Toxic Hotspots from Market Design in Regional Climate Policy

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Abstract

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1. Introduction

Pollution outcomes due to electricity market design matter as regional climate policies have emerged in the absence of national climate regulation. Market design can even reduce environmental benefits if different patterns of emissions across space and time occur because of its effect on electricity dispatch. This can happen if, for example, renewable energy imbalances are more frequently addressed in geographic regions that are close to load centers. Market design's effect on regional emissions is especially important in the case of local pollutants such as nitrous oxide (NOx) and sulfur dioxide (SO_2), which can create localized damages.

Although market design is a potentially important emissions driver, there is limited research at the intersection of differing electricity market designs and climate policies. Due to electricity restructuring, a patchwork of electricity market designs exist in the U.S., particularly in the West, where California has a centralized market and the remaining Western electric region is rate regulated. Using an empirical example of the California Independent System Operator's (CAISO's) Western Energy Imbalance Market (EIM)—a market introduced to Western U.S. to help address last minute energy supply and demand imbalances due to increasing amounts of renewable resources—I aim to determine the temporal and spatial effects of introducing a more centralized and competitive electricity market design on local pollutants. As the EIM changes regional dispatch patterns to fulfill its goal of reducing energy imbalances from intermittent renewables, is it leading to less or more local pollution in some regions?

Balancing markets like the EIM can increase (decrease) local pollutants if fossil-fuel generators are used more (less) frequently or less (more) efficiently to balance intermittent electricity production from renewable resources. To identify the effect of the EIM on local pollution hostpots, I utilize hourly electricity pro-

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duction, emissions, and consumption data in difference-in-differences analyses that account for selection bias. This framework allows me to identify how changes in plant dispatch across the EIM, as well as in response to California's residual electricity demand create temporal and spatial hotspots in the Western electric region.

My study is most closely related to the literature on pollution hotspots due to pollution cap-and-trade markets (Fowlie et al. (2012); Deschenes et al. (2017); Grainger and Ruangmas (2018)). Different from this stream of literature, I identify local pollution outcomes based on a change in market design, which did not have the explicit intent to regulate local pollution outcomes. My approach is also germane to the literature on how electricity market design affects emissions leakage when there are regional climate policies (Fowlie, 2009; Fell and Maniloff, 2015; Tarufelli and Gilbert, 2019). I evaluate my results in the context of existing literature that examines marginal emissions reductions under overlapping or asymmetric regional climate policies. New to the literature, I examine the effect of a change in market design on local pollution outcomes.

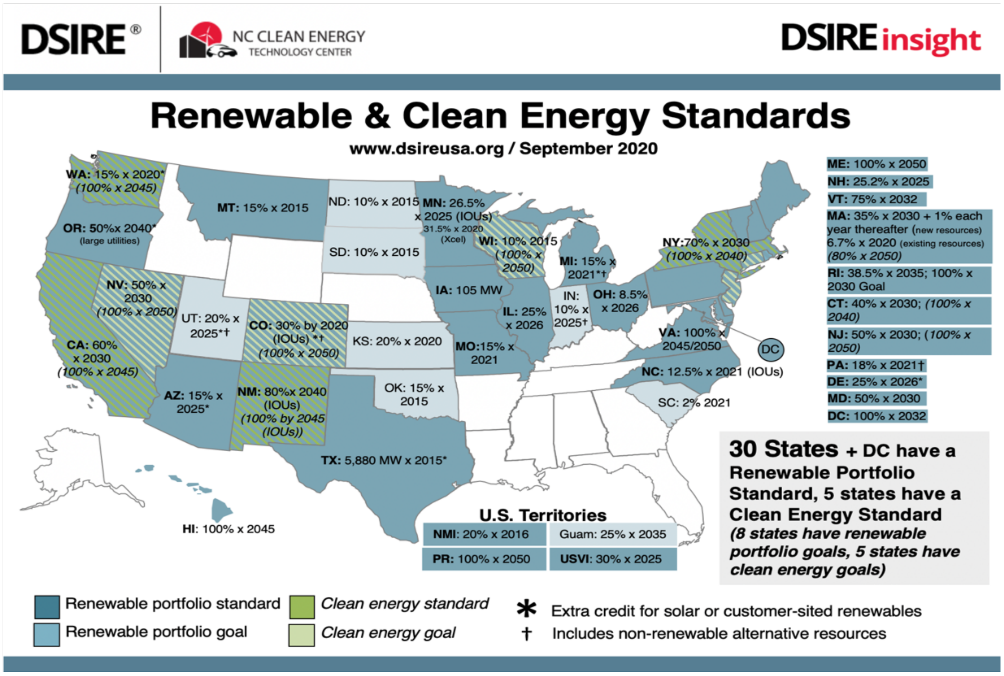
I find that on average, participating in the EIM reduces NOx emissions from gas generators by six pounds per hour—a reduction of 26% of NOx emissions from the average gas generator in the sample—with peak reductions occurring in the working and evening hours, when residual load is high. On an annualized basis, the magnitude of this effect is a reduction of 52,560 pounds of NOx emissions for each EIM generator. However, I find that there is significant heterogeneity in the distribution of local pollution outcomes across different geographic regions. Regions close to California load centers experience negligible to slight increases in NOx emissions from gas generators, while significant reductions from NOx emissions occur in more remote regions. Although I do not find any significant reductions from NOx or SO_2 emissions from coal generators on average, I find that regions close to California—Arizona and Nevada—experience significant increases in local pollution of up to 50% of the average NOx emissions or 31% of the average SO_2 emissions, whereas more remote regions experience a significant decrease in NOx and SO2 emissions of 6 - 15% from coal generators.

This research is important in the current context of regionally driven climate policies that overlap regions with differing electricity market designs. As there is an ongoing agenda to expand regional electricity markets, such as Southwest Power Pool's recent creation of a second energy imbalance market that expands into the Western U.S., in order to better balance renewable resources, it is important to understand how changing electricity dispatch patterns can affect the distribution of local pollutants. Local pollutants can adversely effect human health and have important implications for policy-makers.

2. Background

In the U.S., regional climate policies have emerged in the absence of national climate regulations. Renewable and clean energy standards, which are shown in Figure 1, vary by state. For example, California has a clean energy standard requiring at least 60% of electricity be generated from renewable resources by 2030, and 100% from clean energy by 2045. But other states, like Wyoming, have no clean energy requirements. Despite the varied implementation, these and other climate-related policies have been effective at bringing increasing amounts of renewable resources online, changing the way the grid is operated.

Figure 1: U.S. Renewable and Clean Energy Standards



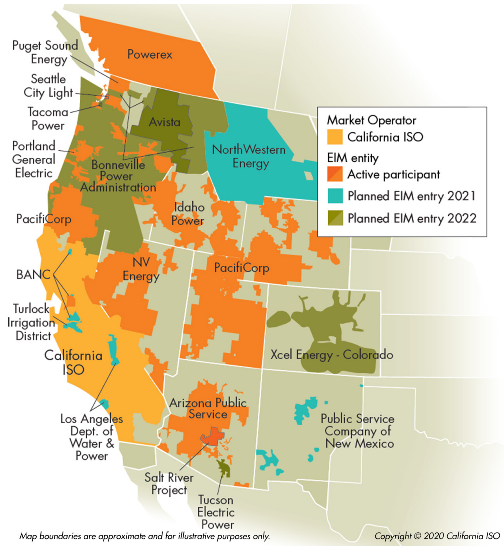
Notes: This figure shows the renewable and clean energy standards in the U.S. as of September 2020.
Source: DSIRE

The EIM was created by CAISO to allow balancing authorities (BAs)[1] outside of the CAISO BA to participate in CAISO's real-time energy market. The real-time energy market is a market utilized by CAISO to address any last minute energy supply and demand (load) imbalances. Participating in the EIM not only enables CAISO's sophisticated market dispatch algorithm to find the lowest cost generation across a wider footprint to meet Western energy load, but also aids in the integration of renewable energy through its increased market footprint and visibility. For example, when residual load (load less renewable resources) is low and solar production is high, CAISO can transfer energy out to other BAs. During the morning and evening hours, when CAISO needs to meet a steep increase in load, the EIM is used to transfer energy into CAISO from other BAs.[2]

The EIM started on November 1, 2014, with PacifiCorp and CAISO. Since that time (through 2020), eleven BAs have joined the EIM, with a further nine slated to join in 2021/2022. During the period of this study, which is April 2010 to December 2016, five BAs authorities joined the EIM, thus results can be interpreted as results from early entrants to the EIM. Figure 2 provides a map of the current footprint of the EIM.

[1]Balancing authorities are responsible for balancing electricity supply and demand within their geographic footprint.
[2]2018 Annual Report on Market Issues and Performance, at 107. `http://www.caiso.com/Documents/2018AnnualReportonMarketIssuesandPerformance.pdf` (accessed 8/13/2020).

Figure 2: Energy Imbalance Market

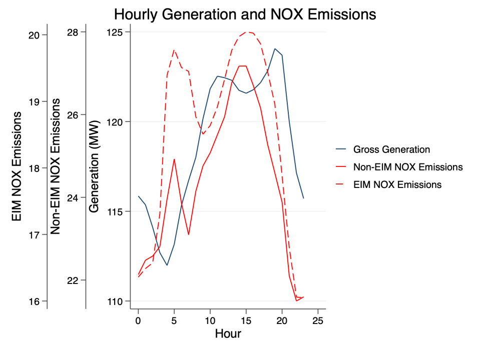


Notes: This figure shows the Western EIM in 2020. During the period of this study, five BAs had joined the EIM: CAISO, PacifiCorp, Arizona Public Service Co., NV Energy, and Puget Sound Energy.
Source: CAISO.

An important aspect of the EIM is that it allows geographically diverse generators from traditionally rate-regulated BAs to access CAISO's sophisticated market dispatch algorithm which not only changes the resource portfolio that CAISO has access to, but also changes the pattern of generator dispatch across a wider geographic area. In examining the EIM's effect on dispatch, Tarufelli and Gilbert (2019) find that the EIM causes the average natural gas generator to produce about 9 MW more power on average, compared to non-EIM generators, and that this increase in gas-power generation in the EIM occurred primarily at night. This overall change in dispatch patterns in the EIM led to a small but significant increase in carbon dioxide (CO_2) emissions. Compared to CO_2, which inflicts global damages, changes in local pollutants from the change in dispatch patterns can disproportionately affect some regions more than others.

The EIM is a balancing market, intended to help address supply and demand imbalances, which can be exacerbated by increasing levels of renewable resources. Because dispatchable fossil-fuel generators must make up the majority of the difference in power supply when renewable resources produce more or less power than anticipated, increasing amounts of renewable resources can increase the amount the fossil-fuel generators need to cycle (ramp up or down, start or stop) their power generation. Cycling can lead to increasing amounts of local pollutants, particularly NOx in gas generators. Cycling's effect on local pollutants can be observed in Figure 3, which plots hourly average NOx emissions for EIM and non-EIM generators, relative to hourly average generation in the sample data. From Figure 3, an obvious pattern emerges in which NOx emissions increase when generation decreases, or generators ramp down. This pattern of emissions depicts how downward adjustments in generation to balance renewables can increase local pollutants.

Figure 3: EIM and Non-EIM Hourly NOx Emissions and Generation from Gas Generators



Notes: This figure shows hourly average NOx emissions for EIM and non-EIM gas generators, relative to hourly average generation in the sample data.

NOx can contribute to development of asthma, aggravate asthma, and can react with volatile organic compounds (VOCs) to produce ozone and particulate matter (PM)—which has been linked to several adverse health outcomes.[3] SO_2 can also make breathing difficult, especially in people with asthma, and can react with other VOCs in the air to contribute to particulate matter (PM) which can cause health problems.[4] Depending on the location of a particular power plant and how its dispatch changes in the EIM, local pollutants could be made better or worse, and impact the health of citizenry in the vicinity of the power plants.

3. Literature

My study and empirical approach is also closely related to the literature that estimates reduced-form econometric models to examine the effects of emissions-specific cap-and trade markets on local pollution and health outcomes (Fowlie et al., 2012; Deschenes et al., 2017; Grainger and Ruangmas, 2018). The underlying premise of this literature is that emissions cap-and-trade markets optimally lower pollution when marginal damages equal marginal costs, but with local pollutants, markets may experience allocative inefficiency as damages are not uniform across space. Further, in the case of cap-and-trade markets, if emitters can purchase permits in lieu of reducing emissions, this can lead to environmental injustice, where pollution flows to poorer areas.

My study is also related to an extensive literature that examines how market design affects pollution outcomes. One stream of this literature examines how market design in the electricity sector impacts emissions leakage (particularly carbon dioxide leakage) from regulated to unregulated areas. Using an ex-ante market-based simulation of the introduction of California's cap-and-trade program, Fowlie (2009) finds

[3] https://www.epa.gov/no2-pollution/basic-information-about-no2#What%20is%20NO2 (accessed 8/13/2020).
[4] https://www.epa.gov/so2-pollution/sulfur-dioxide-basics (accessed 8/13/2020).

that under asymmetric regulation, increased competition from a change in market design increased CO_2 emissions leakage, highlighting the importance of the underlying industry structure to pollution outcomes. However, using an ex-post evaluation of the introduction of the Regional Greenhouse Gas Initiative (RGGI) cap-and-trade program in the Northeastern U.S., Fell and Maniloff (2015) found that the introduction of the program caused a positive leakage externality, as electricity producers outside the RGGI-regulated area where generation shifted to were relatively cleaner, again highlighting the importance of industry structure. Other papers in the simulation of potential outcomes from carbon cap-and-trade programs generally find that California's regional cap-and-trade regulation increases the potential for emissions leakage from regulated to unregulated areas Bushnell and Mansur (2011), Bushnell and Chen (2012), and Bushnell et al. (2014). Although these papers tend to focus on CO_2 emissions leakage, shifts in generation due to asymmetric regulation also have local pollution implications.

Different from Fowlie (2009), Bushnell and Mansur (2011), Bushnell and Chen (2012), Fowlie et al. (2012), Bushnell et al. (2014), Fell and Maniloff (2015), Deschenes et al. (2017), and Grainger and Ruangmas (2018) I do not identify results on local pollution outcomes from studying the effect of a market specifically designed to regulate pollution. Instead, as the EIM was created to lower the cost of addressing energy imbalances due to increasing amounts of renewable resources by balancing supply and demand across a wider geographic footprint, I identify my local pollution outcomes from a change in market design. Changes in local pollution outcomes are from changes in dispatch from the EIM, rather than pollution regulation. In this sense, local pollution outcomes can be thought of as an unintended side effect of the change in market design, which may be exacerbated by regional climate policies (such as California's renewables portfolio standard) that increase the magnitude of the effect of the change in market design on local pollution outcomes.

This research is most similarly related to Tarufelli and Gilbert (2019), which uses a difference-in-difference (DD) as well as triple-differences (DDD) design to determine how the EIM affected generation and CO_2 emissions from the EIM. Different from Tarufelli and Gilbert (2019), who examine the emissions leakage effects from a the EIM reducing transactions costs between regions with different climate policies, this paper specifically focuses on how the change in dispatch due to the EIM caused temporal and spatial changes in the distribution of local pollutants—NOx and SO_2 emissions.

4. Data

To assess the impact of the EIM on local pollutants I compile a comprehensive data set. This data set builds on that of Tarufelli and Gilbert (2019) to encompass local pollutant effects. To my knowledge, this study is the first time any analysis has evaluated the effect of local pollutants from an energy imbalance market. All data sources used in this analysis are publicly available, and are listed in the Data Availability Section 8.

4.1. Pollution Emissions

I obtain hourly pollution emissions from the Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS) program. The measurements for NOx and SO_2 emissions are fairly precise as generators with over 25 MW of capacity are required by the EPA to provide hourly data on SO_2 and NOx emissions for compliance with emissions regulations.

4.2. Generator Characteristics

Both generator location and generator characteristics are important determinants of local pollution outcomes from the EIM. To identify each generator's geographic location, coordinates provided in the CEMS data were utilized to map generators in their respective BAs utilizing a spatial map from the Department of Homeland Security's (DHS) Homeland Infrastructure Foundation-Level Database (HIFLD). Generator characteristics such as generator age and existing pollution control technologies were also obtained from the CEMS data.

4.3. Electrical Load

An electricity market's aggregate load is a key driver of determining which generators are producing electricity at any given hour, and can affect local pollution outcomes. In an energy balancing market, of particular importance is the residual load (net of renewables) that fossil-fuel generators must meet. To calculate residual load, I subtract hourly wind and solar production in CAISO from hourly load. CAISO's hourly load is obtained from CAISO's OASIS System Load and Resource Schedules. CAISO's hourly wind and solar production are obtained from CAISO's Daily Renewables Watch reports. Hourly load within a non-CAISO BA is also important as it can determine which generators are on the margin and available to address energy imbalances from the EIM. Each non-CAISO BA's hourly load is obtained from FERC Form 714 Schedule III, available for all BAs with an annual peak demand that exceeds 200 MW.

4.4. Summary Statistics

Table 1 contains summary statistics for the main generator-level and BA-level variables in my analysis. Means and standard deviations at the generator level are provided for hourly NOx emissions, SO_2 emissions, average heat input in the pre-EIM period,[5] and generator age. Means and standard deviations at the BA level are provided for hourly CAISO residual load, and each BA's own load. Summary statistics are reported by control and treated groups, where EIM indicates the generator can participate in the EIM and is considered treated. The full sample consists of 355 gas generators, of which 108 are able to participate in the EIM, and 97 coal generators, of which 37 are able to participate in the EIM. Summary statistics for coal generators are reported separately in Table 10 in Appendix B.

[5] Hourly heat input (MMBtu) divided by the maximum hourly observed heat input in the pre-EIM period from (2010 - 2012).

Table 1: Summary Statistics: Gas Generators

	(1)		
	Non-EIM	EIM	Total
Nitrogen Oxide Emissions (lbs)	24.57	18.93	22.85
	(48.37)	(30.40)	(43.76)
Sulfur Dioxide Emissions (lbs)	0.651	0.690	0.663
	(4.622)	(0.494)	(3.864)
CAISO Residual Load (MW)	25530.9	25792.3	25610.5
	(5238.8)	(5342.1)	(5271.8)
Hourly FERC Load by Planning Area	2896.1	4630.5	3424.2
	(1891.8)	(2275.6)	(2168.7)
Pre-EIM Heat Input	0.614	0.595	0.608
	(0.140)	(0.110)	(0.132)
Generator Age	17.61	13.62	16.40
	(16.18)	(12.99)	(15.39)

Notes: Summary statistics are for hourly NOx emissions, SO_2 emissions, average heat input, as well as generator age for the full sample of gas generators; hourly CAISO residual load, and each BA's own load. Means of each variable are shown with standard deviations in parentheses. Variables are shown by control and treatment group, where EIM indicates the treated group.

The summary statistics in Table 1 provide a benchmark to measure the similarity in treated and control generators in the full sample. It's clear that on an hourly basis, generators that can participate in the EIM emit less NOx emissions and slightly more SO_2 emissions.[6] EIM generators also use less fuel, as measured by their heat input, and are younger than those that don't participate in the EIM. Further, BAs that join the EIM tend to be larger—by measure of their load—than non-participant BAs. Because these differences in BAs and their portfolio of generators could influence or reflect a BAs decision to join the EIM, this potential bias is addressed in my empirical framework by utilizing matching to create a more plausible counterfactual of control generators.

5. Empirical Framework

Estimating the causal effect of the EIM requires that I isolate the effect of the EIM from other simultaneous changes in electricity markets and regional BAs that could also effect local pollution outcomes. The introduction of the EIM to the Western electric region requires a credible counterfactual to establish a realistic estimate of what NOx and SO_2 emissions would have been absent the EIM.

To build this counterfactual, I exploit the fact that only a subset of BAs joined the EIM, allowing for a control group of electricity generators that are not in the EIM, but are subject to similar regulatory environments and are part of the the same interconnection as BAs in the EIM. Because BAs opted in to the EIM, if the NOx and SO_2 emissions outcomes of generators in BAs that did not join the EIM differ in a systematic way from what the emissions outcomes of generators in BAs that joined the EIM would have been absent the EIM—there will be selection bias in my results.

[6] Because gas generators emit negligible amounts of SO_2 emissions, no further analysis is completed. Coal generator SO_2 emissions are included for further analysis.

To address the issue of selection bias, I first use propensity score matching to create a more credible counterfactual of control generators, and then combine the matching design with a DD and DDD design to econometrically adjust for observed covariates to produce unbiased parameter estimates. Ho et al. (2007), Imbens and Wooldridge (2009), Fowlie et al. (2012), and Ferraro and Miranda (2014) provide evidence that combining designs better replicates the experimental outcome using ex-post econometric methods.

5.1. Matching

The matching design builds on the potential outcomes framework where $D_{i,t'} = 1$ if the ith BA joins the EIM, and $D_{i,t'} = 0$ if it did not. Hourly NOx or SO_2 emissions from generator j in BA i are the potential outcomes $Y_{ijt}(0)$, and $Y_{ijt'}(0)$ or $Y_{ijt'}(1)$, conditional on a BA joining the EIM at time t'. To estimate the average treatment effect on the treated,

$$\gamma_{1,att} = \mathbb{E}[Y_{ijt'}(1) - Y_{ijt'}(0)|D_{it'} = 1],$$

and the marginal treatment effect in response to CAISO residual load,

$$\gamma_{2,mtt} = \frac{\partial\, \mathbb{E}[Y_{ijt'}(1) - Y_{ijt'}(0)|D_{it'} = 1]}{\partial ResidualLoad},$$

I need to construct estimates of the counterfactual outcome $[Y_{ijt'}(0)|D_{it'} = 1]$, which is not observed, from the pool of generators in BAs that did not join the EIM.

I leverage the matching design of Tarufelli and Gilbert (2019), which controls for the EIM selection mechanism by matching on measures of transmission and generator efficiency,[7] a BA's ability to address energy imbalances, and the likelihood that generators within a BA were already marginal sellers to the CAISO market in the pre-EIM period. Tarufelli and Gilbert (2019) establish that using propensity score matching with calipers and trimming improves the balance of propensity scores for both treatment (EIM) and control groups. Because calipers and trimming reduces the sample to a subset, this matching design yields the conditional average treatment effect (CATE) of the EIM. In the matched sample, there are 195 gas generators, of which 87 are located in BAs that participate in the EIM; there are 66 coal generators, of which 35 are located in BAs that participate in the EIM. See Appendix A for further details.

5.2. Econometric Model

I initially estimate the average treatment effect on the treated, $\gamma_{1,att}$, with an unconditional, reduced-form DD estimator. NOx or SO_2 emissions (Y_{ijt}) of the jth generator in BA i at hour t are regressed against a treatment indicator equal to one if the BA joins the EIM. I control for pre- and post-EIM time trends with an indicator for post which turns on when the EIM began (November 1, 2014), as well as a vector of

[7] The measure of generator efficiency used in Tarufelli and Gilbert (2019) is a generator's hourly heat input divided by its maximum hourly heat input.

controls, $\mathbf{X}_{jt}$, to adjust for observable differences in covariates that could lead to differences in local pollution outcomes,

$$Y_{ijt} = \alpha + \lambda Post_t + \gamma EverEIM_i * Post_t + \mathbf{X}_{jt}\beta + \mu_i + \epsilon_{ijt} \tag{1}$$

where μ_i are BA fixed effects and absorb the effect of the indicator of a BA ever being an EIM participant.

Because the EIM can change the dispatch patterns of generators by changing the dispatch (supply) curve of generators used to meet residual load, I also examine the responses of generators to CAISO residual load using a DDD model to estimate how the EIM is affecting marginal NOx and SO_2 emissions.

$$\begin{aligned} Y_{ijt} = \alpha &+ \lambda_1 Post_t + \gamma_1 EverEIM_i * Post_t \\ &+ \lambda_2 ResidualLoad_t + \lambda_3 ResidualLoad_t * EverEIM_i + \lambda_4 ResidualLoad_t * Post_t \\ &+ \gamma_2 ResidualLoad_t * EverEIM_i * Post_t + \mathbf{X}_{jt}\beta + \mu_i + \epsilon_{ijt}. \end{aligned} \tag{2}$$

To operationalize the DD and DDD estimators, I include pre- and post-EIM time period trends as well as several sets of fixed effects. Hour-of-day fixed effects account for factors common to each hour, such as correlation between emissions and residual load as both load and renewable resource production vary throughout the day, allowing me to identify off of within-hour variation. Day-of-Week fixed effects account for factors common to each day, such as differences in load variation on weekends, allowing me to identify off of within weekday variation. Month-by-year fixed affects account for factors common to a month within a year, such as long run trends that may affect emissions outcomes. I include additional generator-level controls to account for differences in emissions due to generator age and heat input,[8] as well as each generator's pollution abatement control technologies for NOx or SO_2. BA-level fixed effects account for regional differences in climate or grid operations, common to a BA. In the DDD specification, additional controls include pairwise interactions, and CAISO residual load. I mean-center interaction terms allowing for the interpretation of marginal effects at the mean. My main results cluster standard errors at the BA level.[9].

The treatment effects of interest are γ_1 and γ_2. After adjusting for fixed effects, generator- and BA-level controls, γ_1 captures the hourly shift in emissions specific to generators in EIM BAs due to the EIM, relative to generators in non-EIM BAs; γ_2 captures the marginal change in EIM-generators' emissions in response to incremental increases in CAISO residual load due to the EIM, relative to generators in non-EIM BAs.

[8] Heat inputs are each generators average hourly heat input divided by their maximum hourly heat input from the pre-EIM period as the EIM may have affected how efficiently generators use fuel.

[9] Although I have 19 clusters for gas generators and 11 clusters for coal generators, because I have many observations per cluster estimates can be reasonably unbiased, but variance can be downward biased (Cameron and Miller, 2015). I follow the recommended correction of Hansen (2007) to normalize the Arellano (1987) estimator by $\frac{G}{G-1}$, where G is the groups of BAs, and use critical values from the T distribution with G-1 degrees of freedom, which will result in an asymptotically unbiased estimator when T $\rightarrow \infty$ (a plausible assumption due to the large time dimension of my data) and G is fixed, provided the iid assumption is met.

The unconditional DD estimator will be biased if variables that systematically effect NOx and SO_2 emissions vary significantly across treated and control groups. To overcome this limitation, I combine matching with the DD estimator to reweight the treated and control groups to account for differences in their control variable distributions. For the matched regressions, I estimate the DD and DDD models on the weighted matched sample where a weight, w_{jk}, is assigned to each control generator, k, that is included in the counterfactual. Using the assigned weights from the propensity score matching, I reweight each EIM gas generator by n^{-1}, where n is the number of matched generators assigned from the control group to each treated generator.[10]

5.3. Identifying Assumptions

Pre-Trends

One of the main assumptions in my identification strategy is that trends in NOx and SO_2 emissions in the control group would have followed the same trajectory as those generators in the treated group absent the EIM. In combination with the matching design, controlling for the EIM selection mechanism not only limits the potential for unobserved variables that are related to both the decision to participate in the EIM and the change in outcomes from participating in the EIM to bias results, but also weakens the parallel trend assumption required in the DD estimator, as parallel trends may be more credible when outcomes are conditioned on observed covariates (Ferraro and Miranda, 2014). Although it is not possible to test the post-EIM appropriateness of the control group, there are several ways to test this assumption in the pre-EIM period. First, I perform an event study which tests the effect of the EIM each year from 2010 to 2016. The event study model is:

$$Y_{ijt} = \sum_{t=2010}^{t=2016} \gamma_t EverEIM_i + \mathbf{X}_{jt}\beta + \mu_i + \epsilon_{ijt} \tag{3}$$

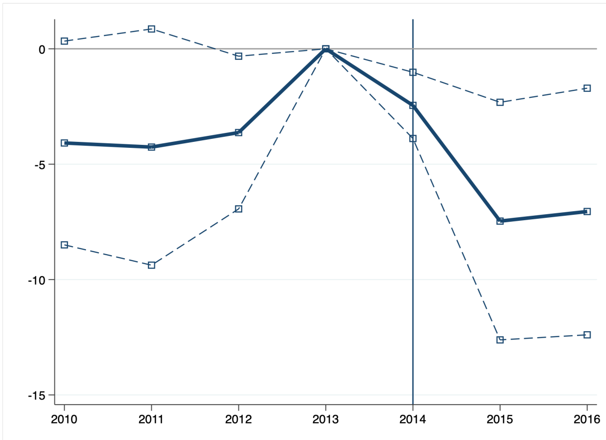
where my coefficients of interest are, $\gamma_{2010}, ..., \gamma_{2016}$, which are the annual average shift in local pollutants (NOx or SO_2), for generators in the EIM, relative to non-EIM generators, conditional on the various time-fixed effects, as well as generator- and BA-level controls in my econometric model. Figure 4 is a plot of the γ_t coefficients for the full sample, where the year 2013 is normalized to zero. Figure 5 is the event-study plot for the matched sample. Coefficients that are not significantly different from zero, prior to 2014, are consistent with a lack of pre-trends.

It is clear from Figure 4 that there are some pre-EIM differences in NOx emissions between the unmatched treatment and control groups. I address this problem by using matching to create a counterfactual set of generators that are more similar to the EIM generators in the pre-EIM period. With the matched sample, as shown in Figure 5, differences in NOx emissions between the treatment and control groups in the pre-EIM period are not statistically significantly different from zero, evidencing that the pre-trends assump-

[10]Each gas generator has three matched control generators, and each EIM coal generator has two matched control generators

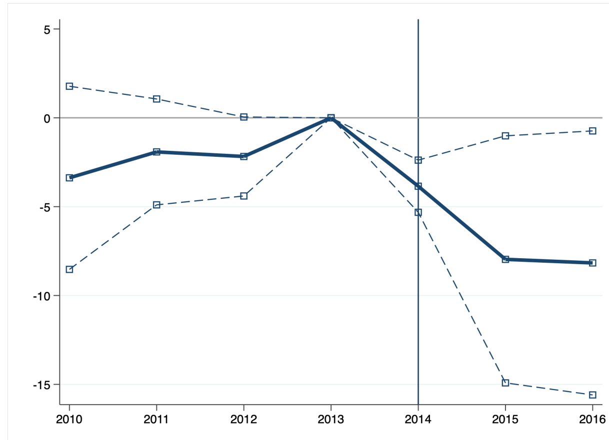
tion is more plausible in the matched sample.

Figure 4: Panel A: Event Study Full Sample



Notes: This figure plots the coefficients γ_t, showing the annual average difference in NOx emissions for generators in the EIM for the full sample.

Figure 5: Panel B: Event Study NOx Matched Sample



Notes: This figure plots the coefficients γ_t, showing the annual average difference in NOx emissions for generators in the EIM for the matched sample.

Second, I also estimate a one-step-up model, as recommended by Bilinski and Hatfield (2018), where I first estimate my baseline regression model with a more complex trend difference between treated and control groups than what I assume is the true model, and test that both the coefficient on the trend and the estimated treatment effect from my one-step-up model is not statistically significantly different than that of the baseline model. Bilinski and Hatfield (2018) show that this approach reduces bias while also considering power in testing for parallel trends. I estimate the one-step-up model with a daily time trend:

$$Y_{ijt} = \alpha + \lambda Post_t + \gamma' EverEIM_i * Post_t + \theta EverEIM_i * Trend_t + \mathbf{X}_{jt}\beta + \mu_i + \epsilon_{ijt} \tag{4}$$

where θ captures the effect of the differential trends between treated and control groups. I test the hypothesis $H_0 : \gamma - \gamma' \geq \delta$ against the alternative that $H_A : \gamma - \gamma' < \delta$, where I set δ equal to zero. Table 2 reports the results of this test for NOx emissions from gas generators. I do not find a significant difference in trends between treated and control groups, nor do I find a significant difference in the estimate of the treatment effect, $\gamma - \gamma'$. I conclude the assumption that there are no differential trends between treated and control groups is plausible. The differential trend test for SO_2 and NOx emissions from coal generators is reported in Appendix B.

Unconfoundedness

In addition to assuming that trends in NOx and SO_2 emissions in the control group would have followed the same trajectory as those generators in the treated group absent the EIM, another equally important assumption is that the potential selection bias in the unconditional DD estimates can be addressed by adjusting for differences in observed covariates. The underlying idea is that after conditioning on variables identified in the selection mechanism, and adjusting for observable differences in covariates, that the distri-

Table 2: Differential Trend Test - NOx Emissions - Gas Generators

VARIABLES	(1) Full Sample	(2) Full Sample
Ever EIM X Post EIM	-4.461*	-6.838**
	(2.310)	(3.030)
Post EIM	-6.039	-6.624
	(3.754)	(3.850)
Ever EIM X Trend		0.020
		(0.00154)
Hourly FERC Load by Planning Area	0.00226***	0.00225***
	(0.000784)	(0.000787)
Generator Age	0.937***	0.936***
	(0.298)	(0.297)
Pre-EIM Heat Input	21.03	20.97
	(18.67)	(18.68)
Constant	-27.47**	-27.80**
	(11.17)	(11.16)
Observations	5,553,701	5,553,701
R-squared	0.250	0.250
Abatement Technology Controls	YES	YES
Hour FE	YES	YES
DOW FE	YES	YES
Month X Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

$H_0 : \gamma - \gamma' \geq \delta$

Chi2: 1.67

Prob > Chi2: 0.1962

Notes: This table reports γ_1 for both the baseline DD and one step up model as recommended by Bilinski and Hatfield (2018). The difference in coefficients from $H_0 : \gamma_1 - \gamma_1' \geq \delta$ is reported using a Chi2 test is reported, and evidences that the difference in coefficients from the baseline and one-step-up model is not statistically different from zero.

bution of the control NOx or SO_2 emissions, $Y_{it'}(0)$, is the same for both treated and control generators. While this assumption can not be tested directly, I assess the plausibility of the assumption by performing an out-of-sample test, where I reassign treatment to occur in the pre-treatment period, and test for observable differences in treated and control generator outcomes. I find that there is no significant difference between treated and control generators in the pre-EIM period for neither coal nor gas generators. The results of this test are shown in Appendix D.

Sufficient Overlap
My identification strategy also requires that there is sufficient overlap in the distribution of the conditioning covariates between treated and control groups. The joint distribution of the conditioning covariates provides evidence that this assumption is satisfied, and is available in Appendix A.

5.4. Treatment Effect Heterogeneity

Because local pollutants can cause disproportionate damages to local areas across time and space, I examine whether treatment effects vary systematically across different levels of residual load, different hours of the day and different regions of the West (i.e. different BAs).

For different quartiles of residual load, hourly regressions, and regional regressions I limit the weighted matched regressions in equations (1) and (2) to a subset of the sample, for example, for residual load quartile 1, for hour 1, or for the PacifiCorp BA. In addition, once a BA joins the EIM, it has the autonomy to decide which generators to bid in to the EIM. To fully explore the distribution of how the EIM affects the dispatch of generators within different regions, and how these in turn affect local pollutants, I also examine how the EIM affects each individual generator relative to its matched counterfactual generators. I estimate the following weighted regression:

$$\begin{aligned} Y_{jt} = \alpha_j + \lambda_{1,j} Post_t + \gamma_{1,j} EverEIM_i * Post_t \\ + \lambda_{2,j} ResidualLoad_t + \lambda_{3,j} ResidualLoad_t * EverEIM_i + \lambda_{4,j} ResidualLoad_t * Post_t \\ + \gamma_{2,j} ResidualLoad_t * EverEIM_i * Post_t + \mathbf{X}_{jt}\beta_j + \mu_{i,j} EverEIM_i + \epsilon_{ijt} \end{aligned} \tag{5}$$

where generator group j includes each treated generator, j, and its n control generator matches. In lieu of BA fixed effects, I include monthly, state-level CityGate natural gas prices which can drive regional differences in generator dispatch. I estimate the regressions with feasible generalized least squares to address for heteroskedasticity and serial correlation in the errors.

6. Results and Discussion

6.1. Gas Generators

The EIM was created to help address energy imbalances, largely due to California's solar energy output, across the wider Western electric region. While the EIM was not specifically created to address pollution outcomes, it did change dispatch patterns by using the least cost generator from a wider geographic area to address energy imbalances, creating the potential for pollution hot spots. Only NOx emissions results are reported for gas generators as SO_2 emissions are caused by burning fossil fuels that contain sulfur—primarily coal and oil.

Table 3 reports the difference in NOx emissions between EIM and non-EIM generators across the Western U.S. before and after the implementation of the EIM, as well as the difference in NOx emissions between EIM and non-EIM generators in response to incremental increases in CAISO residual load. Column (1) reports the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator-level controls for generator age and pre-EIM heat input, and NOx abatement technology controls.

Focusing on Column (4), my preferred specification, I find that participating in the EIM, on average, reduces NOx emissions from natural gas generators by 6 lbs per hour. On an annualized basis, the magnitude of this effect is a reduction of 52,560 lbs of NOx emissions for each EIM generator, or 26% of NOx emissions for the average gas generator in the sample.

Local Pollutants at Different Residual Load Quartiles

Although I do not find a statistically significant difference in NOx emissions in response to incremental increases in CAISO residual load in the DDD specification, it is possible that natural gas generators in the EIM are responding differently than non-EIM generators at different levels of residual load, as residual load levels affect which generators are on the margin. I plot hourly average CAISO load and CAISO residual load (net of solar photovoltaic and wind production) in Figure 6. It's clear that California solar photovoltaic production (which begins around 7 AM and lasts until 8 PM) drives a significant difference between the shape of the load and residual load during daylight hours. However, because load is also higher during the workday, and peaks in the evening hours, residual load remains high throughout the peak solar production hours. As fossil-fuel generators are dispatched to follow residual load, differences in residual load due to renewable resources or other factors can result in different local pollution outcomes within the EIM.

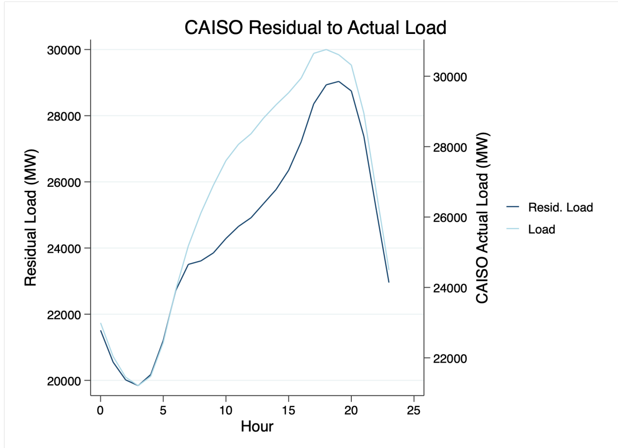
Table 3: Natural Gas Generator NOx Emissions

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Matched Sample	(4) Matched Sample
Ever EIM X Post EIM	-4.461*	-5.043**	-5.912*	-6.004*
	(2.310)	(2.298)	(3.077)	(3.068)
Post EIM (Centered)	-6.039	-5.088	-6.283	-5.811
	(3.754)	(3.697)	(4.251)	(4.115)
Ever EIM X CA Resid. Load		-0.000234		-8.54e-05
		(0.000158)		(0.000150)
Ever EIM X Post EIM X CA Resid. Load		-5.71e-05		3.14e-05
		(0.000204)		(0.000199)
Post EIM X CA Resid. Load		-2.36e-05		-0.000152
		(0.000148)		(0.000130)
CA Resid. Load		0.000361***		0.000267*
		(0.000106)		(0.000141)
Hourly FERC Load by Planning Area	0.00226***	0.00212***	0.00146***	0.00124***
	(0.000784)	(0.000734)	(0.000416)	(0.000365)
Generator Age	0.937***	0.940***	0.862**	0.864**
	(0.298)	(0.298)	0.310)	(0.311)
Pre-EIM Heat Input	21.03	20.99	28.47	28.46
	(18.67)	(18.63)	(20.56)	(20.58)
Constant	-27.47**	8.021*	-10.23	25.12***
	(11.17)	(3.961)	(12.68)	(4.616)
Observations	5,553,701	5,538,481	3,809,659	3,799,099
R-squared	0.250	0.250	0.383	0.383
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in column (1) are from the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, as well as controls for NOx abatement technology, with errors clustered at the BA-level.

Figure 6: Hourly Average CAISO Load and Residual Load



Notes: Hourly average CAISO load vs. CAISO residual load (net of solar photovoltaic and wind production) in MW.

I examine the difference in NOx emissions between EIM and non-EIM generators at four quartiles of residual load, where quartile 1 is 11,609 - 20,815 MW, quartile 2 is 20,816 - 23,479 MW, quartile 3 is 23,750 - 27,054 MW, and quartile 4 is 27,055 - 46,782 MW. As residual load increases, this implies that either CAISO load is increasing, renewable resource output is decreasing, or a combination of both. Columns (1) through (4) report the γ coefficients from the DD model for the full sample for quartiles 1 through 4, respectively, and columns (5) through (8) report these same coefficients for the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator-level controls for pollution abatement technology, generator age, and pre-EIM heat input, with errors clustered at the BA-level. Focusing on Column (4), from the full sample, and Column (8), from the matched sample, I find that the EIM reduces NOx emissions from gas generators significantly more at the highest levels of residual load compared to non-EIM generators. NOx emissions are again reduced by roughly 6 lbs.

Significant NOx emissions reductions could be because the EIM is dispatching an EIM generator more efficiently when it is the marginal generator, or because the EIM is dispatching only relatively cleaner EIM generators to meet residual load from CAISO. Through my design I can rule out that the likelihood that the EIM is favoring relatively cleaner generators as I condition on characteristics that make treatment and control generators more similar, as well as adjust for differences in NOx abatement technologies. Another potential issue is if the effect I detect is due to CAISO buying more electricity from EIM generators (relative to non-EIM generators). To rule out this possibility, I match generators on their likelihood to respond to CAISO load in the pre-EIM period—in effect, matching on marginal sellers to California. Second, the similarity in coefficients between the DD and DDD specification provides evidence that the results are not biased, even when taking into account the effect of residual load on generator dispatch. As a result, the difference in NOx emissions I detect is likely due to the EIM's efficient dispatch mechanism, which reduces generator cycling through enhanced visibility of supply and load throughout the EIM footprint.

Table 4: Natural Gas Generator NOx Emissions at Residual Load Quartiles

VARIABLES QUARTILE	(1) Full 1st	(2) Full 2nd	(3) Full 3rd	(4) Full 4th	(5) Matched 1st	(6) Matched 2nd	(7) Matched 3rd	(8) Matched 4th
Ever EIM X								
Post EIM	-5.349	-3.893	-3.234	-6.420**	-6.615	-5.441	-4.605	-6.244**
	(3.179)	(2.677)	(2.078)	(2.520)	(3.899)	(3.433)	(2.749)	(2.492)
Constant	-9.453	-14.93	-21.92*	-39.40***	-2.248	-4.949	-6.489	-13.18
	(10.61)	(10.24)	(10.99)	(12.15)	(13.30)	(12.23)	(12.25)	(13.86)
Observations	1,048,966	1,215,167	1,373,882	1,900,466	710,596	829,323	947,427	1,311,753
R-squared	0.296	0.261	0.256	0.243	0.386	0.381	0.399	0.397
Abatement								
Technology								
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Quartile 1: 11609 - 20815 MW

Quartile 2: 20816 - 23479 MW

Quartile 3: 23750 - 27054 MW

Quartile 4: 27055 - 46782 MW

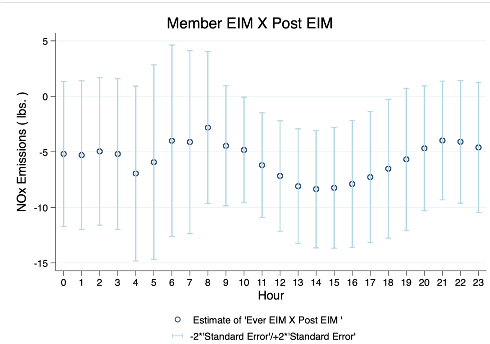
Notes: The coefficient estimates reported in Columns (1) through (4) are the γ coefficients from the DD model for the full sample for quartiles 1 through 4, respectively, and columns (5) through (8) report these same coefficients from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator-level controls for pollution abatement technology, generator age, and pre-EIM heat input. Errors are clustered at the BA-level.

Temporal Distribution of Local Pollutants

As both load and renewable resource output vary throughout the day, the EIM's change in dispatch patterns to meet fluctuations in residual load can also affect the temporal distribution of local pollutants. With local pollutants, when the pollution occurs is important for the extent of local damages. For example, if NOx pollution increases during daylight hours, it could react with volatile organic compounds (VOCs) in the air and create ozone, which has several known adverse health outcomes. To examine how the EIM affects the temporal distribution of local pollutants, I estimate the DDD model separately for each hour of the day, and plot the DD and DDD coefficients in Figures 7 and 8, respectively.

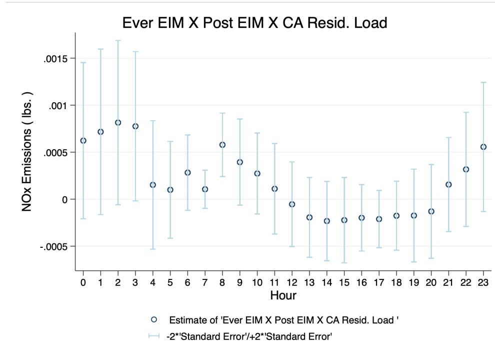
The hourly regression results provide more context as to how the EIM differentially affects generators at higher levels of residual load. When residual load is high, during the workday and evening hours, EIM generators are producing between 5 and 10 lbs less NOx emissions on average than their non-EIM counterparts. In response to incremental increases in CAISO residual load, EIM generators only produce significantly more NOx emissions during the 8 AM hour, which is likely when load is increasing but significant solar power production has not yet come online. Overall, significant reductions in NOx pollution during daylight hours can reduce other copollutants like ozone and reduce negative health outcomes, although I leave the EIM's effects on copollutants to future research.

Figure 7: Hourly Average Gas Generator NOx Emissions (Pounds)



Notes: This figure plots the DD effect of EIM participation at hourly CAISO residual load averages.

Figure 8: Hourly Marginal Gas Generator NOx Emissions (Pounds)



Notes: This figure plots the DDD effect of EIM participation for incremental residual load increases above hourly CAISO residual load averages.

Spatial Distribution of Local Pollutants

Local pollution is non-uniform and has the potential the for significant spatial variation. I estimate equation (2) separately for each BA to examine the regional distribution of NOx emissions. Once an EIM member, BAs can voluntarily offer a generator for power production, and strategic behavior with certain generators may cause spatially heterogenous treatment effects within the EIM. To explore the potential for this effect, I also examine the distribution of NOx emissions at the generator level by estimating equation 5 by region.

Table 5 reports the coefficients for the BA-level regressions for the EIM's effect on NOx emissions from natural gas generators. Column (1) reports the results for Arizona Public Service Company (APS). Column (2) reports the results for the Nevada Power (NP). Column (3) reports the results for PacifiCorp (PAC). Column (4) reports the results for Puget Sound Energy (PSE). In the DDD specification, all covariates and interaction terms are mean-centered so that results can be interpreted at average levels of CAISO residual load. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, and NOx pollution abatement technology. Errors are clustered at the BA level.

I find that there is significant heterogeneity in local pollution outcomes across different BAs. Focusing on column (3), PacifiCorp, the EIM's first participant, experienced a significant reduction in NOx pollution, on average, relative to its non-EIM matched counterfactual generators. With a significant reduction of nearly 25 lbs of NOx per hour, it's clear that PacifiCorp's NOx emissions reductions drive the EIM's overall NOx emissions reductions. Focusing on column (2), Nevada Power, the EIM's second participant, did not experience a meaningful reduction or increase in NOx emissions, relative to its matched counterfactual generators. However, as shown in columns (1) and (4) both Arizona Public Service Co. and Puget Sound Energy experienced small but significant increases in NOx emissions. On the margin, NOx emissions are generally increasing in response to increases in CAISO residual load, with the exception of Nevada Power.

The BA-level results raise some questions. Particularly in Pacificorp, average NOx emissions in the EIM are decreasing, while marginal emissions are increasing. One plausible explanation for this finding is that gas generators are being utilized less overall within a BA, but are more likely to be on the margin and responding to shifts in residual load due to renewable resource uncertainty. I explore this possibility by running regressions on a measure of generator utilization[11] as a robustness check and find that gas generators are less likely to be utilized in APS, PAC, and PSE, while they are more likely to be used in NP. On the margin, only in PAC are gas generators more likely to be responding to shifts in CAISO residual load. While these results corroborate my expectations for NOx emissions findings in NP and PAC, they do not explain results in APS and PSE, which both experience average and marginal increases in NOx emissions despite gas generators being less likely to be used on average and on the margin in these BAs. Generator utilization results for gas generators are provided in Appendix F.

To further explore these counterintuitive results, I examine the spatial distribution of the treatment effect separately for each generator by estimating Equation 5 for generators within each treated BA. This specification includes hourly, day-of-week, and month-by-year fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, as well as NOx pollution abatement technology, and controls for monthly, state-level Citygate natural gas prices. The coefficients plotted in Figure 9 are the $\gamma_{1,j}$ coefficients, which are the level shift in NOx emissions due to the EIM in natural gas generators compared to their three matched counterfactual generators. The generator-level results reflect those of the BA-level, but give more context as to which generators are driving results. In PacifiCorp, smaller gas generators (

[11] Generator utilization is calculated as a generator's hourly generation divided by its estimated maximum capacity. Estimated maximum capacity is the observed highest measure of hourly generation for the generator in the sample.

Table 5: Natural Gas Generator Regional (BAA) NOx Emissions

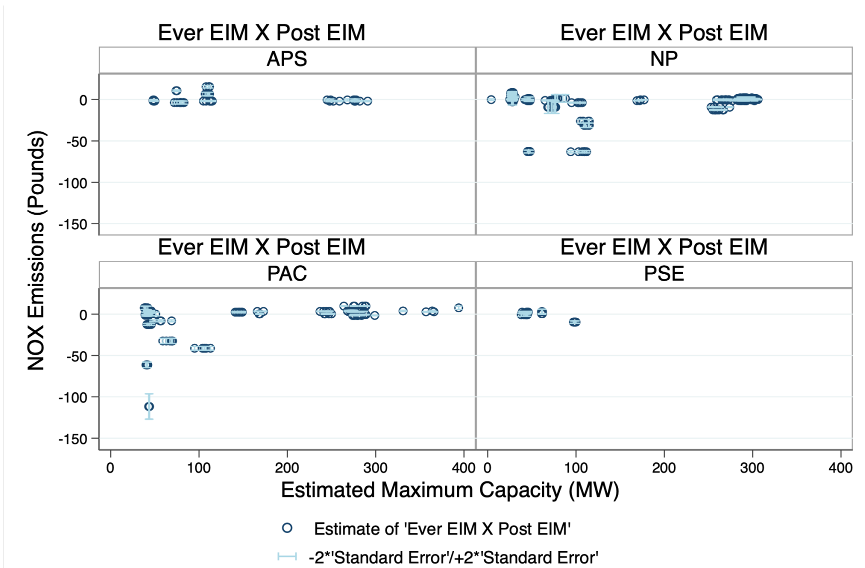
VARIABLES	(1) APS	(2) NP	(3) PAC	(4) PSE
Ever EIM X Post EIM	0.746**	0.0501	-24.93***	1.499***
	(0.324)	(0.283)	(0.706)	(0.403)
Post EIM (Centered)	3.403***	1.744**	7.593***	-3.090**
	(1.074)	(0.848)	(2.173)	(1.252)
Ever EIM X CA Resid. Load	0.000716***	4.49e-05**	-8.29e-05***	-7.59e-05*
	(3.06e-05)	(2.27e-05)	(3.19e-05)	(3.90e-05)
Ever EIM X Post EIM X CA Resid. Load	9.54e-05*	-0.000230***	0.000653***	0.000214***
	(5.00e-05)	(3.83e-05)	(5.39e-05)	(5.87e-05)
Post EIM X CA Resid. Load	0.000238***	-0.000112***	-0.000327***	-0.000101**
	(3.51e-05)	(3.16e-05)	(4.26e-05)	(4.22e-05)
CA Resid. Load	-7.98e-05***	0.000323***	0.000388***	4.90e-05
	(2.62e-05)	(2.22e-05)	(2.98e-05)	(3.36e-05)
Hourly FERC Load by Planning Area	0.00111***	0.000185***	-0.00169***	0.00213***
	(7.63e-05)	(5.95e-05)	(0.000102)	(0.000145)
Pre-EIM Heat Input	-19.89***	45.50***	89.83***	34.48***
	(0.956)	(0.901)	(1.747)	(2.160)
Generator Age	0.140***	1.246***	1.328***	-0.0805***
	(0.00759)	(0.0106)	(0.0163)	(0.0206)
Constant	13.83***	7.203***	22.83***	11.69***
	(0.771)	(0.618)	(1.361)	(1.201)
Observations	412,269	1,451,945	902,221	159,416
R-squared	0.126	0.043	0.027	0.035
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:

$\leq$ 100 MW capacity) generally had fewer NOx emissions than their matched counterfactual generators, whereas larger gas generators did not respond differently than their matched counterfactual generators. In Nevada Power, although some small gas generators did have significant NOx emissions reductions, on average, generators in this BA did not respond significantly differently than their matched counterfactual generators, or produced slightly more emissions. However, in both Arizona Public Service Company and Puget Sound Energy a few smaller gas generators produced significantly more NOx emissions than their matched counterfactual generators. It's plausible that these small generators drive the NOx emissions results, while not impacting overall gas generator utilization results.

Figure 9: Individual Gas Generator NOx Emissions (Pounds) at Average Expected CA Load by Capacity by BAA

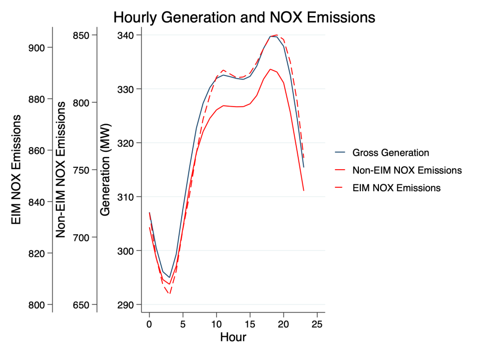


Notes: This figure compares the DD effect of participating in the EIM for each generator and its three matched nearest neighbor control generators based on the propensity score.

6.2. Coal Generators

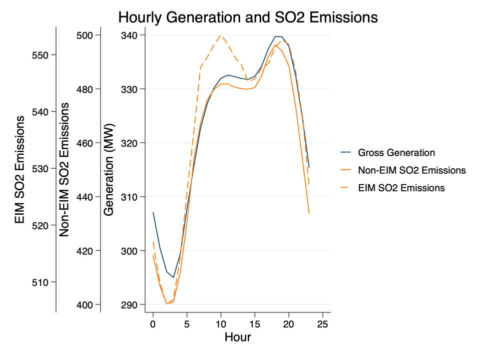
As shown in Appendix B, I do not detect a significant difference in NOx or SO_2 emissions in coal generators relative to their non-EIM counterfactual generators in the overall pooled regressions, nor any differences in local pollution outcomes driven by coal generators being on the margin at different levels of residual load. I do find, however, that coal generators' NOx and SO_2 emissions increased slightly in the early morning hours in response to incremental increases in residual load, as shown in Appendix B, although the magnitudes are very small. Different from gas generators, coal generators' local pollutant emissions tend to follow the shape of generation, as shown in Figures 10 and 11. As coal generators aren't cycling to balance renewable resources, these marginal increases in NOx and SO_2 emissions are likely due to coal generators being on the margin in the dispatch curve.

Figure 10: Average Hourly NOx Emissions and Generation - Coal Generators



Notes: This figure plots hourly average NOx emissions by EIM or non-EIM generators, as well as hourly gross generation for the sample period.

Figure 11: Average Hourly SO_2 Emissions and Generation - Coal Generators



Notes: This figure plots hourly average SO_2 emissions by EIM or non-EIM generators, as well as hourly gross generation for the sample period.

Examining the spatial distribution of the EIM's treatment effect lends more context to the lack of a consistent difference in NOx and SO_2 emissions between EIM and non-EIM generators found in the pooled regressions—only BAs close to California, APS and NP, experienced significant increases in local pollution, whereas PAC experienced a significant decrease in NOx and SO_2 emissions. For BA-level regressions, Column (1) reports the results for APS. Column (2) reports the results for the NP. Column (3) reports the results for PAC.[12] In the DDD specification, all covariates and interaction terms are mean-centered so that results can be interpreted at average levels of CAISO residual load. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator-level controls for generator age, pre-EIM heat input, and NOx or SO_2 pollution abatement technology. Errors are estimated using FGLS.

Focusing first on Table 6, coal generators in APS increased NOx emissions by 386 lbs. in the EIM, which is a 50% increase in NOx emissions for the average coal generator. PAC on the other hand, saw the EIM reduce NOx emissions for the average coal generator by 49 lbs., or a 6% reduction. As shown in Table 7, SO_2 emissions followed similar trends, where coal generators in APS increased their SO_2 emissions by 145 lbs (31%), whereas PAC coal generators' reduced their SO_2 emissions by 69 lbs. (15%).

[12]No coal plants for Puget Sound Energy (PSE) were found in the sample data.

Table 6: Coal Generator Regional (BAA) NOx Emissions

VARIABLES	(1) APS	(2) NP	(3) PAC
Ever EIM X Post EIM	385.9***	171.9***	-49.21***
	(24.07)	(22.26)	(11.84)
Post EIM (Centered)	-569.4***	-300.2***	-142.1***
	(54.22)	(47.70)	(22.59)
Ever EIM X CA Resid. Load	0.00496***	-0.00114***	-0.00145***
	(0.000478)	(0.000298)	(0.000123)
Ever EIM X Post EIM			
X CA Resid. Load	0.000837	-0.000937	-0.00285***
	(0.000859)	(0.000580)	(0.000203)
Post EIM X CA Resid. Load	-0.00221***	0.00106***	0.00213***
	(0.000681)	(0.000362)	(0.000161)
CA Resid. Load	0.00398***	0.00457***	0.00716***
	(0.000500)	(0.000293)	(0.000115)
Hourly FERC Load by Planning Area	0.0613***	0.0261***	0.0122***
	(0.00172)	(0.00136)	(0.000387)
cgenerator_efficiency_matched	882.7***	1,198***	-165.2***
	(63.49)	(64.55)	(31.35)
Generator Age	26.10***	9.910***	-8.156***
	(0.732)	(0.317)	(0.355)
Constant	1,075***	810.4***	652.2***
	(38.10)	(26.77)	(13.64)
Observations	464,411	519,070	1,729,465
R-squared	0.128	0.020	0.028
Abatement Technology Controls	YES	YES	YES
Hour FE	YES	YES	YES
DOW FE	YES	YES	YES
Month X Year FE	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the DDD specification for each individual BA. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, as well as controls for NOx pollution abatement technology. Errors are estimated using FGLS.

Table 7: Coal Generator Regional (BAA) SO_2 Emissions

VARIABLES	(1) APS	(2) NP	(3) PAC
Ever EIM X Post EIM	145.3***	136.2***	-69.43***
	(19.92)	(14.21)	(7.737)
Post EIM (Centered)	-41.21	-275.6***	-204.7***
	(45.46)	(32.87)	(17.23)
Ever EIM X CA Resid. Load	-0.0164***	0.00177***	-0.00270***
	(0.000458)	(0.000279)	(0.000147)
Ever EIM X Post EIM X CA Resid. Load	0.0113***	0.00508***	-0.000386
	(0.000824)	(0.000544)	(0.000244)
Post EIM X CA Resid. Load	-0.00810***	-0.00108***	-4.69e-05
	(0.000654)	(0.000341)	(0.000193)
CA Resid. Load	0.0111***	0.00260***	0.00622***
	(0.000480)	(0.000274)	(0.000138)
Hourly FERC Load by Planning Area	0.0608***	0.0228***	0.000516
	(0.00168)	(0.00128)	(0.000459)
cgenerator_efficiency_matched	3,837***	-1,425***	771.7***
	(73.83)	(64.05)	(21.66)
Generator Age	-76.96***	2.394***	1.587***
	(1.800)	(0.468)	(0.205)
Constant	-2,609***	481.5***	314.1***
	(71.75)	(21.89)	(11.12)
Observations	464,411	519,070	1,729,465
R-squared	0.102	0.040	0.018
Abatement Technology Controls	YES	YES	YES
Hour FE	YES	YES	YES
DOW FE	YES	YES	YES
Month X Year FE	YES	YES	YES

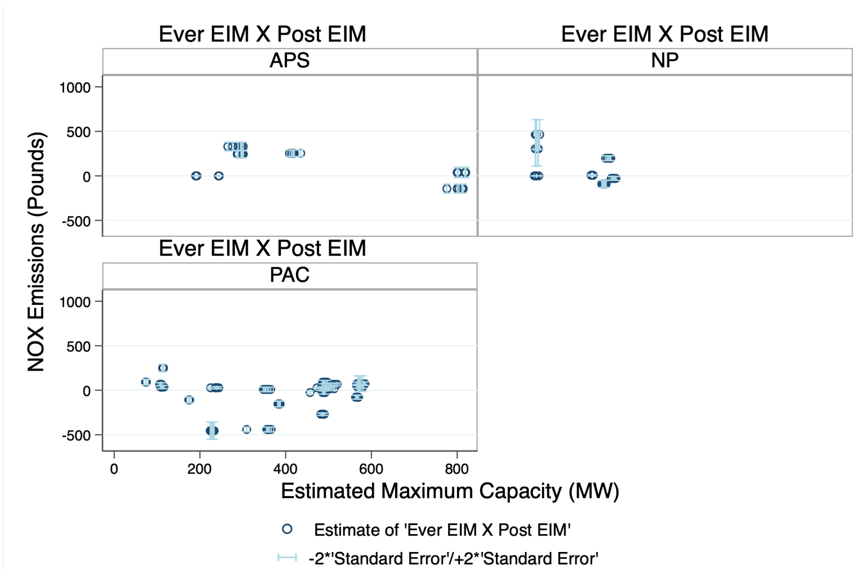
Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the DDD specification for each individual BA. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, as well as controls for SO_2 pollution abatement technology. Errors are estimated using FGLS.

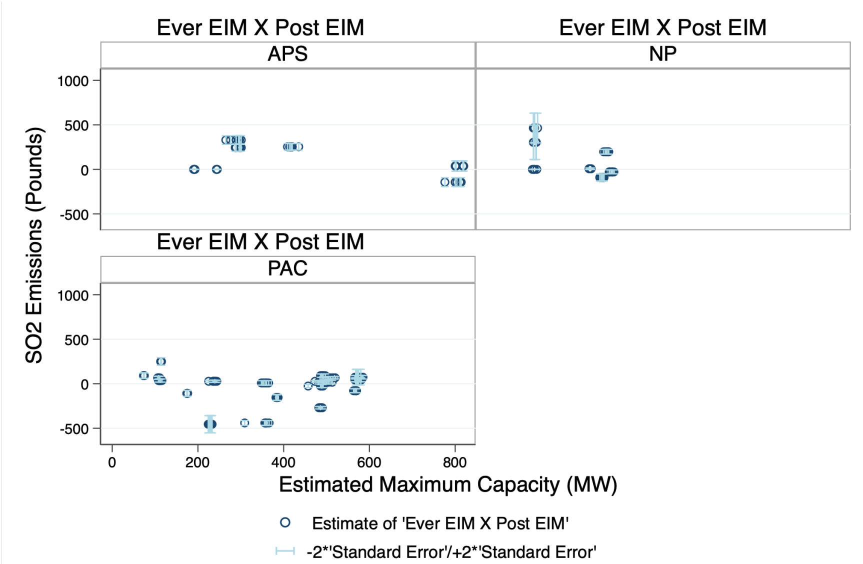
Because both NOx and SO_2 emissions are a concern for policy-makers, due to the large volumes of pollution emitted by coal generators, I also examine the distribution of these emissions at the generator level to better understand which generators are driving results. The generator-level regressions include hourly, day-of-week, and month-by-year fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, as well as NOx or SO_2 pollution abatement technology, and controls for monthly, state-level Citygate natural gas prices. Errors are estimated with FGLS. The coefficients plotted in Figures 12 and 13 are the $\gamma_{1,j}$ coefficients, which are the level shift in NOx or SO_2 emissions due to the EIM in coal generators compared to their three matched counterfactual generators. Figure 12 demonstrates that on average, coal generators in BAs near California load centers, APS and NP, tend to emit more NOx pollution. However, PAC's coal generators generally produce less NOx emissions than their counterfactual generators, as found in the BA-level regressions. SO_2 emissions—as shown in Figure 13—follow analogous regional trends. Small to mid-sized coal plants, with a capacity of 150 - 400 MW drive the variation in response in coal generators.

Figure 12: Individual Coal Generator NOx Emissions (Pounds) at Average Expected CA Load by Capacity by BAA



Notes: This figure compares the DD effect of participating in the EIM for each coal generator and its two matched nearest neighbor control generators based on the propensity score.

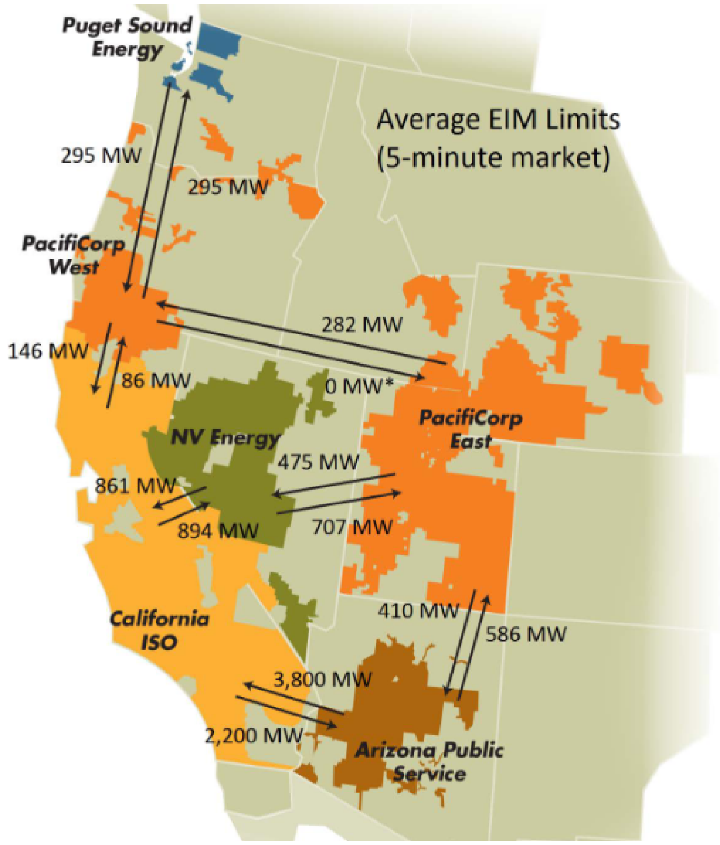
Figure 13: Individual Coal Generator SO_2 Emissions (Pounds) at Average Expected CA Load by Capacity by BAA



Notes: This figure compares the DD effect of participating in the EIM for each coal generator and its two matched nearest neighbor control generators based on the propensity score.

The varied results of the EIM in regional BAs may be because of differences in transfer capability between BAs and CAISO. Figure 14 is reproduced from CAISO's State of the Market Report for 2016, and shows that CAISO has more transfer capability (transmission capacity) with NP and APS than with the PAC BA.

Figure 14: BA Transfer Capability



Notes: This figure depicts the transfer capability between BAs in the EIM footprint. *Source:* CAISO State of the Market Report 2016

Although historical actual EIM transfer capability data is not publicly available for the time period of this study, to estimate the effect of transmission capacity on local pollution results from the EIM, a measure of transmission congestion is obtained from Tarufelli and Gilbert (2019). Transmission congestion is represented by a shadow price of transmission when there is congestion on transmission lines exporting electricity from CAISO to other BAs, importing electricity from other BAs to CAISO, and when there is no congestion. This measure assesses the effect of limited transmission capacity on EIM results. I find that EIM gas generators significantly reduce their average NOx emissions when transmission lines exporting electricity from CAISO are congested, but not when transmission lines importing electricity to CAISO. In hours where there is no transmission congestion, results approximate those found in the pooled regressions. From these results, one can infer that limited transmission capacity results in similar patterns in the overall data as found in the regional Pacificorp BA regressions.

The effect of the EIM on local pollutants raises an interesting possibility: in BAs close to California load centers, gas generators have no to slightly more NOx emissions relative to non-EIM gas generators, but EIM coal generators have more NOx and SO_2 emissions. This result could indicate that these BAs are sending relatively cleaner generation to California and backfilling their own regional demand with relatively dirtier coal generation—a form of reshuffling that California regulators suspect. While I leave the specific mechanism of emissions leakage in the EIM to future research, these results provide insight into how the EIM differentially affects local pollution emissions in EIM regions outside of California.

6.3. Damage Estimates

Average generator-level emissions for each BA are calculated from the γ_1 coefficient from the BA-level regressions. This coefficient is multiplied with the number of generators in each BA and aggregated over the number of hours in a year. A range of monetary damages is estimated by multiplying annual tons of emissions by \$7,000 per ton for NOx and \$41,000 per ton for SO_2, as found in Jaramillo and Muller (2016), or by \$13,000 per ton for NOx and \$24,000 per ton for SO_2, as found in Goodkind et al. (2019). Results are reported in Table C1 in Appendix C.

PAC gas generators significantly reduced their NOx emissions by 25 pounds on average, reducing annual emissions by 2,730 tons, and damages by \$19 - \$36 million dollars. APS gas generators significantly increased their NOx emissions by 0.7 pounds on average, increasing annual emissions by 30 tons, and damages by \$207 - \$384 thousand dollars. PSE gas generators significantly increased their NOx emissions by 1.5 lbs. on average, increasing annual emissions by 11 tons, and damages by \$322 - \$598 thousand dollars.

PAC coal generators significantly reduced their NOx emissions by 49 pounds on average, annually reducing emissions by 2,802 tons, and damages by \$19 - \$36 million dollars. APS coal generators significantly increased their NOx emissions by 385 pounds on average, annually increasing emissions by 8,451.21 tons, and damages by \$59 - \$109 million dollars. NP coal generators also significantly increased their NOx emissions by 172 pounds on average. Annually, this is an increase of 3,765 tons of emissions, increasing damages by \$26 - \$49 million dollars.

PAC coal generators significantly reduced their SO_2 emissions by 69 pounds on average, annually reducing emissions by 3,953 tons, and damages by \$95 - \$162 million dollars. APS coal generators significantly increased their SO_2 emissions by 145 pounds on average, annually increasing emissions by 3,182 tons, and damages by \$76 - \$130 million dollars. Nevada Power coal generators significantly increased their SO_2 emissions by 136 pounds on average. Annually, this is an increase of 2,983 tons of emissions, increasing damages by \$72 - \$122 million dollars.

The generator-level regressions demonstrate that individual generators (especially coal-fired generators) may more severely impact local communities, especially when those generators are in BAs close to California load centers. The BA-level regressions reflect this pattern of local damages.

7. Conclusion

Electricity market design is an important emissions driver. When market design changes electricity dispatch patterns, damages from local pollution emissions (NOx and SO_2) are not uniform across space, causing regional damages. Using an empirical example of the introduction of the EIM to the Western electric region, I identify how a change in market design impacts local pollution outcomes with DD and DDD models, where the data is preprocessed with matching.

I find that the average EIM gas generator reduces its NOx emissions by 26%, a reduction of six pounds per hour, or 52,560 pounds per year, when residual load is high. Despite average reductions in NOx emissions for gas generators, there is significant heterogeneity in the distribution of local pollution outcomes across different geographic regions and generators. NOx and SO_2 emissions in regions close to California load centers are generally increasing for both coal and gas generators, with coal generators' NOx emissions increasing by 50% and SO_2 emissions increasing by 31%, while significant emissions reductions occur in more remote regions, with coal generators NOx and SO_2 emissions decreasing by 6 - 15%. It's estimated that increases in NOx and SO_2 emissions in regions near California led to millions of dollars of damages.

Particularly in the PAC BA, gas generators exhibited a counterintutive finding, where NOx emissions decreased on average, but increased on the margin. One potential mechanism underlying this finding is that gas generators in this BA are being used less overall, but are more likely to respond to shifts in residual load. This potential mechanism was confirmed by regressions measuring the utilization of generators in PAC. However, this finding was not consistent across regions, with other BAs exhibiting different utilization and emissions patterns. Instead, the likely mechanism for this finding is due to limited transfer capability (transmission capacity) within the EIM. I find that when transmission lines are congested, NOx emissions are significantly decreased, although marginal emissions significantly increase.

Given that regional electricity markets are currently expanding into rate-regulated areas, such as Southwest Power Pool's recent creation of a second energy imbalance market that expands into the Western U.S., these findings are important for understanding how changing electricity dispatch patterns affects the distribution of local pollutants and regional environmental damages.

Acknowledgements

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8. Data Availability

Datasets related to this article can be found at:

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Appendix A Matching

I leverage the matching design of Tarufelli and Gilbert (2019) to address the selection mechanism for joining the EIM. Variables in this matching design were specifically chosen to address specific reasons BAs stated for joining the EIM, including improving the dispatch of their available generation and transmission capacity, and to better address energy imbalances within BAs (FERC, 2013). Variables include a measure of a BA's average generation capacity factor, to capture available generation capacity, a measure of transmission capacity, measured as access to high voltage (long-distance) transmission lines, a measure of excess capacity within the BA to meet peak demand, to capture a BAs ability to meet energy imbalances from within the BA, as well as an additional control to capture the likelihood that generators were marginal sellers to the CAISO electricity market.

Reproducing results from Tarufelli and Gilbert (2019), covariate balance between the treated and control group shown in Table 8. The standardized mean difference in column (1) for the full sample and in column (2) for the matched sample compares the difference in means of the treatment and control covariates in units of the pooled standard deviation, where mean differences closer to zero imply better covariate balance. The variance ratio in column (3) for the full sample and column (4) for the matched sample is the ratio of the variance of treated to control generators, variance ratios closer to one imply better balance. Generators are matched with replacement using a caliper of one standard deviation, and the sample is trimmed within [0.05, 0.95].

Although the original sample was not tremendously unbalanced, matching with calipers and trimming does improve balance in the matched sample for natural gas generators. In particular the standardized mean difference improves in all controls but the capacity factor and transmission grid voltage, but matching does reduce the variance ratio for these controls. For further details see Tarufelli and Gilbert (2019).

Table 8: Natural Gas Balance of Sample Covariates

	Standardized Differences		Variance Ratio	
	Full Sample	Matched	Full Sample	Matched
Est. Mean Capacity Factor 2010 - 2012	0.003	0.021	1.221	1.106
Grid Voltage 2012	0.142	-0.250	1.967	1.593
CA Load Response 2011	-0.247	-0.055	0.275	0.312
CA Load Response 2012	-0.344	-0.218	0.092	0.097
Heat Input 2012	-0.172	-0.107	1.000	0.986
BA Avail. Cap. for Peak Demand 2012	-0.176	0.049	1.721	2.500

Notes: This table reports the standardized mean difference and variance ratio of treatment to control units. Perfect balance is a standardized mean difference of zero and a variance ratio of one.

As shown in Table 9, Matching with calipers and trimming also improves covariate balance for coal generators. All variables are better balanced by measure of the standardized difference, and all but one variable is better balanced by the variance ratio. Though the variance ratio between the treatment and control units does not improve for transmission grid voltage, it only increases by an incremental amount.

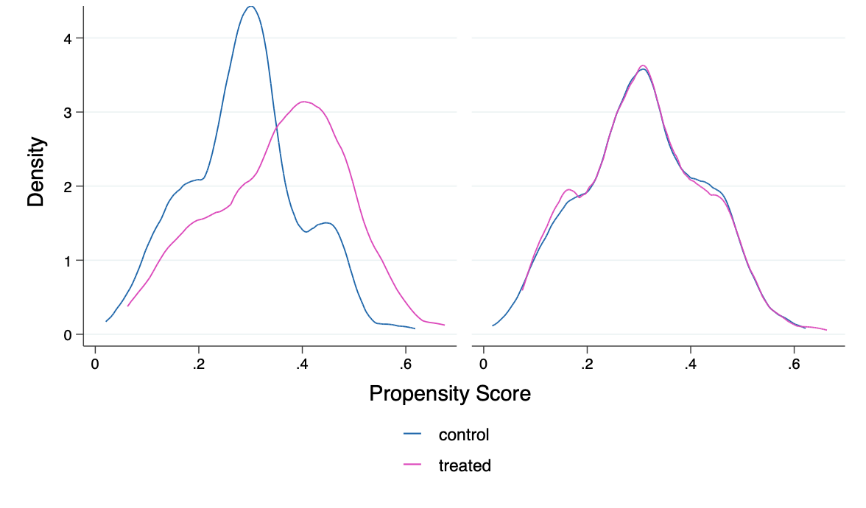
Table 9: Coal Balance of Sample Covariates

	Standardized Differences		Variance Ratio	
	Full Sample	Matched	Full Sample	Matched
Est. Mean Capacity Factor 2010 - 2012	0.014	0.002	1.240	0.982
Grid Voltage 2012	0.285	0.094	0.502	0.385
CA Load Response 2011	-0.229	-0.063	1.837	1.714
CA Load Response 2012	-0.087	0.058	0.923	0.853
Heat Input 2012	-0.173	0.023	0.691	0.727

Notes: This table reports the standardized mean difference and variance ratio of treatment to control units. Perfect balance is a standardized mean difference of zero and a variance ratio of one.

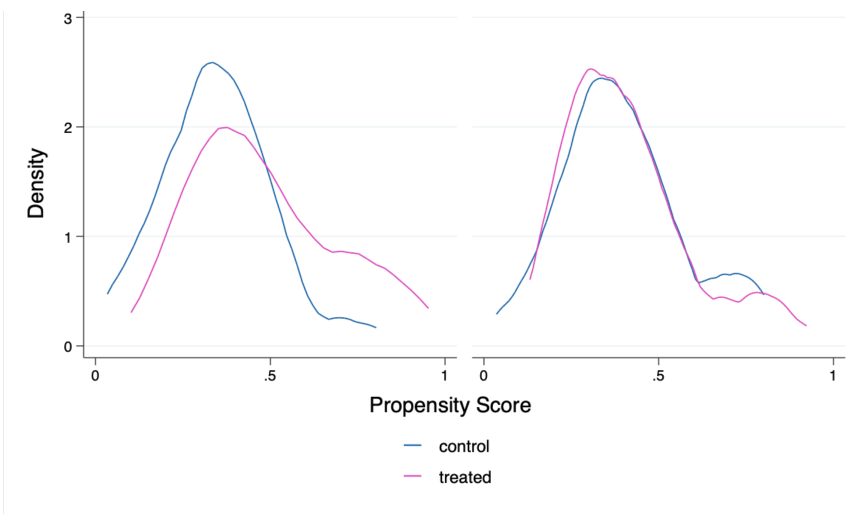
An important identifying assumption of this study is that there is sufficient overlap between treatment and control generators. This assumption can be assessed visually with the propensity score overlap, which I report in Figure 15 for natural gas generators and Figure 16 for coal generators.

Figure 15: Propensity Score Overlap - Natural Gas



Notes: Natural gas propensity score overlap. The full sample is on the right and the matched sample on the left.

Figure 16: Propensity Score Overlap - Coal



Notes: Coal propensity score overlap. The full sample is on the right and the matched sample on the left.

Appendix B Coal Generators NOx Emissions

B.1 Data

Table 10 contains summary statistics for the main generator-level and BA-level variables in my coal generator analysis. Means and standard deviations are provided for hourly NOx emissions, SO_2 emissions, average heat input in the pre-EIM period, generator age, hourly CAISO residual load, and each BA's own load. Summary statistics are reported by control group, where one indicates the generator can participate in the EIM and is considered treated.

Table 10: Summary Statistics: Coal Generators

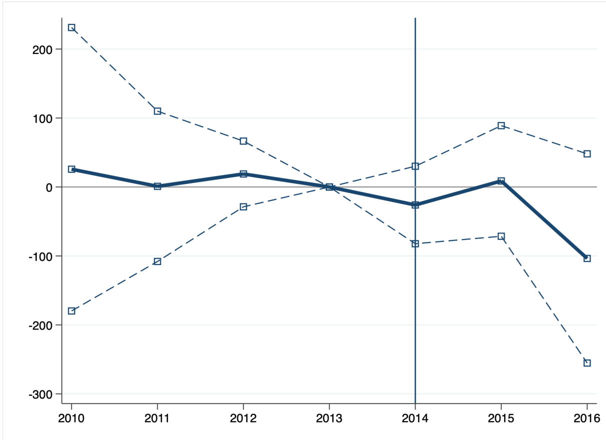
		(1)	
	0	1	Total
Nitrogen Oxide Emissions (lbs)	682.4	886.6	761.8
	(505.5)	(818.4)	(653.1)
Sulfur Dioxide Emissions (lbs)	407.3	549.4	462.6
	(504.0)	(501.3)	(507.7)
CAISO Residual Load (MW)	24620.5	24714.0	24656.9
	(4816.6)	(4817.2)	(4817.1)
Hourly FERC Load by Planning Area	2902.9	5848.0	4048.6
	(1453.5)	(2113.4)	(2256.0)
Pre-EIM			
Heat Input	0.695	0.643	0.675
	(0.120)	(0.0976)	(0.115)
Generator Age	31.41	39.21	34.44
	(13.83)	(10.49)	(13.20)

Notes: Summary statistics are for hourly NOx emissions, SO_2 emissions, average heat input, as well as generator age for the full sample of coal generators; hourly CAISO residual load, and each BA's own load. Means of each variable are shown with standard deviations in parentheses. Variables are shown by control and treatment group, where a 1 indicates the treated group.

B.2 Pre-Trends

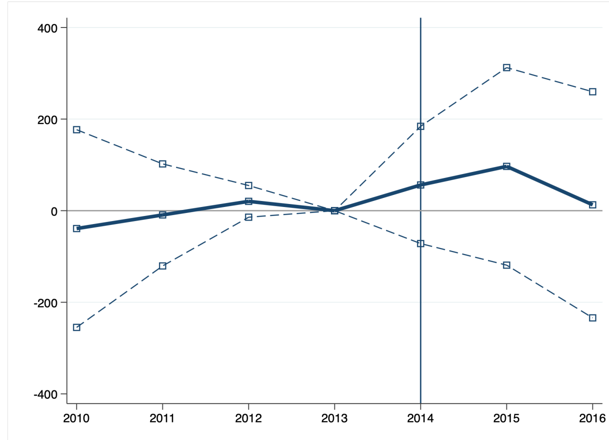
Figure 17 is a plot of the γ_t coefficients for NOx emissions, where the year 2013 normalized to zero, for the full sample. Figure 18 is the event-study plot for the matched sample. Coefficients that are not significantly different from zero, prior to 2014, are consistent with a lack of pre-trends.

Figure 17: Panel A: Event Study NOx Full Sample



Notes: This figure plots the coefficients γ_t, showing the annual average difference in NOx emissions for coal generators in the EIM for the full sample.

Figure 18: Panel B: Event Study NOx Matched Sample



Notes: This figure plots the coefficients γ_t, showing the annual average difference in NOx emissions for coal generators in the EIM for the matched sample.

Table 11 reports the differential trend test for NOx emissions from coal generators.

Table 11: Differential Trend Test - NOx Emissions - Coal Generators

VARIABLES	(1) Full Sample	(2) Full Sample
Ever EIM X Post EIM	-39.99	16.34
	(46.82)	(52.84)
Post EIM	-236.4***	-220.3**
	(64.67)	(72.14)
Trend		-0.0469
		(0.0657)
Hourly FERC Load by Planning Area	0.0318**	0.0324**
	(0.0129)	(0.0126)
Generator Age	3.851	3.860
	(4.362)	(4.331)
Pre-EIM Heat Input	239.5	236.6
	(602.2)	(600.0)
Constant	351.8	356.3
	(388.7)	(389.0)
Observations	4,133,470	4,133,470
R-squared	0.629	0.629
Abatement Technology Controls	YES	YES
Hour FE	YES	YES
DOW FE	YES	YES
Month X Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

$H_0 : \gamma_1 - \gamma_1' \geq \delta$

Chi2: 0.37

Prob > Chi2: 0.5423

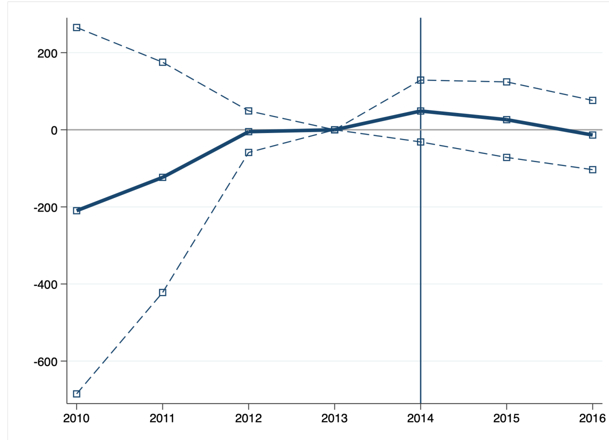
Notes: This table reports γ_1 for both the baseline DD and one step up model as recommended by Bilinski and Hatfield (2018). The difference in coefficients from $H_0 : \gamma_1 - \gamma_1' \geq \delta$ is reported using a Chi2 test is reported, and evidences that the difference in coefficients from the baseline and one-step-up model is not statistically different from zero.

Figure 19 is a plot of the γ_t coefficients for SO2 emissions, where the year 2013 normalized to zero, for the full sample. Figure 20 is the event-study plot for the matched sample. Coefficients that are not significantly different from zero, prior to 2014, are consistent with a lack of pre-trends.

Figure 19: Panel A: Event Study SO2 Full Sample

Notes: This figure plots the coefficients γ_t, showing the annual average difference in SO2 emissions for coal generators in the EIM for the full sample.

Figure 20: Panel B: Event Study SO2 Matched Sample



Notes: This figure plots the coefficients γ_t, showing the annual average difference in SO2 emissions for coal generators in the EIM for the matched sample.

Table 12 reports the differential trend test for SO2 emissions from coal generators.

Table 12: Differential Trend Test - SO2 Emissions - Coal Generators

VARIABLES	(1) Full Sample	(2) Full Sample
Ever EIM X Post EIM	28.91	54.68
	(68.00)	(54.31)
Post EIM (Centered)	-179.4***	-171.9**
	(48.43)	(59.73)
Trend		-.0469
		(.0657)
Hourly FERC Load by Planning Area	0.00806	0.00831
	(0.0163)	(0.0161)
Generator Age	-1.267	-1.263
	(4.618)	(4.625)
Pre-EIM		
Heat Input	474.0	472.9
	(265.8)	(264.4)
Constant	144.7	146.6
	(183.6)	(180.5)
Observations	4,133,470	4,133,470
R-squared	0.281	0.281
Abatement Technology Controls	YES	YES
Hour FE	YES	YES
DOW FE	YES	YES
Month X Year FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Ever EIM X Post EIM Trend = No Trend

Chi2: 0.08

Prob > Chi2: 0.7761

Notes: This table reports γ_1 for both the baseline DD and one step up model as recommended by Bilinski and Hatfield (2018). The difference in coefficients from $H_0 : \gamma_1 - \gamma_1' \geq \delta$ is reported using a Chi2 test is reported, and evidences that the difference in coefficients from the baseline and one-step-up model is not statistically different from zero.

B.3 Results: NOx Emissions

Table 13 reports the difference in NOx emissions between EIM and non-EIM generators across the Western U.S. before and after the implementation of the EIM, as well as the difference in NOx emissions between EIM and non-EIM generators in response to incremental increases in CAISO residual load. Column

(1) reports the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, and NOx abatement technology controls.

Table 13: Coal Generator NOx Emissions

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Matched Sample	(4) Matched Sample
Ever EIM X Post EIM	-39.99	-38.33	58.09	55.77
	(46.82)	(40.02)	(107.5)	(101.0)
Post EIM (Centered)	-236.4***	-216.3***	-381.6**	-364.4**
	(64.67)	(61.21)	(151.6)	(146.4)
Ever EIM X CA Resid. Load		-0.00115		-0.00175
		(0.00257)		(0.00208)
Ever EIM X Post EIM X CA Resid. Load		0.000487		-0.000645
		(0.00279)		(0.00297)
Post EIM X CA Resid. Load		0.00166		0.00229
		(0.00204)		(0.00245)
CA Resid. Load		0.00488**		0.00380*
		(0.00159)		(0.00176)
Hourly FERC Load by Planning Area	0.0318**	0.0271	0.0425***	0.0391**
	(0.0129)	(0.0163)	(0.0121)	(0.0132)
Generator Age	3.851	3.860	0.909	0.911
	(4.362)	(4.359)	(4.275)	(4.276)
Pre-EIM Heat Input	239.5	240.1	-63.64	-63.35
	(602.2)	(602.8)	(600.6)	(600.6)
Constant	351.8	791.7***	734.6	923.9***
	(388.7)	(43.75)	(505.3)	(93.82)
Observations	4,133,470	4,121,621	3,102,396	3,093,354
R-squared	0.629	0.630	0.652	0.652
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in column (1) are from the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in SO_2 emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, as well as controls for NOx abatement technology, with errors clustered at the BA-level.

Table 14 reports the difference in SO_2 emissions between EIM and non-EIM generators at four quartiles of residual load, where quartile 1 is 11609 - 20815 MW, quartile 2 is 20816 - 23479 MW, quartile 3 is 23750 - 27054 MW, and quartile 4 is 27055 - 46782 MW. Columns (1) through (4) report the γ coefficients from the DD model for the full sample for quartiles 1 through 4, respectively, and columns (5) through (8) report these same coefficients from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

Table 14: Coal Generator NOx Emissions At Residual Load Quartiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Full	Full	Full	Full	Matched	Matched	Matched	Matched
QUARTILE	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Ever EIM X Post EIM	-37.94	-17.68	-33.96	-30.79	56.35	80.62	77.16	66.40
	(40.40)	(44.25)	(42.78)	(41.76)	(94.33)	(100.8)	(109.0)	(93.17)
Constant	389.6	372.4	384.5	481.7	783.5	748.8	808.8	899.3
	(372.5)	(385.3)	(404.3)	(420.1)	(461.8)	(485.7)	(536.6)	(546.1)
Observations	979,108	1,028,357	1,035,024	1,079,132	730,203	771,429	779,089	812,633
R-squared	0.614	0.633	0.635	0.637	0.566	0.655	0.688	0.694
Abatement Technology Controls	YES	YES	YES	YES	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Quartile 1: 11609 - 20903 MW

Quartile 2: 20903.24 - 23869

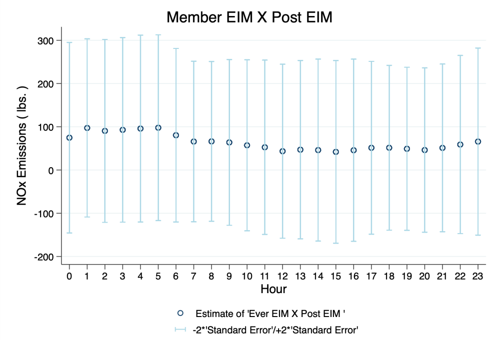
Quartile 3: 23870 - 27142

Quartile 4: 27143 - 46782

Notes: The coefficient estimates reported in Columns (1) through (4) are the γ coefficients from the DD model for the full sample for quartiles 1 through 4, respectively, and columns (5) through (8) report these same coefficients from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

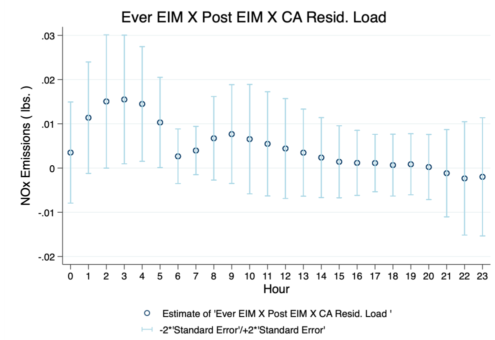
Figures 21 and 22 plot the DD and DDD coefficients for each hour of the day.

Figure 21: Hourly Average Coal Generator NOx Emissions (Pounds)



Notes:

Figure 22: Hourly Marginal Coal Generator NOx Emissions (Pounds)



Notes:

B.4 Results: SO_2 Emissions

Table 15 reports the difference in SO_2 emissions between EIM and non-EIM generators across the Western U.S. before and after the implementation of the EIM, as well as the difference in SO_2 emissions between EIM and non-EIM generators in response to incremental increases in CAISO residual load. Column (1) reports the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in SO_2 emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, and SO_2 abatement technology controls.

Table 16 reports the difference in SO_2 emissions between EIM and non-EIM generators at four quartiles of residual load, where quartile 1 is 11609 - 20815 MW, quartile 2 is 20816 - 23479 MW, quartile 3 is 23750 - 27054 MW, and quartile 4 is 27055 - 46782 MW. Columns (1) through (4) report the γ coefficients from the DD model for the full sample for quartiles 1 through 4, respectively, and columns (5) through (8) report these same coefficients from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

Figures 23 and 24 plot the DD and DDD coefficients for each hour of the day.

Table 15: Coal Generator SO_2 Emissions

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Matched Sample	(4) Matched Sample
Ever EIM X Post EIM	28.91	30.52	69.10	61.82
	(68.00)	(63.20)	(67.22)	(65.56)
Post EIM (Centered)	-179.4***	-165.5***	-285.8	-278.2
	(48.43)	(46.68)	(177.7)	(178.4)
Ever EIM X CA Resid. Load		-0.00242		-0.00536*
		(0.00307)		(0.00261)
Ever EIM X Post EIM X CA Resid. Load		0.00344		0.00397
		(0.00283)		(0.00236)
Post EIM X CA Resid. Load		-0.000465		-0.00117
		(0.000936)		(0.00104)
CA Resid. Load		0.00453**		0.00350
		(0.00153)		(0.00198)
Hourly FERC Load by Planning Area	0.00806	0.00523	0.0362	0.0369
	(0.0163)	(0.0195)	(0.0210)	(0.0219)
Generator Age	-1.267	-1.253	-12.39*	-12.38*
	(4.618)	(4.615)	(5.693)	(5.703)
Pre-EIM Heat Input	474.0	474.8	359.0	359.0
	(265.8)	(266.5)	(419.7)	(420.7)
Constant	144.7	469.3***	768.9*	714.6**
	(183.6)	(77.54)	(409.5)	(237.6)
Observations	4,133,470	4,121,621	3,102,396	3,093,354
R-squared	0.281	0.281	0.486	0.486
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in column (1) are from the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in SO_2 emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to two generator level controls for generator age and pre-EIM heat input, as well as controls for SO_2 abatement technology, with errors clustered at the BA-level.

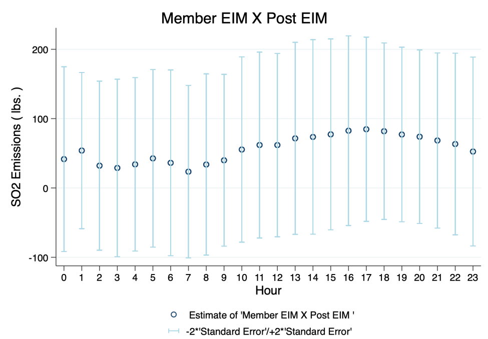
Table 16: Coal Generator SO_2 Emissions At Residual Load Quartiles

VARIABLES	(1) Full 1st	(2) Full 2nd	(3) Full 3rd	(4) Full 4th	(5) Matched 1st	(6) Matched 2nd	(7) Matched 3rd	(8) Matched 4th
Ever EIM X Post EIM	20.61	36.96	29.62	51.98	27.92	53.71	79.88	101.7
	(57.23)	(62.50)	(64.56)	(67.86)	(51.98)	(62.75)	(71.92)	(67.43)
Constant	54.19	133.2	159.0	315.2*	629.6	679.2*	782.2*	960.3**
	(231.3)	(192.5)	(187.1)	(170.8)	(419.8)	(358.8)	(395.6)	(406.1)
Observations	979,108	1,028,357	1,035,024	1,079,132	730,203	771,429	779,089	812,633
R-squared	0.248	0.274	0.293	0.307	0.388	0.477	0.513	0.541
Abatement Technology Controls	YES	YES	YES	YES	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Quartile 1: 11609 - 20903 MW
Quartile 2: 20903.24 - 23869
Quartile 3: 23870 - 27142
Quartile 4: 27143 - 46782

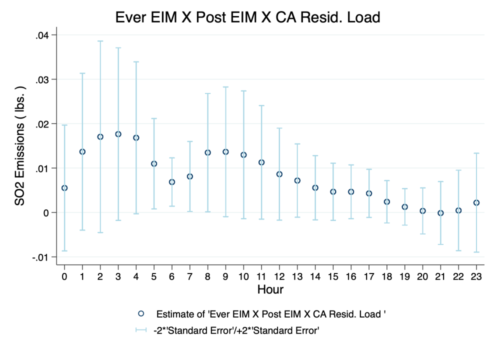
Notes: The coefficient estimates reported in Columns (1) through (4) are the γ coefficients from the DD model for the full sample for quartiles 1 through 4, respectively, and columns (5) through (8) report these same coefficients from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

Figure 23: Hourly Average Coal Generator SO_2 Emissions (Pounds)



Notes: This figure plots the DD effect of EIM participation at hourly CAISO residual load averages.

Figure 24: Hourly Marginal Coal Generator SO_2 Emissions (Pounds)



Notes: This figure plots the DDD effect of EIM participation in response to marginal increases in CAISO residual load averages.

Appendix C Local Pollution Damage Estimates

Table C1 reports average hourly generator-level emissions for each BA, aggregate hourly generator emissions for each BA, annual emissions for each BA, and pollution damage estimates. Average hourly generator-level emissions for each BA are estimated from the differences-in-differences-in-differences model on pooled generator-level regressions for each BA. The DD coefficient from the model is multiplied with the number of generators in each BA and aggregated over the number of hours in a year. A range of monetary damages is estimated by multiplying annual tons of emissions by \$7,000 per ton for NOx and \$41,000 per ton for SO_2, as found in Jaramillo and Muller (2016), or by \$13,000 per ton for NOx and \$24,000 per ton for SO_2, as found in Goodkind et al. (2019).

Table C1: Local Pollution Damage Estimates

Balancing Authority	Generator Type	Avg. Emissions (lbs./hour)	Number of Gen.	Avg. Emissions (lbs./hour)	Annual Emissions (tons/year)	Damages (000 $) (Jaramillo and Muller, 2016)	Damages (000 $) (Goodkind et al., 2019)
NOx Emissions:							
APS	Gas	0.746	9	6.741	29.53	$206.70	$383.89
		(0.324)					
NP	Gas	0.0501	50	2.505	10.97	76.79	142.61
		(0.283)					
PAC	Gas	-24.93	25	-623.25	-2,729.84	-19,108.88	-35,487.92
		(0.706)					
PSE	Gas	1.499	7	10.49	45.96	321.72	597.48
		(0.403)					
APS	Coal	385.9	5	1,929.5	8,451.21	59,158.47	109,865.73
		(24.07)					
NP	Coal	171.9	5	859.5	3,764.61	26,352.27	48,939.93
		(22.26)					
PAC	Coal	-49.21	13	-639.73	-2,802.02	-19,614.14	-36,426.26
		(11.84)					
SO_2 Emissions:							
APS	Coal	145.3	5	726.5	3182.07	$130,464.87	$76,369.68
		(19.92)					
NP	Coal	136.2	5	681	2982.78	122,293.98	71.586.72
		(14.21)					
PAC	Coal	-69.43	13	-902.59	-3953.34	-162,086.94	-94,880.16
		(7.737)					

Notes: This table reports DD estimates for local damages from NOx and SO_2 emissions at the BA level for gas and coal generators using only the matched samples. The 3rd column reports the average emissions for each BA in pounds. The 5th column reports the aggregate hourly BA emissions (in pounds) which is calculated by multiplying the DD coefficient with the number of generators in each BA. The 6th column reports annual emissions by BA, and is the hourly average emissions (in tons) for a full year. Column 7 reports monetary damages based on Jaramillo and Muller (2016)'s local pollution damage estimates. Monetary damages are estimated by multiplying annual tons of emissions by $7,000 per ton for NOx and $41,000 per ton for SO_2. Column 8 reports monetary damages based on Goodkind et al. (2019)'s local pollution damage estimates of $13,000 per ton for NOx and $24,000 per ton for SO_2. FGLS standard errors by BA are in parentheses.

Appendix D Robustness Tests

D.1 Out-of-Sample Tests

To provide evidence for the plausibility of the assumption that after conditioning for variables identified as the selection mechanism, and adjusting for observable differences in covariates, that the distribution of the control NOx or SO_2 emissions, $Y_{it'}(0)$, is the same for both treated and control generators, I perform an out-of-sample test of the effect of the EIM in the pre-treatment period. I assigned the post-EIM period to occur in a random month in 2012, and retained data through March 2013, before the EIM was announced. All data after April 1, 2013 is excluded. Table D2 reports the DD and DDD results for the effect of the EIM on NOx emissions from natural gas generators in the matched sample. Table D3 reports the DD and DDD results for the effect of the EIM on NOx emissions from coal generators in the matched sample. Table D4 reports the DD and DDD results for the effect of the EIM on SO_2 emissions from natural gas generators in the matched sample.The coefficient on the DD and DDD terms are insignificant for both gas and coal generators, providing evidence that there was not a detectable treatment effect in the pre-EIM period between treatment and control generators.

Table D2: Gas Generator Out-of-Sample Test for NOx Emissions

VARIABLES	(1) Matched
Ever EIM X Psuedo Post	0.35
	(1.881)
Pseudo Post EIM	-4.13*
	(2.277)
Ever EIM X CA Resid. Load	-0.00027
	(0.000169)
Ever EIM X Psuedo Post X CA Resid. Load	0.00011
	(0.0000825)
Pseudo Post EIM X CA Resid. Load	-0.0000078
	(0.0000380)
CA Resid. Load	0.00037**
	(0.000163)
FERC Load by Planning Area	0.00092*
	(0.000501)
Pre-EIM Heat Input	26.7
	(17.85)
Generator Age	0.81**
	(0.290)
Constant	23.5***
	(4.285)
Observations	1663359
R-squared	0.45
Abatement Technology Controls	YES
Hour FE	YES
DOW FE	YES
Month X Year FE	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in Column (1) are the DDD estimates for gas generators in the pre-EIM period with an out-of-sample post period. The out-of-sample post variable is a randomly generated month in the year 2012. The dependent variable is measured in mass (lbs.). All interactions are mean-centered so that base coefficients can be interpreted as marginal effects evaluated at the mean. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

Table D3: Coal Generator Out-of-Sample Test for NOx Emissions

VARIABLES	(1) Matched
Ever EIM X Psuedo Post	39.1
	(85.87)
Pseudo Post EIM	-153.8*
	(73.51)
Ever EIM X CA Resid. Load	-0.0018
	(0.00231)
Ever EIM X Psuedo Post X CA Resid. Load	-0.0018
	(0.00146)
Pseudo Post EIM X CA Resid. Load	0.00059
	(0.000995)
CA Resid. Load	0.0034
	(0.00207)
FERC Load by Planning Area	0.040***
	(0.0106)
Heat Input	317.1
	(560.5)
Generator Age	2.22
	(3.909)
Constant	900.9***
	(50.14)
Observations	1500053
R-squared	0.66
Abatement Technology Controls	YES
Hour FE	YES
DOW FE	YES
Month X Year FE	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in Column (1) are the DDD estimates for coal generators in the pre-EIM period with an out-of-sample post period. The out-of-sample post variable is a randomly generated month in the year 2012. The dependent variable is measured in mass (lbs.). All interactions are mean-centered so that base coefficients can be interpreted as marginal effects evaluated at the mean. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

Table D4: Coal Generator Out-of-Sample Test for SO_2 Emissions

VARIABLES	(1) Matched
Ever EIM X Psuedo Post	146.0
	(161.7)
Pseudo Post EIM	-279.5
	(195.9)
Ever EIM X CA Resid. Load	-0.0090**
	(0.00362)
Ever EIM X Psuedo Post X CA Resid. Load	0.0044
	(0.00314)
Pseudo Post EIM X CA Resid. Load	-0.0038*
	(0.00173)
CA Resid. Load	0.0030
	(0.00305)
FERC Load by Planning Area	0.061*
	(0.0305)
Heat Input	754.6***
	(209.9)
Generator Age	-13.6**
	(5.466)
	(4.173)
Constant	711.2***
	(176.0)
Observations	1500053
R-squared	0.53
Abatement Technology Controls	YES
Hour FE	YES
DOW FE	YES
Month X Year FE	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The coefficient estimates reported in Column (1) are the DDD estimates for coal generators in the pre-EIM period with an out-of-sample post period. The out-of-sample post variable is a randomly generated month in the year 2012. The dependent variable is measured in mass (lbs.). All interactions are mean-centered so that base coefficients can be interpreted as marginal effects evaluated at the mean. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to pollution abatement controls and two generator level controls for generator age and pre-EIM heat input, with errors clustered at the BA-level.

Appendix E Robustness of Results to Transmission Congestion

I obtain a measure of transmission congestion from Tarufelli and Gilbert (2019) to assess the impact on limited EIM transfer capability on local pollution hotspots. CAISO provides historical transmission interface and intertie constraint shadow prices which indicate the congested intertie, direction of the constraint, and shadow price for relaxing the constraint by one unit (Tarufelli and Gilbert, 2019).

Table E1 is the results for the subsample of hours in which transmission lines exporting electricity from CAISO were congested, Table E2 is the results for hours in which transmission lines importing electricity to CAISO were congested, and Table E3 is the results for hours in which there was no transmission congestion. Column (1) reports the DD specification for the full sample. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, and NOx abatement technology controls.

Focusing on Column 4, which is DDD for the matched sample, when CAISO export lines are congested, EIM gas generators reduce their NOx emissions by 145 pounds on average, but on the margin slightly increase their NOx emissions. No significant differences are detected when CAISO import lines are are congested. Periods in which there is no transmission congestion exhibit similar results as to those found in the pooled regressions.

Table E1: Gas Generator NOx Emissions when CAISO Export Lines are Congested

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Matched Sample	(4) Matched Sample
Ever EIM X Post EIM	-122.0***	-123.1***	-162.2***	-145.3***
	(0.514)	(1.195)	(1.067)	(0.883)
Post EIM (Centered)	131.2***	133.7***	166.0***	144.0***
	(3.555)	(6.036)	(4.194)	(3.650)
Ever EIM X CA Resid. Load		0.000362		-0.000270*
		(0.000319)		(0.000115)
Ever EIM X Post EIM X CA Resid. Load		-0.00149***		0.00439***
		(0.000370)		(0.000100)
Post EIM X CA Resid. Load		0.000872**		-0.00502***
		(0.000325)		(0.000252)
CA Resid. Load		0.000367		0.00102***
		(0.000351)		(0.000272)
Hourly FERC Load by Planning Area	0.000984***	0.000725***	0.00101***	0.000746***
	(0.000230)	(0.000107)	(0.000240)	(0.000106)
Generator Age	0.928**	0.928**	0.931*	0.932*
	(0.385)	(0.386)	(0.392)	(0.392)
Pre-EIM Generator Efficiency	4.990	4.925	5.733	5.647
		(12.27)		(12.10)
Constant	-12.90	6.903	-8.174	18.37*
	(7.362)	(9.018)	(7.192)	(7.650)
Observations	187,295	187,295	187,086	187,086
R-squared	0.415	0.415	0.423	0.424
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in column (1) are from the DD specification for the full sample when export lines from CAISO are congested. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, as well as controls for NOx abatement technology, with errors clustered at the BA-level.

Table E2: Gas Generator NOx Emissions when CAISO Import Lines are Congested

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Matched Sample	(4) Matched Sample
Ever EIM X Post EIM	-0.686	-0.573	-2.481	-2.334
	(1.293)	(1.635)	(1.392)	(1.630)
Post EIM (Centered)	-0.109	-0.0754	-0.872	-0.612
	(1.009)	(1.164)	(1.634)	(1.757)
Ever EIM X CA Resid. Load		3.02e-06		-2.86e-05
		(0.000137)		(0.000117)
Ever EIM X Post EIM X CA Resid. Load		1.80e-05		-6.43e-05
		(8.32e-05)		(3.82e-05)
Post EIM X CA Resid. Load		6.21e-05		7.17e-05
		(5.97e-05)		(6.84e-05)
CA Resid. Load		-1.27e-05		9.15e-05
		(0.000140)		(9.39e-05)
Hourly FERC Load by Planning Area	0.000861**	0.000757**	0.000965***	0.000784***
	(0.000294)	(0.000244)	(0.000269)	(0.000194)
Generator Age	0.482	0.483	0.582*	0.583*
	(0.266)	(0.267)	(0.298)	(0.298)
Pre-EIM Generator Efficiency	40.50***	40.54***	56.36***	56.29***
	(8.634)	(8.669)	(13.08)	(13.17)
Constant	-33.43***	0.906	-35.92***	9.424***
	(7.886)	(4.894)	(9.745)	(1.750)
Observations	355,917	355,559	309,123	308,818
R-squared	0.122	0.122	0.229	0.229
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The coefficient estimates reported in column (1) are from the DD specification for the full sample when import lines from CAISO are congested. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, as well as controls for NOx abatement technology, with errors clustered at the BA-level.

Table E3: Gas Generator NOx Emissions when CAISO Transmission Lines are not Congested

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Matched Sample	(4) Matched Sample
Ever EIM X Post EIM	-3.882*	-4.464**	-5.024*	-5.128*
	(2.126)	(2.129)	(2.655)	(2.675)
Post EIM (Centered)	-6.482*	-5.457	-6.829	-6.272
	(3.712)	(3.641)	(4.300)	(4.161)
Ever EIM X CA Resid. Load		-0.000249		-8.79e-05
		(0.000161)		(0.000154)
Ever EIM X Post EIM X CA Resid. Load		-1.15e-05		8.99e-05
		(0.000213)		(0.000211)
Post EIM X CA Resid. Load		-1.42e-05		-0.000138
		(0.000145)		(0.000122)
CA Resid. Load		0.000364***		0.000265*
		(0.000104)		(0.000142)
Hourly FERC Load by Planning Area	0.00241***	0.00224***	0.00149***	0.00124***
	(0.000811)	(0.000763)	(0.000427)	(0.000354)
Generator Age	0.960***	0.962***	0.883**	0.886**
	(0.303)	(0.303)	(0.311)	(0.311)
Pre-EIM Generator Efficiency		18.14		25.53
	(19.46)	(19.43)	(21.33)	(21.35)
Constant	-26.14**	8.702**	-8.179	25.88***
	(11.69)	(3.968)	(13.21)	(4.717)
Observations	5,193,121	5,178,259	3,496,076	3,485,821
R-squared	0.252	0.253	0.387	0.388
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The coefficient estimates reported in column (1) are from the DD specification for the full sample when transmission lines to and from CAISO are not congested. Column (2) reports DDD results from the full sample, with covariates and interaction terms mean-centered so that results can be interpreted as the difference in NOx emissions between EIM and non-EIM generators at average levels of CAISO residual load. Columns (3) and (4) report the DD and DDD results from the matched sample. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, as well as controls for NOx abatement technology, with errors clustered at the BA-level.

Appendix F Robustness of Results to Generator Utilization

Table F1 reports the coefficients for the BA-level regressions for the EIM's effect on generator utilization, measured as a generator's hourly generation divided by its estimated maximum capacity, from natural gas generators. Column (1) reports the results for Arizona Public Service Company (APS). Column (2) reports the results for the Nevada Power (NP). Column (3) reports the results for PacifiCorp (PAC). Column (4) reports the results for Puget Sound Energy (PSE). In the DDD specification, all covariates and interaction terms are mean-centered so that results can be interpreted at average levels of CAISO residual load. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, and NOx pollution abatement technology. Errors are clustered at the BA level.

I find that generators in APS, PAC, and PSE are used less to produce electricity on average, while only PAC gas generators are more likely to be used to respond to shifts in residual load. NP gas generators are used more to produce electricity on average, but are less likely to respond to shifts in residual load.

Table F1: Gas Generator Regional (BAA) Utilization

VARIABLES	(1) APS	(2) NP	(3) PAC	(4) PSE
Ever EIM X Post EIM	-0.0367***	0.0649***	-0.00763***	-0.0366***
	(0.00341)	(0.00147)	(0.00245)	(0.00430)
Post EIM	-0.0267**	0.0165***	0.0345***	-0.0836***
	(0.0113)	(0.00441)	(0.00763)	(0.0133)
Ever EIM X CA Resid. Load	3.23e-07	4.26e-06***	-2.42e-06***	2.51e-06***
	(2.58e-07)	(1.28e-07)	(1.79e-07)	(3.89e-07)
Ever EIM X Post EIM				
X CA Resid. Load	-1.17e-06***	-4.01e-06***	7.12e-07**	-2.54e-06***
	(4.14e-07)	(2.18e-07)	(3.16e-07)	(5.85e-07)
Post EIM X CA Resid. Load	-3.65e-06***	7.08e-07***	2.92e-06***	9.17e-07**
	(2.81e-07)	(1.82e-07)	(2.55e-07)	(4.16e-07)
CA Resid. Load	1.65e-05***	8.76e-06***	6.09e-06***	6.16e-06***
	(2.17e-07)	(1.26e-07)	(1.74e-07)	(3.35e-07)
Hourly FERC Load by Planning Area	1.15e-05***	1.40e-05***	2.45e-05***	7.85e-05***
	(7.40e-07)	(3.16e-07)	(4.97e-07)	(1.47e-06)
Pre-EIM Heat Input	0.549***	0.952***	0.0772***	1.292***
	(0.0101)	(0.00467)	(0.00589)	(0.0227)
Generator Age	-0.00241***	7.85e-05	-0.00613***	0.000914***
	(8.00e-05)	(5.46e-05)	(5.49e-05)	(0.000215)
Constant	0.508***	0.542***	0.663***	0.565***
	(0.00789)	(0.00325)	(0.00502)	(0.0127)
Observations	412,269	1,451,945	902,221	159,416
R-squared	0.165	0.165	0.107	0.303
Abatement Technology Controls	YES	YES	YES	YES
Hour FE	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES
Month X Year FE	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the coefficients for the DDD specification for each individual BA. All specifications include hourly, day-of-week, month-by-year and BA fixed effects, in addition to generator level controls for generator age, pre-EIM heat input, as well as controls for NOx pollution abatement technology. The dependent variable is generator utilization, measured as a generator's hourly generation divided by its estimated maximum capacity. Errors are estimated using FGLS.