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A Carrot without a Stick? The impact of a voluntary cap-and-trade system on economic performance inside manufacturing plants: Evidence from the Japanese ETS*

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Abstract

Characterized by higher political acceptability, voluntary environmental policies are becoming increasingly popular, but their effect on economic activity is unclear. In this research, we evaluated the impact of a voluntary cap-and-trade system on the economic performance of manufacturing plants, analyzing the case of the Japanese Saitama ETS (SETS), implemented in 2011. This policy was implemented more than a decade ago, but little is known about its economic impact. We utilize a rich dataset containing data from Japanese plants from 2004 to 2019 and estimate the average treatment effect of the policy using DiD and PSM methods. Our results showed that SETS had a positive effect on value added, estimated between 6.07% to 27.92%, compared with non-targeted plants. This policy also had a positive impact on employment, as wages are shown to increase by 3.66%, along with increased labor productivity (5.26%) of similar magnitude. The positive effects of the policy are mostly experienced by plants in non-energy-intensive sectors, as well as plants belonging to SMEs. The policy also did not affect the plants' competitiveness, as increases in total costs are compensated by higher revenue.

Keywords: environmental regulation, emissions trading scheme, employment, competitiveness, output; carbon pricing
JEL classification: E24, H23, Q5, D22

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1. Introduction

Ten years after the Paris agreement, climate policy stands at a crossroads. On one hand, the threat of climate change has never seemed more urgent, but climate policy has taken a backseat, as many countries shifted their focus towards combating rampant inflation or helping with post-Covid economic recovery. Among them, new carbon pricing schemes, whether carbon taxes or emission trading scheme (ETS), are getting sparer in recent years. Some critics have argued that carbon pricing policies tend to fuel inflation, and some believe that it may adversely impact domestic firms' competitiveness on the global stage, thereby hindering economic recovery. Indeed, Ganapati et al. (2020) showed that 70% of the cost increase from energy taxes is passed onto consumers in the short to medium term. However, the impact of carbon pricing on competitiveness is not as clear. In fact, most of the literature on the topic has found that carbon pricing has no impact on competitiveness, or even a positive one in some cases. Because it is one of the oldest cap and trade scheme, many studies analyzed the case of the EU ETS, but found no adverse effect on output, employment or productivity (Brucal & Dechezlepretre, 2021; Chan et al., 2013; Colmer et al., 2024; Dechezlepretre et al., 2023; Flues & Lutz, 2015; Marin et al., 2018; Martin et al., 2014), though some authors note that results are quite sector-dependent (Martin et al., 2016). In fact, Dechezlepretre et al. (2023) even highlighted that the EU ETS led to an increased revenue and assets. Since then, other countries have introduced ETS at the national level, such as China or South Korea. Some studies found evidence of improved productivity (Feng et al., 2021), fostered innovation and improved export performance in China (Liu, Ren and Li, 2022). Korean ETS also increased energy efficiency gains and improved competitiveness (Kim & Bae, 2022; Choi, Liu and Lee, 2017). If we extend our analysis to carbon pricing in general, Yamazaki (2017) found that the carbon tax introduced in British Columbia resulted in higher employment, though at the cost of lower wages, among non-energy intensive sectors.

Still, many of the policies analyzed in the studies above have either been introduced relatively recently at the time of the study (in the case of China, Canada or South Korea) or were characterized by a relatively low level of carbon price (EU ETS in phase 1 and phase 2). In particular, the price of allowances in the EU ETS has been reaching above 80 USD/tCO_2 in recent years, bringing back fears of carbon leakage, industrial relocation and loss of competitiveness. To protect its domestic industry, the EU introduced the first carbon border adjustment mechanism in 2020, while other economies simply postponed or abandoned further plans for nation-wide carbon price. A third option that is gaining momentum, especially in the developing world, are voluntary carbon markets and crediting mechanisms. Voluntary emission reduction programs have been introduced in Japan (phase 1 of GX-ETS), China (pilot ETS) and Thailand, while Colombia and South Africa offer crediting mechanisms. In future years, it seems that many countries are likely to follow suit, as carbon crediting schemes are under construction in Indonesia, Vietnam, Saudi Arabia, Egypt, Mexico, Ecuador and India. The popularity of these voluntary schemes can be traced back to their higher political acceptance: participation is voluntary, and there is no penalty for non-compliers. However, their impact on economic performance or emission reduction is unknown. Since these schemes are relatively young, very little research has been conducted on the topic until now.

Assessing the impact of voluntary schemes on their trial jurisdiction is crucial in enhancing the political acceptability of carbon pricing. Here, we should distinguish between two types of voluntary cap-and-trade schemes. In many cases, voluntary cap-and-trade schemes are simply a preliminary phase to a nation-wide or mandatory policy. This was essentially the case in the EU ETS between 2005 and 2007, where allowances were freely allocated[1], China with its pilot ETS, or Japan and its GX-ETS (Arimura, 2024). Previous studies showed that targeted plants improved economic performance, increased their competitiveness, wages and output (Chan et al., 2013; Marin et al., 2018), as well as reduced their emissions (Ellerman and Buchner, 2008) during the first phase of EU ETS. Results from the trial period of Chinese ETS are more mixed: Chen et al. (2024) found an increase in labor productivity among new firms and SMEs. However, Quan and Duan (2023) showed a decreased output and profits among iron & steel plants, while Zhang and Duan (2020) showed a reduction in gross output and employment among targeted sectors. Recently, Tian et al. (2025) found that the pilot ETS in Beijing caused a reduction in emissions without having any effect on output or energy intensity, as the plants increased their clean fuel usage. Still, the pilot ETS in China or the trial period in the EU ETS cannot be considered as fully voluntary: despite allowances being allocated freely, fines are still applied to non-compliers.

A second type of voluntary cap-and trade schemes are those that are not expected to be followed by mandatory schemes in the future. Under this type of voluntary scheme, plants have little incentive to adapt their behavior, as it is uncertain whether the policy will ever become mandatory in the future. This type of scheme is closer in design to ETS and voluntary carbon crediting schemes that have been growing in popularity in recent years. Facing political difficulties in introducing nation-wide cap-and-trade scheme in the early 2010s (Arimura, 2024), Japan was one of the first countries to propose a voluntary form of ETS in one of its prefectures, Saitama, in 2011. Since this prefecture is one of Japan's industrial production centers, this scheme targets industrial plants in a similar fashion to existing voluntary schemes in the developing world. Furthermore, the scheme was introduced more than a decade ago, and since then, many studies have assessed whether it fulfilled its emission reduction goals. Specifically, several studies pointed out that, despite being a voluntary scheme, it resulted in a fall in energy consumption (Yajima, Arimura, Sadayuki, 2021) and helped improve previously owned equipment (Hamamoto, 2021a). Previous studies also highlight that Saitama ETS is linked with a fall in CO_2 emissions (Hamamoto, 2021b; Sadayuki & Arimura, 2021). The effects of the scheme are not limited to energy and environmental impacts, as authors point out that the scheme has been shown to drive innovation as well (Jia & Takeuchi, 2024; Lu, Sadayuki & Arimura, 2023). Still, to the best of our knowledge, there has not

[1] Non-complying plants were targeted by 40€ fines.

been any study discussing the economic impact of voluntary cap-and-trade schemes, whether in Japan or in other countries. We bridge the gap in the literature by offering a comprehensive assessment of the effect of a voluntary cap-and-trade scheme on plants' economic performance, namely employment, output and competitiveness. Utilizing Japanese plants' data from 2004 to 2019, we estimate the treatment effect of Saitama ETS (SETS) using a difference-in-differences (DiD) as well as propensity score matching (PSM) methods. In addition to enhancing the understanding of the effect of voluntary ETS, we believe that this study is also relevant to policymakers, as many countries are considering the introduction of similar schemes.

The remainder of the study is structured as follows: section 2 provides additional details on the SETS and the state of carbon pricing in Japan, section 3 describes our methodology and data, section 4 summarizes the main results of the analysis while section 5 discusses their implications. Section 6 concludes this study.

2. Carbon pricing in Japan

2.1 Tokyo and Saitama ETS

While Japan will introduce a full-fledged ETS for its industry from April 2026 onward, two prefectures have been pioneers in this regard. After announcing their intention in 2008, Tokyo and Saitama prefectures introduced a cap-and-trade scheme in 2010 and 2011, respectively. While the starting date of the regional ETS differed, they shared a similar design: facilities whose annual energy consumption exceeded 1,500kl of crude oil equivalent[2] were targeted by the scheme. Emission caps were calculated for each targeted firm, based on past average emissions[3], and emissions allowances were granted via free allocations. However, the schemes differ in several critical ways.

First, they differ in the type of facilities they target. Indeed, it is worth noting that Tokyo prefecture is characterized by a small number of manufacturing plants, whose production only represents 2.3% of the nation's total, ranking 16th out of 47 prefectures in 2021 (METI, 2023). By contrast, Saitama prefecture is one of Japan's manufacturing nerves, whose production represents 4.1% of the nation's total, ranking 6th out 47 prefectures in 2021 (METI, 2023). For this reason, roughly 80% of 600 targeted facilities in Saitama prefecture are manufacturing plants. Furthermore, SETS is essentially a voluntary scheme, as there is no penalty for non-compliers.[4] Since this study aims at analyzing the effect of a voluntary ETS on the manufacturing sector, we choose to focus on the case of SETS. Under this scheme, industrial plants must reduce their emissions by 6% compared

[2] Approximately 2,800 tons of CO_2
[3] For three consecutive years, between 2002 and 2007.
[4] The name and address of non-compliers are publicly disclosed on the prefecture website. Similarly, the name and address of facilities that reduce emission s beyond their obligation is also publicly disclosed.

to the baseline period. From 2015, this figure was raised to 13%, and then 20% from 2020. Table 1 displays various statistics regarding compliance and emission trading under SETS.

Table 1. Compliance and trading under SETS

	Overall		EI industry		Non-EI industry	
	Observations	Plants	Observations	Plants	Observations	Plants
Targeted by SETS	3,068	453	854	132	2214	334
Complied with emission cap	2,999	449	835	132	2164	330
	98%	99%	98%	100%	98%	99%
Traded allowances	386	75	69	14	317	61
	13%	17%	8%	11%	14%	18%
Insufficient reduction	192	48	44	10	148	38
	6%	11%	5%	8%	7%	11%
Reduced beyond obligation	2572	403	757	122	1815	293
	84%	89%	89%	92%	82%	88%
Traded allowances but failed to meet targets	29	8	4	1	25	7
	8%	11%	6%	7%	8%	11%
Traded allowances and met targets	357	70	65	13	292	57
	92%	93%	94%	93%	92%	93%

Source: authors' compilation. Percentage shown for "Traded allowances but failed to meet targets" and "Traded allowances and met targets" is the share of plants or observations among trading plants. Period of analysis: 2011 to 2019. We also provide details regarding the start of the treatment in Appendix A.

Despite the lack of monetary fines, the majority of plants (99%) complied with ETS regulations, a figure that even rises to 100% in the case of EI sector. Furthermore, a sizeable number of plants (89%) even reduced emissions beyond the necessary cap. It also appears that the scheme established an efficient trading system, as the majority of trading plants managed to reach their targets after purchasing additional allowances. There are several possible explanations behind the high compliance level. First, only 17% of plants traded emissions under the scheme, which could reflect that the initial emission allocation might have been too generous, or that the initial cap may not have been ambitious enough. Since the scheme was announced three years prior to its implementation, it is also possible that plants had enough time to prepare and invest in energy efficient technology or emission-reducing technology beforehand[5]. Though the scheme is voluntary, non-compliers' names are still publicly disclosed, which could have encouraged some firms to comply with the scheme. Another possible explanation behind the high level of compliance could lie in cultural specificity: both Arimura et al. (2019) and Mortha et al. (2024) showed examples of successful light-handed policies in Japan, and attribute this success to the consensus between policymakers and industry, despite non-stringent policies. In fact, the design of SETS was also thoroughly discussed through committees between 2008 and 2014. We provide more details on the composition of the committee as well as some selected quotes in appendix A. These quotes show that SETS was designed with an emphasis on energy efficiency efforts rather

[5] The majority of non-compliers were found in the initial phase of the scheme, between 2011 and 2014, which seems to give more ground to this explanation, rather than the lack of ambition of the emission reduction targets.

than credits trading. It also seems that the voluntary nature of the scheme can be traced back to a consensus between the prefecture and industrial players, after the latter expressed concerns over competitiveness and carbon leakage.

2.2 Other carbon prices and future prospects

As of 2025, Japan is one of the few remaining high-income economies without a widespread form of carbon price, whether in the form of a carbon tax or an ETS. To be precise, following the arrival to power of the Democratic Party of Japan in 2012, the country introduced a carbon tax, called the "Tax for climate change mitigation", whose rate was initially set at 95 JPY/t of CO_2 and gradually reached its final level of 289[6] JPY/t of CO_2 in FY2016. This tax is levied on oil, LPG, natural gas and coal. Despite this increase, the tax rate remains low compared with other high-income countries, and thus, its effect on energy consumption as well as emissions is expected to be limited. With rising concerns over climate change in recent years, Japanese policies have been slowly growing in ambition: since FY2023, the country has introduced a nation-wide ETS, called GX-ETS. This ETS was initially implemented on a voluntary basis, and is expected to become mandatory for all Japanese facilities from FY2026 onward. The country is also planning to introduce a new carbon tax, called 'carbon surcharge' in FY2028 whose rate is yet to be determined.

If we extend our definition of carbon prices to other forms of taxation on energy products (OECD, 2013), it becomes apparent why Japan has not yet introduced many additional taxes on fossil fuel products. Indeed, since 1978, the country has introduced the 'Petroleum and Coal tax', levied on a wide variety of energy carriers, such as kerosene, diesel, gasoline, Liquid Petroleum Gas (LPG), natural gas or steam coal. Since 1974, the Promotion of Power Resources Development tax is a tax on electricity whose revenue is used to encourage new forms of electricity generation and ensure the safety of areas surrounding power plants. Finally, the country introduced a Feed-in-Tariff policy in 2012, financed by a renewable levy. While the number of renewable installations has greatly increased, the levy rate has been growing at a fast pace as well, every year. For more details on the levy rate and its effect on the manufacturing industry, we refer the reader to Mortha and Arimura (2024). In general, fuel excises or electricity taxes represent most of the burden on energy taxation on energy carriers for the industry (IEA, 2020). However, it is worth noting that most of the non-ETS taxation in Japan is uniformly applied to all plants, and has remained roughly stable in the past 25 years (with the exception of the renewable levy rate).

3. Methodology and data

3.1 Estimation strategy

[6] Roughly 2 USD/tCO_2 as of 2025.

This section discusses the econometric design used to estimate the effect of SETS on the economic performance of manufacturing plants. As explained in section 2.1, SETS was announced in 2008, and introduced three years later. Since the scheme only targets plants beyond a certain size, it can be seen as a quasi-natural experiment, in which certain plants were 'treated' (targeted by SETS). To identify the treatment effect of SETS, we apply a classic Difference-in-Differences (DiD) methodology. Athey and Imbens (2006) Bertrand et al., (2004) de Chaisemartin and D'Haultfoeuille (2020), D'Haultfoeuille and de Chaisemartin (2022), Sant'Anna and Zhao (2020) and Sun and Abraham (2021) show that, by using a two-way fixed effects (TWFE) in a panel setting, one can identify the treatment effects in such setting. Therefore, we estimate the following equation:

$$\ln(y_{it}) = \alpha + \beta ETS_{it} + X_{it}B + \omega_s + \eta_t + \gamma_i + \varepsilon \tag{1}$$

where y_{it} represents the outcome variable for a given plant i in year t, ETS_{it} is a dummy variable taking the value "1" if a plant is targeted by SETS in the given year, X_{it} is a vector of covariate that is discussed in the next section, ω_s is a product fixed effect, η_t is a year fixed effect, γ_i is a plant fixed effect, and ε is an error term. β is the coefficient of interest, and represents the average treatment effect (ATE) of SETS.

Furthermore, we also wish to explore the medium to long-term effects of SETS, as changes in economic structure of the plant (investment in clean technology, change in production structure) are unlikely to occur instantaneously. To this end, we estimate the following dynamic DiD model:

$$y_{i,t} = \alpha + \sum_l \mu_l 1\{t - E_i = l\} + X_{it}B + \omega_s + \eta_t + \gamma_i + \varepsilon \tag{2}$$

where E_i denotes the time in which plant i is treated. Other variables are the same as equation (1).

Previous literature on SETS has shown that plants targeted by the scheme might be fairly different from their counterparts. Because the eligibility threshold is set at an absolute amount of fuel consumption (1,500kl of crude oil equivalent a year), it follows that SETS plants tend to be larger than most control plants. Furthermore, the choice of prefecture of Saitama itself may lead to a bias in estimation. As Sadayuki and Arimura (2021), this prefecture is located in the Greater Tokyo Area, and is thus more densely populated than the rest of the country. It could mean that plants in Saitama (targeted or not) are sufficiently different from those of the rest of the country, making it difficult to identify the treatment effect. To address these concerns and reduce the sample selection bias, previous studies on SETS have used PSM to identify the treatment effect (Hamamoto, 2021a; Hamamoto, 2021b; Jia and Takeuchi, 2024; Lu, Sadayuki and Arimura, 2023). For robustness, we employ both TWFE and PSM methodology in this study.

3.2 Data source and basic statistics

In this study, we gather data on all manufacturing plants across Japan, between 2004 and 2019. To this end, we use the Census of Manufacture (CEM)[7], an annual survey conducted by the Ministry of Economy, Trade and Industry (METI, 2024a; 2024b). The objective of this survey is to provide data on economic indicators, such factory employment, output, costs and inventory. Participation is compulsory for all plants, all survey fields are mandatory. Our dataset comprised more than 3 million observations across more than 600,000 plants, but only 1,915,870 (across 274,272 plants) of these are usable (i.e. non-missing) for all variables of interest. Furthermore, we exclude plants from Tokyo prefecture in the analysis, as some were targeted by a different type of cap-and-trade scheme. We proceed to match the survey with the list of plants targeted by SETS, available from the prefecture website (Saitama Prefecture, 2025). We present basic statistics of our sample in Table 2.

Table 2. Summary statistics

	Variable name	Observations	Mean	Std. Dev.	Minimum	Maximum
Employment effect	Number of employees	1,899,029	39.73	66.05	1	596
	Wage	1,912,388	344.58	164.48	0.07	1,649.26
	Labor intensity of production	1,915,084	0.00	0.20	3.80e-08	215
Output effect	Shipments	1,897,944	215,068.8	2,692,998	1	9.16e+08
	Value added	1,885,045	70,452.29	692,002	1	2.00e+08
Competitiveness effect	Export share	113,115	18.67	23.22	0.01	100
	Investment	420,465	31,661.51	216,994.6	1	3.17e+07
	Total costs	1,910,081	139,354.5	2,071,368	1	7.7e+08
Control variables	SETS dummy	1,915,870	0.00	0.04	0	1
	Capital	1,915,870	124,739.6	1,420,376	0	1.67e+08
	Tangible fixed assets	1,915,870	39,201.78	370,611.5	-4,448	4.91e+07
	Fresh water usage	1,915,870	833.21	26,132.65	0	3,849,050
	Inventory	1,915,870	6,306.71	59,508.13	-4,228	1.81e+07
	EI dummy	1,915,870	0.49	0.50	0	1
	Material costs	1,915,870	104,829.7	1,333,604	-8,060	4.90e+08
	Consignment costs	1,915,870	10,605.27	138,106.4	-7,091	3.91e+07
	Multiplant dummy	1,915,870	0.26	0.44	0	1

Source: authors' compilation based on data from METI (2024a) and METI (2024b). "Obs." and "Std. Dev." stand for "number of observations" and "standard deviation", respectively. Figures are rounded to two decimals. We only show statistics for the sample of analysis, i.e. the sample without any missing observations for the variables of interest. We also removed zero-valued observations of outcome variables in this sample, as they will undergo logarithmic transformation, explaining the reduced number of observations for investment and export share. The number of

[7] From 2011 onward, the Census of Manufacture is replaced by the Economic Census for Business Activity once every five years. The Economic Census for Business Activity all economic facilities in the country, including manufacturing ones. This is the case for 2011 and 2015, in our data.

observations for wages and employment are slightly different from other dependent variables, as we have removed outliers from the analysis.[8]

In this study, we focus on eight outcome variables to evaluate a plant's economic performance. We use the number of employees inside the plant, their average wage[9] and the labor intensity of production[10]. To understand the scheme's effect on a plant's output, we use the total value added and the shipment's value (i.e., the plant's revenue). We also examine the effect of SETS on a plant's total costs, investment and export share, to approximate the scheme's effect on the plant's competitiveness. Since SETS tends to target larger plants on average, we selected several covariates that can capture a plant's size, namely capital, tangible fixed assets, freshwater usage and inventory amount. We also wish to disentangle the effect of SETS on costs, and control for the plant's material and consignment costs.[11] Finally, we control for the plant's energy intensity (EI) level, based on METI's classification[12].

3.3 Stylized facts

Before presenting the results of the empirical analysis, we first discuss the evolution of various economic indicators, such as employment, output and competitiveness, as shown in Figure 1. This figure shares a dual purpose: they display the evolution of outcome variables between control and treated plants, but also allow us to visually check for the fulfillment of the parallel trend hypothesis.

From panel 1A, it appears that SETS affected employment, as we can see that the number of employees inside treated plants falls after 2011, and this decrease sharpens after 2015. In addition, plants targeted by SETS experience a large increase in the average wages of their employees after 2015, compared to control plants. One possible explanation for this observation could lie in the reduction in total number of employees: if the reduction in the number of employees is not accompanied by a sharp decrease in wage expenditures, the wages of remaining employees would increase. Another explanation could be found in a change in production structure within plants: as

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[8] Outliers are defined as observations that are three standard deviations above or below the mean. The mean of the overall sample is 50.60 employees (standard deviation: 182.12) and 350.13 ten thousands yen for wages (standard deviation: 433.21). In our sample, there were 16,244 observations that classify as outliers in employment (plants with more than 596.96 employees) and 2,560 observations for wages (plants with average wages higher than 1,649.76 ten thousands yens per year). We remove these observations from the analysis to ensure that our estimates are not overestimated.

[9] The average wage is calculated by dividing the plants' total wage expenditures by the number of employees.

[10] Labor intensity of production is calculated as followed: $labor\ intensity = \frac{number\ of\ employees}{production\ value}$. It can be interpreted as the number of employees needed to produce 10,000 yen worth of output.

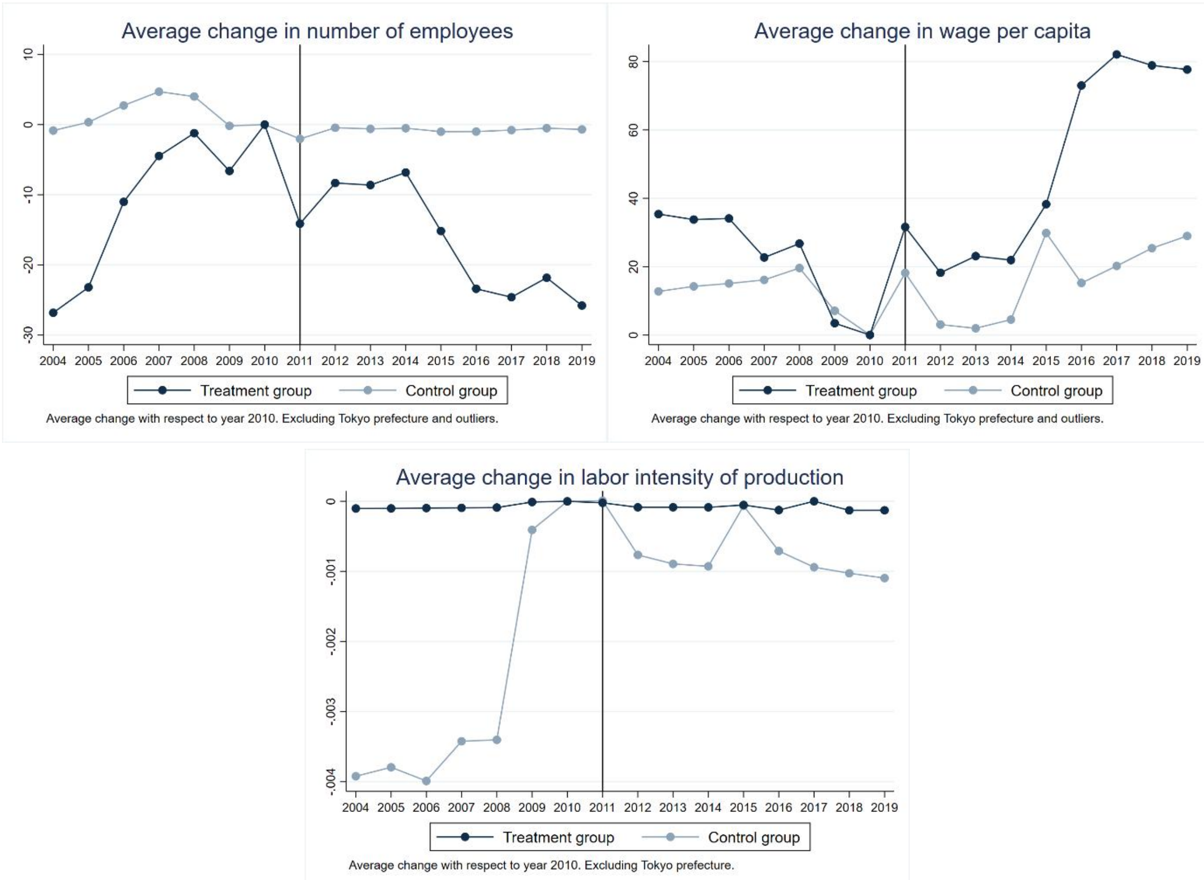
[11] A plant's total costs are the sum of material costs, consignment costs, fuel costs and electricity costs in the survey. By controlling for non-energy related costs, we ensure that the change in total costs is coming from a change in energy-related expenditures.

[12] Every year, METI conducts a specific survey called the Current Survey Energy Consumption in the Selected Industries, which only targets energy-intensive manufacturing plants. The targeted sectors are iron & steel, paper & pulp, cement, heavy machinery, non-ferrous metal, chemicals, chemical fibers and petrochemicals, and glass.

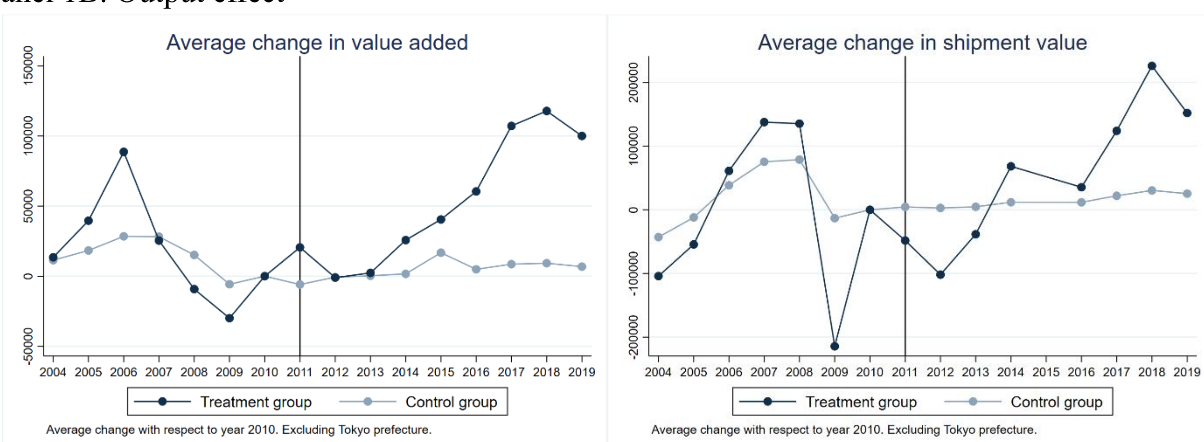
energy-related expenditures increase, some plants might attempt to save some costs by reducing the number of employees, thereby reducing the number of employees needed in the production process. We do not observe a fall in labor intensity throughout the treatment, but it is difficult to attribute it to the introduction of SETS, as both groups greatly differ before treatment. From panel 1B, it would appear that SETS had a positive effect on output, as we observe an increase in both shipments and value added after 2016. Since the output increase coincides with the increase in wages, this could be another explanation as well: plants targeted by SETS increased their value added, possibly thanks to a more labor-efficient production process. Dividends and added benefits from the increase in value added could have been reflected in the wages of the remaining employees. However, these results must be interpreted carefully, as parallel trend hypothesis is not fulfilled in the case of shipments. It is more difficult to draw conclusions from panel 1C, as it appears that treated and control plants differ significantly before the implementation of SETS in terms of costs, investments and export share. Interestingly, we observe a sharp increase in investment among treated plants in 2009: since this peak in investment occurs one year after the announcement of SETS, this could reflect preparation efforts, such as investment in clean technologies. Still, it is difficult to draw any definite conclusions without rigorous econometric estimation.

Figure 1. Evolution of main dependent variables during study period

Panel 1A. Employment effect



Panel 1B. Output effect



Panel 1C. Competitiveness effect

Source: authors' compilation. Average change with respect to year 2010.
Note: 'investment' was only provided in the CEM survey from 2007 onward.

Since this study employs a DiD methodology, we also present a comparison of the mean values of control variables for treated and control groups separately in Table 3. As we suspected, treated plants tend to be larger in size, as nearly all control variables have a higher mean for the treatment group. The difference in size between treated and control plants could largely explain the reason behind the non-fulfillment of the parallel trend hypothesis, as shown in Figure 1. For instance, it explains why we observe larger variations within outcome variables for the treatment group, rather than the control group before treatment. Some large plants within the control group may experience change in employment of magnitude similar to treated plants, but are drowned out by the large number of smaller plants in the control group. Significant differences between the treatment and control groups before the start of the treatment could cloud the interpretation of the DiD estimator, as it becomes difficult to attribute changes in outcome variables to the treatment alone, or to inherent differences between both groups. At the same time, if the reason behind the lack of parallel trend can be traced out to observable characteristics (namely, plant size), then the use of DiD is still warranted, after controlling for such characteristics (conditional parallel trend).

Table 3. Balance of covariates in matched sample

		Mean (Treated)	Mean (Control)	t-statistic
Capital	U	1.1e+06	1.0e+05	38.96***
	M	1.1e+06	1.2e+06	-0.82
Tangible fixed assets	U	4.3e+05	45917	41.08***
	M	4.3e+05	5.0e+05	-2.58***
Fresh water usage	U	3957.1	946.37	5.05***
	M	3957.1	3885.3	0.13
Inventory from production	U	59687	4855.2	53.53***
	M	59687	50278	1.49
Electricity costs	U	19159	2067.5	29.12***
	M	19159	20199	-1.09
Material costs	U	1.0e+06	82231	43.03***
	M	1.0e+06	9.2e+05	0.87
Consignment costs	U	98881	7574.2	47.85***
	M	98881	96964	0.14
Existence of other plants owned by the same firm	U	0.74055	0.23463	60.10***
	M	0.74055	0.74331	-0.22
Rubin's B [Rubin's R]	U	126.8 [1.38]		
	M	13.5 [1.23]		

Source: authors' compilation. "U" and "M" mean "unmatched sample" and "matched sample", respectively. Probability associated with the t-statistic is presented in square brackets, rounded to two decimal points. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Matched based on pre-treatment covariates for the year 2010.

Following previous studies on SETS (Hamamoto, 2021a; Hamamoto, 2021b; Jia and Takeuchi, 2024; Lu, Sadayuki and Arimura, 2023), we match plants from the control and treatment groups based on observable characteristics. Plants targeted by SETS must fulfill a certain threshold of emissions, and thus, it follows that such plants would be larger than average, more energy-intensive than others, or both. To capture the plants' relatively larger size, we include the plants' capital, fixed assets and inventory. We also include a dummy variable on whether the plant is owned by a large or SMEs. Furthermore, it is likely that SETS plants may be relatively energy-intensive: to reduce this bias, we include the cost structure of the plant (electricity, material and consignment).[13] Methodology behind the matching process for panel data is derived following Gerster and Lamp (2024), who recommended using pre-treatment covariates upon matching. We match plants based on their observable characteristics for the year 2010, ensuring that control and treated plants are sufficiently similar before the treatment starts. Furthermore, we follow Rosenbaum and Rubin (1985) and set the caliper at 25% of the standard deviation propensity score, ensuring that matched plants are sufficiently similar to one another. We exclude plants from Tokyo prefecture in the process, as some were targeted by Tokyo ETS, and thus, may not be an appropriate control group.

[13] We also attempted to match plants based on the pre-treatment growth rates of these control variables, as well as the logarithmic form of these variables. However, matching based on growth rate or logarithmic variables fails to capture the sheer size of the plant. For this reason, we use the variables as they are during the matching process.

We also exclude years prior to the treatment, that is, 2004 to 2010. After this adjustment, our sample size is reduced from 1,915,870 observations to 1,097,525 observations. Among them, 2,540 observations belong in the treatment group. In the main body, we show results of nearest neighbor (NN: one to three nearest neighbors) matching with caliper and replacement. Following the matching process, plants that remain in the sample are more similar for both control and treatment group, as the difference in means is no longer statistically significant. Furthermore, the number of standard deviations between the means of the groups ('Rubin's B') and the ratio of treatment variance to control variance ('Rubin's R') fall within the values recommended by Rubin (2001)[14] after treatment. Following the matching process, plants in the matched sample are generally larger in size.

4. Main results

4.1 Primary results

First, we discuss the overall effects of SETS on plant's economic performance in the period of study. Table 4 presents the estimates of SETS' ATE (β) from equation (1) while Figure 2 displays the estimates of μ from equation (2). We provide results of the matching procedure for the sample as a whole. However, we also alter the control group for robustness: we propose excluding neighboring prefectures, as there may be a risk of inter-prefectural leakage that could cloud our results. We also attempt to match SETS plants with plants within the Kanto region, as this region contains many plants that are similar to Saitama plants, in terms of size and industrial structure.

Table 4. Baseline results

Estimates of β		Average treatment effect of SETS overall			
		TWFE	PSM (1:3), full sample	PSM (1:3), excluding neighboring prefectures	PSM (1:3), Kanto prefectures only
Employment effect	Number of employees	0.01	0.21***	0.22***	0.22***
		(0.02)	(0.06)	(0.06)	(0.07)
	Wages	0.04***	0.01	0.00	-0.07***
		(0.01)	(0.03)	(0.02)	(0.02)
	Labor intensity	-0.06***	-0.02	0.01	0.02
		(0.02)	(0.06)	(0.06)	(0.05)
Output effect	Value added	0.06**▼	0.25***	0.43***	0.26***
		(0.03)	(0.08)	(0.08)	(0.08)
	Shipments	0.07***	0.22***	0.19***	0.15**
		(0.02)	(0.07)	(0.07)	(0.08)
Competitiv-eness effect	Export share	0.20▼	-0.77**	-0.41	-0.63**
		(0.13)	(0.31)	(0.29)	(0.27)
	Total costs	0.10***	0.22**	0.15**	0.19***
		(0.03)	(0.09)	(0.07)	(0.07)
	Investments	-0.10**	0.14	0.16	0.04

[14] Rubin (2001) argues that B should be below 25% while R should be a figure between 0.5 and 2 in order to avoid increasing bias within the matched sample.

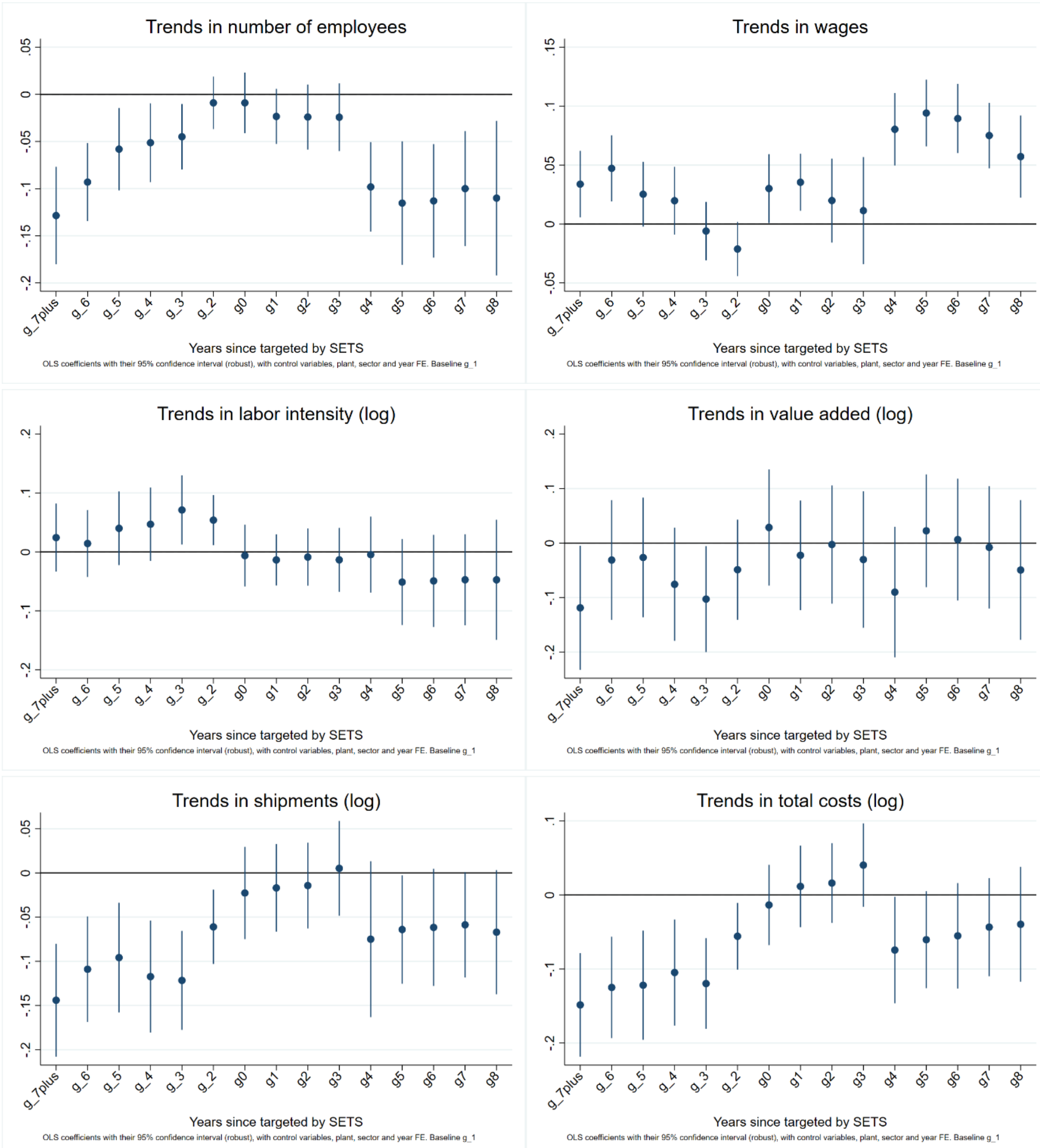
	(0.05)	(0.11)	(0.13)	(0.12)

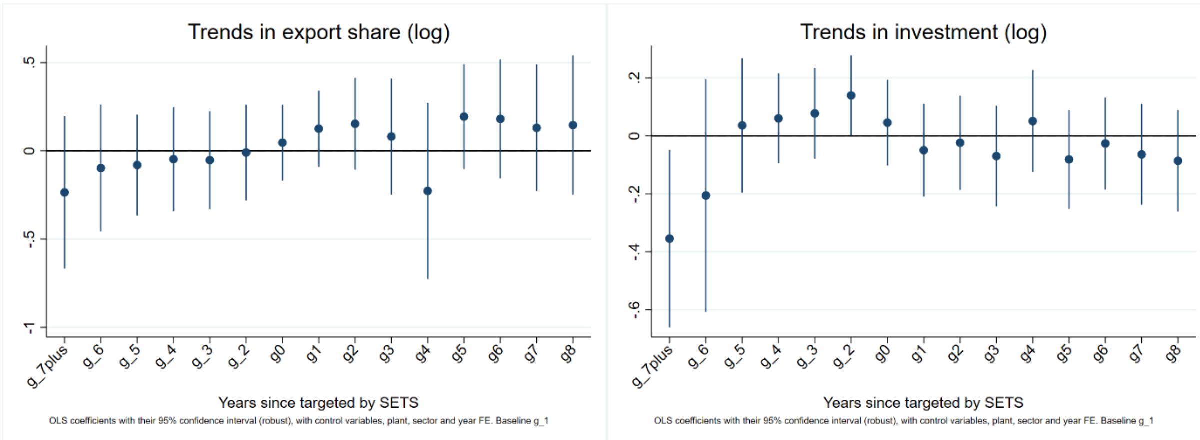
Source: authors' compilation. Standard errors clustered by plant in parenthesis. "▼" denotes variables that fulfill the conditional parallel trend hypothesis, based on pre-treatment coefficients presented in Figure 2. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Standard errors in PSM are calculated based on Abadie and Imbens (2016), caliper is set at 25% following Rosenbaum and Rubin (1985). Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$. Excluding plants in Tokyo prefecture. Matching is performed in post-2010 sample, using pre-treatment covariates from 2010 and matching to three nearest neighbors. We provide additional robustness tests for various DiD assumptions in appendix B .

Results from DiD also tend to confirm that SETS had a positive effect on output. Both methods consistently show that the introduction of SETS resulted in an increase in value added, estimated from 6.07% (TWFE) to 27.92% (PSM). This effect is more pronounced when we compare it with plants from other regions, as it reaches 53.56%. We also find that SETS resulted in an increase in shipments (and thus, revenue) for the plants, with a similar magnitude to the rise in value added.
Furthermore, estimates from TWFE imply that SETS led to an increase in average wages, estimated around 3.66%. It is also clear that the wage increase occurs during phase 2 of SETS, as shown in Figure 2 (wages increase sharply 4 years after the start of treatment). One possible explanation behind the increase in wages stems from a fall in labor intensity of production of a similar magnitude (-5.62%). Interestingly, we observe an increase in the number of employees inside the plants, with a magnitude roughly matching the increase in value added (22.95%, PSM). In contrast, results from the dynamic DiD show a fall in number of employees in the medium to long-term. It is worth noting, however, that regressions in labor intensity and number of employees fail to fulfill the conditional parallel trend hypothesis[15], making it difficult to assert whether these changes are caused by SETS. Furthermore, plants targeted by SETS are reported to have lower wages than other plants located in Kanto (-6.53%), potentially due to inter-prefectural leakage effect. The effect of SETS on competitiveness is not as clear. For instance, both PSM and TWFE imply that the policy resulted in increased costs within targeted plants (10.41%, TWFE to 24.66%, PSM). This result confirms that, despite the voluntary nature of SETS, targeted plants experienced some form of cost increase, likely due to fuel adjustments.[16] Though PSM highlights that targeted plants experienced a fall in export share (-53.88%), especially compared with plants from Kanto region (-46.56%), this effect is not found in TWFE or dynamic DiD. Still, it would appear that the policy resulted in a fall in investments (-9.44%), though this effect that is not consistently picked up by PSM or dynamic DiD.

[15] To verify whether the conditional parallel trend hypothesis is fulfilled, we check the statistical significance of pre-treatment dummy variables from equation (2). These coefficients are also shown on Figure 2.
[16] Total costs is the sum of fuel, electricity, material and consignment costs. Since we match plants with similar cost structure (material, electricity, consignment) prior to the start of SETS, it is likely that any further changes in costs is due to a change in fuel costs. Furthermore, since Japan is a net fuel importer, any shock on fuel prices is experienced by both control and treated plants. Hence, the change in costs cannot be attributed to changes in fuel prices among treated plants, but rather to fuel adjustments.

Figure 2. Dynamic DiD


Trends in number of employees
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in wages
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in labor intensity (log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in value added (log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in shipments (log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in total costs (log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
g_7plus
g_6
g_5
g_4
g_3
g_2
g0
g1
g2
g3
g4
g5
g6
g7
g8



Source: authors' compilation. OLS coefficients with their 95% confidence interval (with standard errors clustered by plant), with control variables and two-way fixed effects. Number of fiscal years since plant is targeted by SETS is represented on horizontal axis. "g_1" should be understood as "one fiscal year before the start of treatment" whereas "g1" should be understood as "one fiscal year after the start of treatment." The validity of the conditional parallel trend hypothesis is detected by the lack of statistical significance of pre-treatment (g_) coefficients.

4.2 Heterogeneity in energy intensity

While the ETS policy is applied uniformly to all targeted plants, it stands to reason that some plants might be more vulnerable than others. Literature on the manufacturing sector has shown that plants belonging to EI sectors are more likely to experience negative effects of climate policies, as their energy consumption is higher. Specifically, Yamazaki (2017) showed that, apart from the power sector and air transportation sector, firms involved in primary metal, pulp and paper, chemical and petrochemical as well as machinery manufacturing experienced a loss of employees following the introduction of a carbon tax. While the majority of the positive employment effects were found in the service sector, some manufacturing sectors (furniture, wood, food and beverages sectors) experienced a slight rebound in employment (Yamazaki, 2017). Therefore, we divide our sample into EI and non-EI plants, and re-estimate the ATE for each sample separately. Results of these estimates are presented in Table 5, and Figure 3.

Table 5. ATE of SETS policy, by energy intensity

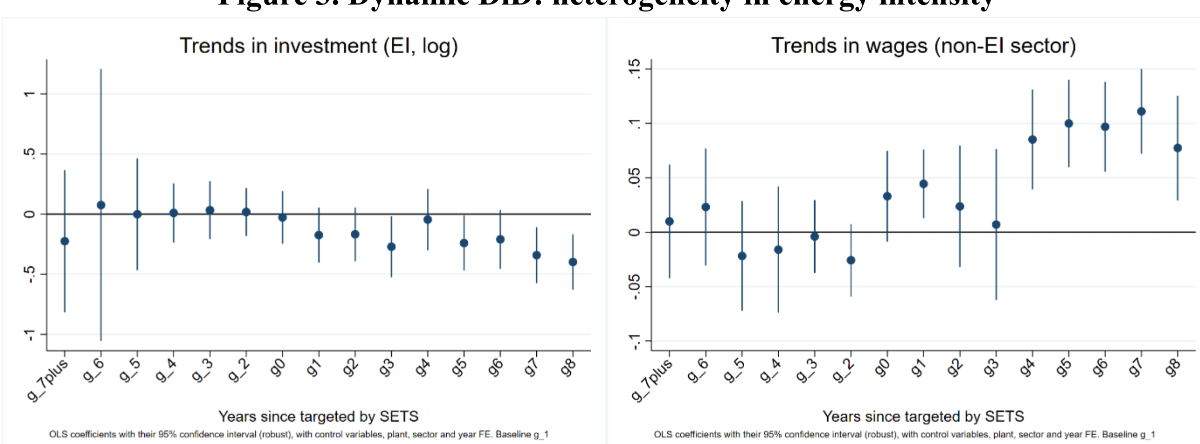
Average treatment effect of SETS		Energy-intensive (EI) plants		Other plants	
		TWFE	PSM (1:3)	TWFE	PSM (1:3)
Employment effect	Number of employees	-0.02	-0.02	0.03	0.13*
		(0.03)	(0.09)	(0.02)	(0.07)
	Wages	0.03***	0.02	0.06***▼	-0.03
		(0.01)	(0.03)	(0.02)	(0.04)
	Labor intensity	-0.01▼	0.03	-0.13***	-0.17**
		(0.03)	(0.08)	(0.03)	(0.08)
Output effect	Value added	-0.05▼	0.17	0.17***	0.27**
		(0.05)	(0.11)	(0.03)	(0.11)
	Shipments	-0.02	-0.05	0.15***	0.31***
		(0.03)	(0.16)	(0.03)	(0.09)

Competitiv-eness effect	Export share	0.38**▼	X	0.06▼	-0.72
		(0.19)	X	(0.13)	(0.45)
	Total costs	0.04	-0.13	0.14***	0.24***
		(0.04)	(0.11)	(0.04)	(0.09)
	Investments	-0.23***▼	0.08	-0.02	0.29**
		(0.07)	(0.18)	(0.07)	(0.13)

Source: authors' compilation. Standard errors clustered by plant in parenthesis. "▼" denotes variables that fulfill the conditional parallel trend hypothesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Standard errors in PSM are calculated based on Abadie and Imbens (2016), caliper is set at 25% following Rosenbaum and Rubin (1985). Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$. Sample size for EI plants is 940,913 observations and 970,210 observations for other plants. Matching diagnosis are available in appendix C. Overlap assumption is violated among EI plants for the export share variable, as the number of observations was greatly reduced.

We first observe that the positive effect of SETS on wages is fairly robust, and does not depend on EI of the plant. However, it appears that its magnitude is stronger among non-EI plants (5.99%), an effect that lingers at most 8 years after the start of treatment. Still, EI plants experience an increase in wages (3.03%). One possible explanation for this positive wage lies in the fall in labor intensity of production among non-EI plants (-12.08% to -15.27%). Since this indicator is calculated by dividing the number of employees by the production value, a fall in labor intensity could come from both from a reduced employment, or an increased production. Our ATEs estimates consistently show a positive output effect, on both value added (18.13%, TWFE to 31.22%, PSM) and shipments (16.63%, TWFE to 36.16%, PSM) for non-EI plants. Part of the benefits from the higher output might explain the increase in wages we observe across non-EI plants. Interestingly, we fail to observe consistent positive effects among EI plants, though their export share is shown to increase (46.17%, TWFE). Finally, SETS is shown to have a negative effect on investments in EI plants (-20.78%. TWFE). Event study shows that this effect mostly occurs in the long-term, 7 to 8 years after the start of the treatment.

Figure 3. Dynamic DiD: heterogeneity in energy intensity



Source: authors' compilation. OLS coefficients with their 95% confidence interval (with standard errors clustered by plant), with control variables and two-way fixed effects. Number of fiscal years since plant is targeted by SETS is represented on horizontal axis. "g_1" should be understood as "one fiscal year before the start of treatment" whereas "g1" should be understood as "one fiscal year after the start of treatment." The validity of the conditional parallel trend hypothesis is detected by the lack of statistical significance of pre-treatment (g_) coefficients. For the sake of brevity, we only show results for variables that pass the conditional parallel trend hypothesis and where the treatment is statistically significant. Complete results are available in Appendix B.

4.3 Heterogeneity in owning firm size

Furthermore, it is important to recognize that the effect of climate policies might differ depending on the size of the plant's owning firm: plants belonging to large firms naturally have access to a larger amount of capital and may be able to cushion this policy shock more easily than small and medium enterprises (SMEs). They may also be capable of redirecting part of their production process to some plants in other prefectures, to an extent. For this reason, the validity of the DiD estimator might be questionable, as the Stable Unit Value Treatment (SUTVA) assumption may be violated in the case of plants belonging to large firms[17]. To ensure the robustness of our results, we divide the sample into two categories: plants belonging to SMEs, identified in the sample as the sole production base inside their company. Since companies only own a single plant, the SUTVA is likely fulfilled in their case, and we refer to these plants as 'single plants', following a similar methodology as Gerster and Lamp (2024). Plants whose companies own several plants in other prefectures are referred to as 'multi plants'. While we re-estimate ATEs for both samples, it is important to recognize that the DiD estimator might be biased in the case of 'multi plants'. Results are presented in Table 6 and Figure 4.

Table 6. ATE of SETS policy, by size of owning firm

Average treatment effect of SETS		Plants belonging to SMEs ('single')		Plants belonging to large firms ('multi')	
		TWFE	PSM (1:3)	TWFE	PSM (1:3)
Employment effect	Number of employees	0.01	0.25**	0.02	0.24***
		(0.03)	(0.12)	(0.02)	(0.07)
	Wages	0.04***▼	0.04	0.01▼	-0.02
		(0.02)	(0.04)	(0.01)	(0.03)
	Labor intensity	-0.05*▼	0.09	-0.03	-0.05
		(0.03)	(0.11)	(0.03)	(0.06)
Output effect	Value added	0.10*▼	0.23**	0.03	0.37***
		(0.06)	(0.11)	(0.03)	(0.09)
	Shipments	0.05▼	0.19*	0.06*	0.24***
		(0.03)	(0.12)	(0.03)	(0.08)
Co mp etit	Export share	0.18▼	-0.81	0.16▼	-0.45
		(0.29)	(0.54)	(0.15)	(0.29)

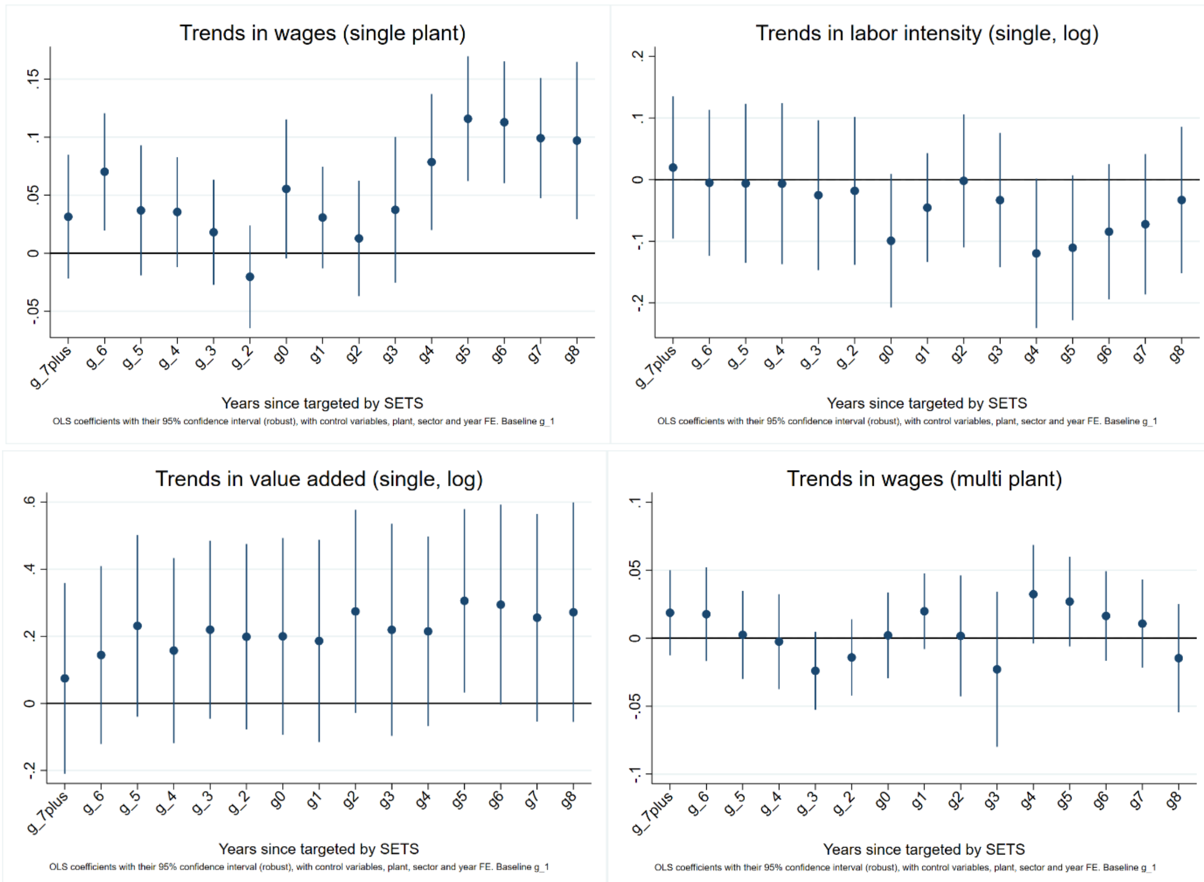
[17] Let us suppose that a firm owns several plants, among which some belong to the treatment group (facing higher production costs), but some do not. Then, it is possible that the firm might wish to redirect its production to plants in the control group. In this sense, SETS might have an indirect effect on plants from the control group, violating the SUTVA assumption.

Total costs	0.05▼	0.13	0.09***	0.25***
	(0.04)	(0.15)	(0.03)	(0.09)
Investments	-0.14▼	X	-0.06▼	0.14
	(0.09)	X	(0.06)	(0.13)

Source: authors' compilation. Standard errors clustered by plant in parenthesis. "▼" denotes variables that fulfill the conditional parallel trend hypothesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Standard errors in PSM are calculated based on Abadie and Imbens (2016), caliper is set at 25% following Rosenbaum and Rubin (1985). Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$. Matching diagnosis are available in appendix C.

Once again, we observe a consistent and robust positive effect of SETS on wages inside the plant, estimated around 4.48% (TWFE). The increase in wages mostly occurs in the medium to long term, from 4 to 8 years after the start of the treatment. Similar to the EI analysis, the positive effect on wages is traced back to a reduced labor intensity among plants belonging to SMEs (-5.35%), which is due to a positive output effect (+10.46%, TWFE to 25.91%, PSM). Rather than reducing the number of workers inside the plant, treated plants witness an increase in value added and shipments in the medium to long term, whose magnitude differs greatly across estimation methods, possibly due to the heterogeneity of plants among this sample. Plants belonging to large firms also experience an increase in shipments (6.04%, TWFE to 26.80%, PSM), which is not consistently reflected in their value added. This could be due to a sharp cost increase (8.96%, TWFE to 28.31%, PSM).

Figure 4. Dynamic DiD: heterogeneity in size of owning firm



Source: authors' compilation. OLS coefficients with their 95% confidence interval (with standard errors clustered by plant), with control variables and two-way fixed effects. Number of fiscal years since plant is targeted by SETS is represented on horizontal axis. "g_1" should be understood as "one fiscal year before the start of treatment" whereas "g1" should be understood as "one fiscal year after the start of treatment." The validity of the conditional parallel trend hypothesis is detected by the lack of statistical significance of pre-treatment (g_) coefficients. For the sake of brevity, we only show results for variables that pass the conditional parallel trend hypothesis and where the treatment is statistically significant. Complete results are available in Appendix B.

4.4 Announcement effect

As explained in the introduction, SETS is a voluntary form of carbon pricing. Despite this voluntary aspect, table 1 showed that the majority of plants fulfilled the emission reduction requirements, in many cases, well beyond the necessary cap. Most interestingly, only 17% of plants traded allowances under SETS. The low number of traders within SETS raises an important question: if not through trading allowances, then how did SETS plants reach their emission cap? The increase in costs (likely, fuel costs) among traded plants could be part of the answer, as carbon pricing is theoretically linked with cleaner fuel consumption. Alternatively, gains in energy efficiency could also explain such fall. Still, fuel switching or energy efficiency gains requires time and, in most cases, investment in new machinery.

Because SETS was announced three years prior to its introduction, it is possible that many plants began to prepare for the policy before the start of the treatment. In fact, we do observe a sharp increase in investments among treated plants in 2009, from figure 1. The literature on other cap-and-trade policies (EU ETS, in this case) highlights that plants start to adjust their behavior (whether in emission reduction or economic indicators) during trial period, before the start of the fully-fledged policy (Chan et al., 2013; Dechezlepretre et al., 2023; Ellerman and Buchner, 2008; Marin et al., 2018). To be precise, the effect of EU ETS only occurs at least a year after the start of the trial period, from 2006 to 2007 (Dechezlepretre et al., 2023).
For this reason, we estimate the following equations:

$$\ln(y_{it}) = \alpha + \xi A_{it} + \beta SETS_{it} + X_{it}B + \omega_s + \eta_t + \gamma_i + \varepsilon \quad (3)$$

where A_{it} is a dummy variable taking the value "1" if plant i became targeted by SETS as early as 2011[18]. Other variables are defined in the same way as equation (1) and (2).

Furthermore, we also attempt to distinguish the anticipation effect across years. Investment in new equipment tends to take time, and is likely not occurring within the year of announcement. Therefore, we also estimate equation (4) as follows:

$$\ln(y_{it}) = \alpha + \sum_{i=2008}^{2010} \xi_i \, A_{it} \times year_i + \beta_1 SETS\_P1_{it} + \beta_2 SETS\_P2_{it} + X_{it}B + \omega_s + \eta_t + \gamma_i + \varepsilon \quad (4)$$

Estimation results for equation (3) and (4) are shown in table 7.

Table 7. Anticipation and treatment effect

TWFE	Employment effect			Output effect		Competitiveness effect		
	Employees	Wages	Labor intensity	Value added	Shipments	Export share	Total costs	Investment
A	0.06***	-0.03***	0.02	-0.01	0.05**	0.06	0.07***	-0.05
	(0.02)	(0.01)	(0.02)	(0.04)	(0.02)	(0.10)	(0.02)	(0.07)
SETS	0.03	0.03**	-0.05**	0.06*	0.09***	0.22	0.12***	-0.12**
	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	(0.15)	(0.03)	(0.06)
2008×A	0.01	0.01	0.02	-0.05	-0.01	0.02	0.01	-0.13*
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.15)	(0.04)	(0.08)
2009×A	0.06**	-0.03**	0.04	-0.01	0.06*	0.03	0.07*	0.05
	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.16)	(0.03)	(0.09)
2010×A	0.09***	-0.02	-0.01	0.04	0.11***	0.04	0.12***	-0.07
	(0.02)	(0.02)	(0.03)	(0.06)	(0.03)	(0.18)	(0.03)	(0.08)

[18] To be precise, to estimate the anticipation effect among plants, we must restrict our treatment group to plants that were aware of the future treatment. Plant awareness is difficult to measure, but we can infer that plants that were targeted as early as 2011 would be most likely to engage in anticipatory behavior. A plant that was large enough to be targeted in 2011 was also likely large enough in 2008. Thus, they may have started to prepare for ETS from 2008 onward. Roughly 74% of all treated plants were targeted by the policy as early as 2011.

SETS P1	0.06***	0.01	-0.04	0.06**	0.10***	0.15	0.14***	-0.11*
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.15)	(0.03)	(0.06)
SETS P2	-0.03	0.07***	-0.09***	0.06*	0.08**	0.17	0.10***	-0.14**
	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)	(0.16)	(0.03)	(0.07)
Obs.	1,769,623 to 1,894,980	1,779,812 to 1,908,246	1,782,46 to 1,910,936	1,754,577 to 1,881,064	1,767,32 to 1,895,813	99,165 to 112,353	1,777,90 to 1,905,931	417,066
Groups	269,852 to 273,547	270,332 to 273,975	270,629 to 274,271	269,592 to 273,232	270,652 to 274,294	19,645 to 20,445	270,089 to 273,715	59,378

Source: authors' compilation. Standard errors clustered by plant in parenthesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$.

From these results, we observe an increase in wages (+2.73%) and revenue (+5.20%) among targeted plants. We also note that plants that would be targeted by SETS in the future reduce their average wages (-3.99%) prior to the start of the policy, perhaps as a natural consequence of the rise in employment (+6.35%). In line with Marin et al. (2018), we find that there is no statistically significant effect of the ETS policy during the preparatory phase, as the increase in revenue is also accompanied by an increase in total costs (7.36%). To ensure that our results can be attributed to anticipation behavior, we also analyze the results from equation (4). In line with Dechezlepretre et al. (2023), we find that the increase in employment, revenue (shipments) and costs occurs at least a year after the announcement of the policy, as we fail to see any statistically significant effect in 2008. In general, the effects of the policy are strongly felt in 2010, one year prior to the start of SETS. If we restrict our attention to the estimates of equation (4), we can conclude that, while the rise in value added is consistent in both phases of the policy (5.98 to 6.07%), the rise in wages (7.62%) and labor productivity (-8.48%) only occurs after 2015. Since the emission reduction targets of SETS were strengthened after 2015, it follows that any effect would be strongly felt during the second phase of the ETS. Alternatively, we can also speculate that preparations for the policies might take longer than 2 years. After all, we note that the effects of the policy during phase 1 strongly resemble those of the anticipation years, with a rise in employment (6.33%), shipments and total costs.

Table 8. Anticipation and treatment effect among EI plants

TWFE	Employment effect			Output effect		Competitiveness effect		
	Employees	Wages	Labor intensity	Value added	Shipments	Export share	Total costs	Investment
A	0.04	-0.04**	0.04	-0.13*	0.01	-0.00	0.06	-0.12
	(0.03)	(0.02)	(0.03)	(0.07)	(0.04)	(0.28)	(0.04)	(0.10)
SETS	-0.02	0.02	0.00	-0.08*	-0.02	0.38*	0.05	-0.28***
	(0.03)	(0.01)	(0.03)	(0.04)	(0.04)	(0.21)	(0.04)	(0.10)
2008×A	-0.04	0.01	0.02	-0.14*	-0.04	-0.40	0.02	-0.23*
	(0.04)	(0.02)	(0.05)	(0.08)	(0.05)	(0.33)	(0.05)	(0.12)
2009×A	0.02	-0.05**	0.06	-0.09	-0.00	-0.34	0.03	-0.07
	(0.04)	(0.02)	(0.05)	(0.08)	(0.05)	(0.33)	(0.05)	(0.13)

2010×A	0.07*	-0.02	-0.00	-0.07	0.08*	-0.03	0.14***	-0.05
	(0.04)	(0.02)	(0.04)	(0.14)	(0.04)	(0.34)	(0.05)	(0.12)
SETS P1	0.02	0.01	-0.01	-0.01	0.04	0.19	0.13***	-0.24**
	(0.03)	(0.02)	(0.03)	(0.05)	(0.04)	(0.22)	(0.05)	(0.10)
SETS P2	-0.08*	0.06***	-0.01	-0.10*	-0.07	0.18	0.01	-0.33***
	(0.04)	(0.02)	(0.04)	(0.06)	(0.05)	(0.24)	(0.05)	(0.10)
Obs.	862,444 to 933,023	867,191 to 939,864	868,120 to 940,814	856,070 to 927,558	860,104 to 932,812	53,162 to 62,557	866,218 to 938,575	200,294
Groups	143,197 to 145,813	144,014 to 146,516	144,082 to 146,582	143,386 to 146,046	144,087 to 146,585	12,118 to 12,858	143,728 to 146,220	37,459

Source: authors' compilation. Standard errors clustered by plant in parenthesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$.

Finally, we also show the estimates of equation (3) and (4) for the EI sample in table 8, while results from non-EI sample are included in Appendix D. Many of the results are in line with the estimates shown in table 5. For instance, we observe an increase in export share among EI plants, estimated around 46.14%. The fall in investments observed in the main model is also consistent: investments among EI firms fall during both phases of SETS (-21.25 to -27.79%). However, we can also note that EI plants experienced some change in their economic indicator following the policy announcement. Most notably, EI plants witness a rise in employment by 7.58% in 2010, one year before the start of the policy while wages are shown to fall by 4.95% in 2009, perhaps as a consequence of the increase in employment. Interestingly, we find no improvement in labor productivity during this period. Overall, their costs are increasing by 15.14% one year before the start of the policy while revenue increases by 8.56%, leading to a lack of significant effect on value added (or a slightly negative one, though only significant at 10% level).

4.5 Heterogeneity in compliance method

Despite it being a voluntary scheme, SETS is characterized by a high degree of compliance among plants. Table 1 also showed that plants met their emission reduction targets via two methods: purchasing carbon offsets and credits (17%) or simply on their own (83%), likely through some investment in energy efficiency or green technology. Each method is likely to bring out a different impact on employment, output or competitiveness, as plants purchasing credits might simply see an increase in costs, while investments on energy efficiency and green equipment might have some long-term effect on the productivity inside the plant. Therefore, in this section, we explore the mechanisms at play for plants that met the emission targets on their own. Specifically, we estimate the treatment effect of SETS among non-trading plants.[19] Results are presented in table 9, and are fairly similar to the main estimates.

[19] Ideally, we should also estimate the treatment effect among trading plants for comparison. However, the number of trading plants is too small (386 observations across 75 plants) to perform such analysis.

Table 9. Heterogeneity in compliance method

	Average treatment effect of SETS among non-trading plants	Overall sample	EI plants	Non-EI plants
Employment effect	Number of employees	-0.01	-0.04	-0.01
		(0.02)	(0.03)	(0.02)
	Wages	0.04***	0.03**	0.07***▼
		(0.01)	(0.01)	(0.02)
	Labor intensity	-0.05**	-0.01▼	-0.11***▼
		(0.02)	(0.03)	(0.03)
Output effect	Value added	0.04▼	-0.04▼	0.13***
		(0.03)	(0.05)	(0.04)
	Shipments	0.04*	-0.05	0.11***
		(0.02)	(0.04)	(0.03)
Competitiv-eness effect	Export share	0.11▼	0.39*▼	-0.03▼
		(0.13)	(0.20)	(0.14)
	Total costs	0.07**	0.01	0.11***
		(0.03)	(0.04)	(0.04)
	Investments	-0.12**▼	-0.26***▼	-0.04
		(0.05)	(0.08)	(0.07)

Source: authors' compilation. Standard errors clustered by plant in parenthesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. "▼" denotes variables that fulfill the conditional parallel trend hypothesis. Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$. "SETS" is a dummy variable taking the value "1" if a plant is targeted by SETS at a given year and did not engage in allowance trading or credits purchases.

In addition, we also examine the cost structure inside the plants, and analyze the effect of SETS on fuel and electricity expenditures separately. Results of this estimation are presented in table 10, as well as figure 5. Overall, we learn that plants who reached their emission targets without engaging in trading saw an increase in their electricity expenditures (4.55%), reflecting a possible electrification of the production process occurring one to three years after the start of the treatment. Electrification, however, is likely difficult for some sectors, namely, EI ones, such as cement, iron & steel or petrochemistry. Thus, we also analyze the change in fuel and electricity among EI and non-EI samples independently. Our results show that the electrification process is mostly driven by non-EI plants (6.77%), while these plants see little to no change in their fuel mix. On the other hand, EI plants are characterized by a stark increase in their fuel expenditures (12.66%), occurring instantly after the start of the treatment, but fading away four years later. This is likely explained by an increased usage of gas, potentially replacing oil inside the production process.[20] Interestingly, EI plants also witness an increase in electricity expenditures in the medium term (2-3 years after the start of the treatment). In other words, EI plants, most of which are 'hard to abate emissions'

[20] Alternatively, one could consider that these plants might be replacing coal with oil or gas. However, such substitution attempts require additional machinery investment from the plants, and are unlikely to occur instantaneously. In comparison, oil is often used in droplets inside production process, and can easily be substituted with gas. For further details on the elasticity of substitution between oil and gas, we refer to Bardazzi et al. (2015)

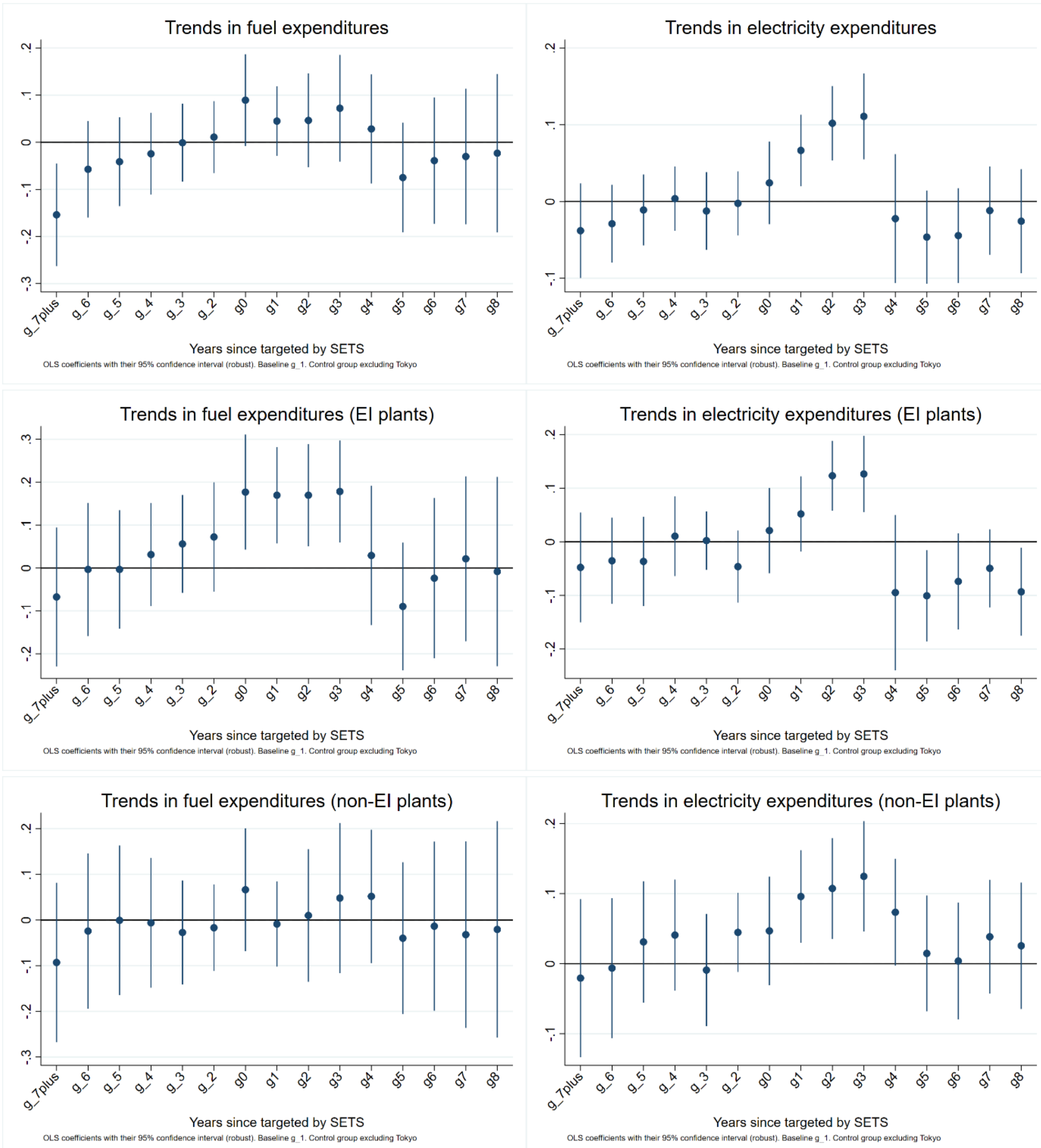
sectors, reach their emission targets via fuel switching as well as electrification, whereas non-EI sectors only engage in electrification.

Table 10. Treatment effect on fuel and electricity expenditures

	Overall sample		EI sample		Non-EI sample	
	Fuel	Electricity	Fuel	Electricity	Fuel	Electricity
SETS	0.06▼	0.04**▼	0.12**▼	0.04▼	0.03▼	0.07**▼
	(0.04)	(0.02)	(0.06)	(0.03)	(0.06)	(0.03)
Obs.	548,960	621,652	263,300	306,766	285,660	314,886
Groups	64,761	69,866	40,042	43,891	41,667	44,877
R^2	0.07	0.10	0.09	0.12	0.06	0.09

Source: authors' compilation. Standard errors clustered by plant in parenthesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. "▼" denotes variables that fulfill the conditional parallel trend hypothesis. Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$. "SETS" is a dummy variable taking the value "1" if a plant is targeted by SETS at a given year and did not engage in allowance trading or credits purchases. Summary statistics for fuel and electricity expenditures as well as the event study are available in Appendix F.

Figure 5. Dynamic DiD for electricity and fuel expenditures



Source: authors' compilation. OLS coefficients with their 95% confidence interval (with standard errors clustered by plant), with control variables and two-way fixed effects. Number of fiscal years since plant is targeted by SETS is represented on horizontal axis. "g_1" should be understood as "one fiscal year before the start of treatment" whereas "g1" should be understood as "one fiscal year after the start of treatment." The validity of the conditional parallel trend hypothesis is detected by the lack of statistical significance of pre-treatment (g_) coefficients.

5. Discussion

This study examines the effect of a voluntary cap-and-trade policy on the economic performance of plants belonging to the manufacturing sector. We analyze the case of the voluntary cap-and-trade policy of Saitama prefecture, introduced since 2011. We distinguish between three types of indicators: employment (as measured by the number of employees inside the plant, average wages and labor productivity), output (revenue and value added) and competitiveness (change in total costs, investment and export share).

One of the most consistent effect we observed was that the introduction of SETS resulted in an increase in wages, estimated at 3.66%, and was most pronounced after 2015. Interestingly, the rise in average wages does not depend on the level of energy intensity inside the plant, as plants in both EI and non-EI sectors experienced this rise, though plants in non-EI sectors witnessed a sharper increase in their wages (5.99%). The rise in wages is also mostly felt among plants that belong to SMEs (4.48%) rather than plants belonging to larger firms. However, we fail to observe any significant impact of the policy on employment inside plants, regardless of the sector of analysis. To be precise, we do observe a slight increase in employment among EI plants shortly before the start of the policy (leading to a fall in wages in the same years): this could be because EI plants tried to increase their production shortly before the start of the policy. The lack of effect of the employment is a departure from the literature, as studies tend to find a positive effect of carbon taxes or ETS on employment (Dechezlepretre et al, 2023; Marin et al., 2017; Yamazaki, 2017). One possible explanation for this effect lies in the job market structure, as it may be difficult to hire new employees in Japan due to ageing population. Overall, we also find that SETS had a positive impact on labor productivity (-5.26% fall in labor intensity). This particular effect is found to be driven by plants in non-EI sectors (-12.08 to -15.27%) and plants belonging to SMEs (-5.35%), in line with the literature (Chen et al., 2024).

We also find that SETS had a positive effect on value added, estimated between 6.07% to 27.92%. This effect is shown to be driven by plants belonging to non-EI sectors (18.13 to 31.22%), as well as plants belonging to SMEs (10.46 to 25.91%). We also observe an increase in plants' shipments (and therefore revenue) by a similar magnitude in the same period, once again driven by plants in non-EI sectors and belonging to SMEs. The increase in production coupled with the lack of effect of the policy on employment is one of the possible explanation behind the improvement in labor productivity. Furthermore, since SETS increases value added, this could be another reason behind the rise in wages in targeted plants: the increase in profits from the targeted plants could have been redistributed among employees in the form of higher annual bonuses, for instance. This result is also a departure from the literature, as many studies highlight that ETS may increase a plant's revenue, but also increases its costs, leaving value added unaffected (Chan et al., 2013; Dechezlepretre et al., 2023; Marin et al., 2017).

The effect of SETS on competitiveness is not as clear, however. On one hand, our analysis showed that the policy contributed to an increase in costs, estimated between 10.41% to 24.66%. This increase in costs is mostly driven by plants belonging to large firms, as well as plants in non-EI sectors. Interestingly, the increase in costs is found even prior to the start of the policy, one or two years following its announcement. The increase in costs can be traced to a fuel costs increase, in line with Tian et al. (2025) who showed that the pilot ETS in Beijing prompted plants to switch to cleaner fuel. Furthermore, we find that SETS resulted in a fall in investments among EI plants (-20.78%) after 2015. This result is a sharp contrast with the literature, as the trial period of EU ETS led to an increase in investment intensity and capital deepening (Marin et al., 2017) or an increase in assets (Dechezlepretre et al., 2023). While these results feed concerns over a loss of competitiveness domestically, we also find that the policy did not affect exporting plants, as the policy had no statistically significant effect on export share.

In other words, our results show that SETS had a mostly positive impact on Japanese manufacturing plants, despite being a voluntary cap-and-trade policy. The fact that SETS had an effect is not entirely surprising, as the literature showed that the scheme indeed resulted in a fall in emissions (Yajima, et al., 2021), and table 1 showed that most targeted plants complied with the policy. The reasons behind this high compliance may be linked with the Japanese context: after all, previous studies have shown that light-handed policies can be successful in the country (Arimura et al., 2019; Mortha et al., 2024). It is also possible that many firms wish to avoid being seen as non-compliers[21], fearing for their public image, leading to an indirect 'fine' system. Finally, since the policy was announced three years before its implementation, it is also likely that the long preparation period allowed many plants to alter their production structure or invest in new equipment, as shown by Hamamoto (2021a).

Still, the increase in value added and wages is a departure from the literature on the effects of the EU ETS in its early days. There are mainly two mechanisms at play in the case of SETS. Our results showed that the total increase in costs is due to an increase in electricity expenditures as well as clean fuel switching (among EI plants), similar to the Beijing pilot ETS (Tian et al., 2025). The rise in electrification or clean fuel expenditure could have provided an incentive for plants to switch their equipment, as well as increase labor efficiency. In their search for efficiency gains (in all production inputs, whether in energy or labor), plants are likely to have increased their R&D expenditures, an effect that is also found by Lu et al. (2023). Jia and Takeuchi (2024) also found that SETS plants increased their patents' holdings in clean energy (renewable and fossil fuel technologies). If targeted plants are indeed using more recent equipment and are shown to increase their R&D expenditure as well as their patents' holdings, it follows that these plants would have higher value added, labor productivity and wages.

6. Conclusion

[21] The names of plants (and their owning firms) that fail to meet their targets are reported by the prefecture

As global temperatures are steadily rising and natural disasters are increasing in frequency and intensity, the necessity to address climate change is becoming more pressing every year. While many environmental regulations were introduced in 2010s, many countries are now pushing back on climate change policies, for fear of hurting economic recovery or fueling inflation. For this reason, we are now witnessing the rise of voluntary actions and policies, which are politically easier to implement than their mandatory counterparts.

In this research, we evaluated the impact of a voluntary cap-and-trade on the economic performance of manufacturing plants, analyzing the case of the Japanese Saitama ETS, implemented in 2011. This policy was implemented more than a decade ago, but little is known about its economic impact. We utilize a rich dataset containing data from Japanese plants from 2004 to 2019, and estimate the average treatment effect of the policy using DiD and PSM methods. Our results showed that SETS had a positive effect on value added, estimated between 6.07% to 27.92%, compared with non-targeted plants. This policy also had a positive impact on employment, as wages are shown to increase by 3.66%, as well as a rise in labor productivity (5.26%) of similar magnitude. The positive effects of the policy are mostly experienced by non-EI sectors, as well as plants belonging to SMEs. The policy also did not affect the plants' competitiveness, despite an increase in total costs. It is likely that the positive impacts of SETS are due to an increase in fuel and electricity costs, prompting plants to invest in R&D and innovative patents, thereby increasing their value added, wages and labor intensity.

Japan is set to implement its first nation-wide cap-and-trade policy in 2026, and many industrial regions are welcoming this policy with unease, as many fear a potential loss of competitiveness. In this sense, the experience of Saitama may serve as a reference point. Since many economies have introduced or are considering voluntary environmental policies, our results may be used to improve our understanding of the effect of the future Japanese ETS. Beyond Japan, these results may be helpful for countries planning to implement cap-and-trade policy as well. Since this study showed that voluntary cap-and-trade policies are mostly having a positive effect on economic performance without harming competitiveness, it could also help enhance the political acceptability of carbon pricing worldwide.

Still, our study suffers from several limitations. First, it is difficult to determine to which extent our results are due to the Japanese specific context. Previous literature showed that carbon pricing policies generally tend to increase employment, but we fail to observe this effect, perhaps due to ageing population trends. In addition, the literature also showed that voluntary policies tend to more successful in Japan, and thus, it is difficult to know whether we could expect similar results elsewhere, especially among developing countries. While we do verify that DiD identifying assumptions are fulfilled (SUTVA, common trends), there is still a possibility of sorting behaviors among plants: plants whose emissions were close to the target threshold might have altered their energy consumption to ensure that they belong in the control group.[22] Furthermore, given that our PSM results slightly differ between Kanto and the rest of Japan, it is possible that SETS might have affected neighboring prefectures (via employment spillover) or plants belonging to the same firm as targeted plants (via knowledge spillover). Finally, our conclusions are limited to large plants, as we are only analyzing plants with non-missing covariates. In general, plants in our sample tend to be larger than the national average[23], as smaller plants tend to have lower response rates or leave many survey items unfilled. We leave these considerations for future research.

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9. Appendix

A. Additional background on SETS

The design of SETS was discussed from 2008 by the Expert Committee on Measures to Combat Global Warming. We provide the composition of the Committee in the table below. In a typical Japanese fashion, these committees feature prefectural and public officials, academic experts as well as representatives from the private sector and union. Two subcommittees were specifically assigned to the design of SETS prior to the implementation of its first and second phase.

A1. Committee Composition

Committee Name	Tenure	Committee Composition
Expert Committee on Measures to Combat Global Warming (地球温暖化対策の検討に関する専門委員会委員名)	FY2015	Saitama Prefecture - Center for the Promotion Global Warming Countermeasures Activity National Institute for Environmental Studies Saitama Consumers' Co-operative Union Saitama University Saitama Prefecture – Environmental Science Division Waseda University Tokyo Denki University Hosei University Saitama Prefectural Industrial Technology Center Saitama Trucking Association Saitama Prefecture Housing Construction Council

Subcommittee on the Study of Target-Based Emissions Trading Schemes (目標設定型排出量取引制度の検討等に関する小委員会)	FY2009 ~ FY2011	Society Environmental Management The Institute of Energy Economics, Japan Tokyo Denki University Saitama University Saitama Employers' Association Waseda University
Subcommittee on Target-Based Emissions Trading Schemes (目標設定型排出量取引制度小委員会)	FY2013~ FY2014	The Institute of Energy Economics, Japan Waseda University Tokyo Denki University Saitama Employers' Association

Source: Saitama Prefecture website. https://www.pref.saitama.lg.jp/a0502/ontaisenmon.html

The composition of past Committee is not readily available on the prefecture website, hence we provide the composition for FY2015 only.

A2. Selected Quotes from the Committees' Meeting regarding SETS

Main theme	Selected quote
Regarding the effectiveness of a voluntary scheme	"We do not believe there will be a significant difference in effectiveness depending on whether penalties are imposed or not. I think it would be a good idea to try a different approach from Tokyo's and compare the results. We will work out the detailed system design and present it to you in the future" (2008/06/16) "While the effectiveness of voluntary emissions trading is questionable, we should announce a specific year for implementation [of a scheme featuring penalties]" (2008/06/16) "We doubt a market can function under a non-binding system. We believe it is necessary to conduct a review in a few years and proceed with further consideration. We also question whether it will be effective." (2008/07/29)
Concerns over potential carbon leakage, loss of competitiveness and additional costs	"Many companies operate across multiple prefectural boundaries, making it extremely difficult to assess reduction effects on a prefectural basis" (2008/07/29) "Strengthening climate change countermeasures in Saitama Prefecture could prompt high-quality companies to relocate outside the prefecture, thereby affecting employment and tax revenue" (2008/07/29) "In emissions trading, costs are incurred for verifying reduction amounts. It is also important to consider measures that do not incur such costs." (2010/03/30)

	“We also need to examine how to handle emission reductions achieved outside the prefecture and how to utilize credits from Tokyo.” (2010/03/30) “While the term “[emission] reduction” might suggest that this scheme is the primary driver, we should also consider factors such as the value of manufactured goods shipped. It will be necessary to compare these indicators as well going forward.” (2011/03/28) “This is not a topic where results can be seen within a single year. It involves transforming the environmental structure of Japanese industry. I believe it is prudent to tackle this issue by taking things step by step.” (2012/03/26)
Comparison with the Tokyo scheme, that features penalties for non-compliers	“While Tokyo’s standards are quite strict, there is concern that Saitama Prefecture’s example—which lacks penalties—could lead the national government’s efforts in a lax direction” (2008/07/29) “If reduction targets are not met by 2014, the end of the first planning period, will the policy be reviewed—including the possibility of imposing penalties, as Tokyo has done?” (2010/03/30) “From Tokyo’s perspective, the city may feel that while it is taking a hard line, Saitama Prefecture is being too lenient by taking practical realities into account. We want them to create a system that applies enough pressure to ensure actual transactions take place. We want them to consider their next steps in preparation for the second planning period.” (2012/03/26) “There has been no progress at the national level regarding the emissions trading system. Don’t you feel that the national government is holding back Tokyo and Saitama Prefecture?” (2012/03/26)
Emphasis on energy saving efforts rather than credit trading	“Regarding a voluntary emissions trading system, wouldn’t it be more acceptable to businesses if we placed greater emphasis on energy-saving support?” (2008/07/29) “Given the difficult circumstances surrounding emissions reductions in the industrial sector, I understand that purchasing emission reduction credits may be a cost-effective way to meet reduction targets; however, I strongly urge policymakers to insist that companies prioritize their own reduction efforts.” (2010/03/30) “How exactly will energy-saving and power-conservation efforts by small and medium-sized enterprises (SMEs) be converted into credits? If SMEs can see how this works, wouldn’t it serve as an incentive for them to reduce emissions?” (2012/03/26)
On the reason why SETS was designed	“Given the lack of clarity regarding the national direction, the decision to launch our own system is quite characteristic of Saitama. It reflects

without any penalty	Saitama's unique approach by balancing the economy and the environment while taking industry opinions into account" (2010/03/30)

Source: Saitama Prefecture website. https://www.pref.saitama.lg.jp/a0502/ontaisenmon.html

Each meeting's log is publicly available on the website. However, the logs do not specify which party (academia, private, union) the comment came from. In this table, we only report the comments that came from external participants (non-prefectural employees), with the exception of "On the reason why SETS was designed without any penalty" and the first two quotes of "Regarding the effectiveness of a voluntary scheme"

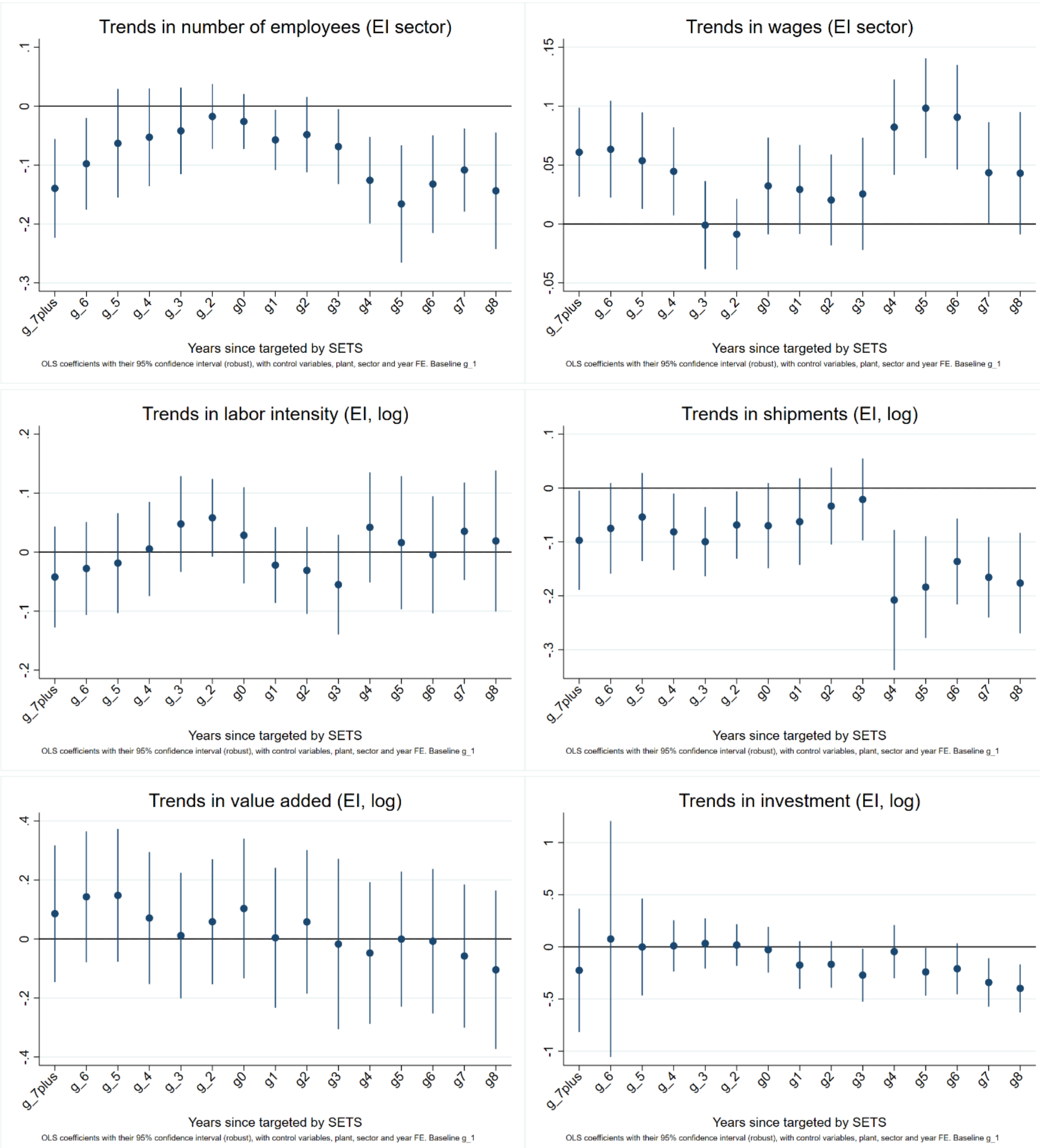
A3. Treatment timing

Year of first treatment for plants belonging to the treatment group	Number of observations	Percentage [Cum.]	Number of plants	Percentage [Cum.]
2011	3,197	56.61% [56.61%]	224	49.12% [49.12%]
2012	1,629	28.85% [85.46%]	138	30.26% [79.39%]
2013	181	3.21% [88.67%]	19	4.17% [83.55%]
2014	65	1.15% [89.92%]	7	1.54% [85.09%]
2015	100	1.77% [91.59%]	9	1.97% [87.06%]
2016	239	4.23% [95.82%]	25	5.48% [92.54%]
2017	70	1.24% [97.06%]	10	2.19% [94.74%]
2018	94	1.66% [98.72%]	15	3.29% [98.03]
2019	72	1.28% [100%]	9	1.97% [100%]
Total	5,647		456	

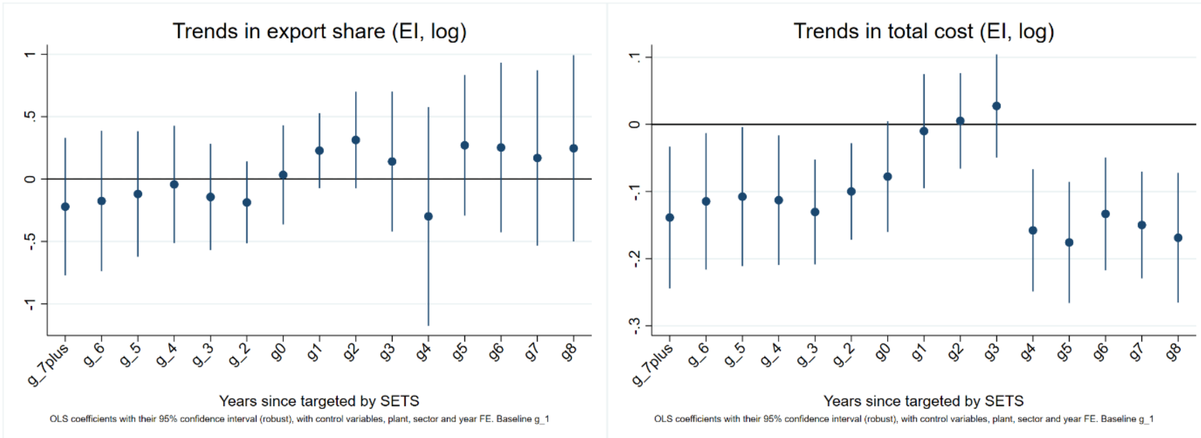
Source: authors' compilation. Cumulative percentage in square brackets.

B. Additional material for DiD event study

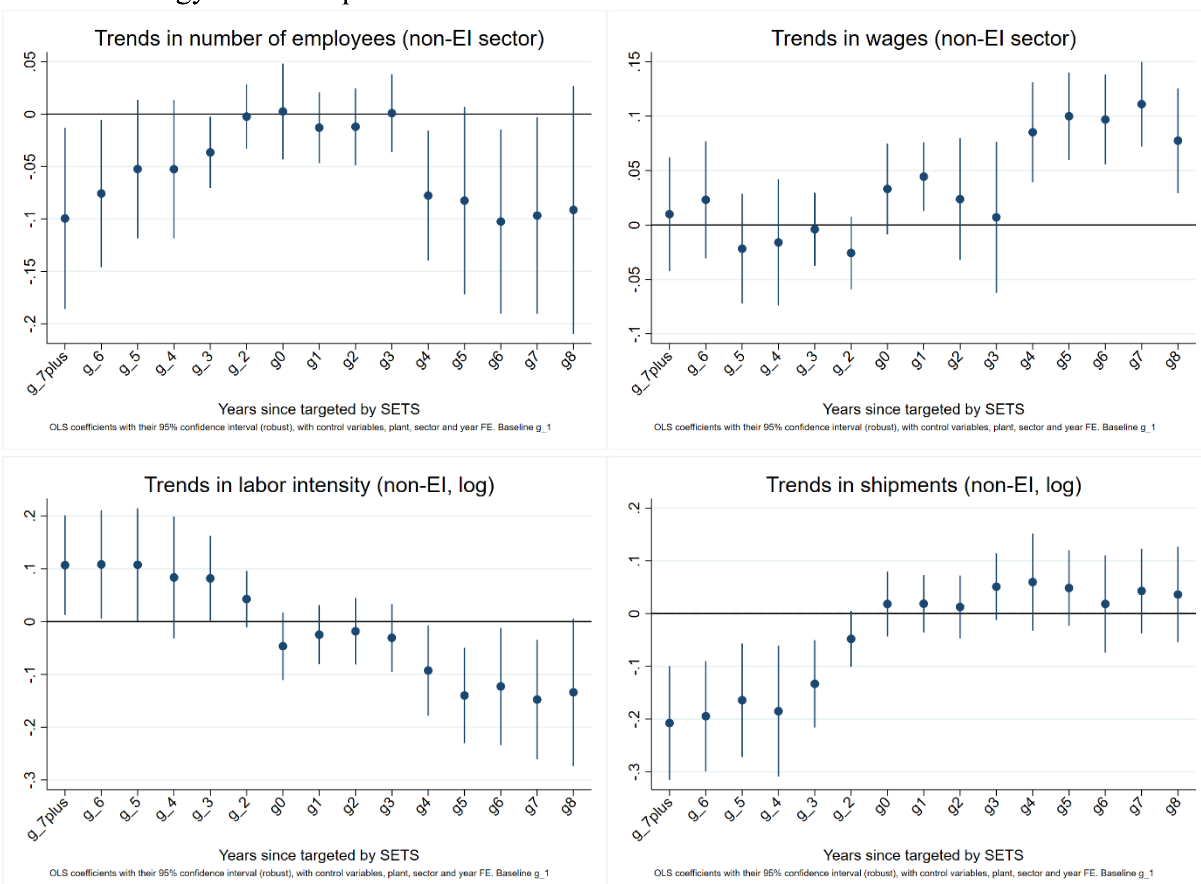
B1. Energy-intensive plants

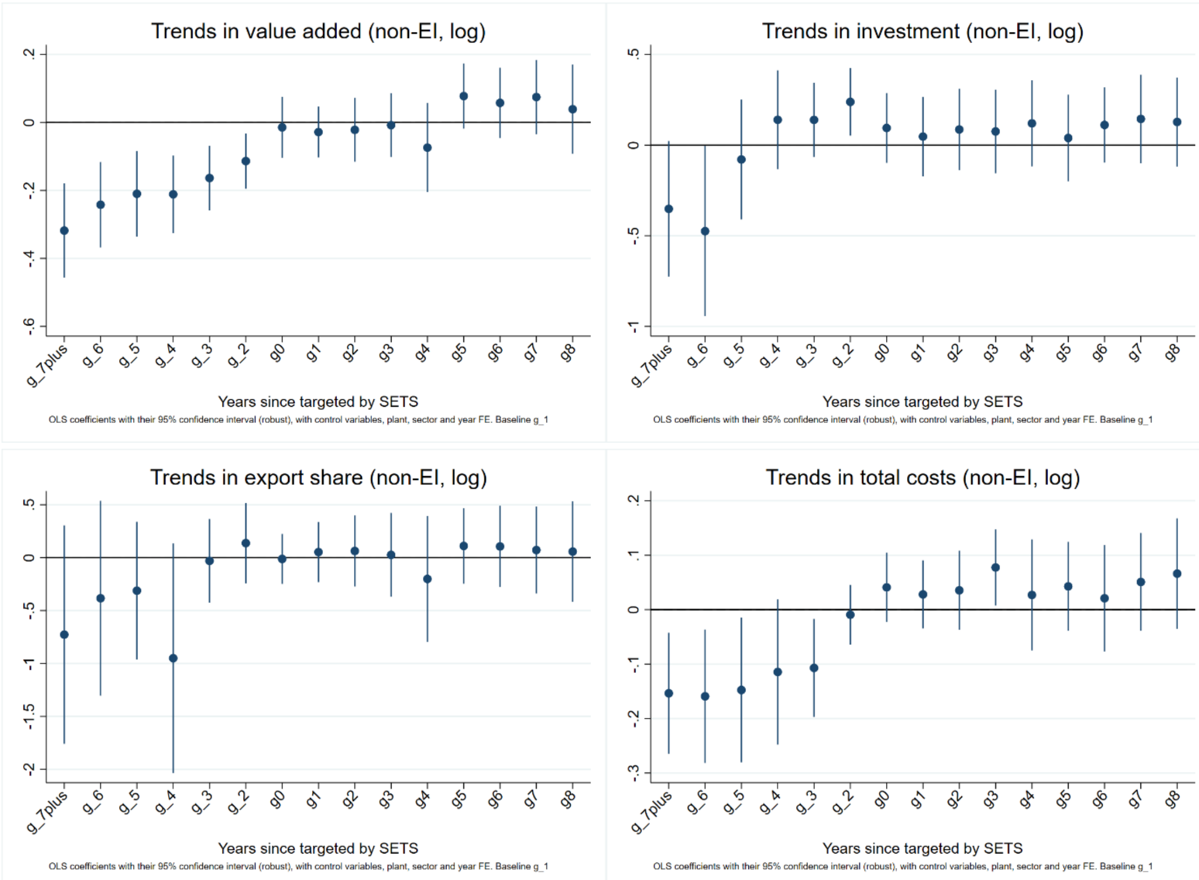


Trends in number of employees (EI sector)
Trends in wages (EI sector)
Trends in labor intensity (EI, log)
Trends in shipments (EI, log)
Trends in value added (EI, log)
Trends in investment (EI, log)
g_7plus g_6 g_5 g_4 g_3 g_2 g0 g1 g2 g3 g4 g5 g6 g7 g8
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1



B2. Non-energy-intensive plants




Trends in value added (non-EI, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in investment (non-EI, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in export share (non-EI, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in total costs (non-EI, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
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g6
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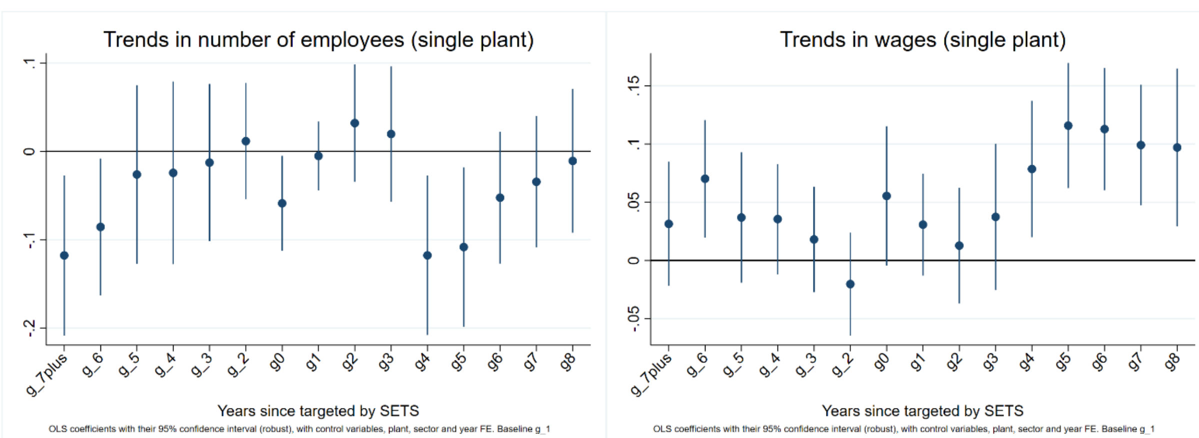
g8

B3. SMEs


Trends in number of employees (single plant)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in wages (single plant)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
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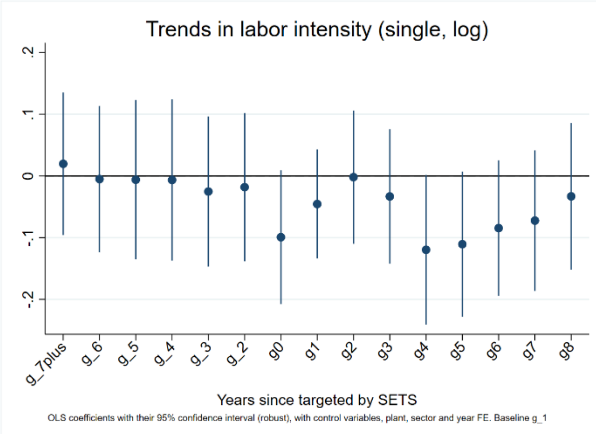
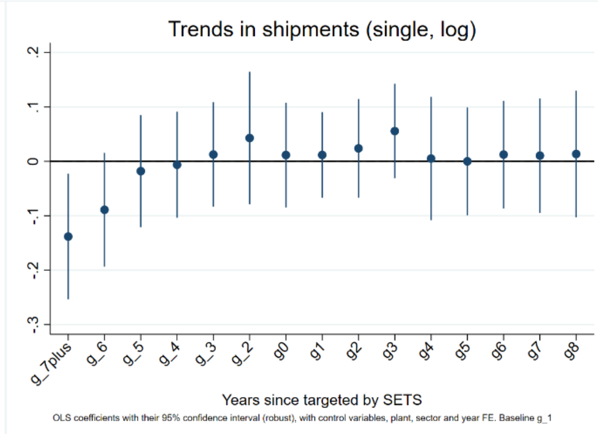
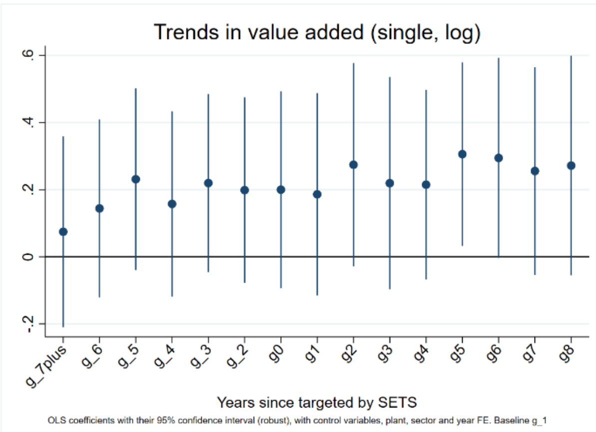
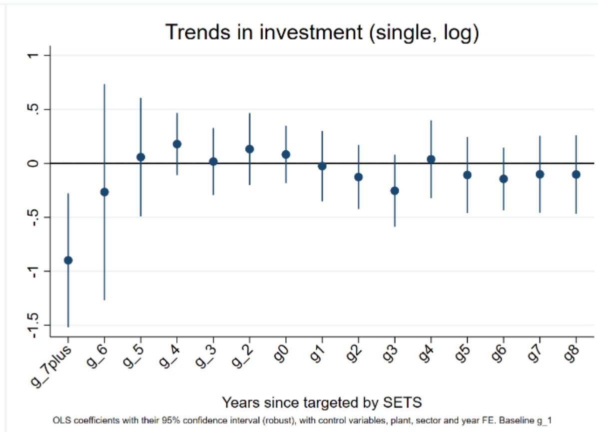
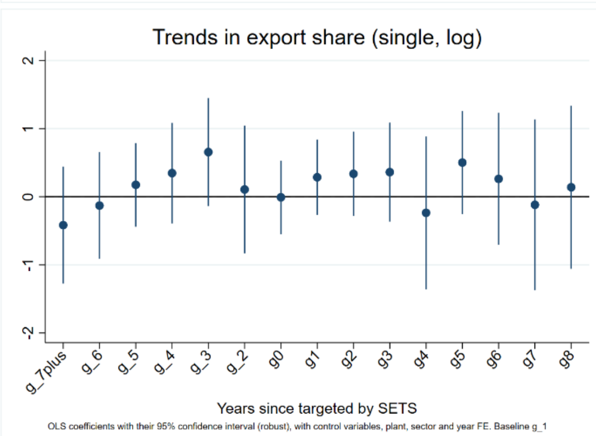
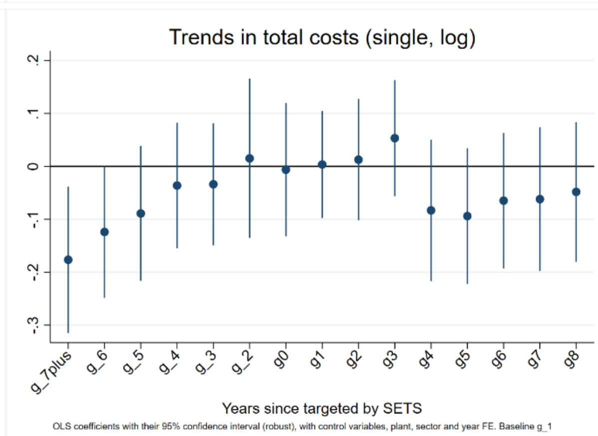




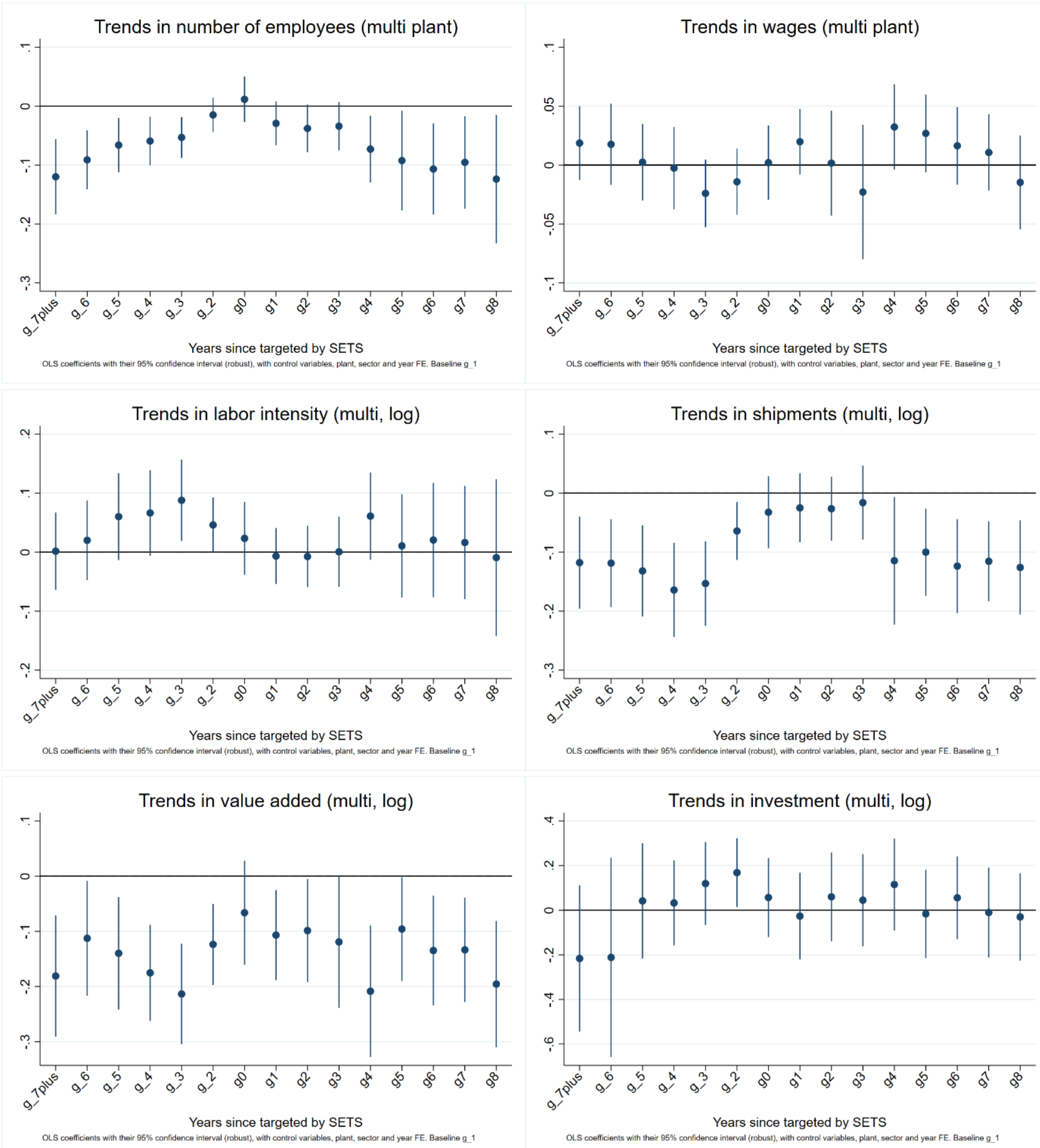








B4. Large firms


Trends in number of employees (multi plant)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in wages (multi plant)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in labor intensity (multi, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in shipments (multi, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in value added (multi, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
Trends in investment (multi, log)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust), with control variables, plant, sector and year FE. Baseline g_1
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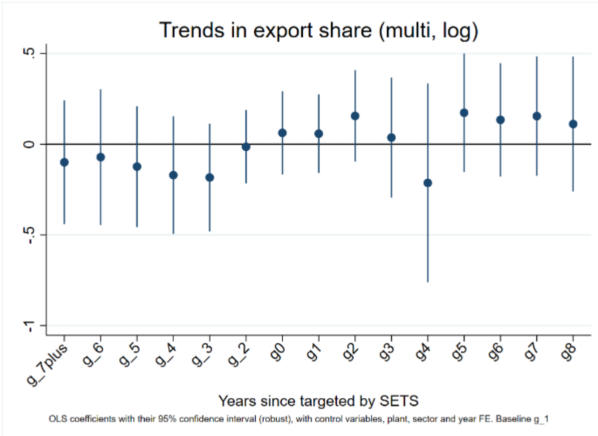
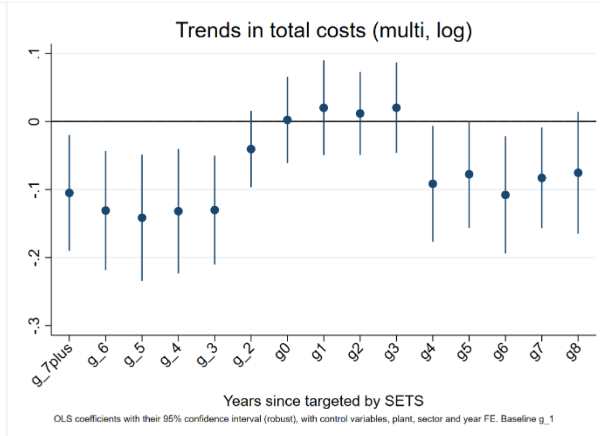




B5. Baseline results. Control group: plants excluding Tokyo as well as non-ETS plants in Saitama.

	Employees	Wages	Labor intensity	Shipment	Value added	Export share	Total costs	Investment
SETS	0.01	0.04***	-0.06***	0.07***	0.06**	0.19	0.10***	-0.10**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.13)	(0.03)	(0.05)
Obs.	1,783,495	1,796,810	1,799,401	1,785,031	1,770,614	105,600	1,794,453	398,143
Groups	256,637	257,071	257,357	257,380	256,353	19,096	256,810	56,320
R^2	0.25	0.03	0.05	0.17	0.16	0.01	0.13	0.04
Control group	All except Tokyo and non-ETS Saitama plants							

Source: authors' compilation. Standard errors clustered by plant in parenthesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. "▼" denotes variables that fulfill the conditional parallel trend hypothesis.

B6. Baseline results. Control group: plants in Kanto, excluding Tokyo as well as non-ETS plants in Saitama.

	Employees	Wages	Labor intensity	Shipments	Value added	Export share	Total costs	Investment
SETS	0.01	0.04***	-0.06***	0.08***	0.06***	0.15	0.11***	-0.06
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.13)	(0.03)	(0.05)
Obs.	310,856	314,450	314,987	312,174	310,291	22,784	313,647	77,135
Groups	44,011	44,143	44,193	44,198	44,024	4,006	44,040	10,827
R^2	0.15	0.00	0.06	0.13	0.07	0.00	0.12	0.03
Contro l group	Kanto plants except Tokyo and non-ETS Saitama plants							

Source: authors' compilation. Standard errors clustered by plant in parenthesis. Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. "▼" denotes variables that fulfill the conditional parallel trend hypothesis.

C. Matching diagnosis on sub-samples and sector composition

C1. Matching diagnosis

		Plants in Kanto prefectures	Plants in non-neighboring prefectures	EI plants	Non-EI plants	Single plants	Multi plants
Unmatched sample	Capital	36.01***	38.69***	30.70***	24.88***	34.96***	16.06***
	Tangible fixed assets	40.38***	42.25***	26.95***	30.61***	45.52***	15.28***
	Fresh water usage	5.08***	5.27***	0.94	6.83***	16.70***	0.40
	Inventory from production	46.13***	55.91***	48.85***	29.16***	39.59***	23.53***
	Electricity costs	22.12***	35.33***	16.66***	33.46***	38.71***	10.47***
	Material costs	41.00***	42.96***	16.43***	42.18***	69.55***	15.62***
	Consignment costs	48.47***	47.14***	51.97***	17.66***	22.72***	23.32***
	Existence of other plants owned by the same firm	59.51***	60.41***	38.92***	45.76***	13.02***	10.67***
	Rubin’s B	121.7^{+}	128.6^{+}	93.7^{+}	131.1^{+}	54.1^{+}	50.1^{+}
	Rubin’s R	1.71	1.41	1.71	1.13	21.30^{+}	1.10
Matched sample	Capital	-1.36	-1.86*	-3.68***	-1.18	2.85***	-3.05***
	Tangible fixed assets	-2.17**	-1.86*	-2.49**	-2.06**	2.28**	-0.20
	Fresh water usage	-1.07	-3.71***	0.47	4.03***	1.90*	1.41
	Inventory from production	3.06***	-0.44	2.24**	0.70	-2.08**	2.53**
	Electricity costs	-0.80	-0.88	-0.87	-0.23	1.16	-0.46
	Material costs	0.42	-0.67	-3.90***	2.58**	0.84	1.15
	Consignment costs	0.14	1.63	1.89*	2.74***	-1.60	0.85
	Existence of other plants owned by the same firm	-0.71	-0.90	-0.53	-0.39	-0.32	-0.21
	Rubin’s B	15.3	16.5	25.1^{+}	23.4	34.0^{+}	16.5
	Rubin’s R	1.70	0.26^{+}	1.17	1.81	0.60	2.37^{+}

Source: authors’ compilation. “*”, “**”, “***” denote statistical significance at 10%, 5% and 1%, respectively. “$^{+}$” denote values that fall outside of the range recommended by Rubin (2001). We report t-statistics for a test in difference in means between matched and unmatched samples. Covariates are based on the year of 2010 (pre-treatment year).

C2. Sector composition

Energy intensive		Non-energy intensive	
Sector name	Number of observations	Sector name	Number of observations
Paper	91,834	Food	259,249
Chemicals	16,118	Beverage	39,096
Petrochemicals	114,887	Textile	115,664
Plastics	32,942	Wood	48,498
Ceramics	45,912	Furniture	53,373
Iron	28,561	Clothing	54,336
Nonferrous metal	232,272	Printing	50,890
Metal products	78,391	Rubber	11,319
Machinery - parts	188,469	Leather	89,560
Machinery - electronics	86,839	Machinery - digital	45,300
Machinery - transportation	27,027	Machinery - accessory	42,332
		Machinery - precision	99,309
		Others	63,692

Source: authors’ compilation.

D. Anticipation Models – other results

Figure D1. Anticipation and treatment effect among non-EI plants

TWFE	Employment effect			Output effect		Competitiveness effect		
	Employees	Wages	Labor intensity	Value added	Shipments	Export share	Total costs	Investment
A	0.08**	-0.01	-0.01	0.11**	0.12***	0.34	0.09**	-0.06
	(0.03)	(0.02)	(0.05)	(0.05)	(0.04)	(0.24)	(0.05)	(0.11)
SETS	0.04*	0.05***	-0.13***	0.21***	0.20***	0.32	0.18***	-0.05
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.24)	(0.04)	(0.09)
2008×A	0.05	0.02	0.02	0.04	0.05	0.42	0.02	-0.10
	(0.04)	(0.03)	(0.06)	(0.06)	(0.06)	(0.31)	(0.07)	(0.12)
2009×A	0.10**	-0.02	0.05	0.03	0.11**	0.44	0.08	0.07
	(0.04)	(0.03)	(0.06)	(0.06)	(0.05)	(0.34)	(0.05)	(0.13)
2010×A	0.10**	-0.02	0.00	0.13**	0.15***	0.36	0.11**	-0.14
	(0.04)	(0.03)	(0.06)	(0.06)	(0.05)	(0.33)	(0.06)	(0.13)
SETS P1	0.09***	0.02	-0.04	0.13***	0.17***	0.39	0.16***	-0.05
	(0.03)	(0.02)	(0.05)	(0.04)	(0.04)	(0.31)	(0.04)	(0.10)
SETS P2	0.01	0.09***	-0.15***	0.21***	0.20***	0.38	0.16***	-0.05
	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.32)	(0.05)	(0.10)
Obs.	907,179 to 961,957	912,621 to 968,382	914,345 to 970,122	898,507 to 953,506	907,219 to 963,001	46,003 to 49,597	911,691 to 967,356	216,772
Groups	154,666 to 157,320	15,102 to 157,714	155,346 to 157,957	154,512 to 157,180	155,321 to 157,932	10,441 to 10,789	154,962 to 157,567	37,311

Rounded up to two decimal points for clarity. "*", "**", "***" denote statistical significance at 10%, 5% and 1%, respectively. Marginal effect for logarithmic model is calculated as: $[\exp(\beta) - 1] \times 100$.

E. Attrition rates

Table E1. Evolution of the number of observations by survey year (overall sample)

	Overall sample	EI sector	Single plants
2004	43,698	24,468	23,492
2005	43,827	24,844	23,529
2006	40,965	23,396	22,105
2007	45,545	26,313	24,000
2008	44,397	20,484	23,185
2009	192,535	94,185	150,019
2010	209,386	98,460	166,562
2011	17,671	9,068	8,261
2012	184,576	90,048	142,607
2013	179,377	87,737	137,743
2014	190,254	91,002	146,793
2015	17,926	9,382	8,130
2016	180,550	86,957	139,318
2017	177,927	86,381	134,939
2018	175,246	85,665	131,878
2019	171,990	84,862	127,348
Total	1,915,870	943,252	1,409,909

Source: authors' compilation.

Table E2. Evolution of the number of observations by survey year (treatment group)

	Overall sample		EI sector		Single plants	
	Observations	Share	Observations	Share	Observations	Share
2004	336	0.77%	192	0.78%	101	0.43%
2005	342	0.78%	194	0.78%	98	0.42%
2006	306	0.75%	172	0.74%	90	0.41%
2007	364	0.80%	204	0.78%	105	0.44%
2008	361	0.81%	149	0.73%	103	0.44%
2009	379	0.20%	166	0.18%	106	0.07%
2010	391	0.19%	170	0.17%	102	0.06%
2011	169	0.96%	77	0.85%	42	0.51%
2012	393	0.21%	170	0.19%	100	0.07%
2013	406	0.23%	178	0.20%	96	0.07%
2014	409	0.21%	176	0.19%	93	0.06%
2015	169	0.94%	81	0.86%	36	0.44%
2016	409	0.23%	176	0.20%	97	0.07%
2017	406	0.23%	175	0.20%	97	0.07%
2018	406	0.23%	172	0.20%	96	0.07%
2019	401	0.23%	167	0.20%	93	0.07%
Total	5,647		2,619		1,455	

Source: authors' compilation. 'Share' represents the percentage of treated observations within the total number of observations for a given year.

Table E3. Attrition rates in the sample after start of treatment

Growth rate in the number of observations		2012-2014	2016-2019
Full sample	Overall	3.08%	-4.74%
	Treatment group	4.07%	-1.96%
	Control group	3.07%	-4.75%
EI sector	Overall	1.06%	-2.41%
	Treatment group	3.53%	-5.11%
	Control group	1.05%	-2.40%
Single plants	Overall	2.94%	-8.59%
	Treatment group	-7.00%	-4.12%
	Control group	2.94%	-8.59%

Source: authors' compilation. We exclude the years where the Survey of Economic Activities (2011, 2015) was conducted, as the number of observations falls considerably.

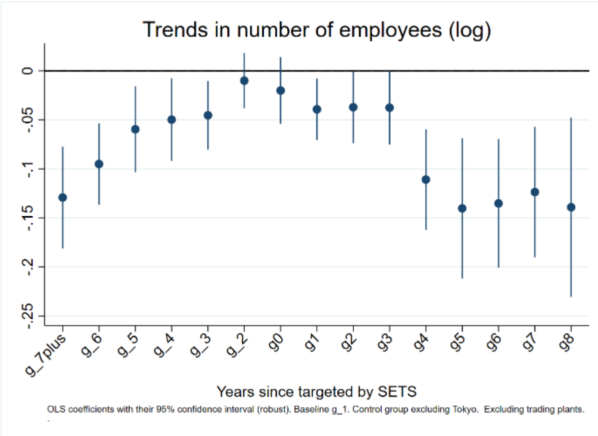
F. Additional material for heterogeneity in compliance method

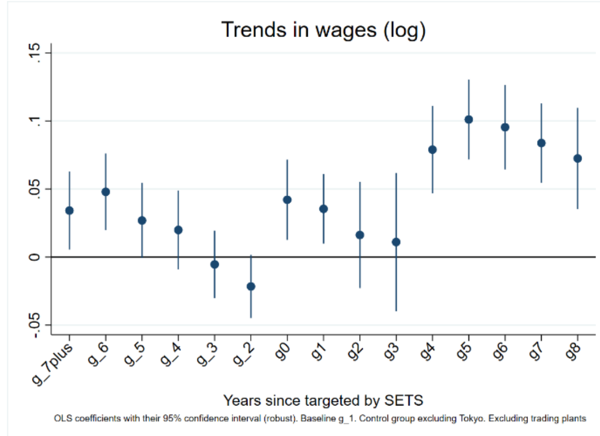
F1. Summary statistics for fuel and electricity expenditures

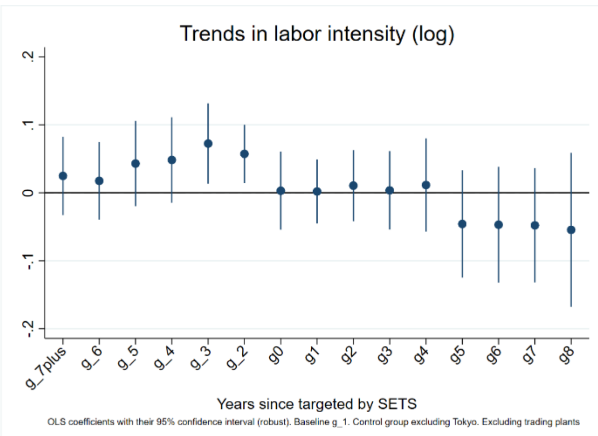
Variable name	Observations	Mean	Std. Dev.	Minimum	Maximum
Fuel expenditures	1,909,963	2,424.64	55,253.65	0	1.13e+07
Electricity expenditures	1,915,497	2,795.12	34,784.79	0	7,605,353

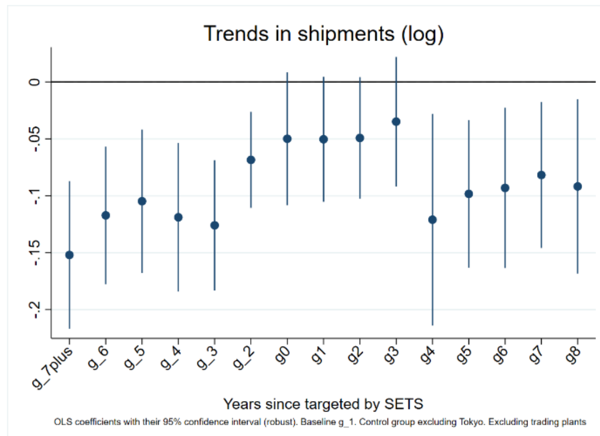
Source: authors' compilation. Rounded up to two decimals for clarity. Number of zero-valued (or missing) observations is 1,387,346 and 1,289,767 for fuel and electricity expenditures, respectively. Unit for expenditures is 10,000JPY.

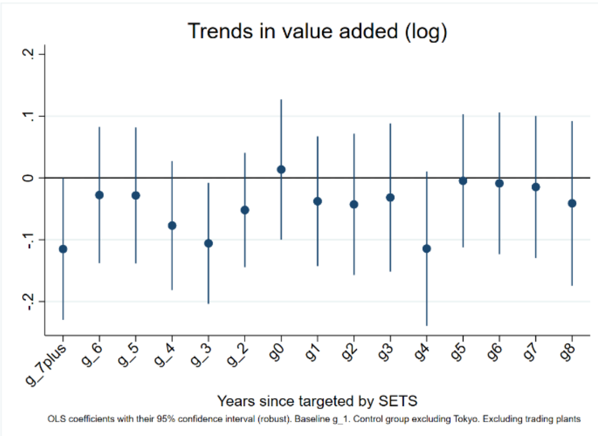
F2. Additional material for event study: overall sample

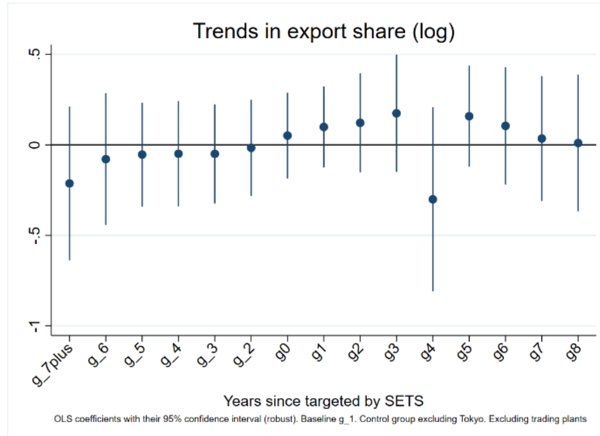


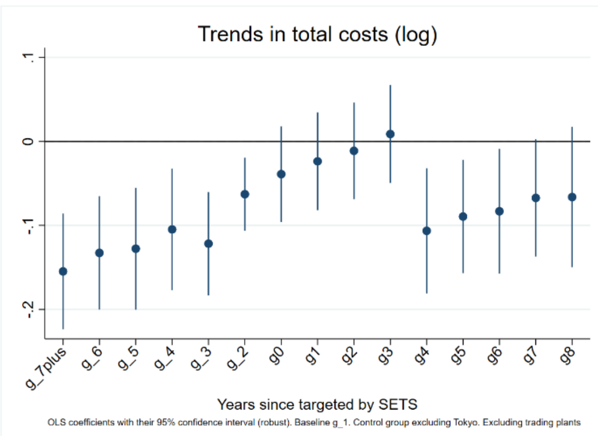


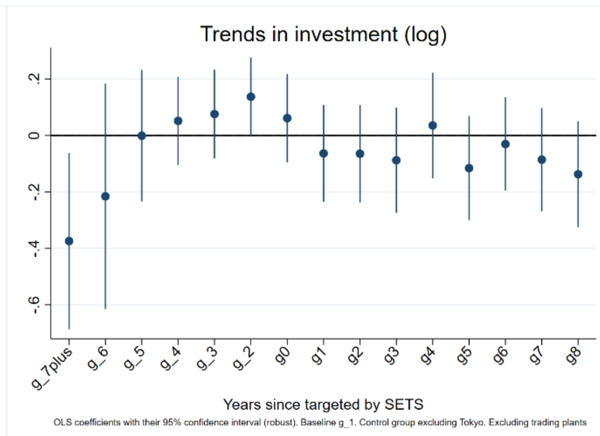




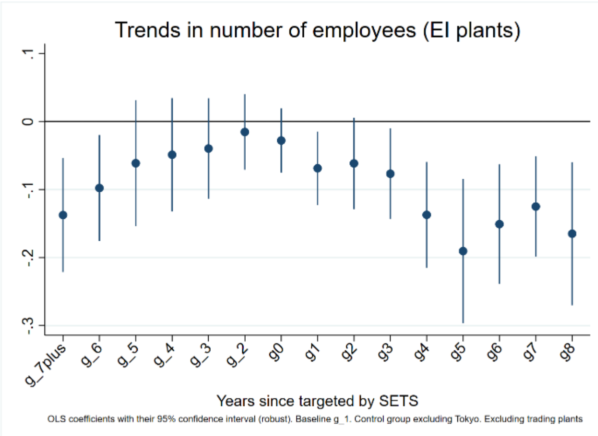


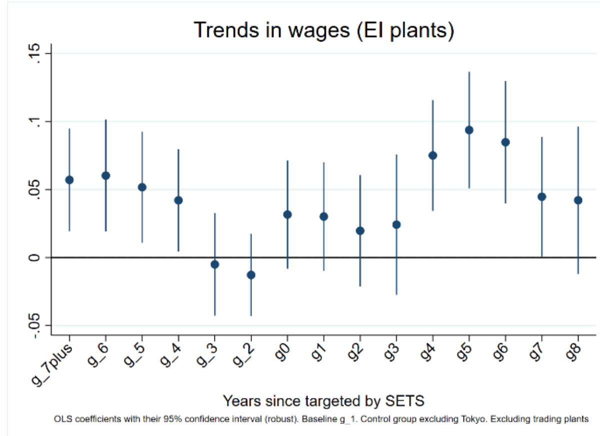


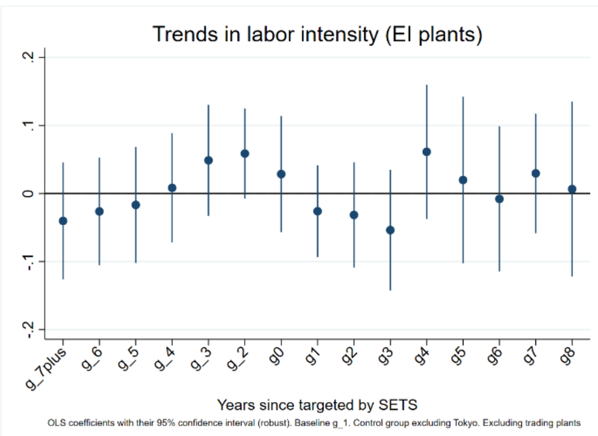


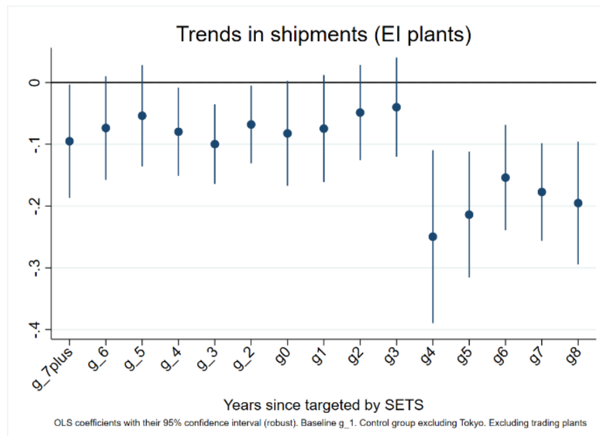


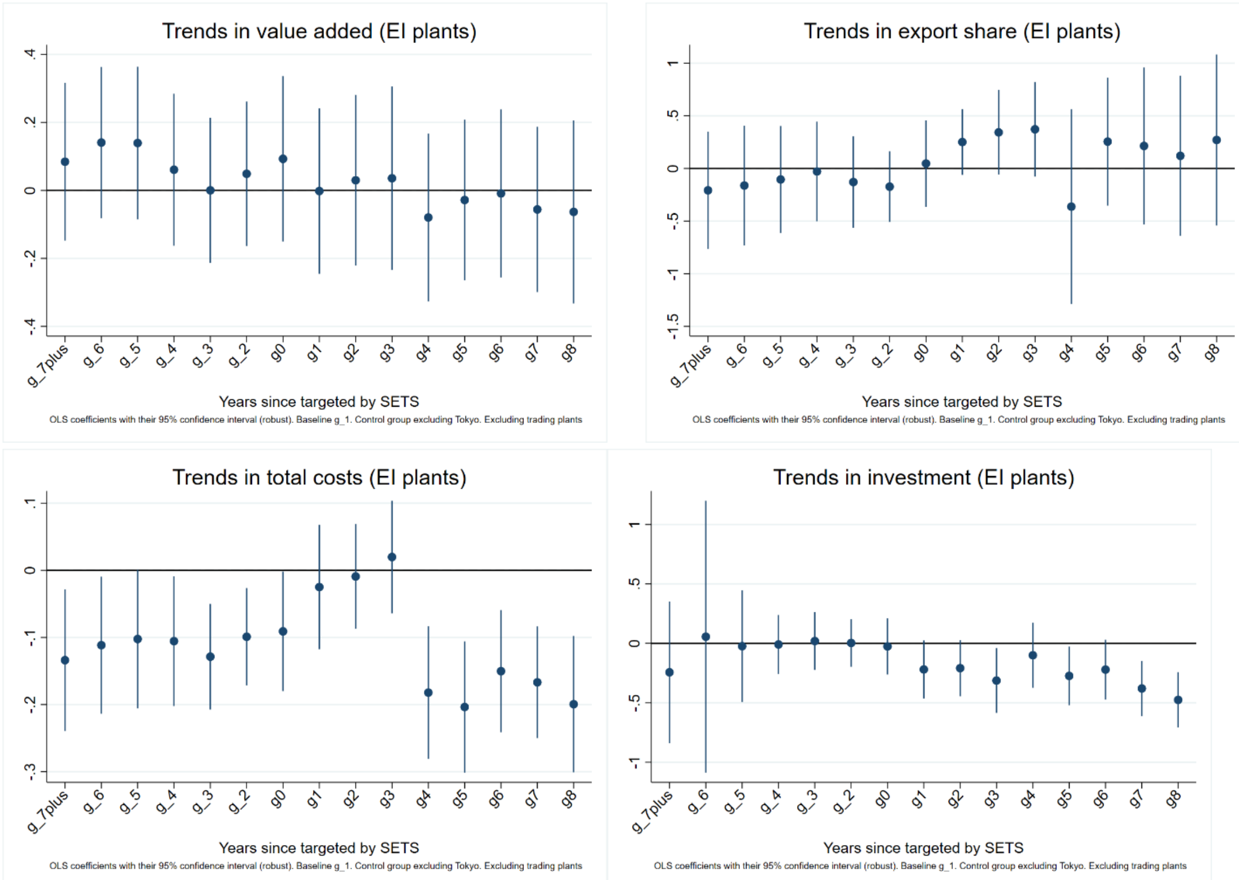
F3. Additional material for event study: EI sample


Trends in number of employees (EI plants)
.1
0
-.1
-.2
-.3
g_7plus
g_6
g_5
g_4
g_3
g_2
g0
g1
g2
g3
g4
g5
g6
g7
g8
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants

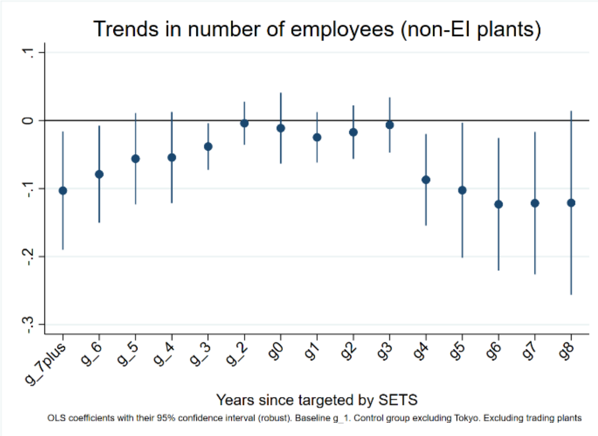

Trends in wages (EI plants)
.15
.1
.05
0
-.05
g_7plus
g_6
g_5
g_4
g_3
g_2
g0
g1
g2
g3
g4
g5
g6
g7
g8
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants

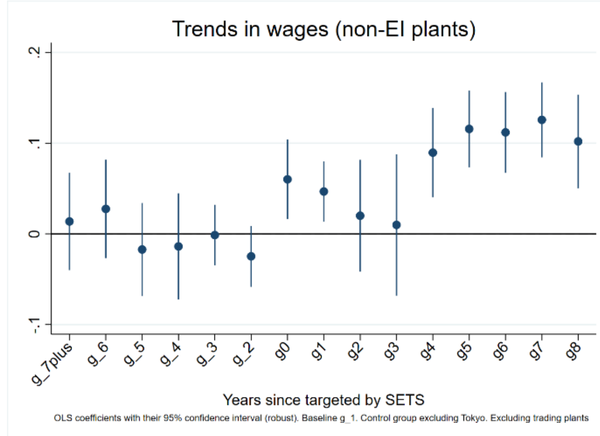

Trends in labor intensity (EI plants)
.2
.1
0
-.1
-.2
g_7plus
g_6
g_5
g_4
g_3
g_2
g0
g1
g2
g3
g4
g5
g6
g7
g8
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants

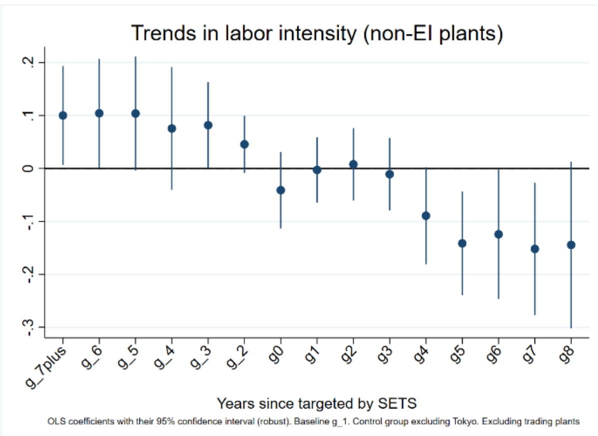

Trends in shipments (EI plants)
0
-.1
-.2
-.3
-.4
g_7plus
g_6
g_5
g_4
g_3
g_2
g0
g1
g2
g3
g4
g5
g6
g7
g8
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants

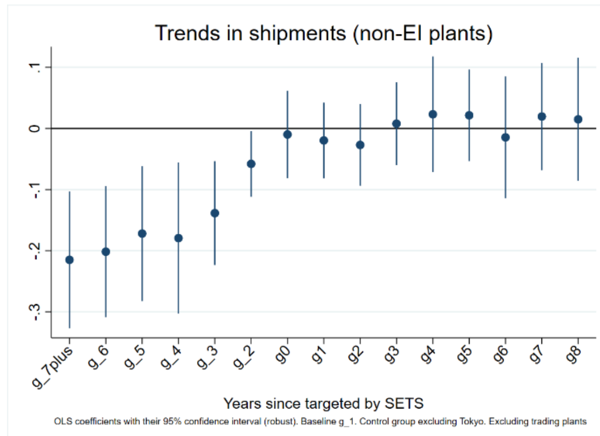


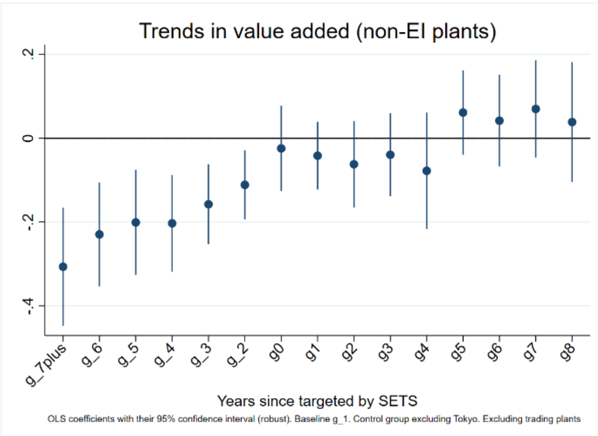
F4. Additional material for event study: non-EI sample

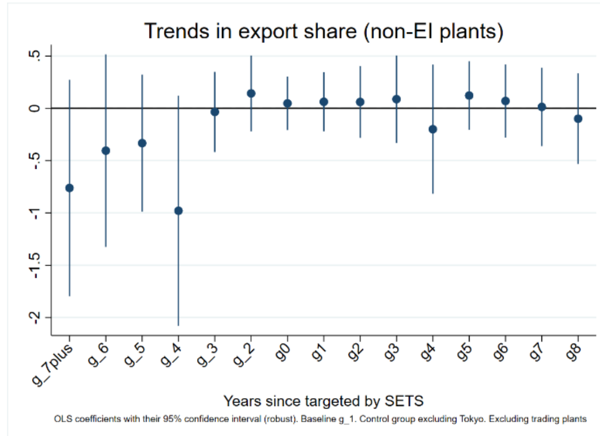

Trends in number of employees (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants

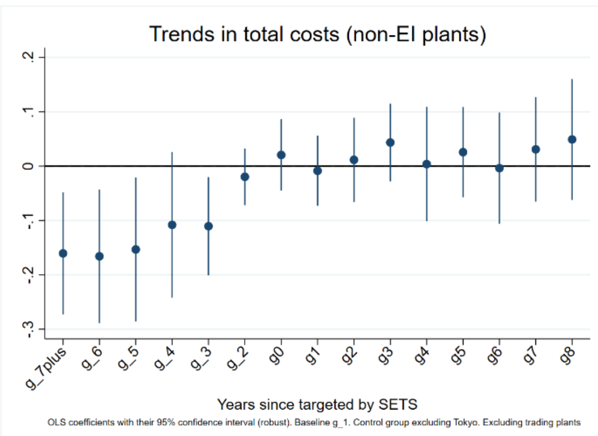

Trends in wages (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants

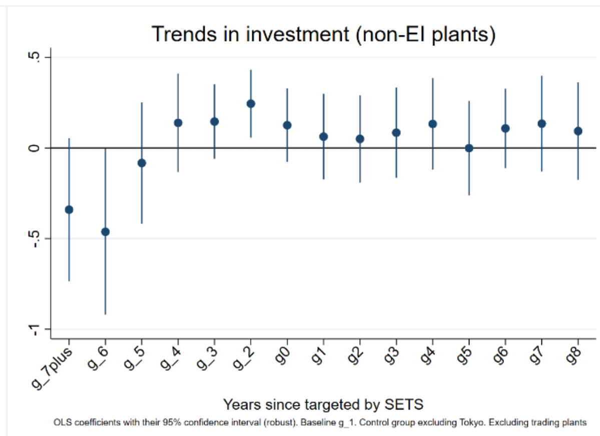

Trends in labor intensity (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants


Trends in shipments (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants


Trends in value added (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants


Trends in export share (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants


Trends in total costs (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants


Trends in investment (non-EI plants)
Years since targeted by SETS
OLS coefficients with their 95% confidence interval (robust). Baseline g_1. Control group excluding Tokyo. Excluding trading plants