or FF innovations. The matched sample contracts to 970 observations from 2006 to 2016 on RE and/or FF patents by 174 innovating firms (87 treatment and

Table 3.2: Table of Balance

Variable	Status [*]	Mean of Treated	Mean of Control	% Balance Improvement
CO ₂ emissions	U	8.83	4.56	
CO ₂ emissions	M	8.70	8.91	95.0
Pre-treatment RE	U	5.26	1.50	
Pre-treatment RE	M	3.72	2.20	59.7
Pre-treatment FF	U	0.88	0.13	
Pre-treatment FF	M	0.25	0.20	94.3

^{*} Matched sample and unmatched sample are indicated by M and U, respectively.

control pairs).⁷ In cases where a firm's initial RE/FF innovation is observed after 2006, we consider the year in which it conducts its first RE/FF innovation as its initial year of active innovation. As some firms initiate RE/FF patent applications after 2006, the sample is unbalanced. In the baseline analysis, we adhere to the active innovation period as defined above, and we then extend the definition to include firms' generic innovation phase in a robustness check to examine whether their market entry decisions and innovation level vary by a different definition of innovation period. We cannot investigate the innovation impact on patents by FF-specialized firms because only FF-specialized firm is included in the control group. Therefore, we conduct regressions solely on RE patents by both types of firms and on FF patents by mixed firms, which corresponds to 969 observations

⁷Data are collected in a patent-oriented sense instead of a sector-oriented one. In other words, firms are included for engaging in RE and/or FF innovation activities, not for belonging to the power sector. We focus on the 2006–2016 period for the following reasons. First, the number of patent applications shows a significant declining trend toward the end of the sample period (in our case, the patent data are available until 2019). The reason for this is the time lag between an actual application and the record of an application, which is a common case in patent databases. Second, we do not want the result to be contaminated by different caps imposed in different compliance periods. The first compliance period ends in 2016. If we were to extend the study period to 2019, then the analysis would cover the second compliance period, which has stricter abatement targets.

from 2006 to 2016.

We select patent application as the dependent variable for multiple reasons. First, patent application offers a means to capture the output of innovation activities. Additionally, its non-negative, discrete nature is conducive to analyzing firms' market entry decisions. Secondly, we opt for patent applications over R&D investments, because the former is technology-specific based on the available data. International Patent Classification (IPC) codes can be used to differentiate between innovations associated with RE and FF power generation technologies. Third, the use of patent count allows us to establish a firm-specific portfolio of successful innovations, enabling us to disentangle the innovation impact led by ETS from the effect of knowledge stock.

The data on patent applications are obtained from the Patent Database provided by the Institute of Intellectual Property (IIP) (Goto and Motohashi, 2007). The database has more than 14,000,000 records, with information dating back to 1964. Applications are categorized based on IPC code, which enables us to differentiate between RE and FF patents, as documented in Johnstone et al. (2008) and Lanzi et al. (2011)⁸. Firm-level pre-sample innovation variables are derived using the same database. Nevertheless, the Patent Database lacks firm-level information, such as addresses and names. Therefore, we refer to the patent data connection tool and company dictionary provided by the National Institute of Science and Technology Policy (NISTEP) to obtain names, addresses, and unique identification numbers for each innovating firm. Summary and analysis of the data

⁸RE innovations include alternative energy production from renewable sources. We refer to the IPC publication provided by the World Intellectual Property Organization (WIPO) for the identification of hydro power, as this classification was not indicated by Johnstone et al. (2008). FF innovations are associated with efficiency-improving FF technologies for electricity generation. The IPC codes for both technology areas are shown in Table A3.2 in the Appendix.

are conducted using the stargazer package (Hlavac, 2018).

To discern the entities subjected to treatment, we refer to the GHG Emissions Dataset provided by the Ministry of Environment. The dataset contains GHG emissions at the facility level declared by establishments surpassing the regulatory threshold and pertinent details regarding the entities overseeing those facilities. Drawing upon corporate-level information, namely, company names and facility archives, we isolate the units subject to treatment and procure the tally of sizeable establishments run by innovating firms each year within the sample period.

We conduct event studies before investigating the average treatment effect to ensure that the parallel trend assumption is satisfied. As indicated in Figures 3.2(a) and 3.2(b), the treatment effects are not statistically different from zero before the introduction of the TSETS and there is little concern about anticipatory effects that could violate the assumption.

3.4 Results

3.4.1 Baselines Results

The baseline results are presented in Table 3.4, wherein the upper panel depicts the coefficients regarding the intensive margin while the lower panel indicates the estimates regarding the extensive margin. Columns (1)–(3) provide estimates for all the firms involved in RE innovation, mixed firms, and RE-specialized firms, respectively. Furthermore, column (4) presents the estimates for FF patents applied by mixed firms.

We find a positive and statistically significant effect of carbon pricing on the

Table 3.3: Descriptive Statistics

<i>Treatment group</i>	Obs.	Mean	St. Dev.	Min	Max
RE patents	567	6.353	9.552	0	61
FF patents	567	0.411	1.147	0	8
RE knowledge stock	567	2.780	1.489	0.000	5.930
FF knowledge stock	567	0.605	1.066	0.000	4.470
Pre-sample innovation	567	4.811	2.069	0.000	8.850
Mixed	567	0.372	0.484	0	1
RE-specialized	567	0.628	0.484	0	1
FF-specialized	567	0.000	0.000	0	0
<i>Control group</i>					
RE patents	403	4.094	11.980	0	120
FF patents	403	0.310	1.320	0	14
RE knowledge stock	403	2.095	1.323	0	6
FF knowledge stock	403	2.095	1.323	0	6
Pre-sample innovation	403	3.658	1.894	0	7
Mixed	403	0.280	0.450	0	1
RE-specialized	403	0.717	0.451	0	1
FF-specialized	403	0.002	0.050	0	1

number of RE patents filed by either type of firm, as indicated by columns (1)–(3). Specifically, RE-innovating firms file additional $e^{0.27} \approx 1.3$ RE patents on average, driven primarily by mixed firms, which increase these firms' RE patent filings by $e^{0.47} \approx 1.6$. Specialized firms also increase their level of RE innovation, albeit to a lesser extent than mixed firms, and the increase is significant only at the 10% level. FF patents filed by mixed firms show the strongest response to carbon pricing, increasing by $e^{0.98} \approx 2.7$, as shown in column (4). Regarding the estimates on knowledge stocks, firms tend to be more innovative in a particular technology area if they have a history of innovation in that area. However, they tend to decrease the level of innovation in an area if they were previously innovative in

another.

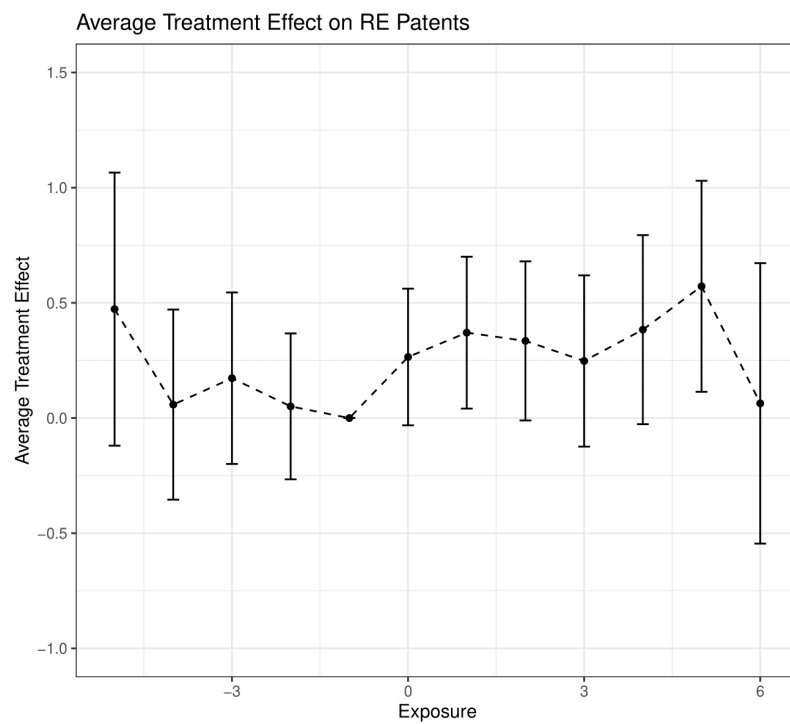
Regarding the extensive margin, we find insufficient evidence to support the idea that firms' technology entry decisions are motivated by the TSETS, as none of the coefficients of the DID estimator is significant. Instead, firms appear to base their technology entry decisions on their past knowledge of the same area. In other words, a firm's success in RE/FF innovation will likely depend on its past accumulated knowledge in the corresponding technology area. This phenomenon holds primarily for mixed firms, as the RE knowledge stock for specialized firms is insignificant.

3.4.2 Regional Heterogeneity

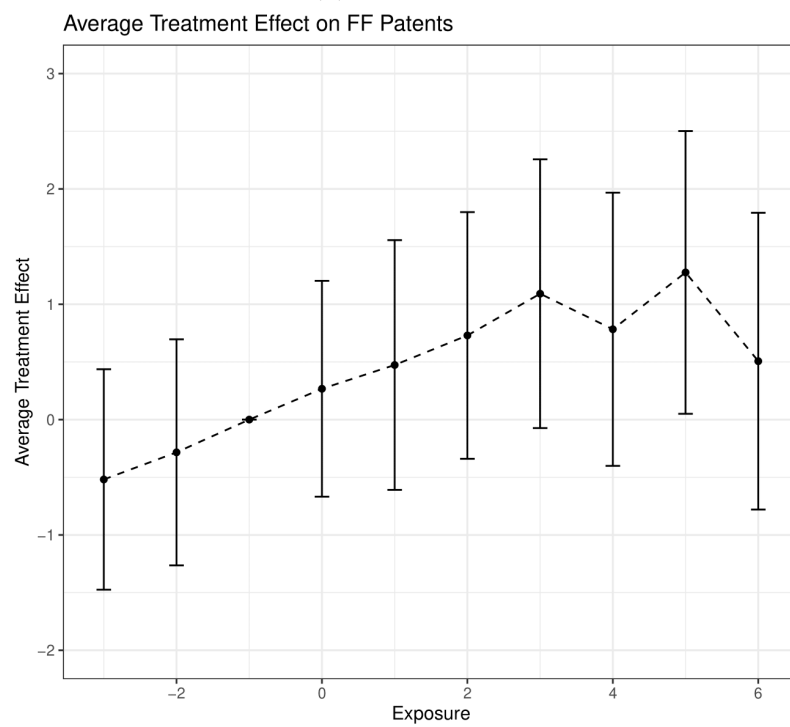
We estimate the following model to test the regional heterogeneity attributable to policy stringency.

$$\begin{aligned} Patent_{it}^c = & \exp(\beta_0 + \beta_1 Tokyo_i + \beta_2 Saitama_i \\ & + \beta_3 Tokyo * Post2010 + \beta_4 Saitama * Post2011 + \beta_5 \log A_{it-1} + X_i + \tau_t) \end{aligned} \quad (3.4)$$

The results are reported in Table 3.5. We observe from the first row of Table 3.5 that the Tokyo ETS provides both types of firms with innovation incentives, which aligns with the baseline results. The Saitama ETS, however, fosters only mixed firms in RE technologies, and the incentive it provides for RE innovation is less strong than that of the Tokyo ETS. The result is intuitive, as firms regulated by a regime that lacks penalties for non-compliance might choose to adopt cheaper emissions reduction plans over technological innovation, which can be costly (Re-



(a) RE patents



(b) FF patents

Figure 3.3: Average Treatment Effect on the Number of Patents

Table 3.4: Baseline Results

	RE patents			FF patents
	All	Mixed	Specialized ^a	Mixed
	(1)	(2)	(3)	(4)
<i>Intensive margin</i>				
DID	0.27*** (0.06)	0.47*** (0.10)	0.13* (0.07)	0.98*** (0.25)
RE knowledge stock	0.78*** (0.01)	0.70*** (0.03)	0.80*** (0.01)	−0.16* (0.09)
FF knowledge stock ^b	−0.10*** (0.01)	−0.10*** (0.02)		0.60*** (0.11)
<i>Extensive margin^c</i>				
DID	0.40 (0.37)	17.34 (2,879.94)	0.04 (0.39)	0.27 (0.70)
RE knowledge stock	−0.16 (0.11)	−0.70** (0.30)	−0.08 (0.11)	0.31 (0.21)
FF knowledge stock	−0.38* (0.22)	0.45 (0.31)		−1.18*** (0.25)
Observations	969	324	645	324

^a FF-specialized firms are excluded from the regression owing to the extremely small number of observations.

^b FF knowledge stock is not included in the regression on RE patents by specialized firms because those firms apply for only RE patents across the sample period.

^c Coefficients for the logit model indicate the change in the likelihood of observing a 0 outcome. A negative and significant coefficient, therefore, indicates an increased likelihood of observing a positive application.

*p<0.1; **p<0.05; ***p<0.01.

quate, 2005; Calel, 2020; Hamamoto, 2021).

We then observe in column (3) that mixed firms become less innovative in FF technologies if they are regulated by the Saitama ETS, as opposed to the case of the Tokyo ETS. The results suggest that the Saitama ETS has led to a technological transformation from energy-intensive to low-emitting. A possible cause for distinct directions of technological innovation could be the different distribution of facility types. On one hand, firms regulated by the Tokyo ETS operate thermal power plants⁹ and have been more innovative in FF than are firms under the Saitama ETS,¹⁰ making it less costly for Tokyo-ETS firms to develop FF technologies that already exist and applied to the facilities. On the other hand, the Saitama ETS firms are likely to withdraw from FF and spare more efforts on RE innovations to comply with the abatement targets, as it operates few regulated power plants.¹¹

Knowledge stocks of RE and FF show a substitute pattern, consistent with the baseline results. Regarding the extensive margin, the lower panel indicates that there is still little evidence of technology entry even when investigated by the regulation scheme, which echoes the baseline results. Estimates on knowledge stocks are also consistent with the baseline in that knowledge stocks in one technology area are associated with a successful future innovation in the same area.

We then test whether the innovation incentive changes by the number of large facilities.¹² Firms operating additional regulated facilities must pay more for car-

⁹On average, 19 power plants operated per year by the Tokyo ETS firms in the post-intervention period and all of which are thermal power plants. The number accounts for 4% of all types of regulated facilities under the Tokyo ETS. Although the large power plants are not necessarily located in the regulated regions, firms could retrieve extra credits through emissions reductions achieved by unregulated power plants.

¹⁰The mean value of logarithmic FF knowledge stock of Tokyo-ETS firms is 0.77, while that of Saitama-ETS firms is 0.31.

¹¹We find only one power plant operated under Saitama ETS through the sample period.

¹²Firms' energy use is also an important driving force for innovations that improve energy

bon pricing than those operating fewer facilities. To test whether innovation decisions respond to a marginal increase in the number of LFs, we interact the DID estimator with the numbers of *additional*¹³ LFs in regulated areas (Tokyo and Saitama).

We construct the following model to test the effect of a marginal increase in the number of regulated LFs operated by an ETS firm:

$$\begin{aligned} Patent_{it}^c = \exp(\beta_0 + \beta_1 Treat_i + \beta_2 DID_{it} \\ + \beta_3 DID_{it} * \#LF_{regulated} + \beta_4 DID_{it} * \#LF_{regulated}^2 + \beta_5 \log A_{it-1} + X_i + \tau_t) \end{aligned} \quad (3.5)$$

The DID estimator gives the average treatment effect of the regulatory scheme, and thus, the marginal innovation effect of an additional regulated LF is thus given by $\beta_3 + 2\beta_4 * \#LF$. The results are presented in Table 3.6.

Regarding the intensive margin, we observe from the first two rows that RE innovations are responsive to additional LFs, because the estimates on interaction terms are statistically different from zero. Negative estimates on the quadratic terms further suggest an inverse U-shaped curve between the number of regulated LFs and the number of RE patents, which indicates that marginal innovation incentive decreases with the number of LFs. Intuitively, firms are incentivized at first when they operate additional regulated facilities, while they might choose carbon strategies other than green innovations when faced with incremental regulations.

efficiency. We do not include energy use as an explanatory variable, however, because data on firm-level energy use are not available. More importantly, energy use could be affected by the TSETS, as supported by Abe and Arimura (2022), which may lead to endogeneity.

¹³Because the DID estimator takes 1 by specification if a firm operates at least 1 LF in the post-intervention period, we define $\#LF$ such that it takes the difference between 1 if greater than 1 and 0 if equal or below 1.

The marginal RE innovation incentive of mixed firms is found to diminish faster than that of specialized firms when we compare the magnitude of the estimates on quadratic terms. This is attributable to the higher substitutability of carbon strategies adopted by mixed firms. Mixed firms, which are more diversified in technology portfolio, tend to be large firms (Noailly and Smeets, 2015) with more financial resources that allow for simultaneous carbon strategies (Weinhofer and Hoffmann, 2010), such as shifting their production activities away from regulated facilities to newly constructed facilities that are not regulated by the ETS.¹⁴ Specialized firms, meanwhile, are more likely to be smaller firms with limited alternatives to carbon strategy and thus, tend to stick to green innovations. The lower panel of Table 6 provides little evidence to support the idea that the number of large facilities determines firms' technology entry decisions. The estimates on knowledge stock are also qualitatively similar to the baseline results.

3.5 Robustness Checks

In the baseline analysis, we define the innovation period such that the year a firm conducts its first RE/FF innovation is treated as its initial year of active innovation. However, in this section, we examine the robustness of the baseline result by extending the innovation period in the baseline analysis to a *generic* one. In other words, we set a firm's innovation period from its initial to its final patent application for *any* type of technology rather than defining it by power generation

¹⁴Sadayuki and Arimura (2021) suggested a negative carbon leakage at the intensive margin. In other words, regulated and unregulated facilities operated by the same company reduced their carbon emissions in response to the ETS. However, carbon leakage at the extensive margin whether regulated firms construct new facilities in unregulated regions, is not examined. Nesta et al. (2014) also argued that firms respond to regulations by having quick-to-start facilities.

Table 3.5: Regional Heterogeneity

	RE patents		FF patents
	Mixed	Specialized	Mixed
	(1)	(2)	(3)
<i>Intensive margin</i>			
Tokyo*Post2010	0.51*** (0.10)	0.23*** (0.07)	0.97*** (0.25)
Saitama*Post2011	0.33*** (0.12)	−0.10 (0.09)	−1.12* (0.66)
RE knowledge stock	0.71*** (0.03)	0.81*** (0.02)	−0.16* (0.09)
FF knowledge stock	−0.12*** (0.02)		0.57*** (0.10)
<i>Extensive margin</i>			
Tokyo*Post2010	16.92 (2,255.37)	0.28 (0.40)	−0.25 (0.77)
Saitama*Post2011	16.48 (2,255.37)	−1.31 (1.28)	−15.77 (2,579.62)
RE knowledge stock	−0.64** (0.32)	−0.03 (0.12)	0.22 (0.23)
FF knowledge stock	0.41 (0.33)		−1.15*** (0.27)
Observations	324	645	324

*p<0.1; **p<0.05; ***p<0.01

Table 3.6: Innovation Effects of Additional Regulated Facilities

	RE patents		FF patents
	Mixed (1)	Specialized (2)	Mixed (3)
<i>Intensive margin</i>			
$DID^* \#LF_{regulated}$	0.29*** (0.04)	0.23*** (0.03)	0.10 (0.13)
$DID^* \#LF_{regulated}^2$	-0.04*** (0.005)	-0.02*** (0.003)	-0.01 (0.01)
RE knowledge stock	0.69*** (0.03)	0.79*** (0.02)	-0.17* (0.09)
FF knowledge stock	-0.13*** (0.02)		0.60*** (0.11)
<i>Extensive margin</i>			
$DID^* \#LF_{regulated}$	1.00 (0.89)	-0.18 (1.56)	-0.91 (0.77)
$DID^* \#LF_{regulated}^2$	-0.25 (0.22)	-0.37 (1.31)	0.06 (0.14)
RE knowledge stock	-0.74** (0.30)	-0.02 (0.11)	0.25 (0.23)
FF knowledge stock	0.44 (0.33)		-1.15*** (0.27)
Observations	324	645	324

*p<0.1; **p<0.05; ***p<0.01

technologies, as in the baseline analysis. For example, if a firm applied for its first RE(FF) patent in 2010 but applied for a patent in another technology area as early as 2007, its generic innovation period starts in 2007. The end of the generic innovation period is defined similarly. Thus, the extensive margin analysis during the generic innovation period investigates whether firms enter the RE/FF market by successfully conducting an RE/FF innovation, even if they have previously been innovating in other technology areas.

Expanding the innovation period to a generic one results in a substantially larger number of observations, particularly for specialized firms, whose sample size doubles. This increase is mainly due to the significant number of zero values observed among specialized firms, indicating that they are less likely to innovate consecutively, as do mixed firms, or they may exit the market soon after a successful innovation. The results are reported in Table 3.7. We find little evidence of market entry for the RE or FF market, which supports the robustness of the baseline results. The estimates for the intensive margin and knowledge stocks are consistent with the baseline results.

We further test the robustness of the baseline results by applying higher depreciation rates than the baseline. The results based on depreciation rates of 20% and 30% are presented in Tables 3.8 and 3.9, respectively. The estimates for the intensive margin are consistent with the baseline results, except that specialized firms are no longer responsive to the TSETS for RE innovations, either in the case of a 20% or a 30% depreciation rate. It suggests that when past knowledge of RE technologies becomes less available for current innovation activities, specialized firms are less incentivized to continue RE innovations in response to the increased costs of carbon. Additionally, the estimates on knowledge stocks reveal a substitution

Table 3.7: Generic Innovation Period

	RE patents		FF patents
	Mixed	Specialized	Mixed
	(1)	(2)	(3)
<i>Intensive margin</i>			
DID	0.42*** (0.10)	0.16** (0.07)	0.97*** (0.26)
RE knowledge stock	0.70*** (0.03)	0.84*** (0.02)	−0.14 (0.10)
FF knowledge stock	−0.02 (0.03)		0.62*** (0.11)
<i>Extensive margin</i>			
DID	0.35 (0.47)	0.09 (0.25)	−0.12 (0.53)
RE knowledge stock	−0.81*** (0.21)	−0.53*** (0.08)	0.001 (0.19)
FF knowledge stock	0.24 (0.22)		−0.99*** (0.24)
Observations	403	1,386	403

*p<0.1; **p<0.05; ***p<0.01

between RE and FF even at the extensive margin when we use different depreciation rates, indicating that successful innovation in one technology area is impeded by the knowledge accumulated in the other. Intuitively, firms are more likely to succeed in RE if they focus on innovation in this field rather than spreading them out across multiple areas. Success in one area builds on previous knowledge and experience, whereas spare resources is less effective in driving innovation.

3.6 Conclusion

This study has estimated the innovation impact of an emissions trading program by comparing patent applications by regulated and unregulated firms. Using patent application data on RE and FF technologies, we found that TESTS boosted RE innovations by specialized and mixed firms and increased FF patents by mixed firms. However, our findings also reveal that FF innovations increased more than RE innovations, and the innovation effect was realized only at the intensive margin, which mixed firms mainly drive. Our analysis also highlights that firms regulated by the Tokyo ETS exhibit greater innovation than those not subject to regulation in both RE and FF technologies. Although the Saitama ETS has provided moderate innovation incentives compared to the Tokyo ETS, it has fostered technological change from FF to RE. Additionally, firms' decision to innovate may be influenced by the number of regulated facilities, and the marginal effect of such facilities varies between specialized and mixed firms.

Several implications can be derived from this study. First, the the TSETS provides insufficient incentives for firms to enter the RE market, at least during the study period. Innovation of firms is highly dependent on its past knowledge,

Table 3.8: Depreciation Rate of 20%

	RE patents			FF patents
	All	Mixed	Specialized	Mixed
	(1)	(2)	(3)	(4)
<i>Intensive margin</i>				
DID	0.28*** (0.06)	0.50*** (0.10)	0.10 (0.07)	0.92*** (0.25)
RE knowledge stock	0.68*** (0.01)	0.46*** (0.03)	0.73*** (0.01)	−0.10 (0.09)
FF knowledge stock	−0.10*** (0.01)	−0.03 (0.02)		0.60*** (0.11)
<i>Extensive margin</i>				
DID	0.41 (0.33)	2.27 (1.98)	0.10 (0.36)	0.22 (0.68)
RE knowledge stock	−0.20** (0.10)	−0.73*** (0.23)	−0.09 (0.11)	0.38* (0.21)
FF knowledge stock	−0.29 (0.19)	0.47* (0.26)		−1.39*** (0.28)
Observations	969	324	645	324

*p<0.1; **p<0.05; ***p<0.01

Table 3.9: Depreciation Rate of 30%

	RE patents			FF patents
	All	Mixed	Specialized	Mixed
	(1)	(2)	(3)	(4)
<i>Intensive margin</i>				
DID	0.12* (0.06)	0.49*** (0.10)	0.09 (0.07)	0.83*** (0.25)
RE knowledge stock	0.74*** (0.02)	0.53*** (0.03)	0.75*** (0.01)	−0.07 (0.09)
FF knowledge stock	−0.12*** (0.02)	−0.03 (0.03)		0.61*** (0.12)
<i>Extensive margin</i>				
DID	16.94 (1,979.49)	13.00 (2,056.49)	0.11 (0.37)	0.17 (0.65)
RE knowledge stock	−0.53** (0.21)	−0.68*** (0.24)	−0.18 (0.11)	0.37* (0.21)
FF knowledge stock	0.28 (0.26)	0.53* (0.28)		−1.64*** (0.33)
Observations	969	324	645	324

*p<0.1; **p<0.05; ***p<0.01

especially for mixed firms, which suggests the presence of path-dependency. Consequently, redirecting innovation activities from FF toward RE technologies would boost the knowledge stock of RE and facilitate self-reinforcing RE in the long run. Second, the impact of the innovation incentives depends on the technology mix of the innovator. Mixed firms exhibit greater innovation in RE and FF technologies, while specialized firms are only moderately responsive. Therefore, a policy challenge lies in enhancing the responsiveness of specialized firms, which are larger in number, to carbon pricing. Lastly, a more stringent regulation scheme outperforms a moderate one in stimulating RE innovations, but it also leads to faster growth of FF than RE ones. Hence, it is necessary to design policies contributing to a net increase in RE technologies.

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Chapter 4

Carbon Disclosure and Corporates' Green Innovations

4.1 Introduction

With the severity of climate change and ambitious climate targets set by governments, an increasing number of firms are voluntarily providing information on their environmental practice to demonstrate their commitment to protecting the environment and promoting social responsibility. The disclosing effort can be considered a form of voluntary environmental regulation, wherein firms report to the public on how they incorporate environmental costs into their business operations and manage environmental risks. Environmental and financial outcomes of environmental disclosure have attained great interest, whereas there is little consensus on its innovation impacts.

This chapter aims to investigate whether the voluntary regulations lead to environmental innovations. We also test if innovations promote environmental disclosure. That is, we focus on the two-way causality between firms' environmental innovation and environmental disclosure. The analysis sheds light on the probability of boosting innovation through a voluntary scheme, and if innovation and disclosure reinforce each other. We could expect this to be a more cost-effective way of inducing innovations, considering the higher costs of mandatory schemes. In addition, we examine the interplay among high-emitting firms, as we expect those firms to behave differently from lower-emitting firms since they are under greater environmental pressure.

Based on data spanning 2013 to 2018, our analysis reveals positive innovation effects of environmental disclosure, whereas the effectiveness depends on the completeness of disclosure. However, disclosure is little likely to be driven by green innovations. Furthermore, the analysis on high-polluting firms also suggests pos-

itive innovation effects but little disclosure effect. While the expected reinforcing relationship is not found, the results suggest the possibility of spurring green innovation through improving environmental information transparency.

The incentives for technological innovation that are aimed at reducing pollutants and improving energy-efficiency have long subject to scrutiny. According to the induced innovation theory by Hicks (1932), increased factor prices encourage the technological innovation that saves specific input factors. Several studies have documented that increased energy prices may lead to technological innovations (Popp, 2002; Noailly and Smeets, 2015; Aghion et al., 2016). Moreover, policy instruments such as carbon cap-and-trade programs that impose mandatory regulations on carbon emissions can also drive technological change (Calel and Dechezleprêtre, 2016; Anderson et al., 2010). Nevertheless, there are few studies that investigate if voluntary incentives lead to firms' innovation activities beyond the mandatory ones in the induced innovation realm. Studies on firms' environmental disclosure mainly focus on the economic and environmental effects (Kim and Lyon, 2011a; Alvarez, 2012) and environmental outcomes (Kim and Lyon, 2011b; Matisoff, 2012, 2013) of firms' environmental disclosure. However, little consensus has been reached on the innovation effect of voluntary environmental regulations that incentive firms to internalize the costs of carbon. This study addresses the research gap by investigating if firms conduct innovation activities in response to carbon disclosure, a form of voluntary environmental regulation.

There is a concern, however, that the disclosure process may not be conducted in a random manner. For example, firms with larger size or better financial condition usually possess better environmental management skills, which enables them to collect and report environmental information more effectively. It is particu-

larly noteworthy that firm's environmental performance can lead to disclosures. Firms with a strong record of environmental performance are more likely to disclose their carbon-related information (Clarkson et al., 2008). Such firms tend to be more confident in convincing consumers and stakeholders of their effort towards environmental protection. We therefore consider green innovations which promote a firm's environmental performance as one of the determinants of carbon disclosure. However, even firms with poor environmental performance have reasons to publicly disclose their carbon-related information. According to the concept of green-washing, firms may reveal minor information to justify their production methods and reduce the pressure from the public (Lyon and Maxwell, 2011; Mahoney et al., 2013). Consequently, it is ambiguous if green innovations are conducive to more active disclosure among highly polluting firms. This study investigates if and how green innovations affect disclosure decisions by considering the environmental performance as the channel through which green innovations exert disclosure effect.

This study contributes to the literature on the economics of environmental innovation by examining the jointly determined relationship between green innovation and carbon disclosure. We also examine whether green innovation incentivizes voluntary disclosure. These disclosure incentives can be explained by sociopolitical theories ¹ as the quest of companies to respond to social and/or political pressures by various stakeholders (Hahn and Lülfs, 2014; Hahn et al., 2015). The economic perspective ² suggests that firms disclose information to stakeholders voluntarily

¹The socio-political view is mainly anchored in stakeholder theory and legitimacy theory, which argue that firms should comply with the normative constraints of society and consider environmental and social needs in the course of their operations (Donaldson and Preston, 1995; Friedman and Miles, 2002; Manrique and Martí-Ballester, 2017; Suchman, 1995; Zhu et al., 2022).

²The economic perspective is represented by signaling theory. The theory argues that car-

based on an assessment of costs and benefits (Clarkson et al., 2008; Hahn et al., 2015). Previous studies have focused on whether firms' voluntary environmental practices due to the pursuit of public recognition (Arora and Cason, 1996) or financial considerations (Arora and Cason, 1995; Chithambo and Tauringana, 2014; Halimah and Yanto, 2018). Geng et al. (2022) suggests that carbon disclosure could also be influenced by green innovations, as it can enhance the environmental performance of firms (Carrión-Flores and Innes, 2010; Weina et al., 2016; Costantini et al., 2017) and prompt firms to demonstrate their superior capacity to adapt to carbon transition risk (Geng et al., 2022). Given the scarcity of research on the disclosure effect of green innovation, our study adds empirical evidence to the field of green innovation and its impact on environmental transparency.

In addition, we focus on firms that emit a greater amount of carbon dioxide which may behave differently in terms of innovation and disclosure activities than firms with lower emissions. On the one hand, high-emitting firms are more likely to report voluntarily when they engage in green innovation (Geng et al., 2022), since marginal benefits of signaling their abatement efforts could be larger for these firms. On the other hand, high-emitting firms are also likely to work harder on green innovation to improve energy efficiency once they become aware of their environmental performance and acknowledge the necessity of reducing emissions. The analysis provides policy makers with implications on encouraging innovation and promoting environmental transparency among polluting firms, which is vital for transition to a low-carbon economy.

The empirical results of this study indicate that firms that disclose environ-

bon disclosure reduces a firm's risk of being scrutinized by environmental pressure groups and improves the firm's reputation (Hahn et al., 2015).

mental information more proactively are more likely to develop green technologies. However, we found little evidence to suggest that carbon disclosure is driven by green innovation. This relationship is also confirmed for high-emitting firms, while the innovation effect of carbon disclosure found in those firms differs from the baseline analysis. The results of our study suggest that the motivation for corporate environmental disclosure could lead to innovative outcomes, ultimately reducing pollutants and improving energy efficiency.

The remainder of the chapter is structured as follows. Section 2 documents the information on carbon disclosure and develops research hypotheses. Section 3 illustrates the empirical strategy and data. Section 4 reports the empirical result. Section 5 presents checks for the robustness. Section 6 concludes.

4.2 Background and Hypothesis

The Carbon Disclosure Project (CDP) is a not-for-profit organization that operates the global disclosure system for investors, companies, cities, states and regions to manage their environmental impacts (cdp, a). In response to the growing demand for corporate environmental transparency, CDP asks companies to report their environmental information, such as carbon emissions, implementation of carbon pricing and whether they are under a third-party verification.

Questionnaires include items such as emission volumes, which are categorized into three groups of coverage,³ whether the firm is regulated by external carbon pricing and whether the firm implements internal carbon pricing. Each firm is

³Scope 1 is the direct emissions generated by firms from the combustion of fossil fuels. Scope 2 emissions are those generated indirectly by the use of purchased electricity. Scope 3 represents emissions generated by a company's supply chain.

scored on the completeness of its answers, and only those scoring over 50 points are given a performance score. Firms are scored on four successive levels that reflect their efforts to manage and protect the environment: Leadership (A score), Management (B-/B score), Awareness (C-/C score), and Disclosure (D-/D score), with a higher ranking score indicating greater efforts by firms to manage environmental impacts. An F score is given to firms that have not disclosed through CDP.⁴ An advantage of using CDP scores is that it allows us to refer to the quality of carbon disclosure alongside the decision to disclose or not.

Firms need to demonstrate both awareness of their environmental impacts and action to reduce them in order to receive high scores (CDP). Since green innovation is a powerful tool for climate change mitigation, firms that receive high performance scores which reflect strong environmental awareness and proactive actions can be more engaged in green innovation. We therefore derive the following hypothesis:

Hypothesis 4.1 *Disclosure of environmental information spurs green innovations.*

However, the effect could be reversed. That is, green technology could lead to different disclosure levels. As discussed in the previous section, we expect green innovations to affect disclosure levels through their impact on environmental performance. On the one hand, green technologies lead to improved environmental performance, which makes firms more confident and active in reporting environmental outcomes. On the other hand, one might be concerned that poor environmental performers might use CDP as a means of greenwashing, making the

⁴We use the five-level ranking in the baseline analysis. A different ranking specification is used as a robustness check.

impact of green innovation on carbon disclosure ambiguous. Nevertheless, as discussed in Section 1, it is the poor performer that is more likely to use disclosure as greenwashing, we thus expect increases in green innovations to promote carbon disclosure among average firms. We develop the second hypothesis as follows:

Hypothesis 4.2 *Increases in green innovations promote carbon disclosure among average firms.*

We further investigate the relationship between firms' innovation and disclosure at different levels of carbon emissions. Specifically, firms can obtain better knowledge about their carbon emissions while collecting information to answer the CDP questionnaire. High-emitting firms become aware of the need to reduce carbon emissions while reporting emissions, and thus may have more incentives to innovate to improve their environmental performance. The following hypothesis is developed:

Hypothesis 4.3 *Carbon disclosure leads to more green patents applied by high-emitting firms than average firms.*

In addition, high emitting firms face greater external pressure to comply with environmental regulations, which leads to the concern that they may exploit carbon disclosure as means of greenwashing. Accordingly, the disclosure incentive for these firms

Hypothesis 4.4 *High-emitting firms disclose more environmental information when they are successful in green innovations.*

4.3 Methodology and Data

4.3.1 Estimation Model

To test the above hypotheses, we construct estimation models as follows:

$$Ranking_{it} = \alpha_0 + \alpha_1 Patent_{it} + \alpha_2 X_{it} + \epsilon_{it} \quad (4.1)$$

$$Patent_{it} = \beta_0 + \beta_1 Ranking_{it} + \beta_2 X_{it} + \eta_{it} \quad (4.2)$$

Equation 4.1 suggests that the disclosure ranking for firm i in year t ($Ranking_{it}$) is determined by the number of green patent applications filed by the firm in the same year ($Patent_{it}$), as well as other financial factors (X_{it}) such as sales (deflated), R&D (deflated), the number of employees and ROE. As the dependent variable of Equation 4.2 has five ordinal categories, the assumption of homoscedasticity and normality can be violated if the model is estimated using ordinary least square (OLS) (Nnorom et al., 2009; Sun et al., 2016; Cho et al., 2021; Oh et al., 2023). We thus estimate the effect on the quality of disclosure using a fixed-effects ordered logit model where a latent variable y^* relate the observable characteristics $\mathbf{x}$ to the observable ordered dependent variable y which takes values 1, ..., K. The latent variable for individual i at time t depends linearly on $\mathbf{x}_{it}$ and the two unobservable characteristics α_i and ϵ_{it} :

$$y_{it}^* = \mathbf{x}_{it}' + \alpha_i + \epsilon_{it} \quad i = 1, \dots, N \quad t = 1, \dots, T$$

The latent variable is tied to the dependent variable through the thresholds τ_{ik} :

$$y_{ik} = k \quad \text{if} \quad \tau_{ik} < y_{it}^* \leq \tau_{ik+1}, k = 1, \dots, K$$

which in our case yields

$$y_{it} = 1 \quad \text{if} \quad -\infty \leq y_{it}^* \leq \tau_1 \quad (F)$$

$$y_{it} = 2 \quad \text{if} \quad \tau_1 < y_{it}^* \leq \tau_2 \quad (D)$$

$$y_{it} = 3 \quad \text{if} \quad \tau_2 < y_{it}^* \leq \tau_3 \quad (C)$$

$$y_{it} = 4 \quad \text{if} \quad \tau_3 < y_{it}^* \leq \tau_4 \quad (B)$$

$$y_{it} = 5 \quad \text{if} \quad \tau_4 < y_{it}^* \leq \tau_5 \quad (A)$$

The error term ϵ_{it} follows a standard logistic cumulative density function:

$$F(\epsilon_{it}|\mathbf{x}_{it}, \alpha_i) = F(\epsilon_{it}) = \frac{1}{1 + \exp(-\epsilon_{it})} \equiv \Lambda(\epsilon_{it})$$

Thus the probability of observing outcome k for individual i at time t is ⁵

$$Pr(y_{it} = k|\mathbf{x}_{it}, \alpha_i) = \Lambda(\tau_{ik+1} - \mathbf{x}_{it}'\beta - \alpha_i) - \Lambda(\tau_{ik} - \mathbf{x}_{it}'\beta - \alpha_i)$$

Equation 4.2 indicates that different rankings can drive different innovation outcomes, holding constant the control variables. In order to examine how firms'

⁵Baetschmann et al. (2020).

innovation decisions respond to the quality of information disclosure, we use a fixed-effects Poisson model. The dependent variable y_{it} is Poisson distributed with a mean of

$$E(y_{it}|\alpha_i, \mathbf{x}_{it}) = \exp(\gamma_i + \mathbf{x}_{it}'\beta) = \alpha_i \exp(\mathbf{x}_{it}'\beta)$$

where $\alpha_i = \exp(\gamma_i)$ and is possibly correlated with $\mathbf{x}_{it}$.⁶ The multiplicative individual effect α_i alleviates the concern of overdispersion which is common in count data analyses. We employ in both equations sales (deflated), the number of employees, R&D expenditure (deflated), capital stock (deflated), and return on equity (ROE) as exogenous variables to control for the effects of time-varying firm characteristics on the dependent variables.

While it would be more efficient to estimate the system of simultaneous equations all at once, due to the different model specifications described above, we estimate equation-by-equation to avoid cross-model bias (Carrión-Flores and Innes, 2010). Specifically, we instrument for green innovation in the ranking equation and then use the fitted values of green innovation as the key explanatory variable in Equation 4.1. Similarly, we instrument for rankings and predict the probability for a firm to receive each ranking and then use the predicted probabilities as independent variables in Equation 4.2.

The choice of instrumental variables (IV) should follow the principle that the IV is related to the endogenous explanatory variable without directly affecting the dependent variable. In our case, the instrument for patent applications in the ranking equation should explain patent applications without affecting disclosure scores. We thus employ the number of patents filed in areas other than green

⁶Cameron et al. (2010).

inventories and lag it by one year to avoid the potential correlation with R&D investment. The estimated probabilities are then used as explanatory variables in the second stage of the patent regression. On the other hand, environmental disclosure is more likely to be driven by green innovations that could improve firms' environmental performance than by those in other technology areas, for which we assume that there is no direct impact of non-environmental innovations on disclosure scores. To identify disclosure decision in the innovation equation, we employ the number of large facilities that are not regulated by the carbon cap-and-trade program as an instrumental variable.⁷ Such facilities generate substantial carbon emissions that hamper environmental performance and thus reduce firms' confidence in disclosing environmental information, resulting in a lower ranking. However, these unregulated emissions are less likely to provide firms with incentives to innovate in technologies that aim at reducing carbon emissions. Hence, we expect the number of unregulated facilities to have little impact on green patents directly.

4.3.2 Data

Our study period spans from 2013 to 2018. Performance scores are obtained from annual reports of the CDP. Listed companies are asked to disclose their environmental information such as carbon emissions, whether they are subject to

⁷Albeit our intuitive arguments on using the number of unregulated facilities as IV, a concern arises that the variable may affect firms green innovations through changing a firm's financial conditions thus violates the exclusion restriction. Another concern lies in the few variations in the number of unregulated facilities operated by a same firm across years. Additional issue that may violate the exclusion restriction is that a large part of green patents may be driven by ETS firms that only operate facilities in Tokyo and/or Saitama. That is, 0 values in the IV for disclosure may have strong correlation with the number of patents. We thus employ a different IV to identify the disclosure ranking in the patent regression in the robustness check section.

Table 4.1: Descriptive Statistics

Variables	Obs.	Mean	St. Dev.	Min	Max
Green patents	2,349	23.051	82.153	0	1217
Sales (logarithm million JPY)	2,257	13.350	1.257	8.636	17.209
Employee (logarithm)	2,248	9.461	1.281	4.419	15.313
R&D investment	1,685	9.260	1.9162	-0.015	13.885
Capital stock (logarithm JPY)	2,083	10.675	1.287	4.590	15.101
ROE (%)	2,087	11.104	91.3997	-441.180	3973.480
Other patents (logarithm)	2,349	2.888	2.731	0	8.980
Facilities (logarithm)	2,341	0.544	0.899	0	3.930

Note: The sample we use for the baseline analysis includes only 1,517 observations due to missing values that come from R&D investments. Dropping R&D investments in the analysis increases the number of observations to 1,685.

external carbon pricing and whether they voluntarily implement internal carbon pricing. CDP assigns each company with a disclosure score based on the responses (a higher score indicates greater transparency), and only companies that scored above 50 are given a performance score ranging from D- to A, while companies that do not disclose are given an F. Table 4.1 summarizes the statistics of the variables.

Data on patent applications by Japanese firms are drawn from the Institute of Intellectual Property (IIP). We refer to the Intellectual Property Code (IPC) of the Green Inventory ⁸ provided by the World Intellectual Property Organization (WIPO) to identify environmental patents. Patents in other technical fields are also obtained from IIP. Financial data are obtained from the eol database which provides information on Japanese listed companies. Financial data are deflated by 2015-based producer price indices reported by the Bank of Japan. The number of

⁸Green Inventory as defined by WIPO consists of seven classifications: alternative energy production, transportation, energy conservation, waste management, agriculture/forestry, nuclear power generation, and administrative, regulatory or design aspects.

large facilities is obtained from the greenhouse gas emissions dataset provided by the Ministry of the Environment.

4.4 Results

4.4.1 Baselines Results

Table 4.2: The first stage of patent regression

<i>Dependent variable: Ranking</i>				
	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Facility	−0.436** (0.182)	−0.432** (0.180)	−0.428** (0.179)	−0.463*** (0.120)
Threshold				
cut1	0	0	0	27.04
cut2	1.54	1.54	1.54	28.66
cut3	3.88	3.89	3.88	30.85
cut4	7.28	7.28	7.28	34.31
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	1,147	1,147	1,147	1,501
No. of individuals	234	234	234	366
Pseudo R ²	0.5876	0.5874	0.5870	
Log-likelihood	*	*	*	−1608.4272

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Baseline results are presented through Table 4.2 to Table 4.5. We interpret the results in the order of first-stage regressions and second-stage regressions. We implement variations of each model by removing R&D investment, which is likely

Table 4.3: The first stage of ranking regression

<i>Dependent variable:</i> Green patents			
	(1)	(2)	(3)
Other patents	0.572*** (0.021)	0.609*** (0.021)	0.608*** (0.020)
Year dummies	Y	Y	Y
R&D investment	Y	N	N
Other controls	Y	Y	N
No. of observations	1,092	1,092	1,092
No. of individuals	236	236	236
Log-likelihood	−3198.3498	−3205.0598	−3232.1872

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.4: The second stage of ranking regression

<i>Dependent variable:</i> Ranking				
	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Green patents	−0.000 (0.003)	−0.000 (0.003)	−0.000 (0.003)	−0.002 (0.002)
Threshold				
cut1	0	0	0	28.98
cut2	1.54	1.54	1.54	30.60
cut3	3.88	3.89	3.88	32.79
cut4	7.27	7.28	7.28	36.26
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	1,147	1,147	1,147	1,501
No. of individuals	234	234	234	366
Pseudo R ²	0.588	0.587	0.587	*
Log-likelihood	*	*	*	−1615.0696

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.5: The second stage of patent regression

<i>Dependent variable:</i> Green patents			
	(1)	(2)	(3)
A rank	2.486** (1.145)	2.374 (6.402)	406.211* (230.967)
B rank	0.536* (0.438)	0.829 (0.644)	−21.642 (14.244)
C rank	0.051 (0.145)	−0.206 (0.175)	1.714 (1.705)
D rank	0.820*** (0.189)	0.747** (0.229)	0.251 (0.741)
Year dummies	Y	Y	Y
R&D investments	Y	N	N
Other controls	Y	Y	N
No. of observations	1,092	1,092	1,092
No. of individuals	236	236	236
Log likelihood	−3161.4937	−3162.6674	−3243.3616

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

to be correlated with patent applications in technology fields other than green inventory, and thus could bias the estimate. We also estimate the ranking equation using the random effects (RE) ordered logit estimator, which tests whether the result is sensitive to different assumptions on unobservable individual effects.

We first instrument for performance rankings in the patent equation by regressing the rankings on the number of unregulated large facilities and all the exogenous control variables. As presented in column (1) of Table 4.2, the coefficient of the IV (number of facilities) is negative and statistically significant at the 5% level, suggesting that firms with a larger number of unregulated facilities tend to have a lower probability of conducting a high-quality disclosure. This is consistent with our expectation that firms tend to be less transparent with environmental information when their environmental performance is hampered by substantial amount of carbon emissions. The remaining columns show qualitatively similar results. We then regress the number of green patents on their IV (patent applications in other technical fields lagged by one year) and all the exogenous control variables. The result is presented in column (1) of Table 4.3. The estimate on the IV indicates a positive relationship between patents in green technologies and those in other areas, which is in line with our expectation that firms are more likely to innovate in green technologies and those in other technology fields. The results are similar across specifications, as indicated by columns (2) and (3).

However, when it comes to the second-stage of Equation 4.1, we found little evidence that an increase in green patents improves firms' environmental disclosure, since the coefficient of green patents is not statistically significant, as shown in column (1) of Table 4.4. The other three columns also suggest the same. Although green innovations could increase transparency by improving firms' environmental

performance, it takes time for a new technology to become effective, which could explain why the number of green patents has little effect on the contemporaneous performance score. Again, it seems that firms' disclosure decisions appear to be negatively related to emissions.⁹ Intuitively, firms which generate a large amount of carbon tend to perform poorly in environmental activities and therefore are less confident in reporting their carbon information. This provides some supports for our hypothesis that transparency is influenced by firms' environmental performance. Moreover, the lower panels of Table 4.2 and 4.4 show incremental differences between the thresholds from lower to higher rankings, suggesting that firms with lower rankings are more responsive to reductions in carbon emissions. That is, carbon abatement realized by unregulated large facilities may have a greater impact on firms that make low-quality disclosures.

Regarding the second-stage of patent regression, we use the predicted probabilities of being ranked from D to A as key explanatory variables. We exclude the probability of F ranking to avoid the perfect collinearity. According to column (1) of Table 4.5, firms that receive an A score, showing a leadership in carbon disclosure, have a substantial positive effect on green innovations. Firms with strong environmental awareness actively engage in green innovations, providing evidence that supports Hypothesis 4.1. While a C or B ranking has only a minor influence on green patents, an increase in the probability of a D ranking has a positive and statistically significant effect on the number of green patents. D scores provide a stronger incentive for green innovations than F rankings, although they are only the starting point of the journey towards environmental disclosure. In other words,

⁹The coefficients on the number of large facilities are -0.453 , -0.450 , and -0.387 in columns (1), (2), and (4), respectively, all statistically significant on a 5% level.

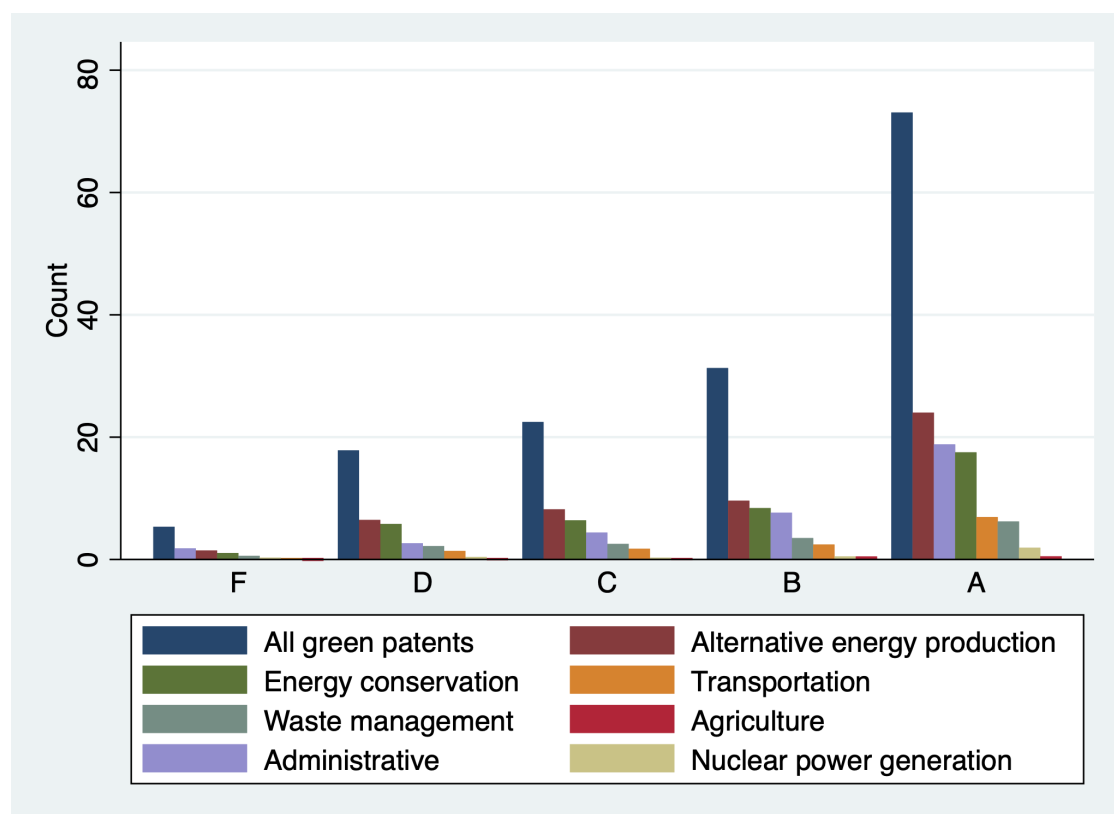


Figure 4.1: Average Patent Applications by Ranking

even a small increase in ranking from F to D makes a difference. However, the results suggest a non-linear relationship between rankings and green innovations, which is contrary to our expectation that innovative output would increase linearly by firms' performance score. We attribute this firstly to the scoring strategy (cdp, b). Firms' disclosure scores are calculated solely on the basis of the questions asked, while the questions not asked may be positively or negatively related to environmental performance. It is therefore possible that firms' environmental awareness and actions that incentivize green innovation are not fully captured by the CDP score, resulting in the insignificance of the C and B rankings. Another reason could be that C- and B-ranked firms are similar to D-ranked firms in their innovation decisions. As indicated in Figure 4.1, the average number of patent applications does not differ substantially among D, C, and B firms, which may explain the insignificant result of C- and B- rankings. In contrast, A-ranked firms are highly innovative, particularly in the areas of alternative energy production, energy conservation, and administrative innovation, which leads to the positive large effect in magnitude.

4.4.2 Results for high-emitting firms

This subsection examines whether the relationship between innovation and disclosure is stronger for high-emitting firms. We calculate firm-level average Scope1 plus local-based Scope 2 carbon emissions over the sample period and define a firm as a high-emitting if its average emissions are above the sample median. Tables 4.6 to 4.9 summarize the estimation results. Both instrumental variables are significant and have the expected signs in the first-stage regressions, as shown in Tables 4.6

and 4.7. In particular, high-emitting firms are even less likely to be transparent if they operate a larger number of unregulated facilities, as indicated by the estimated coefficients reported in Table 4.6 for large facilities, which are larger in magnitude than the baseline result. This contrast with the sociopolitical perspective where polluting firms greenwash by engaging in carbon disclosure. Table 4.7 suggests a similar result to the baseline, that firms with higher innovation capacity are more active in green innovations.

Table 4.6: The first stage of patent regression for high-emitting firms

<i>Dependent variable: Ranking</i>				
	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Facility	−0.556** (0.226)	−0.545** (0.223)	−0.532** (0.220)	−0.575*** (0.134)
Threshold				
cut1	0	0	0	19.30
cut2	1.85	1.64	1.70	20.90
cut3	4.02	3.88	3.79	23.15
cut4	7.29	7.02	6.96	26.47
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	895	895	895	956
No. of individuals	172	172	224	198
Pseudo R ²	0.597	0.579	0.596	*
Log-likelihood	*	*	*	−1097.4464

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.8 summarizes the second-stage regression on the disclosure scores received by emitting firms. The coefficient on green patents is not statistically sig-

Table 4.7: The first-stage of ranking regression for high-emitting firms

<i>Dependent variable:</i> Green patents			
	(1)	(2)	(3)
Other patents	0.573*** (0.022)	0.583*** (0.022)	0.624*** (0.021)
Year dummies	Y	Y	Y
R&D investment	Y	N	N
Other controls	Y	Y	N
No. of observations	780	831	955
No. of individuals	152	163	178
Log-likelihood	−2671.6759	−2681.2218	−2709.9381

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.8: The second stage of ranking regression for high-emitting firms

<i>Dependent variable:</i> Ranking				
	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Green patents	−0.001 (0.003)	−0.001 (0.002)	−0.002 (0.003)	−0.001 (0.001)
Threshold				
cut1	0	0	0	15.69
cut2	1.84	1.84	1.83	17.28
cut3	4.02	4.01	4.00	19.48
cut4	7.28	7.28	7.23	22.70
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	895	895	895	956
No. of individuals	172	172	172	198
Pseudo R ²	0.597	0.597	0.596	*
Log-likelihood	*	*	*	−1099.5751

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.9: The second stage of patent regression of high-emitting firms

<i>Dependent variable: Green patents</i>			
	(1)	(2)	(3)
A rank	3.284*** (0.445)	2.317*** (1.217)	19.528*** (4.542)
B rank	2.666*** (0.519)	1.542*** (0.678)	−2.738** (0.881)
C rank	1.971*** (0.353)	0.885*** (0.355)	0.311 (0.234)
D rank	3.757*** (0.670)	1.948*** (0.832)	−1.964*** (0.717)
Year dummies	Y	Y	Y
R&D investments	Y	N	N
Other controls	Y	Y	N
No. of observations	780	780	780
No. of individuals	152	152	152
Log likelihood	−2642.0772	−2655.6247	−2700.3507
Standard errors in parentheses			
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$			

nificant, which is in line with the baseline result that firms' disclosure decision is unlikely to be driven by their innovative output related to green technologies. Table 4.9 reports the results of the second-stage regression on green patents by emitting firms. As shown in column (1), all performance rankings are positive and statistically significant, with D rankings having the largest impact, followed by A, B, and C rankings. The impact of the A ranking is not as large as in the baseline analysis, while the B and C rankings increase the number of green patents of high-emitting firms. Moreover, the impact of the D ranking is larger than in the baseline analysis, suggesting that a small step taken by high-emitting firms makes a larger difference in innovative outcomes. The results suggest that high-emitting firms are more actively engaged in innovations that improve the environmental performance while collecting and disclosing environmental information, which justifies Hypothesis 4.3. Intuitively, high-emitting firms face greater public pressure to address climate change and are therefore more likely to engage in innovation activities that help them meet the climate target even in the longer run. Improving the environmental transparency of polluting firms may therefore be an effective means of promoting green innovation.

4.5 Robustness Checks

In this section, we first redefine the performance ranking in a different way and check the robustness. We change the performance ranking to a three-category, by defining A and B as high, C and D as medium, and F as low. There are several reasons for this specification. First, the distribution of performance scores ranked from F to A (see Figure 4.2) suggests a substantially larger size of F-ranked firms,

which account for almost 40 percent of the sample. In contrast, D-ranked and A-ranked firms account for only about 10 percent of the sample. The significant difference in the size of subsamples may bias our baseline estimation result. The aggregation yields a 27 percent of the medium-ranked group and a 34 percent of the top-ranked group, which makes the ranking distribution relatively even. Second, the distribution of scores also indicates that the first and third quartiles being F and B, respectively, so we refer to scores above B as high rankings and F scores as low ranking, with C and D in between. Finally, the CDP sets stricter standards for achieving an A or B score. To receive an A or B score, companies must demonstrate both awareness of their environmental impacts and actions taken to be in line with the abatement target set by the Paris Agreement. A and B scores could therefore be seen as high scores, representing a higher environmental awareness and management. C and D firms are not as environmentally aware as the top-ranked firms in the sense that they do not fully disclose their environmental information, for which we believe they should be different from A and B firms. However, these firms do make an effort to disclose environmental information, which distinguishes them from firms that disclose too little information to receive a performance score or those that do not disclose at all.

The results are summarized through Table 4.10 to Table 4.12. As shown in Table 4.10, the coefficient on the IV is negative and statistically significant, parallel to the baseline result. The first-stage patent regression is identical to the baseline analysis, for which we do not report. The results on the second-stage ranking regression are reported in Table 4.11. As can be seen in all columns, disclosure decisions are unlikely to be the result of green innovations. We then regress the predicted probabilities of being medium and high ranked on the number of green

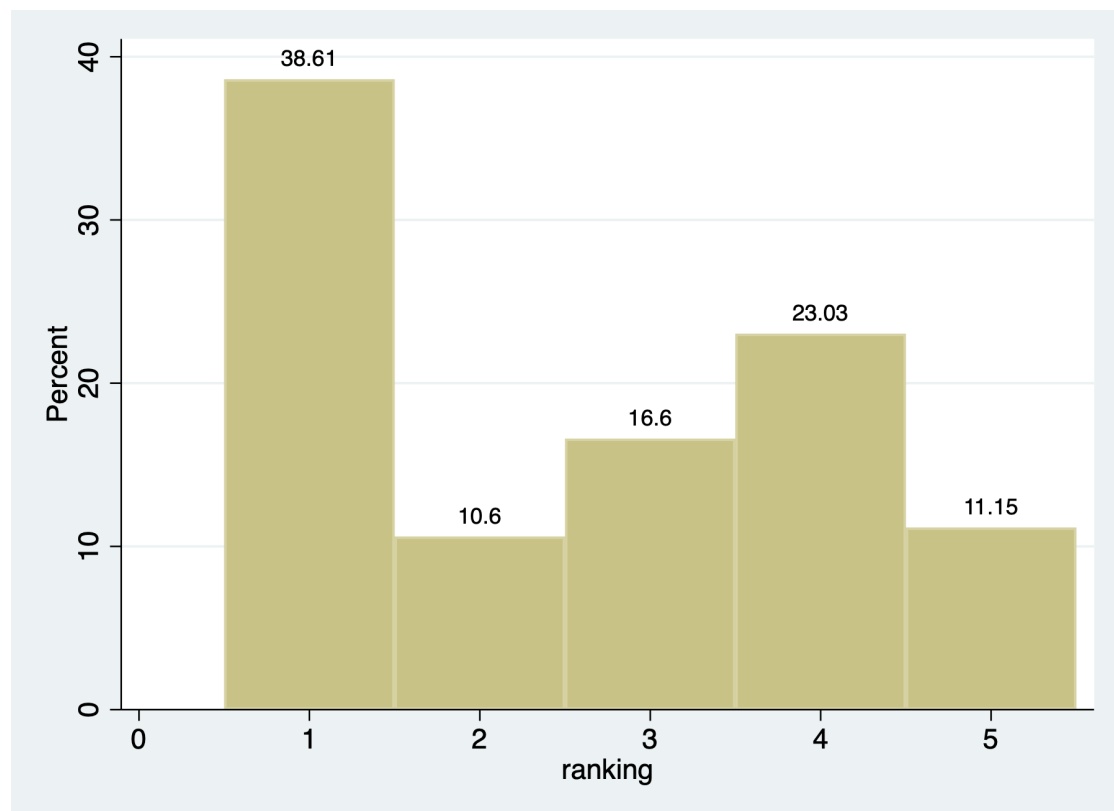


Figure 4.2: Distribution of 5-level performance scores

patents. According to Table 4.12, the coefficient on medium-rank is insignificant when control variables are included, suggesting that innovative output does not respond to the probability of being ranked D or C. However, the number of green patents increases with a higher probability of being ranked B or A, suggesting a positive innovation effect of high transparency in environmental information.

Table 4.10: First-stage Ranking Regression under 3-level Specification

<i>Dependent variable: Ranking</i>				
	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Number of Facilities	−0.459** (0.180)	−0.373** (0.151)	−0.357** (0.146)	−0.576*** (0.148)
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	912	1,101	1,309	1,517
No. of individuals	188	226	265	370
Pseudo R ²	0.4684	0.4595	0.4366	*
Log-likelihood	*	*	*	−1047.8506

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

The robustness is then tested by applying a different instrumental variable to identify rankings in the patent regression. In particular, we use the sector-year specific ranking written as

$$IV_{it} = \frac{\sum_{j \neq i}^J \text{Ranking}_{jt}}{J - 1}$$

where J is the number of firms in year t in the same sector with firm i . We take the one-year lag, IV_{it-1} , to instrument for the ranking score of firm i in year t , as firms

Table 4.11: Second-stage Ranking Regression under Three-level Specification

<i>Dependent variable:</i> Ranking				
	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Green patents	−0.000 (0.003)	−0.000 (0.003)	−0.002 (0.003)	−0.001 (0.001)
Threshold				
cut1	0	0	0	28.28
cut2	3.67	3.54	3.42	32.05
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	912	1,101	1,309	1,517
No. of individuals	188	226	265	370
Pseudo R ²	0.4684	0.4595	0.5901	*
Log-likelihood	*	*	*	−1047.8506

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.12: Second-stage Patent Regression under Three-level Specification

<i>Dependent variable:</i> Green patents			
	(1)	(2)	(3)
High ranking	0.699*** (0.189)	0.648*** (0.189)	0.798*** (0.162)
Medium ranking	0.102 (0.124)	0.183 (0.177)	0.322*** (0.107)
Year dummies	Y	Y	Y
R&D investments	Y	N	N
Other controls	Y	Y	N
No. of observations	1,106	1,106	1,106
No. of individuals	239	239	239
Log likelihood	−3198.3685	−3208.9993	−3752.0809

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 4.13: First-stage of patent regression using sector-level average ranking as IV

<i>Dependent variable:</i> Ranking	FE ordered logit			RE ordered logit
	(1)	(2)	(3)	(4)
Sector-year disclosure ranking	0.796* (0.411)	0.864** (0.423)	0.871** (0.432)	0.858*** (0.337)
Year dummies	Y	Y	Y	Y
R&D investment	Y	N	N	Y
Other controls	Y	Y	N	Y
No. of observations	877	877	877	1,126
No. of individuals	215	215	215	339
Pseudo R ²	0.6338	0.6326	0.6320	*
Log-likelihood	*	*	*	−1239.4504

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

are expected to make disclosure decisions based on observed outcomes of other firms. Consequently, a firm would be removed from the sample if it is the only firm observed in the sector in year t . The results are demonstrated in Tables 4.13 and 4.14. All the four columns of Table 4.13 report positive coefficients that are statistically significant, suggesting the existence of peer effect. That is, firms are more likely to disclose if their rivals are engaged, thus even the disclosure made by a single firm could promote environmental transparency among the whole sector it belongs to. Positive innovation effects are found only among D-ranked firms under the specification, as demonstrated by Table 4.14.

Table 4.14: Second-stage of patent regression using sector-level average ranking as IV

<i>Dependent variable:</i> Green patents			
	(1)	(2)	(3)
A rank	74.047 (128.505)	61.038 (126.933)	185.887 (126.664)
B rank	0.503 (5.540)	1.278 (5.414)	−5.873 (5.335)
C rank	−0.160 (0.600)	−0.100 (0.591)	0.044 (0.567)
D rank	0.776*** (0.323)	0.883*** (0.280)	0.299 (0.215)
Year dummies	Y	Y	Y
R&D investments	Y	N	N
Other controls	Y	Y	N
No. of observations	814	814	814
No. of individuals	211	211	211
Log likelihood	−2056.8126	−2057.0373	−2237.5934

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

4.6 Conclusion

In response to the increasing awareness and importance of corporate environmental management, a number of studies have focused on the determinants or outcomes of corporate carbon disclosure. We contribute to previous studies by investigating the innovation outcome of carbon disclosure. Our study also considers green innovation as a determinant of carbon disclosure, which allows us to explore a two-way causality between innovations and disclosure. The estimation results suggest a positive innovation effect of a comprehensive carbon disclosure.

The finding supports the induced innovation theory in the sense that green innovations can be stimulated by a voluntary regulation scheme, even though the abatement costs are not explicit as they are in a mandatory framework such as carbon pricing. The result thus suggests that green innovations can be stimulated by encouraging firms' participation in voluntary environmental schemes. While there is little evidence that carbon disclosure is driven by green innovation, our results suggest that firms' disclosure behaviors are hampered by emissions that are not yet regulated. Given the positive innovation effect of carbon disclosure, the finding implies the importance of bringing emissions under regulations, which facilitates firms' environmental performance and thereby encourages carbon disclosure.

We also examine the relationship between innovation and disclosure among high-emitting firms. Green innovation by these firms is still not driven by disclosure decisions. However, high-emitting firms are responsive to all disclosure levels, suggesting that improving environmental transparency among such firms is essential for promoting green innovations. Moreover, since disclosure decisions are found to be more sensitive to carbon emissions in these firms, a stricter policy is

needed to achieve carbon abatement in high-emitting firms, which in turn promotes green innovations.

Finally, alternative energy patents, a technology classification covered by the Green Inventory, are cited more frequently and by a wider range of other technologies (Popp and Newell, 2012) and thus may affect a broader range of industries than other innovations (Amore and Bennedsen, 2016). Encouraging firms' carbon disclosure therefore not only improves efficiency within participating firms, but also benefits society as a whole.

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Chapter 5

Concluding Remarks

This dissertation explored the effectiveness of three environmental schemes in Japan. We examine their effects on consumers, the environment, and environmental technologies. Specifically, we focus on power prices, changes in carbon emissions generated by burning fossil fuels for power generation, and the number of applications for green patents.

Regarding the power market liberalization, we found that power bills paid by residential consumers are reduced by market competition following the liberalization. However, retail power prices are increasing again as the result of increases in fuel prices.¹ The market exit by power retailers are also under a nationwide decrease, which may further cause. We thus suggest appropriate policy supports, such as subsidies, should be provided for competitive fringes to let them start the business and help them survive the market. This could enhance market competition thus make electricity more affordable. Regarding the environmental aspect, carbon emissions increased as a consequence of incumbent firms' switching to cheaper fossil fuels so as to suppress costs and retain market shares. The result suggests that power companies choose fuel switching over other strategies when faced with competition. Therefore, we suggest regulatory efforts on reducing carbon emissions from power plants together with inducing technological change in power generation technologies.

Given the importance of alternative power production technologies, we investigate the innovation effect of TSETS. As a result, firms are found to become more innovative in power generation technologies in response to emissions caps. However, a greater increase is found in FF innovations than RE ones, indicating the direction of technological change in the current power mix. Moreover, the change

¹https://www.enecho.meti.go.jp/en/category/brochures/pdf/japan_energy_2021.pdf, page 3

is mainly driven by large mixed firms which are smaller in number but highly capable of innovating. Marginal innovation incentive also decreases faster among such firms. Therefore, we suggest policy design to be tailored to companies so as to bring about net increase in RE innovations.

Furthermore, by focusing on firms' innovative responses to a voluntary environmental scheme (CDP), we confirmed the compliance to the program as another spur for green innovation. Firms are incentivized to engage in innovation activities as they voluntarily collect information and report their environmental impacts. That is, carbon disclosure leads to innovative outcomes while enhancing the transparency of environmental information. We suggest that environmental disclosure costs should be lowered in order to get more corporates engaged, particularly those generating substantial carbon emissions.

Appendix A

Appendix

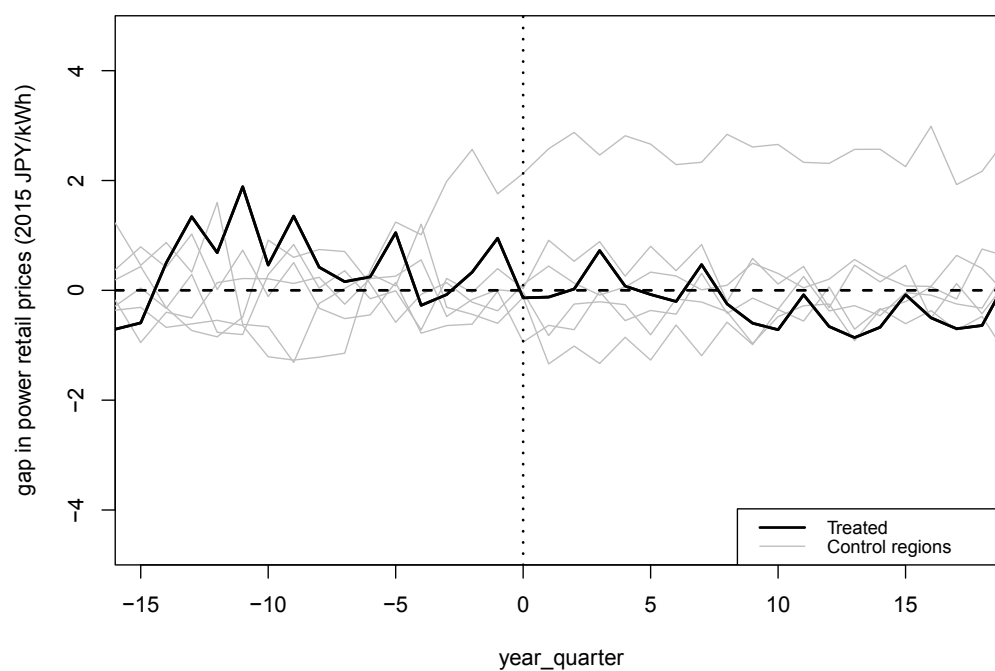
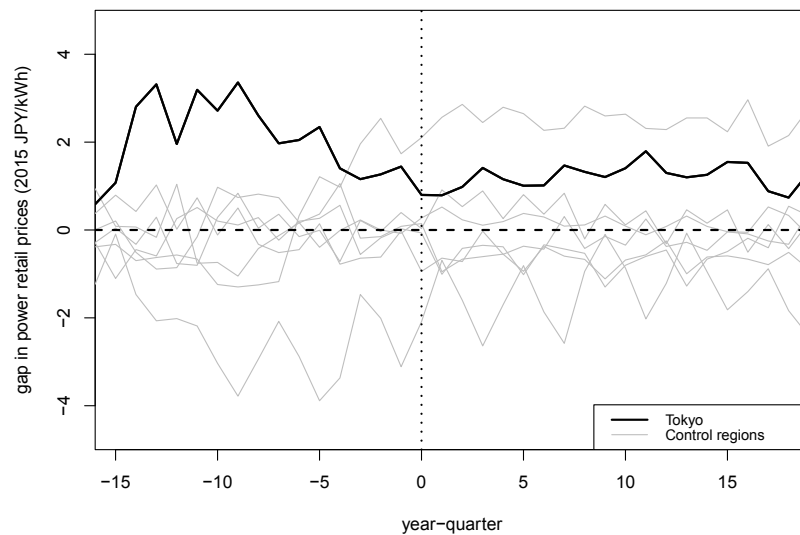


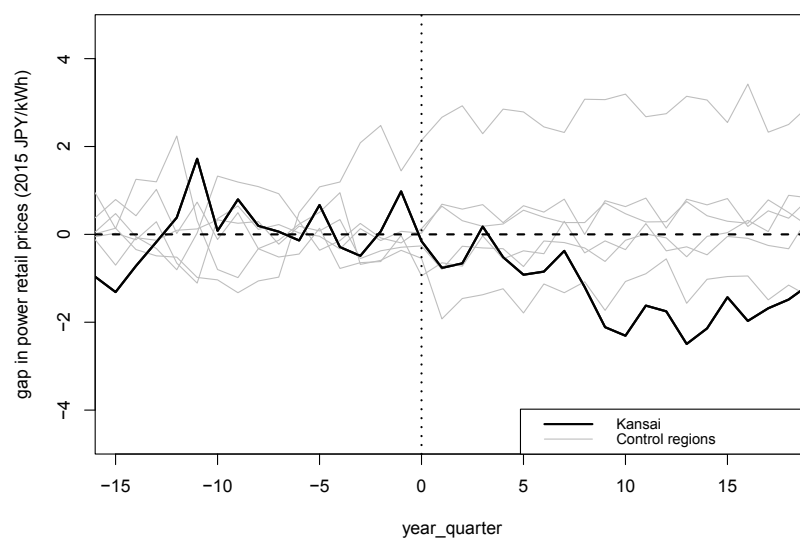
Figure A1: Gaps in retail prices in competitive regions

Table A3.1: Summary of the Matching Procedure

-
1. Randomly order the treated firms.
 2. Find all available untreated firms whose propensity scores fall within the 0.2 caliper for the first treated firm. If there is no such untreated firm, drop the treated firm.
 3. If there are multiple eligible untreated firms, select one at random as the control unit.
 4. Remove the matched pair from the list of treated and untreated firms.
Repeat steps 2 and 3 for the remaining treated firms.
-



(a) Gaps in retail prices in Tokyo



(b) Gaps in retail prices in Kansai

Figure A2.2: Gaps in retail prices in Tokyo/Kansai versus synthetics (Placebo by permutation)

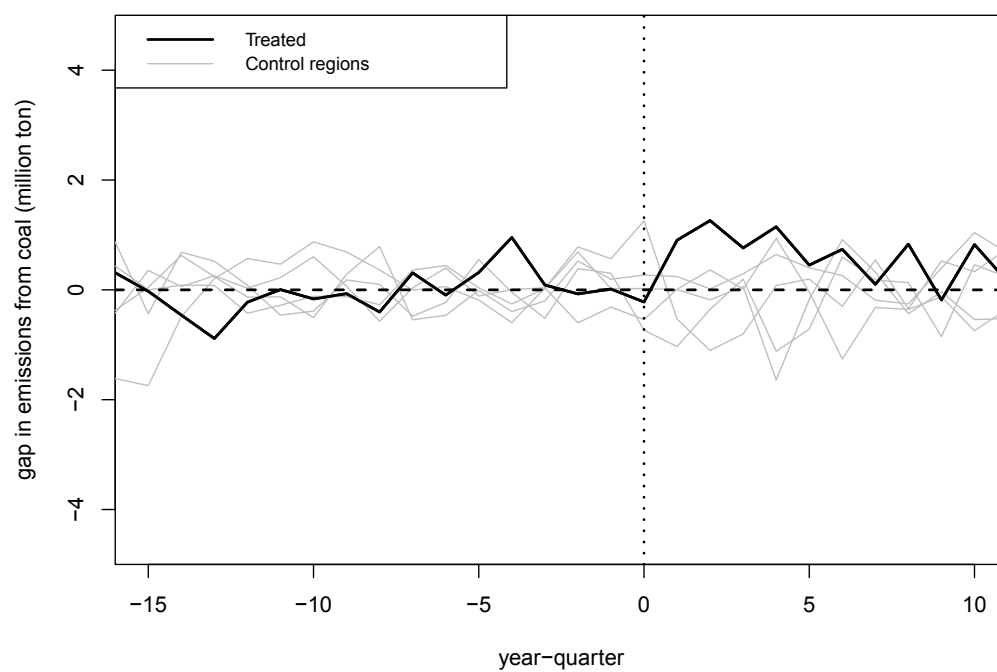
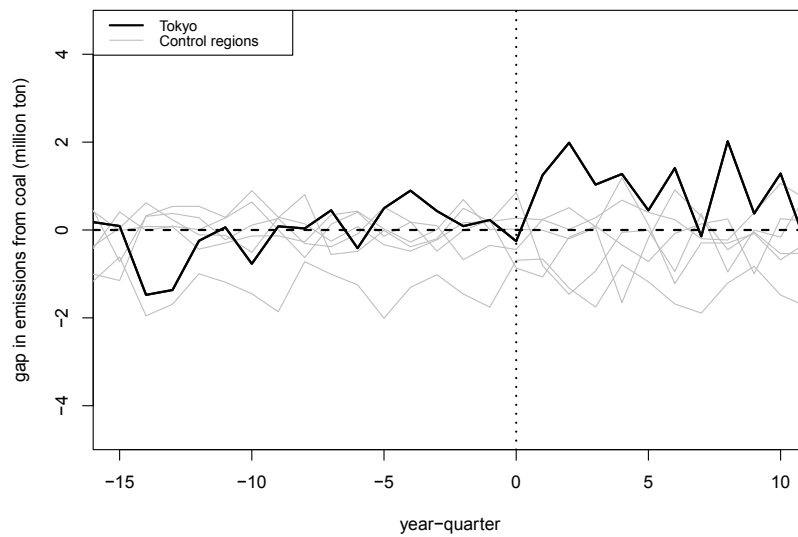
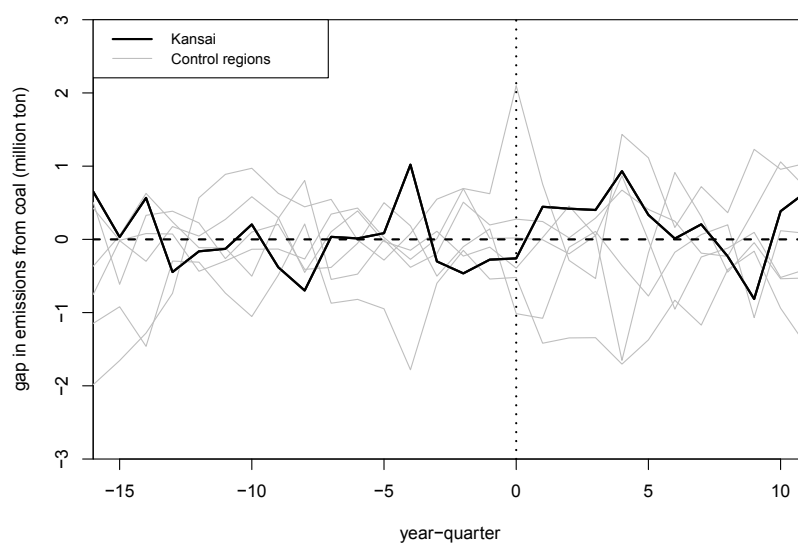


Figure A2.3: Gaps in emissions from coal in competitive regions



(a) Gaps in emissions from coal in Tokyo



(b) Gaps in emissions from coal in Kansai

Figure A2.4: Gaps in emissions from coal in Tokyo/Kansai versus synthetics (Placebo by permutation)

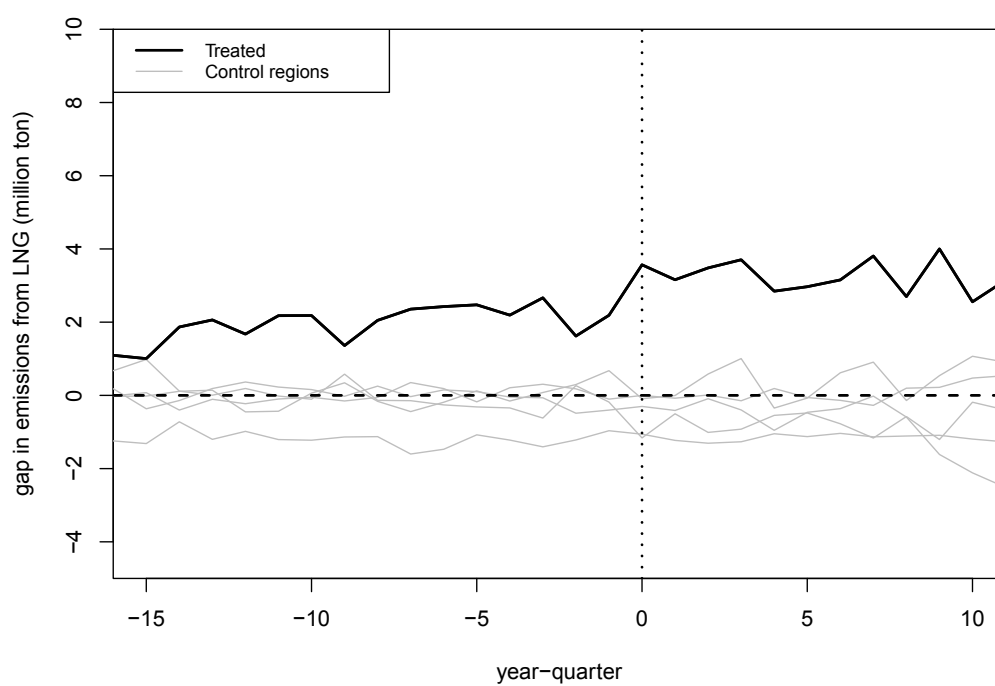
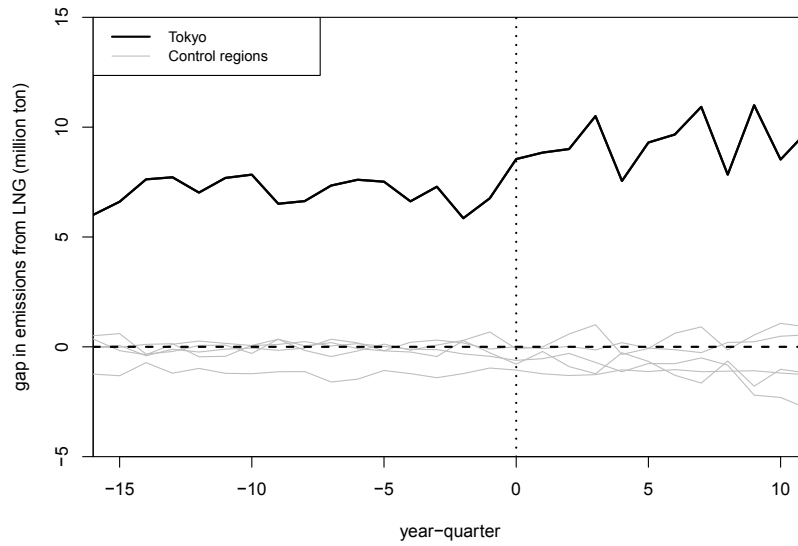
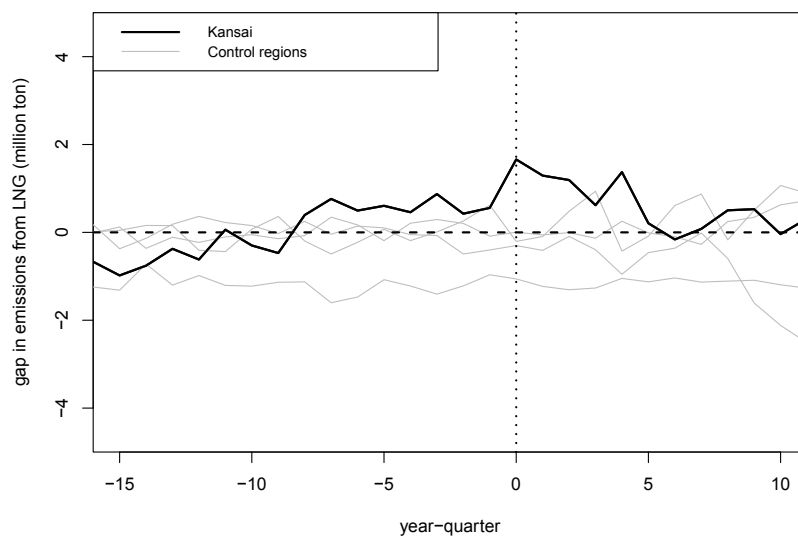


Figure A2.5: Gaps in emissions from LNG in competitive regions



(a) Gaps in emissions from LNG in Tokyo



(b) Gaps in emissions from LNG in Kansai

Figure A2.6: Gaps in emissions from LNG in Tokyo/Kansai versus synthetics (Placebo by permutation)

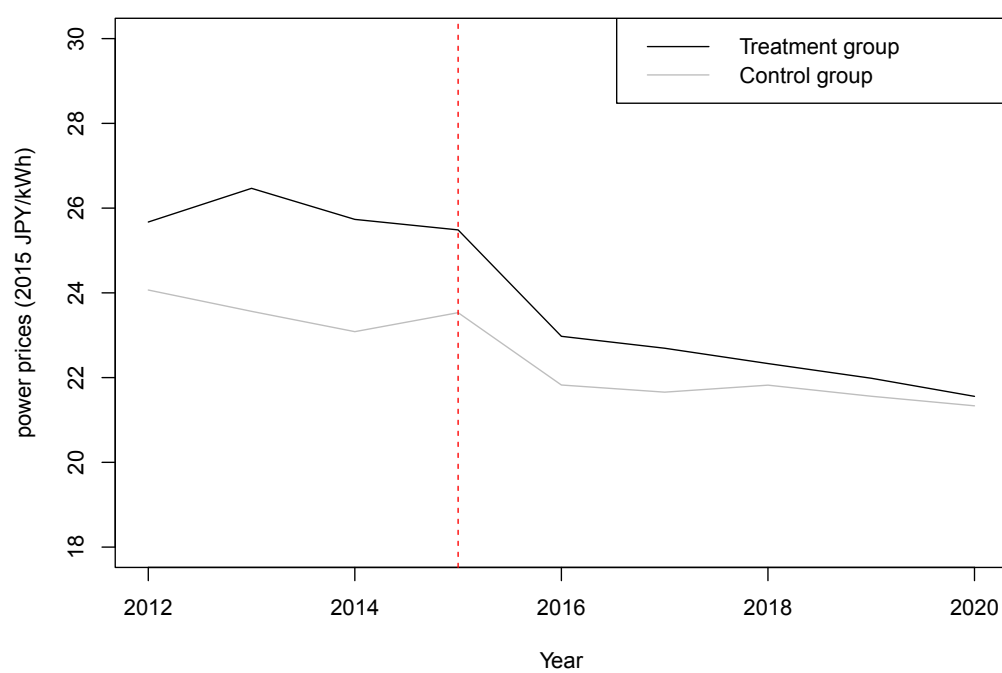
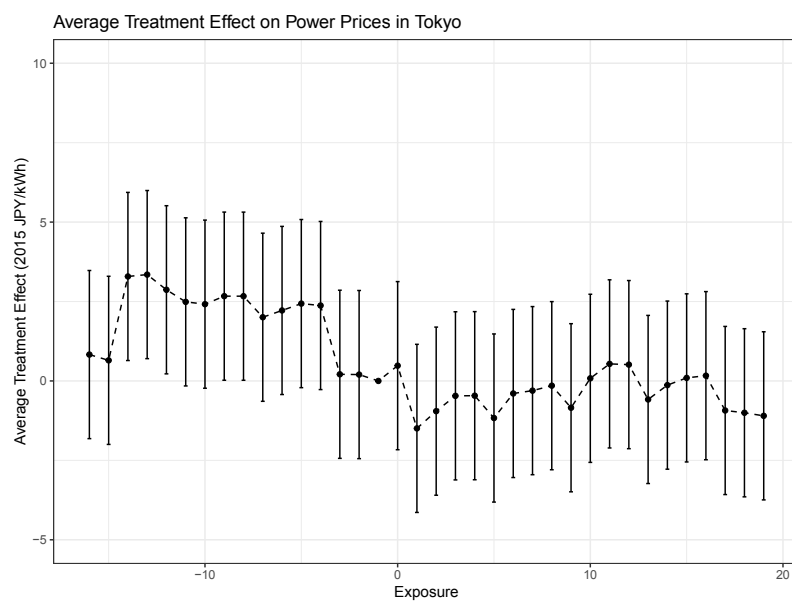
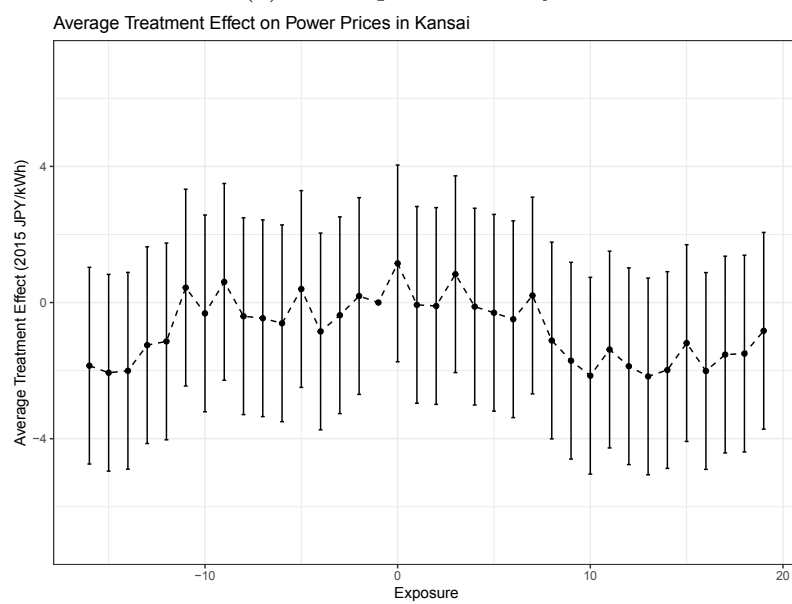


Figure A2.7: Power prices in treatment and control groups

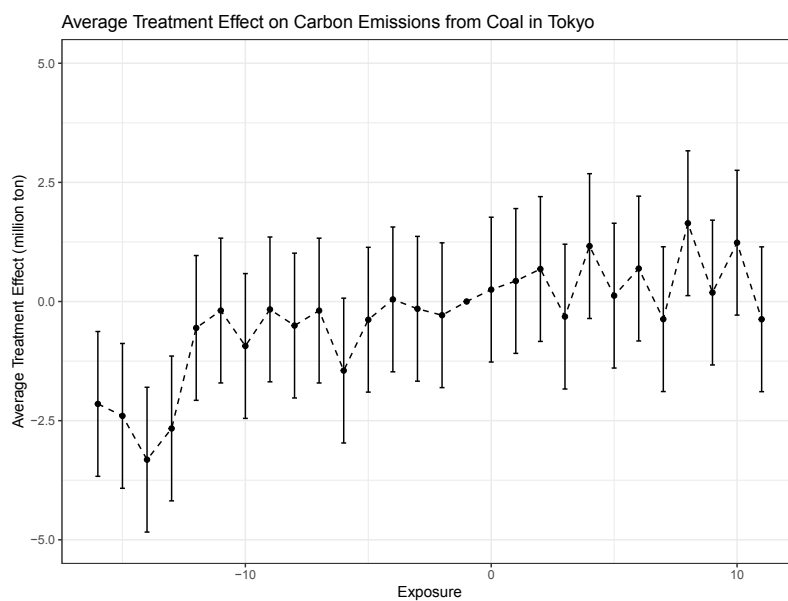


(a) Power prices in Tokyo

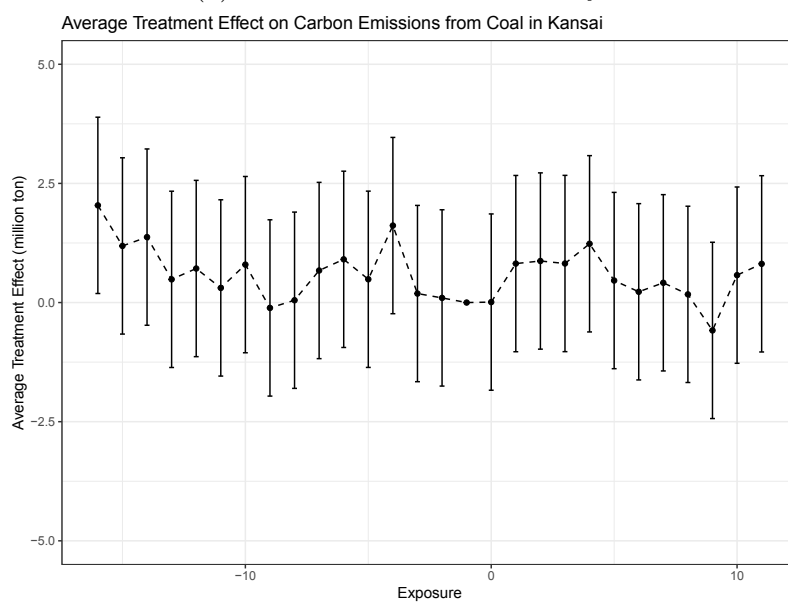


(b) Power prices in Kansai

Figure A2.8: Average Price Effect on Tokyo/Kansai

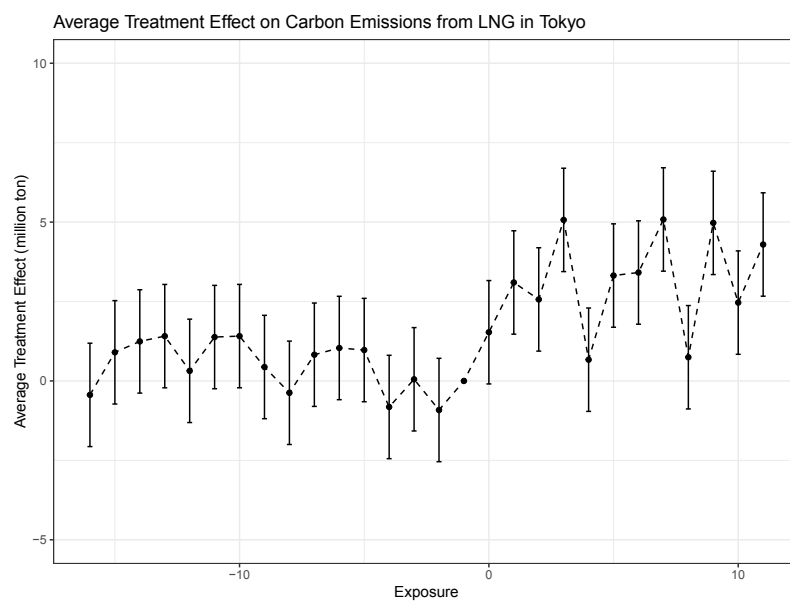


(a) Emissions from coal in Tokyo

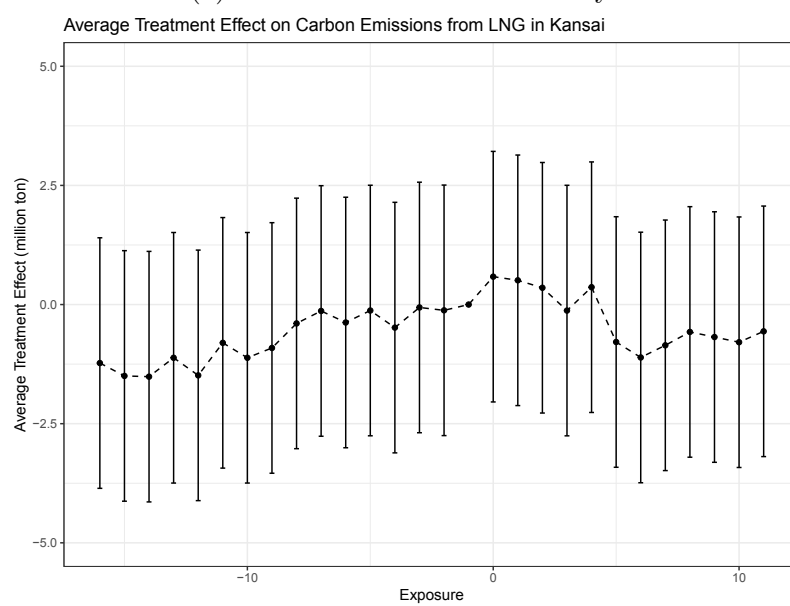


(b) Emissions from coal in Kansai

Figure A2.9: Average treatment effect on emissions from coal in Tokyo/Kansai



(a) Emissions from LNG in Tokyo



(b) Emissions from LNG in Kansai

Figure A2.10: Average treatment effect on emissions from LNG in Tokyo/Kansai

Table A3.2: IPC codes for RE and FF technologies

IPC Code	Description
RE technologies	
Solar	
F03D 11	Devices for producing mechanical power from solar energy.
F24J 2	Use of solar heat, e.g. solar heat collectors.
H01L 27/142	Devices consisting of a plurality of semiconductor components sensitive to infra-red radiation, light — specially adapted for the conversion of the energy of such radiation into electrical energy.
H01L 31/04-078	Semiconductor devices sensitive to infra-red radiation, light — adapted as conversion devices.
H02N 6	Generators in which light radiation is directly converted into electrical energy.
E04D 13/18	Aspects of roofing for energy collecting devices — e.g. incl. solar panels.
Wind	
F03D 1	Wind motors with rotation axis substantially in wind direction.
F03D 3	Wind motors with rotation axis substantially at right angle to wind direction.
F03D 5	Other wind motors.
F03D 7	Controlling wind motors.
F03D 11	Details, component parts, or accessories not provided for in, or of interest apart from, the other groups of this subclass.
Hydro	
E02B 9/02	Water-ways.
E02B 9/04	Free-flow canals or flumes; Intakes.
E02B 9/06	Pressure galleries or pressure conduits; Galleries specially adapted to house pressure conduits; Means specially adapted for use therewith, e.g. housings, valves, gates.
F03B	Machines or engines for liquids.
Biomass and waste	
C10L 5/40-48	Solid fuels essentially based on materials of non-mineral origin — animal or vegetable substances; sewage, town, or house refuse; industrial residues or waste materials.
F02B 43/08	Engines or plants operating on gaseous fuel generated from solid fuel, e.g. wood.
C10L 1, 3, 5	Liquid carbonaceous fuels; Gaseous fuels; Solid fuels; Dumping solid waste.

Table A3.2 Continued

IPC Code	Description
B09B1	Destroying solid waste or transforming solid waste into something useful or harmless.
B09B	Incineration of waste; Incinerator constructions.
F23G5	Incinerators or other apparatus specially adapted for consuming specific waste or low grade fuels, e.g. chemicals.
F23G 7	Plants for converting heat or fluid energy into mechanical energy; use of waste heat.
F01K 25/14	Plants or engines characterized by use of industrial or other waste gases.
F23G 5/46	Incineration of waste — recuperation of heat.
FF technologies	
Coal gasification	
C10J 3	Production of combustible gases containing carbon monoxide from solid carbonaceous fuels.
Improved burners	
F23C 1	Combustion apparatus specially adapted for combustion of two or more kinds of fuel simultaneously or alternately, at least one kind of fuel being fluent.
F23C 5/24	Combustion apparatus characterized by the arrangement or mounting of burners; disposition of burners to obtain a loop flame.
F23C 6	Combustion apparatus characterized by the combination of two or more combustion chambers.
F23B 10	Combustion apparatus characterized by the combination of two or more combustion chambers.
F23B 30	Combustion apparatus with driven means for agitating the burning fuel; combustion apparatus with driven means for advancing the burning fuel through the combustion chamber.
F23B 70	Combustion apparatus characterized by means for returning solid combustion residues to the combustion chamber.
F23B 80	Combustion apparatus characterized by means creating a distinct flow path for flue gases or for non-combusted gases given off by the fuel.
F23D 1	Burners for combustion of pulverulent fuel.
F23D 7	Burners in which drops of liquid fuel impinge on a surface.
F23D 17	Burners for combustion simultaneously or alternatively of gaseous or liquid or pulverulent fuel.

Table A3.2 Continued

IPC Code	Description
Fluidized bed combustion	
B01J 8/20-22	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; with liquid as a fluidizing medium.
B01J 8/24-30	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; according to "fluidized-bed" technique.
F27B 15	Fluidized bed furnaces; Other furnaces using or treating finely divided materials in dispersion.
F23C 10	Apparatus in which combustion takes place in a fluidized bed of fuel or other particles.
Improved boilers for steam generation	
F22B 31	Modifications of boiler construction, or of tube systems, dependent on installation of combustion apparatus; Arrangements or dispositions of combustion apparatus.
F22B 33/14-16	Steam generation plants, e.g. comprising steam boilers of different types in mutual association; combinations of low- and high-pressure boilers.
Improved steam engines	
F01K 3	Plants characterized by the use of steam or heat accumulators, or intermediate steam heaters, therein.
F01K 5	Plants characterized by use of means for storing steam in an alkali to increase steam pressure, e.g. of Honigmann or Koenemann type.
F01K 23	Plants characterized by more than one engine delivering power external to the plant, the engines being driven by different fluids.
Super-heaters	
F22G	Steam superheating characterized by heating method.
Improved gas turbines	
F02C 7/08-105	Features, component parts, details or accessories; heating air supply before combustion, e.g. by exhaust gases.
F02C 7/12-143	Features, component parts, details or accessories; cooling of plants.
F02C 7/30	Features, component parts, details or accessories; preventing corrosion in gas-swept spaces.

Table A3.2 Continued

IPC Code	Description
Combined cycles	
F01K 23/02-10	Plants characterized by more than one engine delivering power external to the plant, the engines being driven by different fluids; the engine cycles being thermally coupled.
F02C 3/20-26	Gas turbine plants characterized by the use of combustion products as the working fluid; using special fuel, oxidant or dilution fluid to generate the combustion products.
F02C 6/10-12	Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; supplying working fluid to a user, e.g. a chemical process, which returns working fluid to a turbine of the plant.
Improved compressed-ignition engines	
F02B 1/12-14	Engines characterized by fuel-air mixture compression; with compression ignition.
F02B 3/06-10	Engines characterized by air compression and subsequent fuel addition; with compression ignition.
F02B 7	Engines characterized by the fuel-air charge being ignited by compression ignition of an additional fuel.
F02B 11	Engines characterized by both fuel-air mixture compression and air compression, or characterized by both positive ignition and compression ignition, e.g. in different cylinders.
F02B 13/02-04	Engines characterised by the introduction of liquid fuel into cylinders by use of auxiliary fluid; compression ignition engines using air or gas for blowing fuel into compressed air in cylinder.
F02B 49	Methods of operating air-compressing compression-ignition engines involving introduction of small quantities of fuel in the form of a fine mist into the air in the engine's intake.
Co-generation	
F01K 17/06	Use of steam or condensate extracted or exhausted from steam engine plant; returning energy of steam, in exchanged form, to process, e.g. use of exhaust steam for drying solid fuel of plant.
F01K 27	Plants for converting heat or fluid energy into mechanical energy.
F02C 6/18	Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; using the waste heat of gas-turbine plants outside the plants themselves, e.g. gas-turbine power heat plants.

Table A3.2 Continued

IPC Code	Description
F02G 5	Profiting from waste heat of combustion engines.
F25B 27/02	Machines, plant, or systems, using particular sources of energy; using waste heat, e.g. from internal-combustion engines.

Source: Johnstone et al. (2008), Lanzi et al. (2011), and WIPO.