Evaluating Emissions Reductions through the Regional Greenhouse Gas Initiative: A State and Plant-Level Analysis

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Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
Apr 11 2025

Acknowledgements

I am extremely grateful for the invaluable support and guidance of my primary faculty advisor, Professor Jeffrey DeSimone, throughout this thesis. Our weekly sessions helped me navigate the complexities of this research and significantly shaped its direction and strengthened its contributions. I am equally indebted to Professor Michelle Connolly, whose mentorship and engaging classroom instruction in my Honors Thesis course sharpened my methodological approach and greatly enriched my analysis. Her insights and support elevated both the rigor and clarity of this work.

I would also like to express my sincere gratitude to Professor Peter Arcidiacono and Matthew Lilley for their guidance in the DEAL Lab, as well as their insightful discussions that refined my research ideas and provided me with essential technical skills for this project. I am very appreciative of Professor Dakshina De Silva for guiding me toward the primary datasets utilized in this analysis, and of Professor Alexander Glass at the Nicholas School for inspiring my exploration of emissions policy within a broader environmental context.

Special gratitude goes to Karianna Klassen, Isabella Antonio, and Maggie Hu for numerous enlightening conversations that expanded my background knowledge and added depth to this research. I also thank Marcos Hirai Catao for his valuable feedback and constructive suggestions.

Finally, I am deeply thankful to my parents for their endless moral support, thoughtful input, and meticulous review of countless drafts throughout this journey.

Abstract

In this study, I examine the impact of the Regional Greenhouse Gas Initiative (RGGI) on emission reductions in the electricity sector, focusing on three critical dimensions. First, I analyze temporal trends in emissions reductions to evaluate whether previously demonstrated progress has slowed as states exhaust low-cost mitigation pathways. Second, I assess regional impacts within electricity grid management areas, particularly the Pennsylvania-Jersey-Maryland Interconnection Regional Transmission Organization (PJM ISO) where participating and non-participating states coexist, including investigating emissions leakage where reductions in RGGI states are offset by increases in neighboring non-RGGI states. Third, I extend the analysis to other greenhouse gases and co-pollutants. Employing difference-in-differences and synthetic control methods, the findings show that the RGGI has a significant on the intensive margin, significantly reducing operating hours and heat input across all types of power plants. Alongside these reductions, RGGI spurs net facility exits and promotes fuel switching toward lower-carbon sources. As a result, both pollutant intensity and aggregate emissions decline over time, underscoring the program's effectiveness. Examining these shifts in the context of regional electricity grids indicates that comprehensive coverage across interconnected markets can minimize leakage and better achieve environmental objectives, offering insights for the design of future regional climate policies.

JEL classification: Q41, Q48, Q52, Q58

Keywords: Cap-and-Trade, Emissions Leakage, Environmental Policy, Regional Greenhouse Gas Initiative

1. INTRODUCTION

Climate change is one of the greatest global challenges of the 21st century, with carbon dioxide (CO_2) emissions widely identified as the primary driver of global warming. CO_2 is responsible for approximately 64% of the warming influence of human-produced greenhouse gases (NASA, n.d.). Once released, CO_2 can persist in the atmosphere for hundreds of years, leading to long-lasting environmental consequences. In response to these challenges, policymakers have increasingly turned to market-based mechanisms to attempt to mitigate emissions. Among these, the Regional Greenhouse Gas Initiative (RGGI) stands out as the first mandatory cap-and-trade program in the United States targeting CO_2 emissions.

The origins of the RGGI trace back to 2003, when governors from Connecticut, Delaware, Maine, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont initiated discussions to develop a regional cap-and-trade program for CO2. An important milestone occurred on December 20, 2005, when seven of these states signed a Memorandum of Understanding outlining the program's framework. Massachusetts, Rhode Island, and Maryland later joined the RGGI in 2007, birthing a regional market for CO_2 allowances.

The RGGI was officially implemented in 2009 to reduce carbon dioxide emissions from power plants with a capacity of 25 megawatts (MW) or larger. States can opt in to participate in the program, which sets a per-state cap on total emissions and requires power plants to obtain one RGGI CO_2 allowance for each ton of CO_2 they emit. These allowances are primarily acquired through quarterly region-wide auctions, which account for 94% of all allowances used in the program. During these auctions, states participating in the RGGI proportionally receive the proceeds for a fixed number of allowances, and power companies bid on them in a competitive process. The auction is structured as a sealed-bid, uniform-price auction, meaning that all winning bidders pay the same price per allowance, which is determined by the lowest successful bid. Winning bids initially started at \$3 per allowance, and remained below \$10 during every quarterly period until 2022. More recently, however, they have risen, reaching a high of \$25.75 per allowance in September 2024, reflecting tightening emissions caps. Revenues generated from the auctions are typically reinvested by the states into clean energy initiatives, energy efficiency improvements, and consumer bill assistance programs.

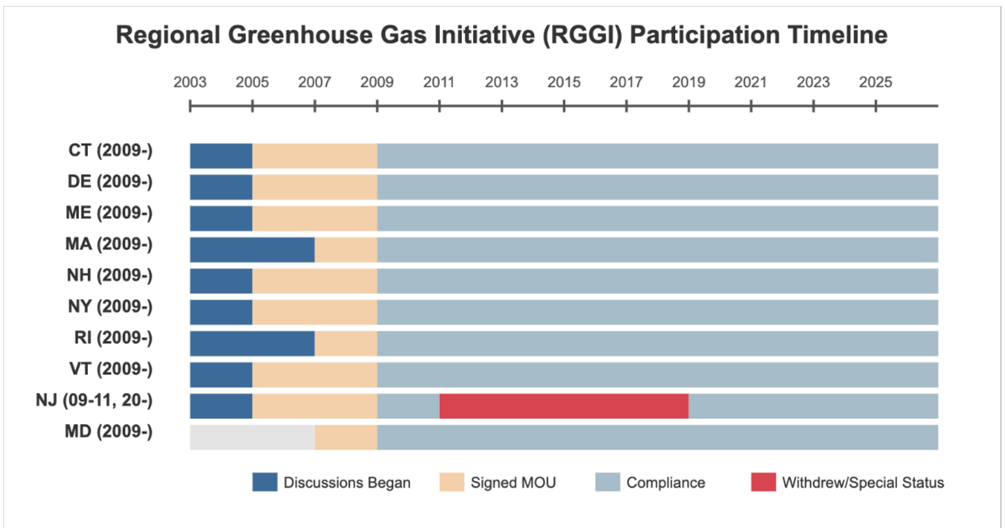


Figure 1: Regional Greenhouse Gas Initiative (RGGI) timeline from initial 2003 discussions to the 2005 MOU signing and subsequent program evolution. The first compliance period began in 2009, with certain states (e.g., New Jersey) withdrawing or rejoining over time.

The number of allowances permitted for each state is determined through a combination of regional and state-specific factors. Each RGGI state establishes its own CO_2 Budget Trading Program, based on the RGGI Model Rule [1] and implemented through each state's statutory or regulatory authority. The programs collectively form a regional cap-and-trade system, with the total regional cap divided among the states according to an agreed methodology that considers historical emissions, electricity generation, and policy goals. Companies

[1] The Model Rule is a set of proposed regulations that form the basis for each RGGI state's CO_2 emissions.

can purchase allowances to cover their current emissions, hold them in reserve for future compliance, or trade them with other companies. These allowances can be traded across state lines in secondary markets. Compliance is monitored at the state level, and companies must demonstrate that they hold enough allowances to cover their emissions over a set three-year compliance period, while holding at least 50% of the necessary credits each year. If a company does not hold sufficient allowances, it faces steep financial penalties, with violators having to surrender CO_2 allowances equal to three times the number of tons of excess emissions and also potentially being subject to state-specific penalties for non-compliance. However, non-compliance does not appear to be a significant issue, with 99.5% of power plants (221 out of 222) and 99.9% of emissions falling under compliance, with the sole violator forfeiting three times the amount of emissions of their shortfall. There have been five control periods so far[2], and we are currently in the sixth.

While RGGI implementation has been associated with notable reductions in CO_2 emissions within participating states, questions remain about its long-term effectiveness and potential spillover effects. This thesis seeks to contribute to the growing body of research on the environmental impacts of cap-and-trade programs by focusing exclusively on RGGI's influence on emissions reductions. Specifically, I examine four interrelated aspects of RGGI's performance. First, I examine whether the pace of emissions reductions has diminished over time as states potentially exhaust low-cost mitigation opportunities. Understanding this trend is essential for assessing whether RGGI's declining cap remains sufficiently stringent to produce continued environmental benefits. Second, I investigate how RGGI has affected emissions across different electricity grid management regions—particularly within the Pennsylvania-

[2]The control periods are 3-year periods as follows: Period 1: 2009-2011; Period 2: 2012-2014; Period 3: 2015-2017; Period 4: 2018-2020; Period 5: 2021-2023.

Jersey-Maryland Interconnection Regional Transmission Organization (PJM ISO), where both participating and non-participating states operate under the same regional transmission organization. I evaluate the presence of emissions leakage, whereby reductions in RGGI states may be offset by increases in nearby non-RGGI states. This analysis provides insight into how partial geographic coverage within a shared grid can affect the spatial distribution of emissions and regulatory effectiveness. Third, I explore whether RGGI participation has influenced emissions and emission intensities of other pollutants—namely sulfur dioxide (SO_2) and nitrogen oxides (NO_x)—which are often co-produced with carbon dioxide. These co-pollutants have significant implications for local air quality and public health, and their behavior under carbon regulation helps reveal whether RGGI produces ancillary environmental benefits beyond its stated carbon targets. Finally, I look at the mechanisms through which the emissions changes occur by separating the analysis into intensive versus extensive margins. I specifically look at intensive margin adjustments as shifts in the operating profile or efficiency of existing generating units and the extensive margin changes as entry or exit via fuel switching, where carbon-intensive plants shut down in favor of more carbon-efficient ones.

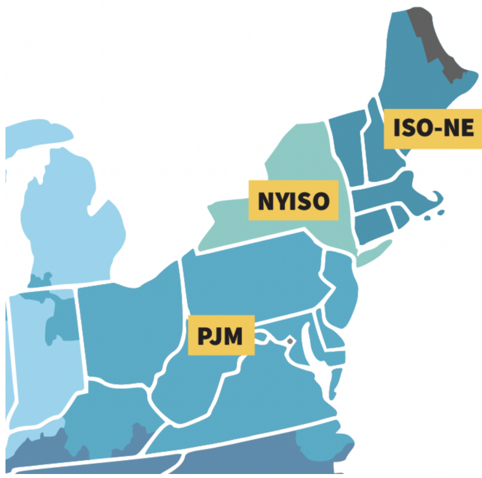
To achieve these objectives, I employ the synthetic control method developed by Abadie and Gardeazabal, 2003 and extended by Abadie et al., 2010. This approach constructs counterfactual scenarios for RGGI states by creating a weighted combination of non-RGGI, non-Leaker states to simulate emissions trajectories in the absence of the program. This analysis uniquely explicitly incorporates the announcement period in the baseline estimates (2006–2008), contrasting with previous research which typically begins at program implementation in 2009. Furthermore, I employ a difference-in-differences (DiD) methodology to analyze plant-level emissions data, examining the differential impact of RGGI participation on emissions, operating hours, heat input, and pollution intensity across various treatment groups. Extending the analysis through the fifth control period (2021–2023) provides insights into whether RGGI's progressively declining emissions cap has continued driving meaningful reductions or if the effects have diminished over time.

Moreover, I extend this analysis to the three electricity grid management regions that the RGGI operates within: ISO New England (ISO-NE), New York ISO (NYISO), and PJM Interconnection RTO (PJM). ISO-NE, which encompasses the states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont, and NYISO, which covers New York, are entirely within the RGGI region. In contrast, PJM spans both RGGI and non-RGGI states, including Delaware, Maryland, and New Jersey (RGGI states) as well as Virginia, West Virginia, Pennsylvania, Ohio, Kentucky, and Indiana (non-RGGI states). These grid operators play a critical role in managing the electrical grid, coordinating electricity flows, and facilitating energy market transactions across their respective regions.

In this analysis, I make the decision to include New Jersey continuously while excluding Virginia and Pennsylvania to create a more cohesive treatment sample that captures potential lingering policy effects and institutional path dependencies. I also exclude Virginia and Pennsylvania's brief participation periods to prevent introducing noise from partial treatments that could obscure the measurement of RGGI's established, longer-term impacts. This classification strategy creates a cleaner contrast between consistently regulated and unregulated states, enhancing the interpretability of your difference-in-differences results and providing a more reliable assessment of RGGI's sustained influence on emissions outcomes.

Since the PJM is the only region with a grid that contains a mixture of RGGI and non-RGGI states, it creates conditions conducive to emissions leakage. Consequently, generation from RGGI states that face capped emissions and higher compliance costs can easily be dis-

Figure 2: Independent Service Operating and Regional Transmission Organization Regions in the United States.



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Source: Federal Energy Regulatory Commission (2024). Regional Transmission Organizations/Independent System Operators. RTOs and ISOs. Retrieved November 17, 2024.

placed by generation from neighboring non-RGGI states within PJM. For instance, reduced output from regulated plants in Delaware or Maryland can be offset by increased production in non-regulated states within PJM, which have no comparable emissions constraints.

The designation of "Leaker" states in this analysis follows a specific methodology based on both geographic proximity and electrical grid interconnection with RGGI states. Pennsylvania, Ohio, West Virginia, Kentucky, and Virginia were classified as potential "Leakers" based on two key criteria: (1) they operate within the same PJM Interconnection transmission organization as several RGGI states, and (2) they had substantial coal and natural gas generation capacity that could potentially increase production in response to reduced output from RGGI-regulated facilities. This classification expands on previous research by Fell and Maniloff (2018) and Lee and Melstrom (2018), who primarily focused on Pennsylvania and Ohio as the most likely to experience generation shifting due to their integrated transmission systems and generation mix. The PJM region is uniquely positioned for examining leakage effects because it represents the only electricity market where both regulated and unregulated states operate under a single dispatch system, allowing for frictionless substitution between generators across state lines. This contrasts with ISO-NE and NYISO, which are entirely within the RGGI regulatory boundary. By analyzing emissions per megawatt-hour across RGGI, Leaker, and unaffected control regions, I assess how significantly leakage dynamics may compromise the emissions reduction objectives of the RGGI program.

The remainder of this thesis is organized as follows. Section 2 presents a comprehensive review of related literature, covering the theory behind cap-and-trade policies, empirical evaluations of RGGI, and evidence from similar programs. Section 3 describes the data and variables used in the analysis, including plant-level emissions, state-level policy indicators, and macroeconomic controls. Section 4 outlines the empirical methodology, beginning with an intensive-extensive margin framework, an associated difference-in-differences model to estimate plant-level impacts, followed by a synthetic control approach for state-level counterfactuals. Section 5 reports the main results on emissions outcomes, leakage, and co-pollutant effects, with additional robustness checks. Section 6 concludes.

2. LITERATURE REVIEW

Cap-and-trade systems have emerged as a cornerstone of climate policy, offering a flexible, market-based mechanism to reduce greenhouse gas emissions. These systems operate by setting an emissions cap and allowing the trading of allowances as needed, enabling cost-effective reductions where they are most feasible. Alongside carbon taxes and hybrid policy instruments, cap-and-trade mechanisms are widely recognized as economically efficient strategies to address climate change (Aldy, 2015, Edenhofer et al., 2015, Metcalf and Weisbach, 2009).

A robust body of theoretical and empirical literature underscores the efficacy of cap-and-trade mechanisms. Du et al. (2011) utilize a game-theoretic model to investigate emission-dependent supply chains, analyzing interactions between firms purchasing permits and emission permit suppliers. By exploring Nash equilibria under diverse policy and market conditions, they demonstrate how permit trading can significantly enhance compliance flexibility and reduce abatement costs. Complementing this perspective, Zhou et al. (2022) employ a computable general equilibrium model to contrast the macroeconomic impacts of cap-and-trade policies and carbon taxes. Their findings suggest cap-and-trade systems mitigate sectoral disruptions by redistributing abatement costs across industries, whereas carbon taxes maintain stable shadow prices, achieving superior national-level cost-effectiveness.

Empirical evaluations of prominent cap-and-trade programs, such as the European Union Emissions Trading Scheme and California's cap-and-trade offer insights into existing cap-and-trade systems. Narassimhan et al. (2018) analyze these programs through criteria including environmental effectiveness, economic efficiency, and stakeholder engagement. They highlight the importance of gradually tightening emission caps and benchmark-based allocation methods, both of which reduce market volatility and promote fairness among participants. The auction-generated revenues, when reinvested into renewable energy and energy efficiency initiatives, were shown to amplify the environmental benefits of these programs. Similarly, Haites (2018) emphasizes adaptive cap-setting mechanisms and comprehensive sectoral coverage as attributes essential for success in a cap-and-trade, observing that effective systems achieve emissions reductions without significant economic disruptions.

The RGGI represents the first mandatory cap-and-trade program in the United States targeting CO_2 emissions, requiring firms in participating states to comply with the program's emissions cap and trading mechanisms. While previous literature suggests the RGGI has successfully reduced emissions within participating states, significant emissions leakage into neighboring non-RGGI states has been also documented. Leakage occurs when production shifts to unregulated states, such as those within the PJM ISO, where compliance costs are lower. Studies by Roach and Gittings (2021) and Fell and Maniloff (2018) illustrate how emissions reductions in RGGI states coincide with increased natural gas generation in adjacent non-RGGI states. Yan (2021) quantifies this leakage, documenting a 30% reduction in natural gas use for electricity in RGGI states coupled with a 237% increase in neighboring states, translating to an additional 3.5 million tons of CO_2 annually. Addressing such leakage, Murray and Maniloff (2015) argue, may require broader regional coordination or mechanisms like border adjustments, ensuring emissions reductions are not compromised by shifts in production location. Notably, few existing studies incorporate the policy announcement period preceding RGGI implementation in their main results, presenting an opportunity for novel analysis in this thesis.

In addition to CO_2, researchers have examined whether RGGI influences emissions of other greenhouse gases and co-pollutants such as sulfur dioxide (SO_2) and nitrogen oxides

(NO_x). Roach and Gittings (2021) find reductions in SO_2 and NO_x emissions in some RGGI states though these reductions are not uniform across all plants and are primarily driven by fuel switching and reduced coal usage. These reduced emissions have significant health implications, as Chan and Morrow (2019) and Perera et al. (2020) find that when SO_2 and NO_x emissions do decline, resulting improvements in air quality yield considerable public health benefits, including fewer respiratory and cardiovascular disease cases. These findings underscore the necessity of evaluating broader environmental co-benefits alongside carbon reductions.

Synthetic control methods have emerged as a powerful tool for evaluating policy impacts, particularly when addressing counterfactual scenarios. Abadie and Gardeazabal, 2003 first created the SCM approach and later Abadie, 2010 formalized the approach to construct counterfactual scenarios in regions unaffected by specific policy interventions. This methodology has been applied extensively in environmental economics to isolate the causal effects of cap-and-trade programs on emissions. Specifically, studies examining the Regional Greenhouse Gas Initiative have highlighted synthetic's utility in evaluating environmental and economic outcomes. For instance, Lee and Melstrom (2018) used synthetic controls to assess leakage effects, demonstrating increased electricity imports into RGGI regions post-policy implementation as local emissions were curtailed but production shifted elsewhere. Similarly, Lee and Park (2019) utilized a quasi-experimental design incorporating synthetic controls to reveal significant public health benefits, such as reductions in infant mortality rates, attributed to improved air quality following RGGI's implementation.

By situating RGGI within the broader literature on cap-and-trade systems and employing synthetic control methods to assess its impacts, this thesis provides a comprehensive evaluation of the program's environmental performance across multiple dimensions. This research makes four distinct contributions to our understanding of regional carbon markets. First, it extends analysis through the fourth (2018-2020) and fifth control period (2021-2023), capturing the most recent outcomes of RGGI's progressively tightening emissions cap. Second, unlike previous studies that primarily relied on difference-in-differences frameworks, this paper employs synthetic control methodology as its primary analytical approach. This relaxes the parallel trends assumption and can improve the accuracy of the estimate of the treatment effect, as a weighted combination of control regions often provides a closer approximation to the treated region's pre-intervention trajectory than a single region can. Third, this is one of the few RGGI studies uniquely incorporates the announcement period (2006-2008) prior to implementation, allowing for examination of anticipatory behavioral changes among regulated entities. These methodological advances enable more precise isolation of RGGI's causal impact on emissions reductions while accounting for potential leakage effects and co-pollutant outcomes, ultimately providing valuable insights for the design of future regional climate policies. Finally, this thesis provides a regional breakdown of the RGGI electricity markets, providing insight as to how policy harmonization impacts the effectiveness of cap-and-trade programs.

3. DATA

This paper draws on a combination of firm-level, facility-level, and state-level data from the U.S. Environmental Protection Agency's Clean Air Markets Program (CAMP), which provides unit-level emissions data for major CO_2, SO_2, and NO_x from 1996 to 2023. According to the EPA, CAMP data covers approximately 96% of the fossil fuel generation in the U.S.. The entirety of this thesis focuses on the 10 RGGI states, the 5 Leakers, and 32 control states plus the District of Columbia[3]. This data facilitates an analysis of both the intensive margin—changes in emissions at operating facilities—and the extensive margin—entries or retirements of power plants. Plant-level characteristics such as heat input, operational hours, and fuel type were used to construct control period averages by group.

While CAMP is the main source for facility-level behavior, the RGGI Emissions Dashboard supplements these data by offering a view into operating schedules, gross load, and unit retirement timing for regulated states. Table 1 summarizes the total number of facilities by RGGI region and control period, and how they change over time. Notably, the years closer to the onset of the RGGI saw the greatest number of operational declines, whereas the later periods seemed to have the greatest net changes in unit counts across all regions.

To control for macroeconomic and demographic variation, I incorporate data from the U.S. Energy Information Administration's (EIA) State Energy Data System (SEDS), which reports annual information from 1960 to 2023 on variables such as population, real GDP (in chained 2017 dollars), fuel prices, and total energy consumption by sector. State-level climate variation is captured through annual heating and cooling degree days. A comparison

[3]California is excluded from the control group because it started its own cap-and-trade program in 2013, while Alaska and Hawaii are omitted because they aren't part of the contiguous U.S. and due to their unique electricity grids and limited comparability.

Table 1: Plants by Control Period Start Year and Region

Year	Region	Total Units	Units Added	Units Retired	Net	Decline ≥50% Hrs
2006	CONTROL	2598	63	43	–	303
2009	CONTROL	2594	80	84	-4	640
2012	CONTROL	2593	49	50	-1	377
2015	CONTROL	2654	93	32	+61	392
2018	CONTROL	2677	38	15	+23	163
2021	CONTROL	2705	52	24	+28	197
2006	ISO-NE	179	2	0	–	30
2009	ISO-NE	187	8	0	+8	32
2012	ISO-NE	184	3	6	-3	33
2015	ISO-NE	183	1	2	-1	24
2018	ISO-NE	189	6	0	+6	16
2021	ISO-NE	182	0	7	-7	15
2006	LEAKER	691	7	7	–	99
2009	LEAKER	689	9	11	-2	133
2012	LEAKER	687	11	13	-2	115
2015	LEAKER	684	12	15	-3	86
2018	LEAKER	703	22	3	+19	58
2021	LEAKER	708	7	2	+5	35
2006	NYISO	338	7	5	–	110
2009	NYISO	344	8	2	+6	110
2012	NYISO	333	2	13	-11	27
2015	NYISO	328	3	8	-5	27
2018	NYISO	320	2	10	-8	24
2021	NYISO	318	2	4	-2	21
2006	PJM_RGGI	246	1	11	–	62
2009	PJM_RGGI	245	1	2	-1	102
2012	PJM_RGGI	261	16	0	+16	57
2015	PJM_RGGI	264	7	4	+3	65
2018	PJM_RGGI	275	15	4	+11	27
2021	PJM_RGGI	274	1	2	-1	13

Notes: (1) "Net" is computed as the difference in Total Units from the prior row for each region. (2) "Decline ≥50% Hrs" indicates the number of units whose operating hours fell by at least half relative to the previous period.

of summary statistics across RGGI, Leaker, and Non-RGGI states for the pre-announcement and first two control periods is shown in Table 2. Several key differences emerge: Leaker states consistently have higher average GDP per state, significantly larger populations, and

Table 2: Summary Statistics for Primary Control Variables

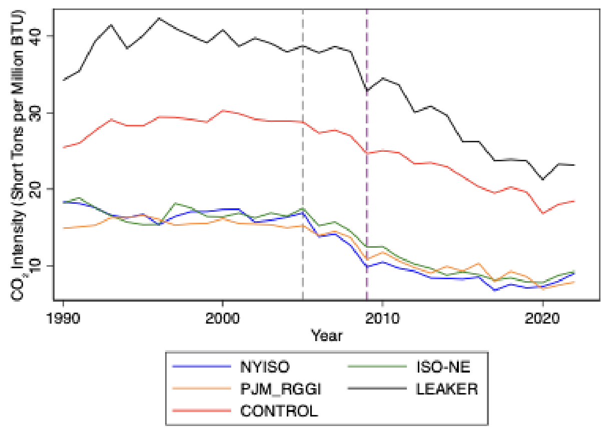
	NYISO	**ISO-NE**	**PJM-RGGI**	**Leaker**	**Control**
Pre-Announcement (Period 0)					
Total Population (Thousands)	19,150	14,288	15,210	37,903	176,393
Total GDP (Thousands USD)	1,340,488	930,840	963,785	1,942,851	9,140,899
Avg. Population (Thousands)	19,150	2,381	5,070	7,581	5,345
Avg. GDP (Thousands USD)	1,340,488	155,140	321,262	388,570	276,997
Avg. Heating Degree Days	5,848.67	6,716.06	4,555.44	4,912.93	4,969.81
Avg. Cooling Degree Days	605.33	391.06	1,060.22	933.20	1,314.37
Avg. Natural Gas Price ($/MMBtu)	8.720	8.431	8.653	8.597	7.310
Avg. Coal Price ($/MMBtu)	2.443	1.937	2.813	2.009	1.603
First Control Period (Period 1)					
Total Population (Thousands)	19,402	14,469	15,481	38,462	182,036
Total GDP (Thousands USD)	1,417,158	941,305	969,084	1,955,995	9,095,971
Avg. Population (Thousands)	19,402	2,412	5,160	7,692	5,516
Avg. GDP (Thousands USD)	1,417,158	156,884	323,028	391,199	275,635
Avg. Heating Degree Days	5,892.67	6,647.00	4,705.33	5,097.80	5,196.28
Avg. Cooling Degree Days	671.67	430.72	1,161.56	996.87	1,330.02
Avg. Natural Gas Price ($/MMBtu)	5.407	5.224	5.218	5.062	4.972
Avg. Coal Price ($/MMBtu)	2.990	2.365	3.622	2.575	2.021
Second Control Period (Period 2)					
Total Population (Thousands)	19,618	14,651	15,706	38,871	186,863
Total GDP (Thousands USD)	1,511,158	973,424	1,004,033	2,064,635	9,724,731
Avg. Population (Thousands)	19,618	2,442	5,235	7,774	5,662
Avg. GDP (Thousands USD)	1,511,158	162,237	334,678	412,927	294,689
Avg. Heating Degree Days	5,872.67	6,666.44	4,712.11	5,087.13	5,022.10
Avg. Cooling Degree Days	632.33	429.61	1,040.67	900.13	1,305.67
Avg. Natural Gas Price ($/MMBtu)	4.740	5.571	4.164	4.290	4.315
Avg. Coal Price ($/MMBtu)	3.057	2.709	3.502	2.599	2.220
Third Control Period (Period 3)					
Total Population (Thousands)	19,629	14,769	15,835	39,125	192,322
Total GDP (Thousands USD)	1,593,735	1,025,567	1,048,890	2,167,718	10,473,508
Avg. Population (Thousands)	19,629	2,462	5,278	7,825	5,828
Avg. GDP (Thousands USD)	1,593,735	170,928	349,630	433,544	317,379
Avg. Heating Degree Days	5,735.00	6,612.39	4,514.44	4,712.47	4,586.85
Avg. Cooling Degree Days	707.00	453.28	1,155.44	1,011.33	1,388.71
Avg. Natural Gas Price ($/MMBtu)	3.150	3.812	2.794	2.840	3.214
Avg. Coal Price ($/MMBtu)	2.517	2.662	2.994	2.253	2.067
Fourth Control Period (Period 4)					
Total Population (Thousands)	19,704	14,916	16,087	39,440	197,127
Total GDP (Thousands USD)	1,675,168	1,067,586	1,077,113	2,237,519	11,144,494
Avg. Population (Thousands)	19,704	2,486	5,362	7,888	5,973
Avg. GDP (Thousands USD)	1,675,168	177,931	359,038	447,504	337,712
Avg. Heating Degree Days	5,879.67	6,708.56	4,532.44	4,829.40	5,019.38
Avg. Cooling Degree Days	744.00	520.94	1,236.44	1,104.67	1,416.33
Avg. Natural Gas Price ($/MMBtu)	2.947	4.000	2.706	2.721	2.717
Avg. Coal Price ($/MMBtu)	2.323	1.722	2.729	2.056	2.033
Fifth Control Period (Period 5)					
Total Population (Thousands)	19,764	15,114	16,447	39,713	200,353
Total GDP (Thousands USD)	1,743,998	1,128,274	1,121,770	2,318,428	11,867,320
Avg. Population (Thousands)	19,764	2,519	5,482	7,943	6,071
Avg. GDP (Thousands USD)	1,743,998	188,046	373,923	463,686	359,616
Avg. Heating Degree Days	5,683.00	6,340.33	4,526.67	4,859.70	4,902.94
Avg. Cooling Degree Days	752.00	527.42	1,184.17	1,014.30	1,417.49
Avg. Natural Gas Price ($/MMBtu)	5.640	6.757	5.515	5.170	6.115
Avg. Coal Price ($/MMBtu)	0.000	1.756	2.729	2.469	2.172

lower average heating degree days, implying a warmer climate that may alter seasonal demand for power. RGGI states, meanwhile, tend to have higher heating degree days and lower natural gas prices relative to the other groups, suggesting different baseload generation conditions. These differences support the use of a synthetic control approach that flexibly weights pre-treatment trends rather than relying on simple difference-in-differences models.

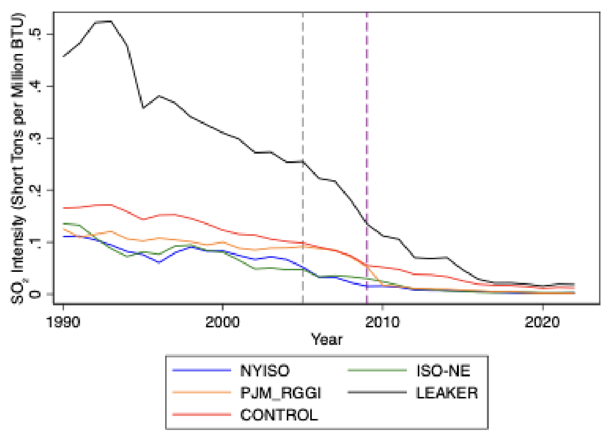
State-level emissions trends are further illustrated in Figure 3, which shows per capita emissions of CO_2, SO_2, and NO_x by group. Each panel includes vertical lines for the 2005 RGGI announcement and the 2009 implementation period. A sharp decline in emissions is observable in RGGI states post-2009 for all pollutants, while Leaker and Control states exhibit flatter or more gradual declines. This clear divergence in emissions paths post-2009 further supports the credibility of the intervention and provides visual evidence in support of a treatment effect.

Figure 4 plots the fraction of total electricity generation (coal, natural gas, oil, and other) from 1997 through 2021 for the five regions. I obtain these percentages by aggregating total heat input (`heatinputmmbtu`) at the region-year-fueltype level, identifying each facility's primary fuel, and then summing the total heat input contributed by that fuel. I then divide this figure by the region-year's overall heat input, yielding a fuel-specific share of the region's total energy input. As shown, the RGGI states in the PJM region experience a dramatic decline in coal's share while natural gas rises. Although not bound by RGGI, non-Leaker states nonetheless show a moderate shift away from coal after 2010. Overall, these figures confirm that all regions moved toward lower-carbon resources, especially since the inset of the RGGI states appearing to accelerate that transition.

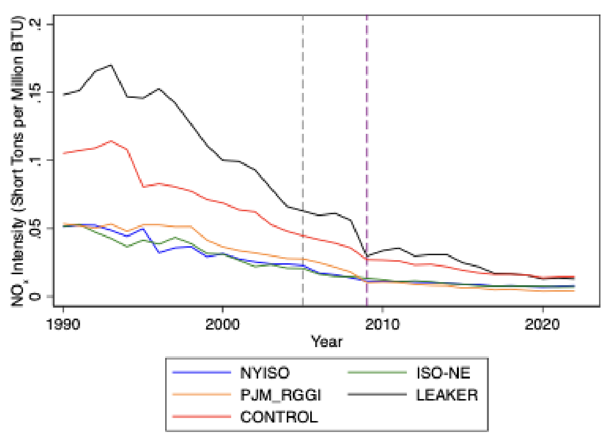
Firm-level allowance trading data are obtained from the CO_2 Allowance Tracking System



(a) Per capita CO_2 emissions



(b) Per capita SO_2 emissions



(c) Per capita NO_x emissions

Figure 3: Time-series plots of per capita CO_2, SO_2, and NO_x intensities (from 1990 through 2023) across five groupings: NYISO, ISO-NE, and PJM_RGGI (these three form part of the RGGI), plus LEAKER and CONTROL (states not subject to RGGI). The dashed vertical line at 2006 marks the RGGI announcement, and the dotted line at 2009 indicates the start of the first compliance period. The data are aggregated at the regional level based on total emissions divided by total energy generation, producing a per capita emissions metric for each region.

(COATS), which records market behavior and compliance activities under the RGGI cap-and-trade system. These data are used to characterize the exposure of power plants to carbon pricing across time and facilitate plant-level treatment assignment for 1996-2022.

To control for renewable energy policy heterogeneity, I incorporate data on Renewable Portfolio Standards (RPS) from Berkeley Lab's Energy Markets and Policy Group, which provides state-by-state information on renewable mandates, implementation dates, and stringency from 2000-2023.

I assess the quality of the pre-treatment match for each outcome variable using covariate balance tables in the Appendix (Tables A1–A3). These tables compare average pre-policy emissions between treated units and their synthetic controls, constructed using the weights optimized in the SCM procedure. For most outcomes, the synthetic matches closely track the treated regions over the pre-treatment period, particularly for mid-sized states. However, consistent with prior findings, I observe less precise fits for the smallest (e.g., Vermont) and largest (e.g., New York) RGGI states, reflecting the difficulty of constructing counterfactuals for states with few natural comparators in the donor pool. Overall, the balance statistics support the validity of the synthetic control approach in this setting.

In this analysis, I make the decision to include New Jersey continuously while excluding Virginia and Pennsylvania to create a more cohesive treatment sample that captures potential lingering policy effects and institutional path dependencies. I also exclude Virginia and Pennsylvania's brief participation periods to prevent introducing noise from partial treatments that could obscure the measurement of RGGI's established, longer-term impacts. This classification strategy creates a cleaner contrast between consistently regulated and unregulated states, enhancing the interpretability of my difference-in-differences results and providing a more reliable assessment of RGGI's sustained influence on emissions outcomes.

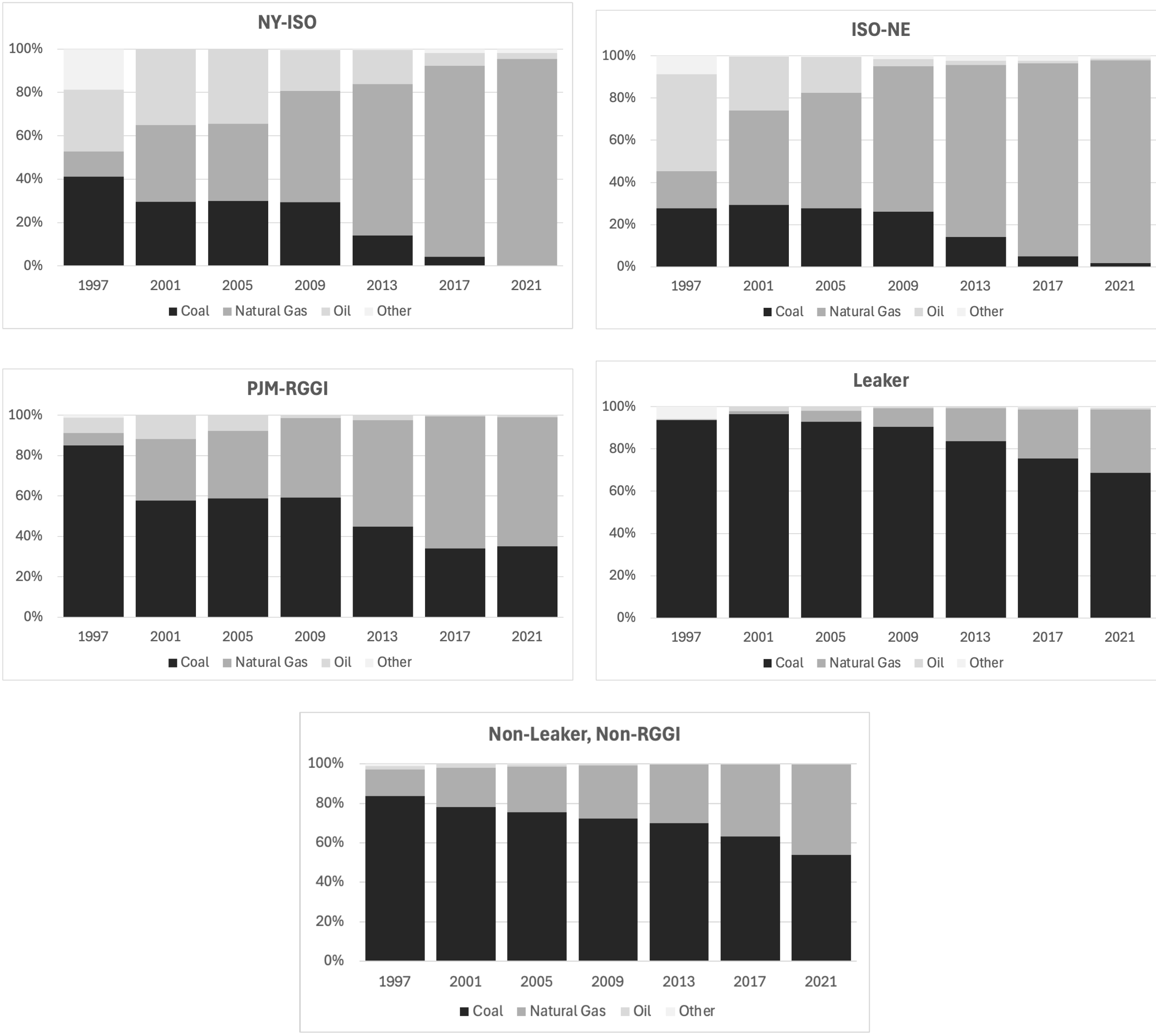


Figure 4: Fuel share over time for the five selected regions. The "fuel share" in each region-year was calculated by grouping all plants in that region by their primary fuel, summing the total heat input for each fuel type, and dividing by the region's total heat input in that year. Leaker states refer to the PJM states that are not in the RGGI, namely Virginia, West Virginia, Kentucky, Ohio, and Pennsylvania.

4. EMPIRICAL SPECIFICATION

This study begins with a difference-in-differences (DiD) regression to capture impacts from disaggregated plant-level data. Looking at plant operating hours, capacity, energy production, and acitivity can reveal changes in intensive and extensive margins as firms respond to the RGGI mandate. Then a state-level linear synthetic control model (SCM) is constructed to estimate counterfactual emissions trajectories.

4.1 Intensive vs. Extensive Margins Framework

In order to explore the changes in emissions, this paper examines shifts in intensive and extensive margins. In the context of emissions from electricity generation, the *intensive margin* refers to adjustments made within existing facilities, such as changes in operational intensity, hours of operation, fuel efficiency improvements, or fuel switching decisions. The *extensive margin* encompasses shifts resulting from the entry or exit of facilities, plant retirements, new plant construction, or broader structural shifts in the generation mix.

Formally, let total emissions E_{it} from state i at time t be expressed as the sum of emissions from continuing facilities (intensive margin), $E_{it}^{intensive}$, and emissions from new or retiring facilities (extensive margin), $E_{it}^{extensive}$:

$$E_{it} = E_{it}^{intensive} + E_{it}^{extensive} \tag{1}$$

To empirically disentangle these margins, I proceed as follows. For the intensive margin, the analysis focuses on the subset of plants that provided complete information of emissions, heatinput, and operating time across the study period (this encompassed 83000 out of 114000 observations). Within this group, changes in the operating profile including heat input, operating hours, gross load, and emissions intensity reflect the plant-level responses.

For the extensive margin, the empirical approach evaluates whether RGGI participation leads to systematic changes in the entry and exit behavior of plants. Specifically, I look at (1) The changes in the number of operating plants (entry/exit dynamics) and (2) Changes in fuel type shares within total electricity generation, switching from coal to a source less carbon-intensive such as gas, reflecting structural shifts across generation sources.

Distinguishing between intensive and extensive margin effects can provide insights into how RGGI primarily achieves emission reductions. Understanding these channels offers crucial implications for designing future cap-and-trade policies that efficiently target both margins to maximize environmental and economic outcomes.

4.2 Plant-Level Difference-in-Differences

The first empirical approach in this study is a plant-level difference-in-differences (DiD) model designed to estimate the impact of RGGI participation on emissions. This approach distinguishes between the announcement period after the RGGI was announced before 2009 and the post-implementation period, and it separately identifies the behavior of "Leaker" states that may have been affected indirectly by the policy. The model is specified as follows:

$$\begin{aligned}\text{Emissions}_{pkit} = \alpha \;&+\; \delta_1\,\text{TREAT}_i \;+\; \delta_2\,\text{ANNOUNCEMENT}_i \;+\; \delta_3\left(\text{TREAT}_i \times \text{ANNOUNCEMENT}_i\right)\\ &+\; \theta_1\,\text{POST}_t \;+\; \theta_2\left(\text{TREAT}_i \times \text{POST}_t\right) \;+\; \gamma_1\,\text{LEAKER}_i\\ &+\; \gamma_2\left(\text{LEAKER}_i \times \text{ANNOUNCEMENT}_i\right) \;+\; \gamma_3\left(\text{LEAKER}_i \times \text{POST}_t\right) \;+\; \beta\,X_{kit}\\ &+\; f\left(\text{Price}_{it}\right) +\; \lambda_t \;+\; \nu_k \;+\; \epsilon_{kit}.\end{aligned} \tag{2}$$

where Emissions_{pkit} represents emissions of pollutant p (such as CO_2, NO_x, or SO_2) from plant k in state i at time t. The variable TREAT_i equals 1 if the plant is located in a state that ultimately participates in RGGI. The model accounts for the possibility of anticipatory behavior during the announcement period by including a ANNOUNCEMENT_i indicator for the years 2006 to 2009, equivalent to the announcement period, during which states publicly committed to joining the initiative but before formal implementation began. The POST_t variable is equal to 1 in years following the official start of RGGI in 2009. The coefficient δ_1 captures baseline differences between treated and control plants prior to any RGGI activity, while δ_2 and δ_3 capture how treated plants differed during the announcement period, both on average and in interaction with treatment status. The coefficient θ_1 captures time effects common to all plants after implementation, and θ_2 estimates the treatment effect of RGGI in the post-implementation period.

In addition, LEAKER_i identifies plants located in states adjacent to or economically linked with RGGI states that did not formally join the program but may have been affected by emissions leakage. The coefficients γ_1, γ_2, and γ_3 estimate differences in emissions outcomes for Leaker states relative to the control group in each phase of RGGI's rollout. This structure allows the model to separately capture both direct treatment effects and potential spillovers to neighboring jurisdictions.

The model includes a rich set of plant-level and contextual controls, summarized in the vector X_{kit}. These include the prices of natural gas and coal, which are key input costs for electricity generation. Natural gas prices are modeled using a fractional polynomial function, $f(\text{Price}_{it})$, to capture the nonlinear effects of the shale gas boom on emissions, consistent with the methodology of Yan (2021). Coal prices are included to reflect the relative cost competitiveness of more carbon-intensive power sources. Additional variables include state renewable portfolio standards (RPS), which account for overlapping climate policies that may affect emissions outcomes independently of RGGI. Weather-driven fluctuations in energy demand are controlled for using population-weighted heating and cooling degree days, following the approach of Murray and Maniloff (2015). State-level employment and population variables capture broader economic and demographic trends that may influence electricity consumption and, by extension, emissions levels.

To account for unobserved heterogeneity, the model includes plant fixed effects (ν_k), which control for time-invariant characteristics such as technology, location, and ownership. Time fixed effects (λ_t) absorb national or region-wide shocks that affect all plants equally, such as fuel market shifts or broader macroeconomic trends. A Hausman test indicates that fixed effects are preferred over random effects, suggesting that unobserved plant characteristics are correlated with the included covariates and that fixed effects yield unbiased coefficient estimates. I also cluster standard errors at the plant level to better account for within-facility correlation over time, capture the heterogeneity in plant-specific responses to RGGI, and improve statistical inference with a larger number of clusters.

A core requirement for a DiD specification is the "parallel trends" assumption—that in the absence of the RGGI, the treated and control units would have had similar outcome trajectories over time. In other words, any systematic changes over time would have affected both groups equally if RGGI had not been implemented. To bolster this assumption, I conduct an event-study analysis (Appendix 8E: Figure 8), plotting leads and lags of the treatment indicator and showing that there is no significant evidence of pre-trends in the years prior to RGGI for each comparable type of plant. Although it is never possible to prove parallel trends empirically, the event-study estimates and the graphical evidence suggest that emissions trajectories for treated and control plants were similar prior to RGGI and did not diverge in a statistically significant way. In addition, I include mixed DiD placebo tests, which randomly assign "fake" treatments in space and time to see whether the estimated effects for the true treatment appear spuriously large. Finally, by controlling for multiple covariates (fuel prices, plant characteristics, local economic factors) and including plant and year fixed effects, I work to absorb any remaining differences over time are more plausibly attributed to the policy rather than to differing regional or temporal shocks.

Overall, this DiD specification follows common best practices in the empirical literature on environmental policy. By distinguishing pre-, announcement, and post-treatment periods; accounting for leakage effects; and including both time and plant fixed effects, the model aims to isolate the causal impact of RGGI participation on emissions while controlling for a wide range of observed and unobserved confounders.

4.3 State-Level Synthetic Control Model

This study's second empirical approach uses the synthetic control method to evaluate the effect of the RGGI on state-level emissions and emission intensity. Developed by Abadie and Gardeazabal (2003) and formalized by Abadie et al. (2010), SCM is a robust methodology for estimating causal impacts in policy interventions. It constructs a weighted combination of control units to create a synthetic counterpart for the treated unit, enabling the estimation of counterfactual outcomes in the absence of treatment. Unlike difference-in-differences (DiD) models, which rely on the parallel trends assumption, SCM uses pre-treatment characteristics to select optimal comparison groups, offering greater flexibility in accounting for time-varying unobserved confounders. While DiD models account for time-invariant traits through fixed effects, SCM improves robustness in contexts where baseline characteristics differ substantially between treated and control units, or when the treatment is applied to a limited number of units (e.g., single states or firms). This flexibility ensures that any observed differences in outcomes are less likely to result from biased group selection.

In this study, SCM is applied to emissions data for all states within the study period, including both RGGI and non-RGGI states. This comprehensive approach ensures that all potential control states contribute to the construction of synthetic counterparts, improving precision and minimizing selection bias.

The synthetic for the treated unit is constructed by assigning weights to non-treated, non-PJM units called "donor states." These weights are optimized using a linear regression approach to replicate the pre-treatment characteristics of the treated region as closely as possible. Let $X_{\mathrm{RGGI},m}$ represent the vector of pre-treatment characteristics for the treated region, and $X_{\mathrm{non-RGGI},m}$ denote the corresponding matrix of characteristics for non-treated regions in the donor pool. The weights, w_j, are selected to minimize the mean squared prediction error (MSPE) of pre-treatment outcomes, subject to the constraints that the weights are nonnegative and sum to one:

$$\min_{w} \sum_{m=1}^{k} v_m \left(X_{\mathrm{RGGI},m} - X_{\mathrm{non-RGGI},m}\mathbf{W}\right)^2 , \tag{3}$$

where v_m captures the relative importance of each characteristic m, k is the total number of pre-treatment characteristics, and $\mathbf{W}$ is a vector of weights w_j, constrained such that $0 \leq w_j \leq 1$ and $\sum w_j = 1$. The weights v_m are determined through an optimization process that minimizes the weighted sum of squared differences between the pre-treatment characteristics of the treated unit and the weighted average of the control units (the synthetic counterpart). This ensures that the synthetic control closely mirrors the pre-treatment behavior of the treated unit, providing a valid counterfactual in the absence of treatment.

After constructing the synthetic control, the effect of the RGGI intervention is calculated as the difference between the observed outcome for the treated region and the outcome for the synthetic counterpart. The treatment effect at time t, denoted as Effect_t, is given by:

$$\text{Effect}_t = Y_{\text{RGGI},t} - \sum_{j=2}^{J+1} w_j^* Y_{j,t} \tag{4}$$

where $Y_{\text{RGGI},t}$ represents the observed emissions outcome for the treated unit at time t, $Y_{j,t}$ is the corresponding outcome for donor state j, J is the total number of states in the donor pool, and w_j^* are the optimized weights derived from the pre-treatment period.

The variables I use in constructing the synthetic controls include lagged emissions paths (1990–2005), and pre-treatment covariates from 2005: natural gas and coal prices, real GDP, population, total energy production, and climate variables (CDD and HDD). These variables ensure a strong pre-treatment match between the treated ISO and its synthetic counterpart and reflect the economic and environmental factors most relevant for emissions behavior (Yan, 2021; Xu, 2017). By explicitly constructing a counterfactual that accounts for pre-treatment differences, the SCM provides a robust framework for evaluating policy interventions in the presence of unobserved time-varying confounders (Xu 2017, Gilchrist et al. 2018)).

5. FINDINGS

5.1 Plant-level Findings

5.1.1 Intensive Margin

I begin by examining how RGGI participation affected emissions at the plant level via the DiD specifications outlined in Section 4.2. Table 3 reports the estimates of how participating and leaker states were impacted by the RGGI.

The coefficient on RGGI $\times$ POST for CO_2 is both substantively and statistically significant, indicating that RGGI adoption is associated with a meaningful reduction in carbon emissions after 2009. Moreover, the announcement period also shows significance, suggesting that some plants began curtailing or reallocating emissions prior to the policy's formal start—likely through anticipatory behavior, a finding contrasting previous literature. One possible avenue through which emissions could have been reduced is increased fuel switching, where high-emitting coal units may have switched to lower-carbon fuels such as natural gas, or invested in efficiency upgrades, to mitigate the new costs of carbon allowances.

Interestingly, NO_x outcomes reveal a positive and significant coefficient in RGGI states, whereas SO_2 exhibits a negative coefficient that is statistically smaller. One plausible explanation is that the largest NO_x emitters—often the same units producing substantial CO_2 and SO_2—had already installed substantial NO_x-control technologies (e.g., selective catalytic reduction) under previous federal rules, potentially muting additional NO_x reductions attributable solely to RGGI.

Turning to the Leaker-state coefficients, Table 3 indicates more modest or even mixed

Table 3: Plant-Level Difference-in-Differences Estimates of RGGI and Leaker State Effects on Emissions

Variables	$\mathbf{CO_2}$	$\mathbf{SO_2}$	$\mathbf{NO_x}$
ANNOUNCEMENT	$-168,314^{***}$	$-2,399.09^{***}$	$-1,090.15^{***}$
	(28,294)	(251)	(95)
RGGI × ANNOUNCEMENT	$-50,161^{**}$	76.84	202.86^{***}
	(21,914)	(290)	(61)
POST	$-178,194^{***}$	$-1,816.26^{***}$	$-1,301.46^{***}$
	(39,768)	(393)	(139)
RGGI × POST	$-92,921^{***}$	−351.48	269.22^{***}
	(35,732)	(525)	(104)
LEAKER × ANNOUNCEMENT	$-25,679^{*}$	-979.26^{***}	53.79
	(13,691)	(217)	(58)
LEAKER × POST	−32,913	$-2,443.35^{***}$	−112.81
	(27,305)	(571)	(116)
Observations	49,925	51,739	61,122
R^2 (within)	0.0766	0.1180	0.1304

Notes: All regressions include plant and year fixed effects, with robust standard errors clustered by plant (`plantunitid`). Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. `ANNOUNCEMENT` indicates years 2006–2008; `POST` indicates years ≥ 2009.

responses. The Leaker states show surprising decreases in emissions across all emissions, though most notably for SO_2. While one might expect neighboring unregulated states to absorb some generation capacity from RGGI states, thereby raising their emissions ("leakage"), the magnitude of these estimates is unanticipated. This suggests that both market forces (e.g., relative fuel prices) and plant-level decisions (e.g., capacity expansions or retirements) may interact to produce shifts in dispatch patterns, possibly in ways that amplify emissions in certain unregulated regions.

Much of the aggregate emission decreases measured here seem to be coming from the highest-emitting plants, as shown in Figure 7. The top 10% of emitters in RGGI states exhibit steeper post-2005 declines than their non-RGGI counterparts. This is consistent with carbon pricing exerting its greatest pressure on units that can reduce emissions most cost-effectively through fuel switching or curtailed operation. Since this is a measure of the intensive margin, it is impossible without looking at additional measures to determine the effects on overall output. Though the results are suggestive that plants started shifting their behavior prior to 2009 when the RGGI was officially implemented.

There are a couple limitations to this analysis that later sections aim to address. Primarily, the fuel-share changes associated with the shale revolution had an especially large effect on the Leaker states, which were primarily reliant on coal prior to the RGGI, and thus had the greatest margins to transition. This can be especially difficult to disentangle in the DiD analysis, even with the specification controlling for factors such as state fuel share and natural log pricing. Moreover, another critique of DiD models that operate on the plant level comes from Roach and Gittings (2021), who find that intensive changes are masked by changes in fuel share compositions. Indeed, holding constant the primary fuel type for coal and natural gas plants reveals that much of the leaker's substantive effects come from the Coal plants, especially when it comes to CO2 (Table: C3). For the RGGI, it's the coal plants that experience the greatest decreases in emissions across all pollutants, which corroborates the hypothesis that RGGI reduces emissions.

An analysis of different types of plants reveals what is driving the overall changes in emissions. Table 4 presents the estimated effects of RGGI policy on coal and natural gas plant operations over the announcement and post-implementation period. For coal-fired generating units in RGGI states, perating time shows a substantial and significant decline in the post-implementation period of 1,105.7 hours per unit, which is significant at the 1% level, although though effects during the announcement period are more modest. However, heat input exhibits significant reductions in both periods, with effects intensifying from

$-1{,}128{,}493$ MMBtu during transition to $-3{,}780{,}412$ MMBtu post-implementation. The gross load, or maximum generation in a day, follows a similar pattern, with particularly strong reductions post-implementation ($-355{,}349$ MWh, significant at the 1% level). Leaker states contrast these findings, especially post-implementation. While operating time decreases modestly, heat input increases significantly (+864,897.8 MMBtu) and gross load shows a positive though statistically insignificant coefficient. This divergent pattern provides initial evidence consistent with the emissions leakage hypothesis, suggesting potential substitution of generation from RGGI to neighboring non-RGGI states.

Natural gas plants in RGGI states exhibit significant operational reductions across all metrics and in both time periods. Operating time decreases by a highly significant level during transition (579 hours) and and post-implementation (1311 hours). Heat input follows a similar pattern of escalating reductions, indicating that each unit is operating for less time with lower intensity. Gross load shows substantial declines in both periods, though proportionally smaller than the reductions observed for coal plants.

Interestingly, natural gas plants in leaker states show a more nuanced response. During the transition period, these plants exhibit significant reductions in heat input and gross load, potentially reflecting anticipatory adjustments to regional market conditions. However, in the post-implementation period, coefficients for all operational metrics are small and statistically insignificant, suggesting minimal long-term impacts on natural gas plant operations in these neighboring states.

These findings have several important implications. First, they demonstrate that RGGI had substantial effects on power plant operations in participating states, with impacts extending beyond the targeted high-emission coal plants to affect natural gas generation as well. The magnitude of effects suggests that even modest carbon pricing can induce significant operational changes in electricity markets.

Second, the differential impacts across fuel types highlight the policy's effect on relative generation costs. While coal plants experienced the largest absolute reductions in operations, natural gas plants in RGGI states also faced significant constraints, contrary to the common expectation that carbon pricing would primarily shift generation from coal to natural gas.

Third, the contrasting patterns between RGGI and leaker states, particularly for coal plants, provide evidence consistent with emissions leakage. The positive coefficients for heat input and gross load in leaker states post-implementation suggest that some of the generation reduced in RGGI states may have been replaced by increased generation in neighboring states, potentially undermining the policy's effectiveness in reducing aggregate emissions.

Table 4: RGGI Policy Effects on Coal and Natural Gas Plant Operations

Panel A: Coal Plants

Outcome	**RGGI States**		**Leaker States**	
	Transition	**Post**	**Transition**	**Post**
Operating Time (hrs)	-81.877	-1105.703^{***}	-82.228	-120.628
	(185.987)	(320.403)	(92.645)	(205.444)
Heat Input (MMBtu)	$-1,128,493^{**}$	$-3,780,412^{***}$	$-160,348.8$	$864,897.8^{**}$
	(566,395.6)	(841,237.4)	(236,969.5)	(434,149.6)
Gross Load (MWh)	$-24,941.65$	$-355,349^{***}$	$-25,098.98^{***}$	$19,716.16$
	(67,903.68)	(98,606.85)	(3,262.8)	(52,056.75)

Panel B: Natural Gas Plants

Outcome	**RGGI States**		**Leaker States**	
	Transition	**Post**	**Transition**	**Post**
Operating Time (hrs)	-578.912^{***}	$-1,311.049^{***}$	1.019	-9.695
	(113.541)	(137.934)	(68.391)	(132.688)
Heat Input (MMBtu)	$-400,650.8^{*}$	$-1,448,420^{***}$	$-257,830.2^{***}$	$24,712.39$
	(227,768.4)	(212,303)	(68,956.08)	(207,754.9)
Gross Load (MWh)	$-73,014.89^{***}$	$-165,026.8^{***}$	$-63,080.23^{***}$	$15,957.8$
	(20,898.29)	(27,940.34)	(9,349.306)	(30,678.79)

Notes: Each cell reports the coefficient from fixed-effects (within) regressions with plant-unit and year fixed effects and standard errors clustered by plant-unit. Standard errors in parentheses. Transition period refers to 2006-2008, Post period refers to 2009 onwards. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.1.2 Extensive Margin

Table 5: Impact of RGGI on Power Generation Units

	(1)	(2)
RGGI × Post	-21.241^{***}	—
	(7.702)	
Leaker × Post	-5.095	—
	(9.902)	
RGGI Region Effects:		
ISO-NE × Post	—	-24.004^{***}
		(5.808)
NYISO × Post	—	28.352^{***}
		(5.133)
PJM RGGI × Post	—	-32.248^{***}
		(5.580)
Leaker × Post	—	-5.095
		(9.909)
Year Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Observations	1,351	1,351
R-squared (within)	0.399	0.416
Number of States	48	48

Notes: Robust standard errors clustered at the state level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable in both columns is the count of unique generation units in each state-year. Column (2) breaks RGGI states into ISO-NE (CT, MA, RI, VT, NH, ME), NYISO (NY), and PJM RGGI (NJ, DE, MD).

This section investigates how RGGI participation influenced facility-level entry and exit decisions, focusing on the extensive margin at the plant level. The "units" I am looking at are those large enough enough to fall under RGGI and EPA reporting requirements. When a facility shuts down or downsizes below the reporting threshold, my dataset treats that as an exit, because both scenarios appear as a reduction in the total unit count.

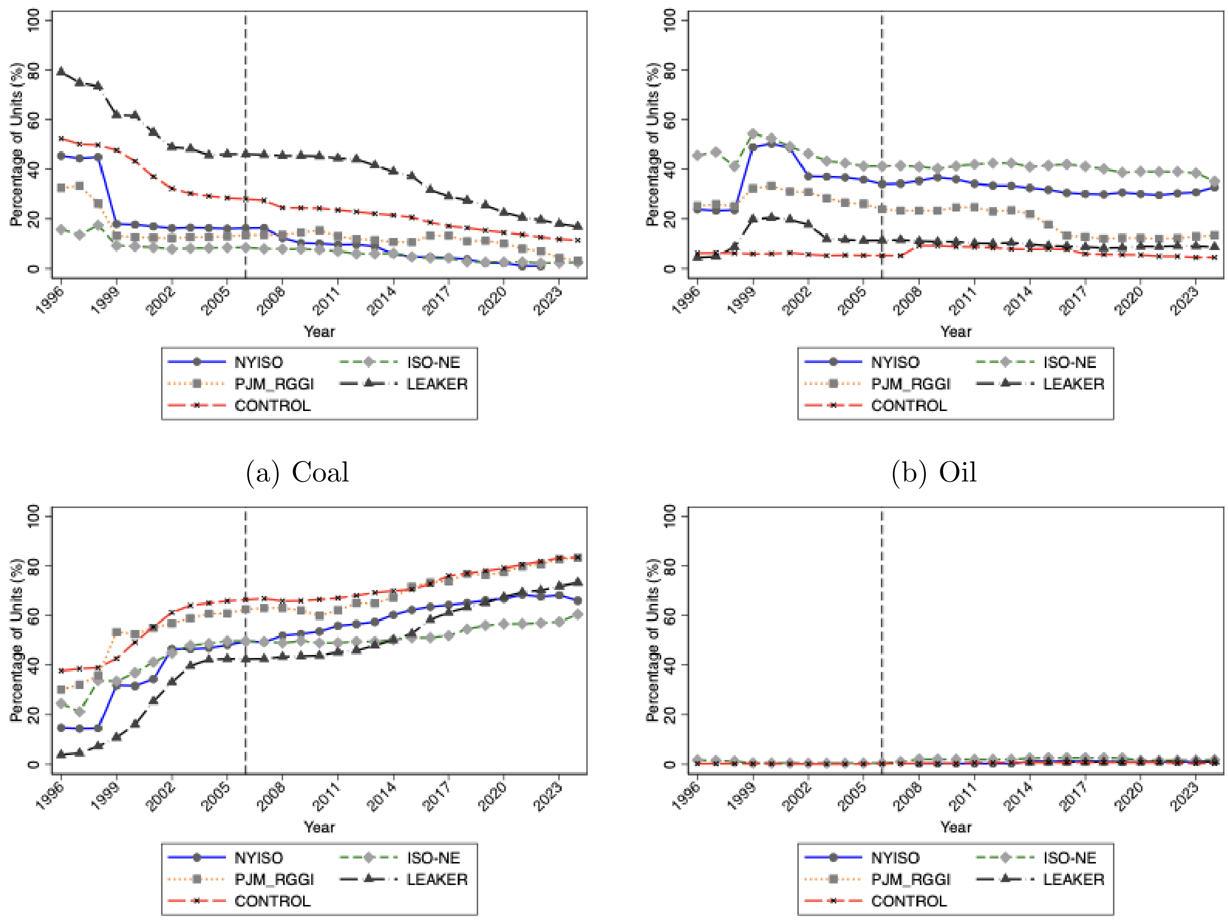
Existing literature suggests that cap-and-trade programs often prompt net facility exits, especially for plants dependent on carbon-intensive fuels like coal (Yan, 2021). At the same time however, RGGI participation may encourage newer, lower-carbon sources such as natural-gas or renewable-based facilities. To capture these dynamics, I explicitly track changes in the absolute number of operational units at the state level, measuring how the RGGI affects facility entry and exit decisions over time.

Table 5 presents two specifications for how RGGI participation affects the number of operational units in each state-year, using fixed-effects to estimate the aggregate and regional effects on number of units. Column (1) indicates that, on average, RGGI states experienced a statistically significant decrease of about -21.24 units after the policy was implemented ($p < 0.01$), a significant change in the extensive margin. By contrast, Leaker states show a smaller and statistically insignificant reduction of around -5.10.

Turning to column (2), I separate RGGI states into subgroups based on the unit's ISO region. The ISO-NE states exhibited a sizable and statistically significant decline of about -24.00 units. Interestingly, the PJM RGGI states record the largest drop in units which are the most statistically signficant, at -32.25 units, a possible result of leakage. This also stands out since the PJM region had less units to begin with than did NYISO and the Leaker region.

By contrast, NYISO sees a significant increase of $+28.35$, suggesting that the effects of RGGI may vary with market structure and the composition of new generating units. Notably, the vast majority of NYISO's newly added units over this period were natural gas plants, indicating that New York's net capacity expansion was largely driven by gas-fueled generation rather than coal or oil, which is reflected in the temporal composition change of unit production in 4. Once again, the coefficient for Leaker states is negative (approximately -5.10) but remains statistically insignificant in this regional breakdown.

In addition to the RGGI affecting the overall count of operating units, I am interested



(a) Coal

(b) Oil

(c) Gas

(d) Other

Figure 5: Percentage of generation units by fuel type across regions (1996–2023). Each panel shows the share of active units categorized as Coal, Oil, Gas, or Other.

in looking at whether the *fuel composition* also shifted. The dataset includes each unit's `primaryfueltype`, which I group into four broad categories: Coal, Oil, Gas, and Other. Figure 5 plots the percentage of active units in each category, broken down by region and year, with a vertical reference line at 2006 to mark the RGGI's announcement.

A clear pattern emerges for coal, where RGGI regions such as ISO-NE and NYISO display a sharper decline in coal-based units relative to non-RGGI areas, especially after the program's implementation. This trend aligns with the difference-in-differences findings in Table 4, indicating that RGGI states retire coal capacity more aggressively once the policy takes effect. By contrast, gas grows more quickly outside the RGGI boundary, particularly in "Leaker" states like Pennsylvania and Ohio, suggesting a possible relocation of capacity to avoid carbon compliance costs (Fell and Maniloff, 2018), (Chan and Morrow, 2019), (Lee and Melstrom, 2018). Oil remains a small fraction of total units across all regions and steadily declines over time, implying a minor role for oil-fueled generation under RGGI. Meanwhile, the "Other" category— which includes biomass, waste, and other uncategorized fuels—remains modest throughout the sample period.

5.2 State-Level Findings

I then move on to the synthetic control specification to examine the aggregate RGGI changes. I start by constructing a *counterfactual* for RGGI at the state level, employing the synthetic control method as implemented in the `synth2` package for `Stata`.[4] The algorithm estimates an optimal weight vector w^* by minimizing the discrepancy between pre-treatment characteristics of the treated region (RGGI or Leaker) and a weighted average of control regions (non-RGGI, non-Leaker).

While RGGI was announced in December 2005, formal allowance trading and compliance began in 2009. Hence, my main specification assigns 2006 as the policy onset (with alternative timing analysis conducted for robustness and displayed in Appendix D). Table C1 displays the estimated donor weights that compose the "Synthetic RGGI" region. Notably, only a handful of high-emitting states—Texas, Michigan, Indiana, Florida, and Tennessee—receive positive weights, implying they best match RGGI's pre-2006 emissions trend. Figure 6 reports the *Actual* vs. *Synthetic* trajectories for total CO_2, SO_2, and NO_x emissions. The paths closely align before 2006, easing concerns about a poor pre-treatment

[4]See `http://web.stanford.edu/~jhain/synthpage.html` for documentation.

fit. From 2006 onward, the treated RGGI emissions diverge downward, suggesting that states under the program cut emissions more sharply than their synthetic counterparts would have predicted.

Table D2 further quantifies these gaps over each control period. For instance, from 2006–2008, the treatment effect (T.E.) for CO_2 is approximately -1.97×10^7 tons, corresponding to a statistically significant 11.2% reduction relative to the counterfactual synthetic RGGI, which estimates where the RGGI would have been absent the policy (% CH in the table). This already suggests some early impact, even before formal compliance began in 2009. The gap then widens considerably over subsequent periods: by 2018–2020, the difference reaches -5.96×10^7 tons (-40.9%). Likewise, SO_2 exhibits a small initial effect of around -11.4% during 2006–2008, but that grows to -65.4% by 2021–2022. NO_x follows a similar pattern, moving from a modest -3.6% difference at the start to a substantial -34.4% gap by the final period. Thus, preliminary results seem to indicate that the greatest impacts manifest in the later control periods, suggesting that RGGI's cumulative abatement effect was maintained as time went on.

A regional breakdown in Tables C4–C6 provides further insight into how RGGI's impacts evolve across time and differ by sub-region. Focusing on NYISO (Table C5), the treatment effect for CO_2 starts at about -1.06×10^7 tons (-17.4%) over 2006–2008 and deepens to -1.84×10^7 tons (a -39.1% reduction) by 2018–2020, indicating a progressive abatement within New York's portion of the grid. Analogous patterns emerge in ISO-NE (Table C5), where the early period also shows moderate reductions and escalate to -36.2% in later control intervals. In contrast, for the PJM RGGI states (Table C6), I observe a smaller initial CO_2 gap of roughly -6.5% but still see it widen in later periods. Meanwhile, SO_2 and NO_x trends similarly intensify over time, showcasing that the program's effects become more pronounced in successive compliance periods for all pollutants.

Overall, these sub-regional estimates reinforce two key conclusions. First, RGGI's abatement effect does not manifest evenly across states. The areas that don't have the spillover effect, like NY-ISO and ISO-NE appear to adopt cleaner generation mixes more rapidly than others. Second, despite some heterogeneity in timing, each region under RGGI exhibits growing emission reductions in later years—particularly noticeable for SO_2 and NO_x, where many states faced co-pollutant rules or installed additional scrubbers. The consistent deepening of the gap by 2018–2020 underscores that RGGI's cumulative abatement effect persisted (and even accelerated) well after its initial launch, complementing the broad patterns found in the aggregate analysis (Table D2).

A potential caveat to our synthetic control analysis is that total emissions can be dominated by a few large states, potentially over-weighting high-emission donors in our limited donor pool. While I have accounted for a number of major covariates, states differ substantially in population, baseline energy mix, industrial output, and there could be some omitted variable bias. These differences can confound the analysis, as comparisons of raw emission tonnage may obscure important nuances in regional characteristics and trends.

To mitigate the above concerns, I re-estimate the synthetic control on all three pollutants using a per-capita measure of emissions per unit of energy produced, which I call "emission intensity." This approach normalizes emissions by the magnitude of electricity generation (e.g., MWh), capturing whether RGGI states reduced their carbon intensity *per unit of output* more rapidly than their synthetic counterparts.

The emission intensity results reaffirm that after the policy onset in 2006 RGGI emissions drift further below the synthetic trajectories, and the gap expands over each subsequent control period. Table D2 illustrates how the RGGI's effects persist and intensify over time.

Reductions of SO_2 and NO_x likewise show larger negative percentage changes, suggesting that co-pollutant abatement proceeded in tandem with greenhouse gas reductions.

For instance, CO_2 emissions in RGGI are roughly 83% below synthetic projections by 2018–2020, indicating that the policy's effect on intensity strengthens over time. In tandem with the plant-level DiD evidence, these findings suggest that RGGI cut emissions both in absolute terms and at an accelerating rate, even after accounting for variations in population or baseline economic activity.

From our regional results, the ISO-NE region (Table D5) shows particularly strong reductions, with CO_2 emissions reaching 85.9% below the synthetic control by 2018–2020, alongside substantial decreases in SO_2 (69.8%) and NO_x (95.9%). The results suggest that the northeastern power market responded most dramatically to the policy intervention, likely to changes in fuel composition. By contrast, the NYISO region (Table D4) exhibits a different pattern in earlier periods, with $CO_2 CO2$ emissions actually 30.9% higher than synthetic projections during 2006–2008. However, this anomaly reverses by 2009–2011, after which emissions steadily decline below synthetic expectations, culminating in a 78.4% reduction during 2018–2020.

The PJM-RGGI region (Table D6) demonstrates the highest absolute CO_2 levels in the early period (129.5 units compared to 93.4 overall RGGI average), but achieves comparable percentage reductions (84.2% below synthetic projections) by 2018–2020. This region also shows the most dramatic improvement in NO_x abatement, reaching 97.1% below synthetic projections in the 2018–2020 period. Interestingly, and in accordance with the leakage hypothesis, the Leaker region (Table D7) presents a stark contrast to other regions, with CO_2 emissions consistently higher than synthetic projections after 2012. By 2018–2020, emissions are 15% above synthetic control estimates, suggesting possible emissions leakage or displacement from regulated to unregulated areas. However, SO_2 reductions remain substantial even in this region (31.9% below synthetic projections during 2018–2020).

The temporal dynamics across all regions reveal that the largest marginal improvements often occur between the 2012–2014 and 2015–2017 periods, with the percentage gap between actual and synthetic emissions widening substantially. Though it is important to note, that a large reason why the effect grows during that time is due to a spike in the emissions intensity of the controls. I will perform robustness checks modifying the control units to establish the result's validity. Nonetheless, the consistent acceleration of emission reductions during this period could suggest that policy refinements enhanced RGGI's effectiveness. The data also demonstrate that energy-normalized emissions fell most dramatically for NO_x (reaching 95.8% below synthetic projections overall by 2018–2020), followed by CO_2 (83.1%) and SO_2 (62.6%). This hierarchy of reduction intensities may reflect the interaction between RGGI and other concurrent regulations targeting criteria pollutants, as well as the relative technical and economic constraints governing abatement options for each pollutant.

5.3 Robustness Checks

I perform a number of robustness checks to assess the stability of the estimated treatment effects. I begin by following the process of Yan (2021) by restricting the set of potential control states to those within the Eastern Interconnection (hence removing Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Texas, Utah, Washington, and Wyoming as controls). States in the western grid may be weaker controls due to fundamentally different market structures and greater geographical distance from the RGGI region. By selecting only Eastern Interconnection states outside of RGGI and the Leaker definitions, I improve the comparability between treated and control observations. Re-running the SCM under this restriction yields effectively the same significance levels with similar coefficients for all RGGI regions, which confirms that the results are not driven by including distant western states. For the Leaker region, solely using eastern weights changes the findings from the earlier periods as the treatment effect switches from positive to negative, but the effects converge after control period 3 and the number of donors reduce from 11 to 4 in the exclusion specification, making it weaker than the baseline analysis.

Another important check involves redefining which states are considered "Leaker" states. In my main model, I designate Ohio, Pennsylvania, Kentucky, Virginia, and West Virginia as Leaker states. I then restrict the Leaker group to include only Ohio and Pennsylvania, the two states that had been identified as the largest Leakers in most previous research. In both cases, the resulting estimates of the treatment effect remain similar in magnitude and significance, indicating that the primary findings on emissions leakage are robust to how the boundary of the Leaker region is drawn.

To validate the robustness of the plant-level DiD estimates, I employ a mixed placebo test that combines in-space and in-time placebo assignments, following the approach of Chen and Yan (2023). The mixed placebo test uses a fake treatment time prior to the actual treatment and applies the in-space placebo framework as if the fake treatment time were the real one. This approach takes an otherwise visual validation approach and allows for p-values, providing a way to evaluate the significance of treatment effects (Firpo and Possebom, 2018). The use of the mixed placebo test ensures that the observed effects are unlikely to be driven by chance or random noise, strengthening confidence in the findings. I implement it using the `didplacebo` Stata module that Chen and Yan created (Chen et. al, 2023). Specifically, I randomly assign treatment *units* and *timing* over 500 simulated draws among potential donor states, then compare how often the observed DiD coefficient is matched or exceeded by these placebos. Turning to the results from the mixed placebo tests, the CO_2 and SO_2 estimated effects are highly significant at conventional levels. By contrast, the NO_x estimates lie higher in the placebo distribution, offering no robust evidence of emission reductions (Appendix Table: E1).

Finally, I perform three robustness checks on the synthetic-control estimates. First, for each treated region, I re-run the synthetic control methodology but treat each donor state (separately) as if it were "treated," examining the post-treatment gaps in those placebo assignments. Across the placebo distribution, the actual RGGI effect is consistently among the most pronounced and negative, with the highest Mean Square Prediction Error ratio from the pre-intervention period to the post. This reaffirms that the estimated impact is significant compared to random reassignments of treatment. This result holds for both aggregate emissions and intensity, across all types of pollutants. Second, I apply the Leave-One-Out approach (Figure: 9) by removing each donor state in turn from the synthetic control and then re-estimating the treatment effect. The finding that no single donor state is disproportionately driving the estimated impact, reinforces the robustness of the findings. Third, I use 2009 as the treatment date as has been done in most previous literature, and I find a slightly more muted, yet significant effect (Table: E2.

5.4 Limitations

Although the findings are robust to many specifications, four principal limitations should be acknowledged. First, this thesis makes a very precise specification for leaker states and treated units in this analysis. It makes the assumption that all leakage is confined to the leakage states with geographic proximity, though that may not be the case. In reality, emissions leakage may occur through more complex channels, including through electricity imports from regions beyond the designated leaker states or through industrial production shifts that cross multiple state boundaries.

Second, if electricity companies found New Jersey's exit from the RGGI as credible in the long-term, it may have also had a role as both a leaker state and an RGGI state that hasn't been thoroughly addressed in this analysis. This dual status creates identification challenges that could confound the estimated treatment effects, particularly during the period when New Jersey temporarily withdrew from the program.

Third, the methods used—particularly difference-in-differences—rely on assumptions of parallel trends that may not perfectly hold for all states or plant types. While I conducted event study analyses and placebo tests to validate these assumptions, heterogeneous plant characteristics and regional electricity market structures may introduce unobserved time-varying factors that affect the parallel trends assumption.

Fourth, many of the plant-level characteristics used in the DiD were state-level observations, such as state renewable energy policies. Unfortunately, due to data and time constraints, I wasn't able to find more granular data that would capture facility-specific regulatory environments or compliance strategies. This aggregation may mask important heterogeneity in how individual plants responded to RGGI, potentially introducing measurement error in the estimated effects. Future studies could work to collect more granular data on facility-specific environments, including using geospatial data on proximity to the nearest plant from a non-neighboring state.

6. CONCLUSION

Climate change mitigation strategies are gaining greater momentum across regions, with more states signing onto voluntary and mandatory climate initiatives in an effort to balance environmental protection and economic growth. As the cost of inaction on global warming grows clearer, programs like the Regional Greenhouse Gas Initiative have drawn heightened scrutiny and interest.

This analysis shows that, over time, the RGGI framework has been increasingly effective at driving down emissions within its participating states by making the cost of fossil-fuel-based electricity more expensive and thereby nudging power producers toward lowering output or seeking cleaner energy sources. I find that a moderate degree of emissions "leakage" does arise when electricity demand shifts toward facilities in neighboring states not covered by RGGI's cap. Nevertheless, the net result remains a measurable drop in overall carbon emissions, supported by plant-level responses that involve both intensive (reduced operating hours, heat inputs, or altered efficiency) and extensive shifts (retirements or operating fewer units and fuel switching). I identify the changes in the extensive margin, particularly through switching from carbon-intensive coal power plants to more carbon-efficient natural gas, as the most significant driver of emissions reductions across all regions.

The findings highlight how, despite its success at cutting emissions in the original states, a partial regional program is unlikely to be seamless: without broader adoption, at least some portion of the pollution may migrate. On balance, the results from the regional analysis suggest that policy harmonization where every state within a shared electricity market participates leads to more effective outcomes.

Particularly noteworthy are the emissions reductions that continue to grow over time, with the greatest impacts observed in later control periods (2018-2023). This suggests that RGGI's progressively tightening emissions cap has maintained its effectiveness even as states exhaust their initial low-cost abatement opportunities. Additionally, the significant co-benefits observed for SO_2 and NO_x emissions highlight how carbon pricing policies can simultaneously address multiple environmental objectives, potentially yielding substantial air quality and public health improvements beyond their climate targets.

Future policy designs should consider these findings by prioritizing comprehensive regional coverage to minimize leakage effects, implementing mechanisms to address cross-border electricity transfers, and recognizing the value of gradually increasing stringency over time. As more jurisdictions contemplate similar market-based approaches to emissions reduction, the RGGI experience demonstrates that regional cap-and-trade programs can be effective climate policy tools when thoughtfully structured and adaptively managed.

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8. APPENDIX

8A. Synthetic Balance

For the first three tables in this appendix, the *V.weight* column indicates the importance assigned to each predictor variable during the optimization procedure that minimizes the pre-treatment root mean squared prediction error (RMSPE). Higher weights suggest a stronger contribution to the synthetic control's ability to approximate the treated unit's pre-treatment outcomes. For example, CO_2 emissions in the early 2000s (e.g., 2005, 2004, 1999) receive relatively higher weights, implying that these years were especially influential in constructing the synthetic control.

The *Bias (Synth.)* column shows the percentage difference between the treated unit and its synthetic counterpart for each predictor, calculated as:

$$\text{Bias (Synth.)} = \frac{\text{Synthetic} - \text{Treated}}{\text{Treated}} \times 100$$

Smaller values (closer to 0%) reflect better balance and a more credible counterfactual.

These results were generated using the `synth2` and `allsynth` commands in Stata, which internally optimize both the predictor weights (v-weights) and donor unit weights (w-weights) through a nested minimization procedure. The `fig` option was used to automatically produce covariate balance, unit weight, and treatment effect plots. The predictor balance table was manually recreated based on the output returned by `synth2`.

`synth2` was developed by Guanpeng Yan and Qiang Chen as a Stata wrapper to expand over traditional synthetic controls and include placebo tests, robustness test, and visualization, while `allsynth` was developed by Justin C. Wiltshire as a tool for synthetic bias correction.

Table A1: Covariate Balance in the Pretreatment Periods: CO_2

Covariate	**V.weight**	**Treated**	**Synthetic Control**	**Average Control**	**Bias (Synth.)**
CO2(1990)	0.0520	1.698e+08	1.503e+08	4.070e+07	-11.48%
CO2(1991)	0.0511	1.654e+08	1.501e+08	4.078e+07	-9.29%
CO2(1992)	0.0491	1.583e+08	1.479e+08	4.142e+07	-6.57%
CO2(1993)	0.0534	1.523e+08	1.572e+08	4.351e+07	3.28%
CO2(1994)	0.0527	1.556e+08	1.568e+08	4.449e+07	0.76%
CO2(1995)	0.0546	1.590e+08	1.570e+08	4.468e+07	-1.29%
CO2(1996)	0.0580	1.563e+08	1.639e+08	4.643e+07	4.82%
CO2(1997)	0.0639	1.719e+08	1.675e+08	4.791e+07	-2.52%
CO2(1998)	0.0684	1.781e+08	1.750e+08	5.014e+07	-1.72%
CO2(1999)	0.0696	1.763e+08	1.779e+08	5.068e+07	0.94%
CO2(2000)	0.0731	1.745e+08	1.823e+08	5.327e+07	4.47%
CO2(2001)	0.0684	1.729e+08	1.768e+08	5.259e+07	2.27%
CO2(2002)	0.0700	1.696e+08	1.771e+08	5.216e+07	4.38%
CO2(2003)	0.0701	1.729e+08	1.762e+08	5.266e+07	1.94%
CO2(2004)	0.0714	1.730e+08	1.791e+08	5.393e+07	3.53%
CO2(2005)	0.0741	1.796e+08	1.808e+08	5.482e+07	0.65%
coal_price(2005)	0.0000	1.9310	1.4332	1.3215	-25.78%
natural_gas_price(2005)	0.0000	9.4380	6.8388	7.9403	-27.54%
population(2005)	0.0000	4843.8000	17127.2120	6106.5294	253.59%
real_GDP(2005)	0.0000	3.129e+05	5.550e+05	3.174e+05	173.21%
CDD(2005)	0.0000	751.6000	1917.8000	1312.0000	155.16%
HDD(2005)	0.0000	6333.3000	3965.1840	4835.5882	-37.39%
total_energy_bil_btu(2005)	0.0000	1.116e+07	7.935e+06	2.111e+06	-28.90%

Table A2: Covariate Balance in the Pretreatment Periods: SO_2

Covariate	**V.weight**	**Treated**	**Synthetic Control**	**Average Control**	**Bias (Synth.)**
SO2(1990)	0.1022	1.217e+06	1.119e+06	2.794e+05	-8.05%
SO2(1991)	0.0975	1.118e+06	1.162e+06	2.771e+05	3.85%
SO2(1992)	0.0843	1.030e+06	1.012e+06	2.711e+05	-1.79%
SO2(1993)	0.0791	9.400e+05	1.037e+06	2.720e+05	10.36%
SO2(1994)	0.0709	8.495e+05	1.010e+06	2.638e+05	18.86%
SO2(1995)	0.0521	8.482e+05	8.060e+05	2.366e+05	-4.97%
SO2(1996)	0.0585	8.200e+05	8.536e+05	2.510e+05	4.09%
SO2(1997)	0.0697	9.580e+05	9.038e+05	2.609e+05	-5.66%
SO2(1998)	0.0716	1.019e+06	8.723e+05	2.619e+05	-14.38%
SO2(1999)	0.0629	9.409e+05	8.482e+05	2.479e+05	-9.86%
SO2(2000)	0.0508	9.272e+05	7.767e+05	2.251e+05	-16.23%
SO2(2001)	0.0401	8.011e+05	7.081e+05	2.147e+05	-11.60%
SO2(2002)	0.0416	7.272e+05	7.019e+05	2.144e+05	-3.48%
SO2(2003)	0.0396	7.707e+05	7.144e+05	2.048e+05	-7.30%
SO2(2004)	0.0393	7.514e+05	7.469e+05	1.999e+05	-0.59%
SO2(2005)	0.0397	7.133e+05	7.455e+05	1.990e+05	4.53%
coal_price(2005)	0.0000	1.9310	1.3866	1.3594	-28.19%
natural_gas_price(2005)	0.0000	9.4380	8.4517	8.1913	-10.45%
population(2005)	0.0000	4843.8000	9958.2770	5350.8438	105.59%
real_GDP(2005)	0.0000	3.129e+05	4.930e+05	2.701e+05	57.54%
CDD(2005)	0.0000	751.6000	1455.8180	1315.4062	93.70%
HDD(2005)	0.0000	6333.3000	4745.0700	4919.8750	-25.08%
total_energy_bil_btu(2005)	0.0000	1.116e+07	4.988e+06	2.024e+06	-55.31%

Table A3: Covariate Balance in the Pretreatment Periods: NO_x

Covariate	**V.weight**	**Treated**	**Synthetic Control**	**Average Control**	**Bias (Synth.)**
NOx(1990)	0.0978	5.161e+05	4.768e+05	1.754e+05	-7.61%
NOx(1991)	0.1002	5.022e+05	4.970e+05	1.758e+05	-1.04%
NOx(1992)	0.0867	4.726e+05	4.636e+05	1.709e+05	-1.90%
NOx(1993)	0.0926	4.486e+05	4.860e+05	1.790e+05	8.33%
NOx(1994)	0.0854	4.183e+05	4.674e+05	1.777e+05	11.73%
NOx(1995)	0.0711	4.718e+05	4.111e+05	1.306e+05	-12.86%
NOx(1996)	0.0672	4.129e+05	4.073e+05	1.346e+05	-1.35%
NOx(1997)	0.0719	4.522e+05	4.025e+05	1.352e+05	-11.00%
NOx(1998)	0.0732	4.537e+05	4.275e+05	1.370e+05	-5.77%
NOx(1999)	0.0599	3.690e+05	4.031e+05	1.285e+05	9.23%
NOx(2000)	0.0540	3.476e+05	3.934e+05	1.233e+05	13.18%
NOx(2001)	0.0388	3.080e+05	3.328e+05	1.153e+05	8.07%
NOx(2002)	0.0374	2.874e+05	2.851e+05	1.148e+05	-0.80%
NOx(2003)	0.0255	2.807e+05	2.663e+05	9.832e+04	-5.13%
NOx(2004)	0.0206	2.666e+05	2.409e+05	9.095e+04	-9.61%
NOx(2005)	0.0178	2.614e+05	2.186e+05	8.674e+04	-16.36%
coal_price(2005)	0.0000	1.9310	1.6843	1.3594	-12.78%
natural_gas_price(2005)	0.0000	9.4380	8.2903	8.1913	-12.16%
population(2005)	0.0000	4843.8000	18694.2060	5350.8438	285.94%
real_GDP(2005)	0.0000	3.129e+05	9.326e+05	2.701e+05	198.08%
CDD(2005)	0.0000	751.6000	2826.0000	1315.4062	276.04%
HDD(2005)	0.0000	6333.3000	1661.4000	4919.8750	-73.77%
total_energy_bil_btu(2005)	0.0000	1.116e+07	7.791e+06	2.024e+06	-30.19%

8B. Summary Statistics

Table B1: Summary Statistics by Fuel Category

Panel A: Coal Plants

Variable	**Mean**	**SD**	**Min**	**p25**	**Median**	**p75**	**Max**
CO_2 Mass (short tons)	1932187	1786287	0	529967	1297322	3068205	12400000
CO_2 Rate (short tons/mmBtu)	0.10	0.06	0	0.10	0.10	0.10	6.20
SO_2 Mass (short tons)	6669	9799	0	1025	3087	8442	173285
SO_2 Rate (lbs/mmBtu)	0.96	2.39	0	0.19	0.59	1.30	308.5
NO_x Mass (short tons)	2612	3678	0	522	1364	3288	81109
NO_x Rate (lbs/mmBtu)	0.33	0.26	0.001	0.17	0.31	0.43	22.16
Heat Input (mmBtu)	17400000	17100000	0	4127945	11100000	27800000	121000000
Operating Time Count	6289	2378	0	5284	7241	8027	8784
Sum of Operating Time	6273	2380	0	5260	7226	8015	8784
Gross Load (MWh)	2016625	1803128	0	592224	1388023	3194285	13900000

Panel B: Gas Plants

Variable	**Mean**	**SD**	**Min**	**p25**	**Median**	**p75**	**Max**
CO_2 Mass (short tons)	209506	299598	0	9489	47039	340430	4200325
CO_2 Rate (short tons/mmBtu)	0.06	0.14	0	0.059	0.059	0.059	21.71
SO_2 Mass (short tons)	20	402	0	0.06	0.36	2.21	42457
SO_2 Rate (lbs/mmBtu)	0.01	0.08	0	0.001	0.001	0.001	7.38
NO_x Mass (short tons)	83	327	0	4.4	19.2	56.5	13140
NO_x Rate (lbs/mmBtu)	0.11	0.16	0	0.03	0.05	0.13	3.91
Heat Input (mmBtu)	3186285	4772625	0	134750	683495	4553272	105000000
Operating Time Count	2559	2725	0	295	1232	4664	8784
Sum of Operating Time	2488	2724	0	254	1096	4549	8784
Gross Load (MWh)	393637	630085	0	11011	61943	539746	8557859

Panel C: All Plants (Total)

Variable	**Mean**	**SD**	**Min**	**p25**	**Median**	**p75**	**Max**
CO_2 Mass (short tons)	658407	1222715	0	13055	129784	687716	12400000
CO_2 Rate (short tons/mmBtu)	0.07	0.14	0	0.059	0.059	0.10	21.71
SO_2 Mass (short tons)	1770	5782	0	0.12	1.53	274	173285
SO_2 Rate (lbs/mmBtu)	0.27	1.28	0	0.001	0.001	0.14	308.5
NO_x Mass (short tons)	712	2149	0	6.1	37.0	287	81109
NO_x Rate (lbs/mmBtu)	0.21	0.27	0	0.04	0.11	0.31	22.16
Heat Input (mmBtu)	6425414	11300000	0	143993	1236562	8403424	121000000
Operating Time Count	3275	3127	0	293	2057	6581	8784
Sum of Operating Time	3223	3134	0	254	1932	6535	8784
Gross Load (MWh)	724062	1228238	0	11112	117701	982852	38700000

Note: This table shows summary statistics for power plant emissions and operations by fuel type. Panel A shows statistics for coal plants, Panel B for gas plants, and Panel C for all plants combined. All mass values are in short tons.

8C. Aggregate Outcomes

8C.1 Overall RGGI

Table C1: Optimal Unit Weights by Pollutant

State	$\mathbf{CO_2}$	$\mathbf{SO_2}$	$\mathbf{NO_x}$
TX	0.5560	0.2230	0.5230
MI	0.4440	–	–
IN	–	0.7770	–
FL	–	–	0.3330
TN	–	–	0.1440

Table C2: RGGI Overall Synthetic Control Results by Control Period for Pollutants

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	1.59e+08	-1.97e+07**	-11.2	5.89e+05	-6.85e+04	-11.4	2.20e+05	-7.78e+03	-3.6
2009–2011	1.25e+08	-4.70e+07**	-27.5	3.83e+05*	-1.25e+05	-33.4	1.32e+05	-1.66e+04	-11.4
2012–2014	1.12e+08	-6.21e+07**	-36.2	1.10e+05**	-1.76e+05	-63.8	1.18e+05	-1.96e+04	-15.0
2015–2017	1.07e+08	-6.12e+07**	-37.9	7.59e+04*	-7.29e+04	-58.6	9.47e+04	-2.94e+04	-25.5
2018–2020	9.52e+07	-5.96e+07**	-40.9	4.50e+04	-3.96e+04	-59.0	7.77e+04	-3.20e+04	-30.6
2021–2022	8.69e+07	-5.50e+07**	-38.7	2.19e+04	-3.34e+04	-65.4	6.40e+04	-3.36e+04*	-34.4

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a) CO_2 (b) SO_2 (c) NO_x

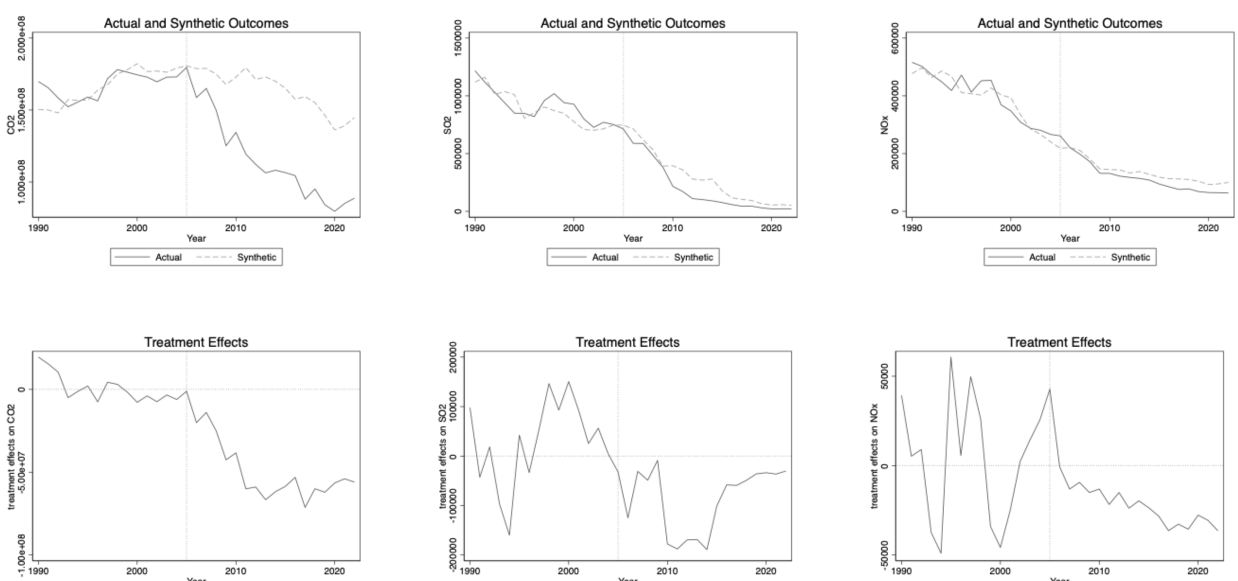
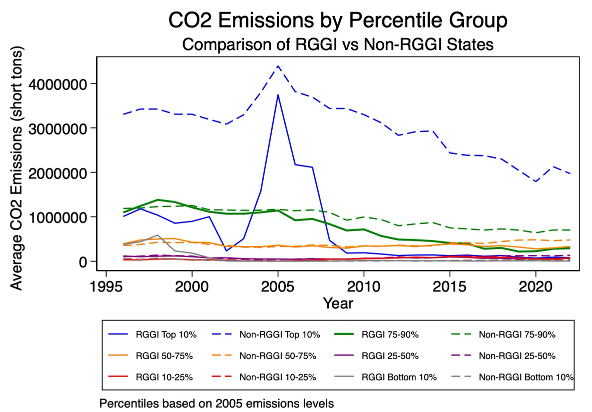
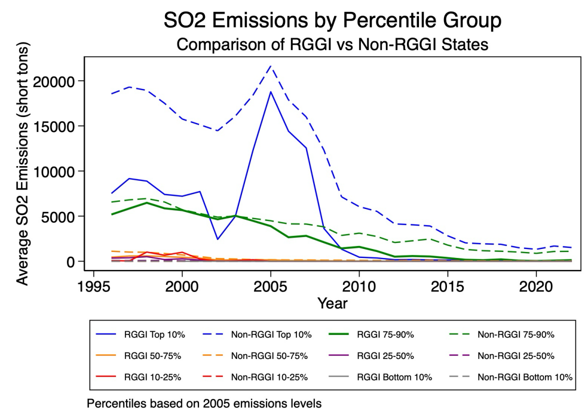


Figure 6: Synthetic Control Results for Aggregate RGGI Region.

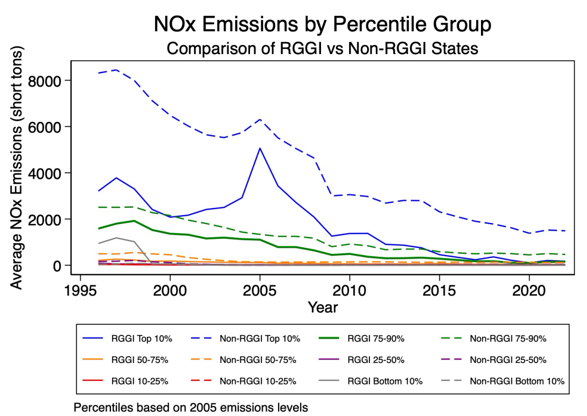
Plant Pollutant Decomposition



(a) CO_2 Emissions by Percentile Group (RGGI vs Non-RGGI, 1995–2022)



(b) SO_2 Emissions by Percentile Group (RGGI vs Non-RGGI, 1995–2022)



(c) NO_x Emissions by Percentile Group (RGGI vs Non-RGGI, 1995–2022)

Figure 7: Comparison of CO_2, SO_2, and NO_x emissions by percentile group (based on 2005 baselines), contrasting facilities in RGGI vs. Non-RGGI states. Vertical lines in the original plots mark the 2009 start date of RGGI implementation.

Discussion: The graphs indicate that the largest CO_2 and SO_2 emitters (top 10%) in RGGI states exhibit a notably sharper decline in emissions than their Non-RGGI counterparts. There was an immediate drop after the announcement, and a similar nosedive after the implementation of the RGGI program in 2009. This divergence suggests that carbon pricing has a greater influence on high-emitting facilities, likely through fuel switching, investments in efficiency, or curtailed operation of the highest-emitting units. Interestingly, the top 10% fall below the 75-90% after 2009, likely indicating the higher-polluting plants closed down. This effect only happened for the RGGI states, with similar trends not seen for the non-RGGI, further providing evidence to support the hypothesis that RGGI accelerated fuel-switching (as the dirtiest coal plants with highest emissions shut down). NO_x emissions follow a similar, though more modest pattern to the other pollutants, with the highest-emitting percentile groups driving overall reductions. While emissions for SO_2 and NO_x seemed to follow similar trends to the non-RGGI regions, CO_2 uniquely sees a much greater drop following implementation.

Table C3: Plant-Level DiD Estimates of RGGI and Leaker State Effects on Emissions

	Panel A: Coal Plants		
Variables	**CO_2**	**SO_2**	**NO_x**
ANNOUNCEMENT	$180,079.4$	$-1,639.32^{*}$	$-1,394.81^{***}$
	$(115,383.5)$	(893.06)	(335.23)
RGGI × *ANNOUNCEMENT*	$-39,508.7$	-295.52	-601.05^{**}
	$(64,859.88)$	$(1,014.38)$	(248.73)
POST	$-305,782.1^{*}$	$-1,795.94$	$-3,945.78^{***}$
	$(157,741.7)$	$(1,743.83)$	(552.19)
RGGI × *POST*	$-370,007^{***}$	$-4,196.38^{**}$	-931.82^{**}
	$(92,872.57)$	$(1,714.03)$	(395.82)
LEAKER × *ANNOUNCEMENT*	$-40,872.69$	$-1,511.11^{***}$	110.92
	$(28,814.55)$	(422.04)	(112.88)
LEAKER × *POST*	$9,713.94$	$-4,041.64^{***}$	-241.91
	$(47,179.74)$	$(1,143.4)$	(245.05)
Observations	12,279	12,416	13,943
R^2 (within)	0.3789	0.3555	0.3628
	Panel B: Gas Plants		
ANNOUNCEMENT	$-78,543.62^{***}$	-38.85^{**}	-171.19^{***}
	$(13,298.99)$	(17.32)	(21.77)
RGGI × *ANNOUNCEMENT*	$-36,750.44^{***}$	-17.57	10.07
	$(12,098.46)$	(27.63)	(7.48)
POST	$-101,858.2^{***}$	-6.70	-126.09^{***}
	$(19,143.01)$	(20.94)	(20.27)
RGGI × *POST*	$-77,474.31^{***}$	-23.45	-1.60
	$(17,183.71)$	(33.16)	(7.92)
LEAKER × *ANNOUNCEMENT*	$-17,117.42^{***}$	15.11^{**}	7.56
	$(5,100.51)$	(7.70)	(5.14)
LEAKER × *POST*	$11,637.78$	26.04^{***}	6.37
	$(14,948.91)$	(8.63)	(7.57)
Observations	32,254	33,484	38,127
R^2 (within)	0.1041	0.0184	0.0848

Notes: All regressions include plant and year fixed effects, with robust standard errors clustered by plant (`plantunitid`). Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. `ANNOUNCEMENT` indicates the announcement period (2006-2008); `POST` indicates the post-implementation period(2009-Present).

8C.2 Regional Analysis

For Tables C3-C5,

Table C4: NYISO Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	5.14e+07	-1.06e+07**	-17.4	1.22e+05	-1.06e+05*	-46.5	6.40e+04	-1.60e+04	-22.2
2009–2011	3.81e+07	-1.83e+07**	-37.7	5.89e+04	-6.66e+04	-53.1	4.41e+04	5.56e+03	14.7
2012–2014	3.57e+07	-1.80e+07**	-34.3	3.08e+04	-6.06e+04	-67.0	4.03e+04	1.16e+04	40.4
2015–2017	3.27e+07	-1.91e+07*	-38.7	2.17e+04	-2.43e+04	-58.5	3.53e+04	6.65e+03	25.3
2018–2020	2.79e+07	-1.84e+07*	-39.1	1.07e+04	-2.39e+04	-77.2	2.89e+04	6.65e+03	32.4
2021–2022	2.84e+07	-1.50e+07	-33.5	7.10e+03	-2.38e+04	-75.8	2.64e+04	8.37e+03	46.0

Table C5: ISO-NE Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	5.04e+07	-6.57e+06	-11.9	1.09e+05	-5.06e+04	-32.6	5.43e+04	-1.05e+04	-17.5
2009–2011	4.11e+07	-1.22e+07**	-24.3	9.91e+04	-1.95e+04	-19.6	4.45e+04	1.84e+03	4.8
2012–2014	3.48e+07	-1.76e+07**	-35.8	3.25e+04	-3.59e+04	-58.5	3.91e+04	1.86e+03	5.5
2015–2017	3.20e+07	-1.70e+07*	-36.2	1.89e+04	-2.54e+04	-57.0	3.09e+04	-1.31e+03	-4.4
2018–2020	2.73e+07	-1.55e+07*	-36.3	1.22e+04	-2.31e+04	-70.4	2.53e+04	-8.70e+02	-3.5
2021–2022	2.74e+07	-1.34e+07	-33.3	8.24e+03	-2.20e+04	-71.4	2.21e+04	-1.51e+03	-6.5

Table C6: PJM Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	5.68e+7	-3.99e+6*	-6.5	3.57e+5	18,568	5.9	1.01e+5	-1,835	-2.0
2009–2011	4.59e+7	-9.28e+6	-16.6	2.25e+5	-19,934	-14.3	43,133	-16,343	-27.3
2012–2014	4.18e+7	-1.08e+7	-20.6	46,791	-28,099	-39.2	38,187	-17,565	-32.5
2015–2017	4.18e+7	-7.43e+6	-15.6	35,243	-11,432	-29.5	28,479	-19,179	-42.7
2018–2020	3.99e+7	-8.38e+6	-19.7	22,117	-15,290	-53.5	23,442	-18,815	-49.5
2021–2022	2.93e+7	-1.22e+7	-29.3	6,562	-20,003	-77.9	15,989	-19,736	-56.0

8D. Intensity Outcomes

8D.1 Overall RGGI

Table D1: Optimal Unit Weights for RGGI by Pollutant (Intensity Specification)

State	CO_2	SO_2	NO_x
AR	0.4940	–	–
AZ	0.2230	–	0.0320
DC	0.1040	0.2290	0.0790
MN	0.0680	–	–
FL	0.0630	0.0380	0.0930
GA	0.0360	–	0.0960
NV	0.0110	0.0590	0.0010
TN	0.0010	0.0810	0.0340
WA	–	0.2430	–
IL	–	0.2150	–
MI	–	0.1010	–
IA	–	0.0340	–
ID	–	–	0.2010
CA	–	–	0.1950
ND	–	–	0.1490
MS	–	–	0.0650
NC	–	–	0.0550

Table D2: Overall RGGI Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x per Unit of Energy

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	93.4	-2.1	-2.1	0.3464	0.0824	32.5	0.1294	-0.0050	-4.1
2009–2011	66.9	-39.0	-36.7	0.2044	-0.1326	-49.2	0.0704	-0.0261	-27.6
2012–2014	60.3	-42.2	-42.2	0.0592	-0.0627	-53.9	0.0632	-0.0427	-41.5
2015–2017	54.6	-126.2*	-71.1	0.0389	-0.0381	-55.5	0.0485	-0.5440*	-92.5
2018–2020	48.3	-216.4*	-83.1	0.0229	-0.0274	-62.6	0.0395	-0.8145	-95.8
2021–2022	43.5	-69.8	-60.7	0.0112	-0.0240	-67.9	0.0330	-0.2769	-89.3

8D.2 Regional Analysis

Table D3: Optimal Unit Weights by Region and Pollutant

State	**NYISO**			**ISO-NE**			**PJM-RGGI**			**Leaker**		
	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x
AL	–	–	–	–	–	–	–	–	–	0.0850	–	–
AR	0.5890	–	–	0.3090	–	–	–	–	–	–	–	–
AZ	–	–	–	–	–	–	0.5880	–	–	0.0320	0.0100	–
CO	0.0920	–	–	0.1190	–	–	–	–	–	–	–	0.1240
DC	0.1110	0.2170	0.0870	0.0700	0.1430	0.0210	0.1400	0.1730	0.1000	–	–	–
FL	0.0290	0.0650	0.0540	0.0740	0.0240	0.0200	0.0930	0.0480	0.1260	0.0020	0.0160	0.0210
GA	0.0370	–	0.0070	0.0760	0.0060	0.0590	0.0030	–	0.0750	0.0010	0.0300	–
IA	0.0700	–	0.0460	–	–	–	0.0010	0.1120	0.0120	–	0.0410	–
ID	–	0.0040	0.4830	0.3190	–	0.2540	–	–	–	–	–	–
IL	–	–	–	–	0.7860	–	–	–	–	–	–	0.0210
IN	–	–	–	–	0.1210	–	–	0.1210	–	0.0070	0.0230	–
KS	–	–	–	–	–	–	–	–	–	–	–	0.0750
LA	–	–	–	–	–	–	–	–	0.5100	0.0070	0.6960	0.5100
MI	–	–	–	–	–	–	0.0610	0.0080	0.2410	–	–	–
MN	–	0.5080	–	–	–	–	0.0810	0.5080	–	–	0.0710	–
MO	–	–	–	–	–	–	–	–	–	–	0.0120	–
MS	–	–	–	–	–	–	–	–	0.3590	–	0.0980	–
NC	0.0370	–	0.1030	–	–	0.0440	–	–	–	–	–	0.0370
ND	–	–	0.0220	–	–	0.1330	–	–	–	–	–	–
NE	–	–	–	–	–	–	–	–	0.0290	0.0050	–	–
NM	–	–	–	–	–	–	–	–	–	–	–	0.0100
NV	0.0350	0.1230	0.0140	0.0130	0.0260	–	–	–	–	0.0010	–	–
OK	–	–	–	–	–	–	–	–	–	0.6400	–	–
SC	–	–	0.1850	–	–	–	–	–	–	–	–	–
SD	–	0.1000	–	–	–	–	–	–	–	–	–	–
TN	–	0.0460	–	0.0210	0.0140	0.0830	–	0.0290	0.0570	0.0260	0.0040	0.0250
TX	–	–	–	–	–	0.3870	–	–	–	–	–	–
UT	–	–	–	–	–	–	–	–	–	0.1930	–	–
WA	–	0.4460	–	–	–	–	–	–	–	–	–	–
WI	–	–	–	–	–	–	0.0330	–	–	–	–	–
WY	–	–	–	–	–	–	–	–	–	–	–	0.1760

Table D4: NYISO Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x per Unit of Energy

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	79.9	22.4	30.9	0.1733	0.0096	4.7	0.0860	0.0145	18.0
2009–2011	68.9	-12.0*	-15.3	0.1659	-0.0582	-30.8	0.0745	0.0091	15.6
2012–2014	59.6	-20.8*	-27.1	0.0558	-0.0428	-47.3	0.0671	-0.0214	-25.7
2015–2017	53.6	-80.3*	-62.3	0.0318	-0.0354	-60.9	0.0518	-0.1499*	-76.9
2018–2020	43.2	-146.1*	-78.4	0.0192	-0.0193	-54.4	0.0401	-0.2127	-84.9
2021–2022	44.0	-46.8	-51.4	0.0132	-0.0106	-43.6	0.0354	-0.0660	-65.4

Table D5: ISO-NE Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x per Unit of Energy

	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	81.8	-25.8	-23.8	0.1937	-0.0004	-0.2	0.1018	-0.0260	-21.5
2009–2011	58.2	-63.4	-50.8	0.0899	-0.1403	-60.7	0.0673	-0.0326	-32.1
2012–2014	55.2	-63.5	-54.8	0.0477	-0.0633	-58.7	0.0623	-0.0881	-58.9
2015–2017	47.1	-143.4	-77.0	0.0312	-0.0291	-52.4	0.0508	-0.6142*	-93.0
2018–2020	38.6	-233.4	-85.9	0.0148	-0.0285	-69.8	0.0399	-0.9010*	-95.9
2021–2022	41.4	-72.1	-61.8	0.0104	-0.0235	-67.2	0.0385	-0.3025*	-88.3

Table D6: PJM-RGGI Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x per Unit of Energy

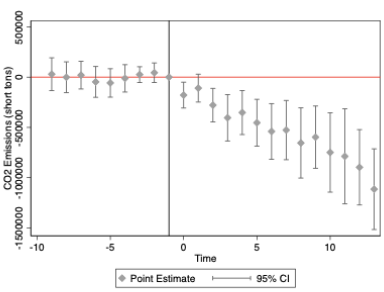
	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	129.5	-0.9	-0.8	0.8144	0.1595	30.8	0.2313	-0.0053	-2.8
2009–2011	74.1	-39.5	-34.7	0.3629	-0.1941	-50.3	0.0697	-0.0635	-47.9
2012–2014	66.2	-36.5	-35.7	0.0741	-0.1130	-62.2	0.0605	-0.0403	-41.2
2015–2017	63.3	-157.6*	-71.4	0.0533	-0.0469	-52.4	0.0431	-0.6783	-94.4
2018–2020	65.2	-292.3*	-84.2	0.0361	-0.0224	-51.3	0.0382	-1.0393	-97.1
2021–2022	45.3	-109.5	-70.1	0.0102	-0.0232	-72.0	0.0247	-0.3675	-93.8

Table D7: Leaker Region Synthetic Control Results by Control Period for CO_2, SO_2, and NO_x per Unit of Energy

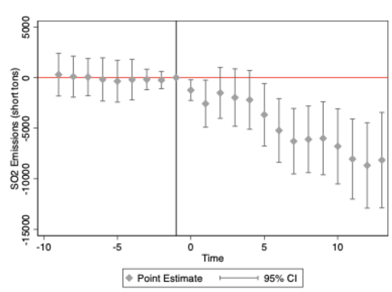
	CO_2			SO_2			NO_x		
Period	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.	Actual	T.E.	% Ch.
2006–2008	34.8	-0.9	-2.6	0.2042	-0.0189	-9.2	0.0547	0.0067	14.5
2009–2011	31.9	-0.7	-2.0	0.1313	-0.0255	-18.0	0.0288	-0.0004	-1.3
2012–2014	32.0	0.5	1.5	0.0748	-0.0293	-27.6	0.0316	0.0034	11.1
2015–2017	29.1	1.0	3.8	0.0520	-0.0147	-29.2	0.0275	-0.0029	-11.1
2018–2020	25.8	3.2	15.0	0.0233	-0.0095	-31.9	0.0179	-0.0045	-21.6
2021–2022	23.0	2.6	13.4	0.0190	-0.0049	-21.2	0.0134	-0.0030	-19.0

8E Robustness

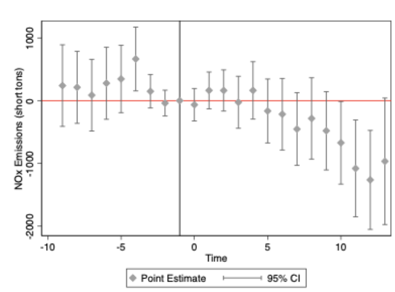
8E.1 Parallel-Trends Event Study



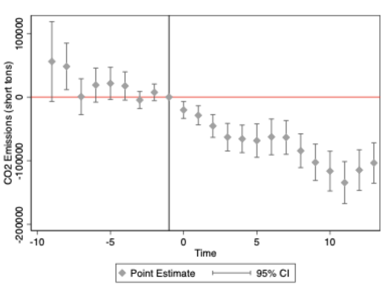
(a) Coal: CO_2



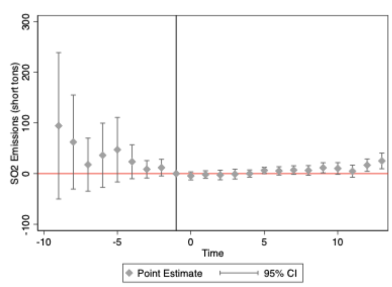
(b) Coal: SO_2



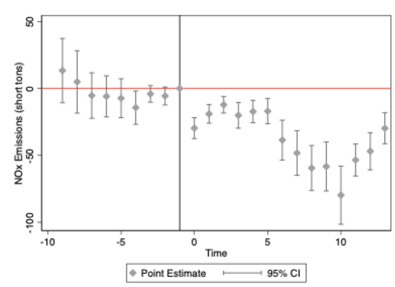
(c) Coal: NO_x



(d) Natural Gas: CO_2



(e) Natural Gas: SO_2



(f) Natural Gas: NO_x

Figure 8: **Event-Study Estimates of Pre-Trends in Emissions**

Each subfigure plots point estimates and 95% confidence intervals from the event study, which I create using `eventdd` package for `Stata` (Clarke, 2021) of the form:

$$\text{Emissions}_{it} = \alpha + \sum_{\substack{k=-10 \\ k\neq-1}}^{10} \beta_k \not\Vdash\big(\text{timeToTreat}_{it} = k\big) + \mathbf{X}'_{it}\Gamma + \mu_i + \lambda_t + \varepsilon_{it}\,, \tag{5}$$

, where $t^* = 2006$ is the RGGI implementation year, and $\mathbf{X}_{it}$ including the controls in the DiD specification (population, weather, GDP, energy prices, fuel mix, and energy consumption). The top row shows effects on coal plants' CO_2, SO_2, and NO_x emissions; the bottom row shows effects on natural gas plants (all in short tons). Time 0 indicates RGGI implementation, with the pre-period coefficient at $t = -1$ normalized to zero. The models use facility fixed effects μ_i with standard errors clustered at the plant unit level. The x-axis spans from 10 years before to 10 years after the event, showing emissions changes relative to the year before RGGI began.

8E.2 DiD Placebo

Table E1: Mixed Placebo Test Results

Pollutant	**Treatment**	**Left-Sided**	**Two-Sided**
CO_2	RGGI Post	0.038	0.092
	RGGI Transition	0.038	0.116
	Leaker Post	0.046	0.128
	Leaker Transition	0.050	0.132
SO_2	RGGI Post	0.032	0.134
	RGGI Transition	0.894	0.142
	Leaker Post	0.018	0.036
	Leaker Transition	0.240	0.100
NO_x	RGGI Post	0.876	0.154
	RGGI Transition	0.862	0.168
	Leaker Post	0.032	0.174
	Leaker Transition	0.852	0.182

Note: P-values from 500 repetitions of mixed placebo tests. Left-sided and two-sided p-values are reported for each pollutant and treatment combination.

8E.3 Synthetic LOO Placebo

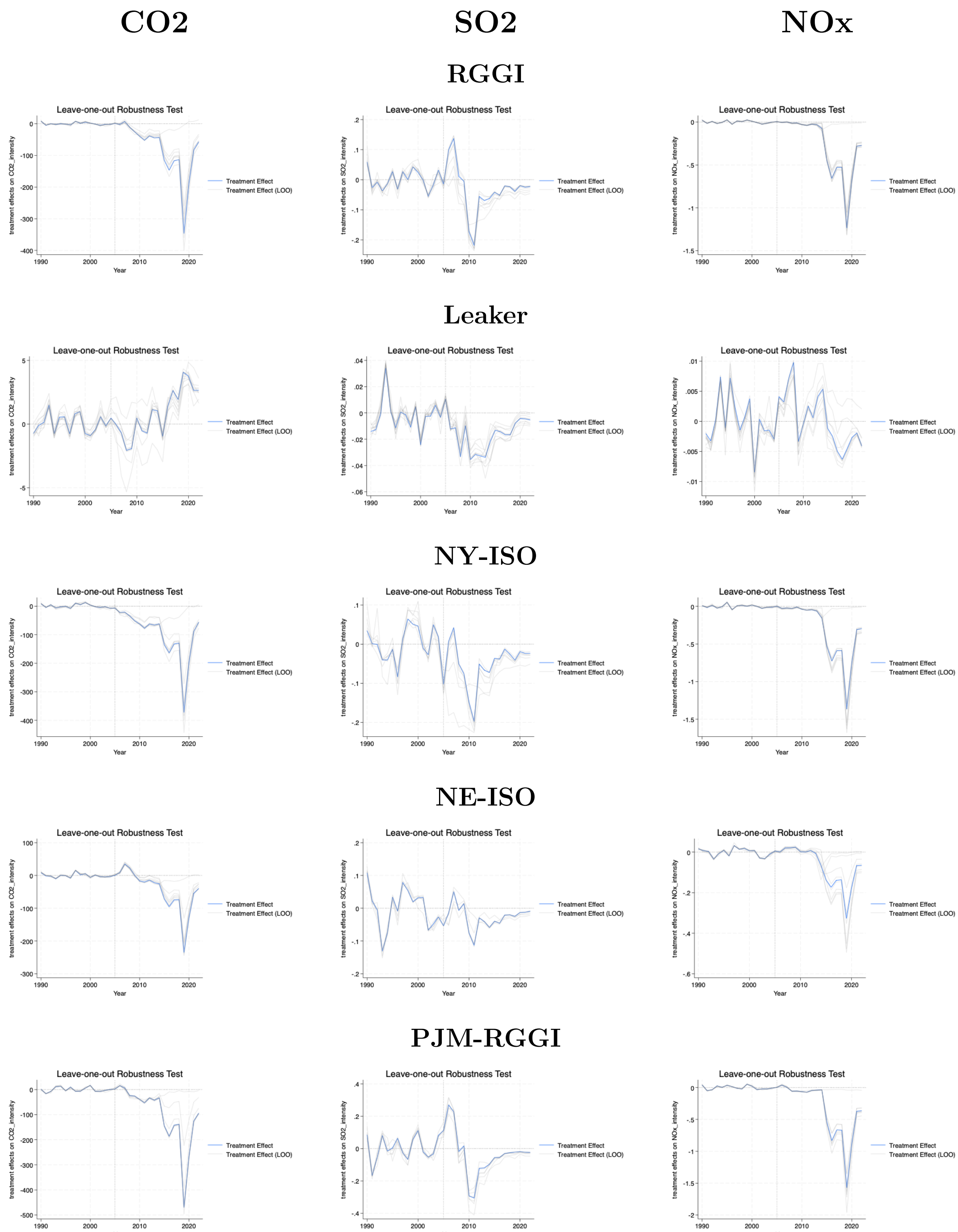
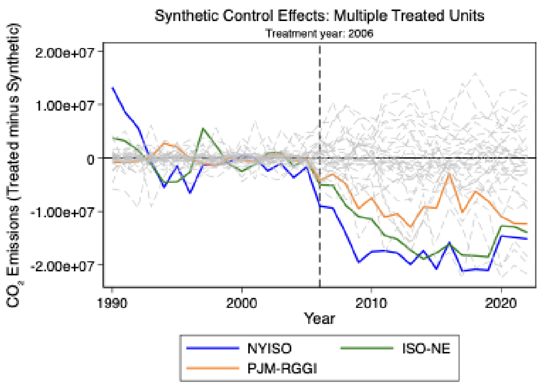
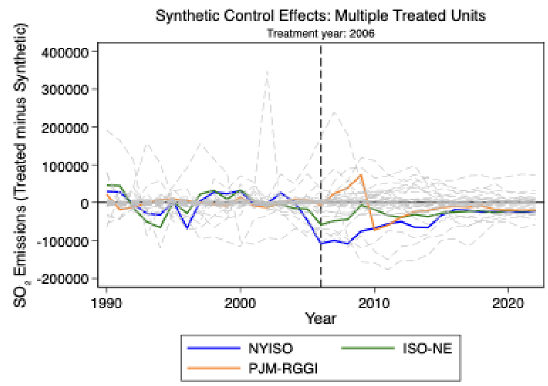


Figure 9: Leave-one-out (LOO) synthetic control results for each pollutant across the five regions. In each panel, LOO lines represent treatment effects estimated after sequentially removing individual control units that received positive weights in the baseline synthetic control model. This sensitivity analysis assesses whether any single control unit disproportionately influences the estimated treatment effects. Across all pollutants and regions, the results remain mostly consistent when individual donors are excluded, indicating that the estimated effects are robust and not driven by any one control unit.

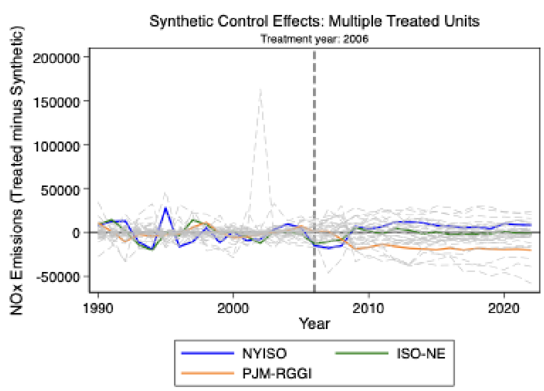
8E.4 Synthetic In-Space Placebo



(a) (a) CO_2 Emissions by Region.



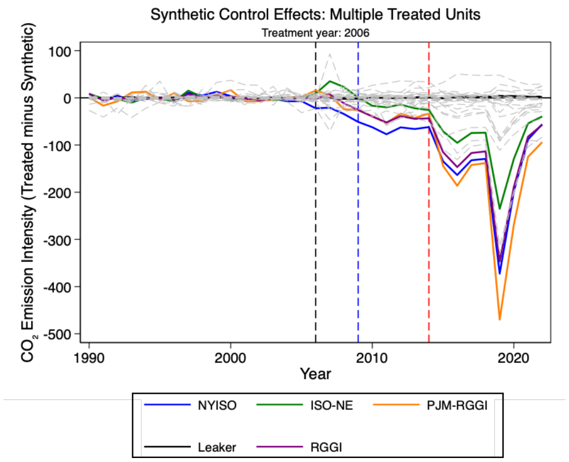
(b) (b) SO_2 Emissions by Region.



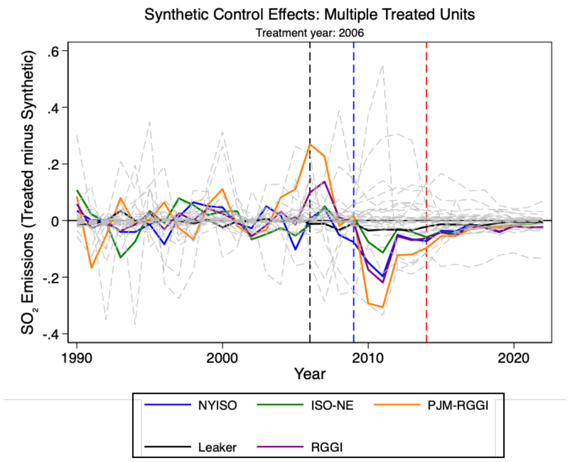
(c) (c) NO_x Emissions (Placebo).

Figure 10: **Aggregate Emissions Over Time.** Three illustrations of average CO_2, SO_2, and NO_x emissions by region (including a "placebo" specification). The top row compares CO_2 and SO_2 by region, while the bottom plot shows NO_x emissions under a placebo specification.

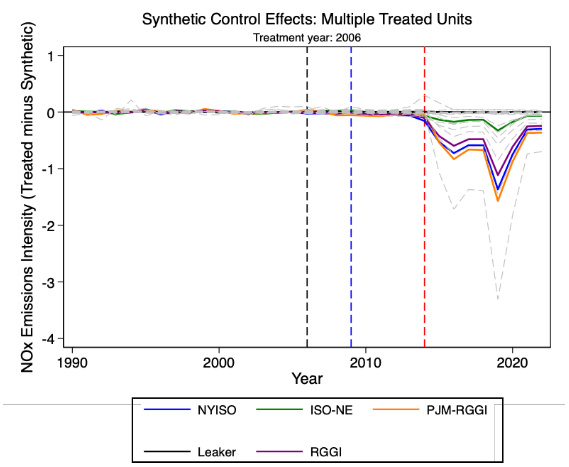
Note: The leaker and RGGI specifications were omitted from the placebo tests due to their unique characteristics. Given their size and the constraint that synthetic control weights must sum to one, there were no comparable control units available. Both specifications would have received the majority of their weight from Texas, which is the largest state that minimizes the difference between treatment and control. This reliance on a single state as the primary control unit undermines the interpretability of the results for aggregate emissions. Synthetic regions could have been constructed as more useful counterparts, but that would have required subjective judgment with no established precedent in the literature.



(a) **CO_2 Emission Intensity.**



(b) **SO_2 Emission Intensity.**



(c) **NO_x Emission Intensity.**

Figure 11: **Emission Intensities Over Time.** The top row shows CO_2 and SO_2 intensities (per unit of output), and the bottom plot shows NO_x intensity under a placebo specification. Black vertical lines mark 2006 and 2009 (announcement and implementation), and the red line marks 2014 (cap reduction).

8E.5 Using 2009 as Implementation

Table E2: Avg. Treatment Effects by Control Period & Pollutant (Short Tons/Bil BTU)

Control Periods	Avg. Actual	Avg. Synthetic	Avg. Effect	% from Synthetic
CO_2 — RGGI States				
1 (2009–2011)	67.36	90.57	-23.21	-25.63%
2 (2012–2014)	57.82	79.89	-22.07	-27.63%
3 (2015–2017)	51.26	159.61	-108.35	-67.88%
4 (2018–2020)	44.12	245.43	-201.31	-82.02%
5 (2021–2023)	45.17	110.18	-65.01	-59.01%
CO_2 — Leaker States				
1 (2009–2011)	33.25	32.49	0.76	2.35%
2 (2012–2014)	33.32	31.40	1.92	6.10%
3 (2015–2017)	28.11	26.68	1.43	5.37%
4 (2018–2020)	24.91	21.55	3.37	15.62%
5 (2021–2023)	22.36	19.00	3.36	17.66%
SO_2 — RGGI States				
1 (2009–2011)	0.1371	0.2880	-0.1508	-52.38%
2 (2012–2014)	0.0536	0.1273	-0.0737	-57.88%
3 (2015–2017)	0.0306	0.0776	-0.0469	-60.51%
4 (2018–2020)	0.0164	0.0469	-0.0305	-65.01%
5 (2021–2023)	0.0114	0.0440	-0.0327	-74.20%
SO_2 — Leaker States				
1 (2009–2011)	0.1160	0.1259	-0.0099	-7.86%
2 (2012–2014)	0.0768	0.0974	-0.0207	-21.21%
3 (2015–2017)	0.0356	0.0449	-0.0094	-20.92%
4 (2018–2020)	0.0204	0.0264	-0.0061	-23.08%
5 (2021–2023)	0.0182	0.0195	-0.0013	-6.43%
NO_x — RGGI States				
1 (2009–2011)	0.0684	0.0915	-0.0231	-25.24%
2 (2012–2014)	0.0602	0.0975	-0.0373	-38.24%
3 (2015–2017)	0.0438	0.6237	-0.5799	-92.97%
4 (2018–2020)	0.0360	0.9110	-0.8750	-96.05%
5 (2021–2023)	0.0333	0.3324	-0.2991	-90.00%
NO_x — Leaker States				
1 (2009–2011)	0.0326	0.0352	-0.0027	-7.57%
2 (2012–2014)	0.0336	0.0307	0.0029	9.46%
3 (2015–2017)	0.0233	0.0246	-0.0013	-5.28%
4 (2018–2020)	0.0163	0.0180	-0.0016	-9.09%
5 (2021–2023)	0.0128	0.0142	-0.0013	-9.54%

NYISO

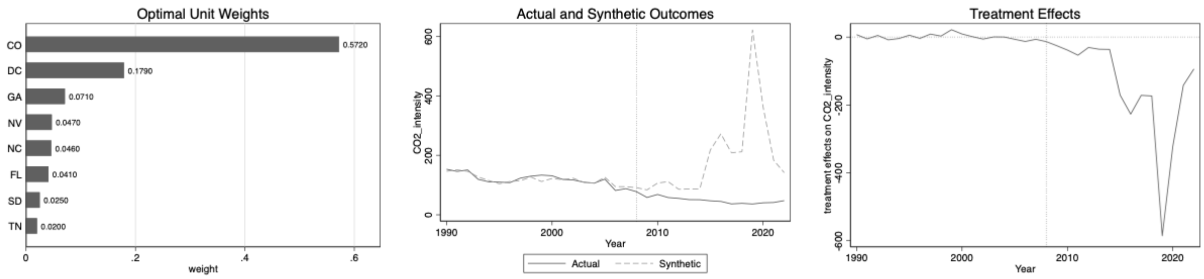


Figure 12: Synthetic control analysis for CO_2 emissions in NYISO, which primarily covers the state of NY.

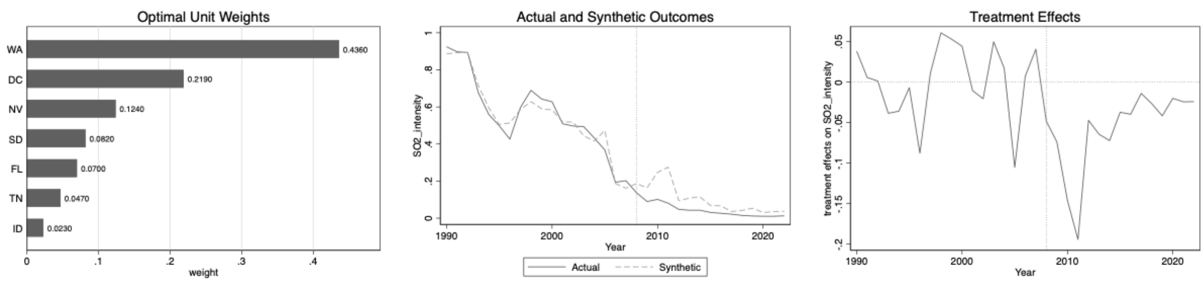


Figure 13: Synthetic control analysis for SO_2 emissions in NYISO.

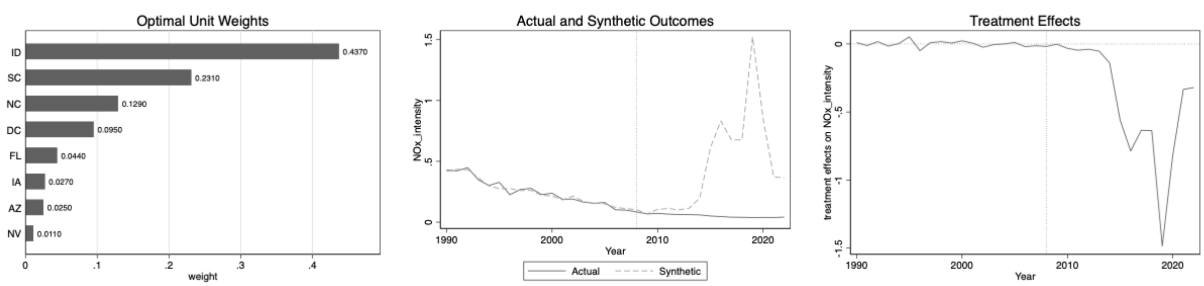


Figure 14: Synthetic control analysis for NO_x emissions in NYISO.

ISO-NE

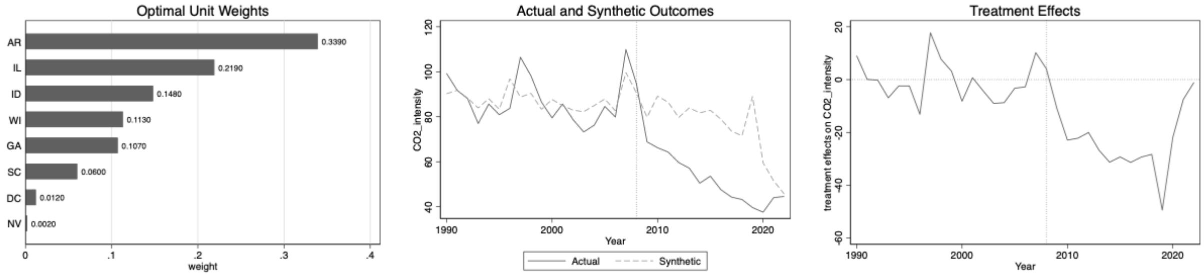


Figure 15: Synthetic control analysis for CO_2 emissions in ISO-NE. This includes Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, and Vermont.

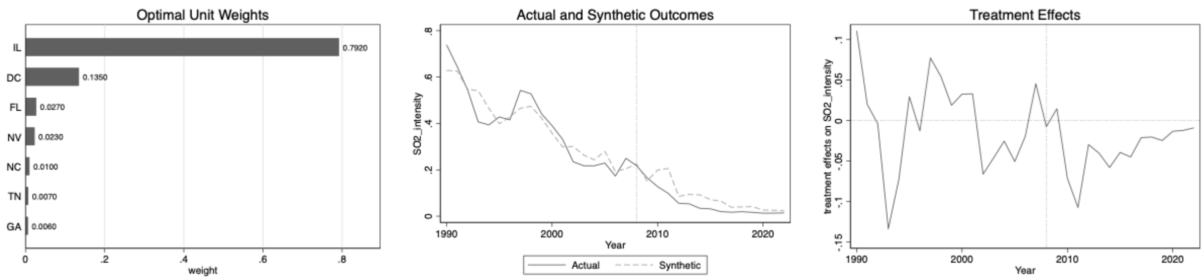


Figure 16: Synthetic control analysis for SO_2 emissions in ISO-NE.

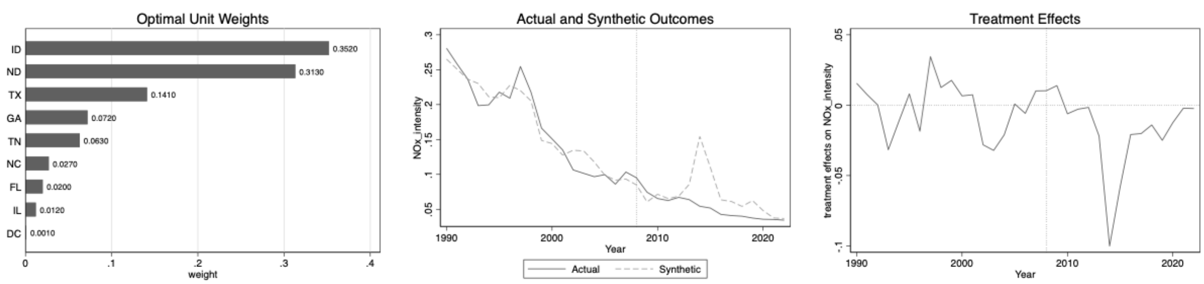


Figure 17: Synthetic control analysis for NO_x emissions in ISO-NE.

RGGI-PJM

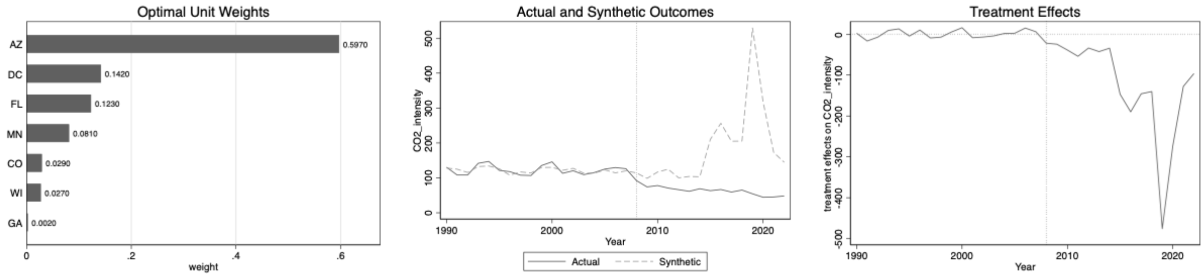


Figure 18: Synthetic control results for CO_2 emissions in PJM. This includes New Jersey, Maryland, and Delaware.

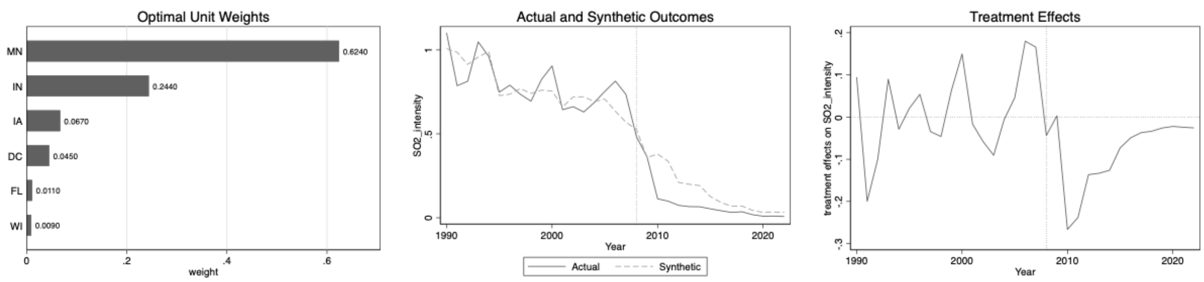


Figure 19: Synthetic control results for SO_2 emissions in PJM.

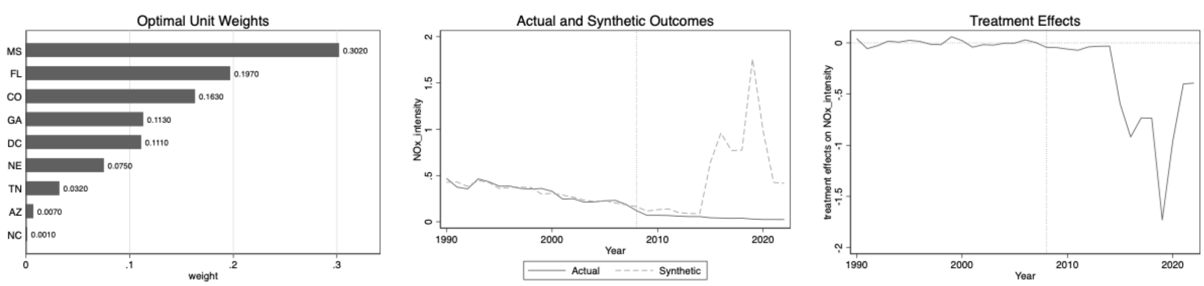


Figure 20: Synthetic control results for NO_x emissions in PJM.