Targeted Regulation for Reducing High-Ozone Events

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Abstract

Nitrogen oxides (NOx) are a precursor to ground-level ozone, a pernicious pollutant that is harmful to human health and ecosystems. Despite decades of regulations and a precipitous decline in NOx emissions, episodic high-ozone events prevent many areas from attaining air quality standards. Theoretically, spatially or temporally differentiated emissions prices could be more cost effective at reducing such events than a uniform price. To test this prediction, with data from EPA and NOAA spanning 2001–2019, we use novel empirical strategies to estimate (1) the link between hourly emissions and high-ozone events and (2) hourly marginal abatement costs. These estimates form the basis for simulations that compare uniform and differentiated emissions pricing. Consistent with economic theory, differentiated pricing is substantially more cost effective at reducing high-ozone events, but this advantage depends on the accuracy of the estimated NOx–ozone relationship.

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1 Introduction

Ground-level ozone harms human health and the environment. Emissions of nitrogen oxides (NOx) and volatile organic compounds (VOCs) cause ground-level ozone, and decades of regulating these emissions from electricity generators, industrial facilities, vehicles, and other sources has dramatically reduced ozone levels in much of the United States. The Environmental Protection Agency (EPA) assesses attainment with ozone standards based on not average ozone levels but the frequency of ozone exceedance events, defined as an eight-hour period over which the average ozone concentration exceeds 70 parts per billion (ppb). Despite reductions in average ozone levels and the frequency of exceedances, many regions, including areas inhabited by 37 million residents of the northeastern United States, fail to attain current ozone standards.[1]

EPA has been considering options to help states reduce exceedances and achieve the ozone standards. Currently, EPA enforces annual and summer (May–September) NOx emissions caps for electricity and large industrial sources in the eastern United States. Regulated sources retire allowances according to their NOx emissions. Standard economic theory indicates that a uniform price, which does not depend on the location or time of emissions, is the efficient policy for a global or uniformly mixed pollutant, such as carbon dioxide. However, economic theory also indicates that a uniform NOx price may not be cost effective. The effect of NOx emissions on high-ozone events (which we define as hours in which ozone concentration exceeds 70 ppb) varies over space and time depending on VOCs, temperature, and sunlight. For example, high ambient air temperature exacerbates the marginal effect of NOx emissions on the probability of an event. Consequently, a temporally or spatially varying emissions price that accounts for variation of the marginal effects of NOx emissions could be more efficient at reducing events, and in this context, EPA may seek alternatives to continuing to tighten uniform caps.

However, as Fowlie and N. Muller (2019) point out, for such a differentiated pricing policy, the regulator must commit in advance to trading rules that depend on the forecasted marginal effects. The cost savings of a differentiated price depend on forecast accuracy and emissions abatement costs; if forecasts are sufficiently inaccurate, a uniform price could be less costly.

Motivated by this theory, we consider an alternative to tightening existing emissions caps: a differentiated NOx emissions price that varies according to the hourly and region-specific propensity to cause high-ozone events. We ask whether a spatially and temporally differentiated price would be more cost effective than tightening the emissions caps.

Comparing these two types of policies requires estimating (1) the spatially and temporally varying relationship between NOx emissions and high-ozone events and (2) marginal abatement costs. We implement novel empirical strategies to estimate both. We assemble data on emissions, ozone concentrations, temperature, and allowance prices from the annual and seasonal cap-and-trade programs. The analysis focuses on the Northeast and mid-Atlantic, which have experienced some of the highest ozone levels in the eastern United States. Our primary data sources are the

[1] Source: EPA Greenbook. The number in the text reflects populations of nonattainment counties in Connecticut, Delaware, District of Columbia, Maryland, New Jersey, New York, Pennsylvania, and Virginia.

EPA Continuous Emissions Monitoring System (CEMS) for hourly unit-level emissions, generation, and fuel consumption at fossil fuel-fired electricity generators; the EPA Air Quality System (AQS) for hourly ozone concentrations; the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database (ISD) for hourly meteorological data; and EPA for monthly NOx allowance prices. Our combined data set includes hourly observations from 2001 to 2019 (except for the allowance prices, which vary monthly).

We use the emissions, ozone concentrations, and meteorological data to estimate the effect of NOx emissions on high-ozone events, allowing this effect to vary across three subregions within the Northeast, hour of the day, and 5-year subperiods between 2001 and 2019. The key explanatory variable is hourly NOx emissions across fossil-fuel-fired generators within 100 miles of each ozone monitor. The dependent variable is an indicator equal to 1 for a high-ozone event, meaning that the hourly concentration exceeds 70 ppb at a given monitor.[2] We use the indicator variable rather than the level of ozone because an area's compliance with the air quality standard is evaluated based on the number of days on which ozone levels exceed the threshold.

A challenge to estimating the effect of emissions on high-ozone events is that ozone levels also depend on other factors, such as vehicle and industrial facility emissions. To account for the endogeneity of electricity generator emissions, we follow Johnsen, Lariviere, and Wolff (2019) and instrument for emissions using the generator operation computational model from Linn and McCormack (2019). Temporal variation in coal prices, natural gas prices, and electricity demand, combined with cross-sectional variation in generator fuel type and efficiency, creates rich variation in the instrument. It is a strong predictor of observed emissions because the model accurately predicts hourly generation levels. As in Johnsen, Lariviere, and Wolff (2019), the validity of the instrument rests on the assumption that spatial variation in generator fuel types and marginal costs is uncorrelated with omitted variables (that is, somewhat analogous to a Bartik-style instrument).

Across subregions, we find fairly consistent patterns in the relationship between NOx emissions and high-ozone events. Emissions during late-afternoon hours have the largest effect on ozone levels; early morning emissions affect ozone levels by only about one-third as much. For all hours, the estimated effects are statistically significant at the 1 percent level. The effects vary relatively little across the subregions but vary by factors of 3–4 across 5-year subperiods. The hour-of-day variation is more stable across 5-year subperiods than the spatial variation is, which demonstrates the importance of considering temporal variation.

Next, we estimate a marginal abatement cost curve for each subregion. The three subregions we focus on faced seasonal emissions prices under the Cross State Air Pollution Rule (CSAPR). A region's cost curve is the marginal cost of reducing emissions across all generators in the regulated portion of the subregion. We define abatement relative to a counterfactual baseline that has an emissions price of $0.

Existing models of NOx emissions abatement, such as the EPA Integrated Planning Model,

[2]Using the hourly concentration rather than the eight-hour average simplifies the analysis. Section 4 provides further explanation for the rationale for these measures of emissions and high-ozone events.

characterize investments in abatement equipment. For example, these models estimate investment in technologies such as low-NOx burners, which reduce temperature and NOx formation in the power plant's boiler. However, a spatially or temporally differentiated price could affect emissions through other mechanisms. For example, a power plant operator facing a time-varying price may adjust boiler operation to reduce its emissions during periods of the day when the price is high. A price increase may also affect generator use, causing a shift from high- to low-emitting sources. Consequently, relying on conventional models to characterize abatement could omit some of the response to a time-varying price.

To avoid these limitations, we take a reduced-form approach to estimate marginal abatement costs by regressing the hourly average NOx emissions rate in a subregion on the monthly NOx allowance price, allowing the price coefficient to vary by subregion and hour of the day. The price coefficients include responses of generator operation and dispatch. We estimate each region's marginal abatement costs under two assumptions: costs are linear in the level of abatement, and all firms choose levels of abatement such that marginal costs equal the permit price. Under these assumptions, we can infer the slope of marginal abatement cost curves for each hour of the day and subregion using the coefficient estimates from our regressions; costs vary somewhat across hours of the day and significantly across subregions.

Using the estimated NOx–ozone relationship and marginal abatement costs, we compare a uniform price and one that varies across hours and subregions in accordance with the estimated effect of emissions on high-ozone events. We simulate the effect of either price on emissions, the attendant effect on high-ozone events, and generators' abatement costs. To facilitate comparison, we calibrate both prices to achieve the same predicted reduction in event frequency.

The regulator announces the differentiated and uniform prices before generator operation. Because the regulator must set the prices in advance, the differentiated price may be less cost effective than the uniform price if the NOx–ozone relationship is different from expectations when the prices are chosen. To examine the effect of imprecisely set prices, we define two differentiated prices: an *ex ante* price, which is based on information before the implementation of the policy about the statistical NOx–ozone relationship, and an *ex post* price, which is based on updated, and therefore more accurate, information about that relationship. We find that both prices are 15–21 percent less costly than the uniform price in reducing the occurrence of high-ozone events.

This paper contributes to literature examining differentiated environmental taxes (Nicholas Z Muller (2012), Fowlie and N. Muller (2019)) that stems from the foundational literature on market-based regulation (e.g., William J Baumol et al. (1988), Montgomery (1972), Tietenberg (1990)). Fowlie and N. Muller (2019) show that a spatially differentiated tax for addressing heterogeneous damages welfare dominates a uniform tax in the presence of perfect information; under uncertainty, the gains are ambiguous. This area of research has often focused on spatially heterogeneous damages. Important distinctions of our analysis are that we consider both temporal and spatial variation (Fowlie and N. Muller (2019) consider only spatial) and that our variation pertains to marginal effects of a precursor pollutant rather than variation in damages. Our results also differ from Fowlie and N. Muller (2019) in that we find evidence that the spatially and temporally differentiated emissions prices outperform the uniform prices. Our differing results are explained by our estimation of larger temporal than spatial variation in the effects of emissions on high-ozone events, as well as the relative stability of the temporal patterns across years, which reduces prediction error. These results cause the temporally differentiated price to outperform the uniform price.[3]

We also contribute to literature on the statistical relationship between NOx and tropospheric ozone levels (e.g., Xiao, Cohan, Byun, and Ngan (2010) and Grewe, Dahlmann, Matthes, and Steinbrecht (2012)). We are not aware of other papers in this literature that address the endogeneity of observed NOx emissions using an instrumental variables strategy. Our results confirm findings in the literature of a complex and nonlinear relationship between NOx emissions and high-ozone events, which poses a challenge to policy makers: differentiated prices are only cost-effective if the predicted relationship used to inform the policy is sufficiently accurate. A distinction between our analysis and most of the literature is that we consider how the NOx–ozone relationship has varied over the period in which NOx emissions decreased dramatically, complementing research that examines the value of improvements in air quality during the same period (e.g., Stephen P Holland, Erin T Mansur, Nicholas Z Muller, and Andrew J Yates (2020)).

We estimate marginal costs of abatement using econometric methods. These estimates further highlight the distinction between economic abatement costs and estimates that rely on engineering data (e.g., Linn and McCormack (2019) and Fowlie and N. Muller (2019)). The advantage of the econometric approach is that abatement costs reflect observed rather than predicted behavior and include a large range of choices plant operators have in reducing emissions. A limitation of our approach is that our estimates reflect short-run costs. This approach is appropriate because we are interested in understanding short-run responses to a dynamic price that varies by the hour and is announced a short period ahead. However, this approach cannot give insight into long-run responses to a differentiated price, which could include installing abatement equipment or closing plants. Nonetheless, the econometric approach may be useful in other policy contexts in which short-run abatement costs vary temporally or spatially. For example, NOx and sulfur dioxide (SO_2) emissions contribute to fine particulates, which are linked to a wide range of health problems. Estimating short-run marginal abatement costs for NOx and SO_2 could be useful for evaluating the near-term effects of policies aiming to reduce ambient levels of particulates.

Finally, our results pertain to the engineering literature estimating the costs of reducing NOx and ozone. Our policy simulations imply that, as a result of a differentiated tax, power plant operations would be adjusted to reduce NOx emissions, thereby averting high-ozone events. The idea of dynamically managing the dispatch of electric generation units to avert harmful pollution events has been considered by EPA and explored in the power sector and engineering literature. Couzo et al. (2016) simulated the effects of the early shutdown of power plants on ozone concentrations

[3] Our paper also differs from Fowlie and N. Muller (2019) in that we evaluate the cost-effectiveness of policies that achieve a common environmental outcome, whereas they characterize optimal Pigouvian taxes. Our approach is motivated by the structure of the air quality standards and that, by statute, the standards are set without considering costs; consequently, the standards need not be set at the economically efficient level.

in seven geographic regions, focusing on two study days in which concentrations were relatively high. They confirm that reducing or eliminating NOx emissions from individual generation units can reduce ozone concentrations. Luo, Johnson, and Garcia-Menendez (2021) internalize spatially and temporally varying damages from NOx and SO_2 through the formation of fine particulates into a unit commitment model of the Texas electricity system. By incorporating these costs into the dispatch order of generation units, dispatch is adjusted to minimize total (generation and health) costs. Our paper complements this literature by using econometric estimates of the NOx–ozone relationship and abatement costs rather than computational models.

2 Background

This section provides an overview of ozone formation and regulatory history.

2.1 Overview of Ozone Formation, Health Effects, and Emissions Trading Programs

Tropospheric, or ground-level, ozone has been linked to mortality and morbidity (see, e.g., M. L. Bell et al. (2007), Ito, De Leon, and Lippmann (2005)) and harms plant life (see, e.g., Ashmore, J. Bell, and Treshow (2002), Davison and Barnes (1998)). NOx and VOCs are the primary ingredients that react with the air to form ozone. Although the process is highly complex, in broad terms, ozone formation occurs in two "regimes": NOx sensitive, in which an additional amount of NOx in the atmosphere is a likely contributor, and NOx limited, in which ozone formation depends less on the additional NOx emissions and more on the additional VOC emissions. Which regime a particular mass of air belongs to depends on the ratio of NOx to VOCs and other factors, including the composition of the particular species of VOCs present and meteorological conditions. Sunshine and high temperatures are the most important meteorological factors conducive to ozone formation; low wind speeds and low relative humidity are also associated with higher ozone concentrations (Sillman (1999), Blaszczak (1999)).

The Clean Air Act requires EPA to set air quality standards to protect public health and welfare. These National Ambient Air Quality Standards (NAAQS) for ozone have existed since 1971. Standards have been subject to periodic revision since, and current standards require that the three-year average of the year's fourth-highest eight-hour moving average concentration not exceed 70 ppb (Brown, Bowman, et al. (2013)).

That ozone pollution is increasingly harmful at higher levels of concentration underlies the form of the standards; 70 ppb is the concentration level that EPA has determined is necessary to protect human health and welfare. Periods of high ozone concentrations tend to be sporadic (hence averaging across years) and short lived, approximately 3.5 hours on average (hence averaging across hours).[4] The structure of the ozone standard motivates our focus on high-ozone events, because the more frequent they are, the more likely an area is to fail to attain the NAAQS.

[4] In our 19-year sample, the median and mean durations of concentrations greater than 70 ppb are 3 and 3.5 hours.

After setting the NAAQS, EPA requires states to submit plans and implement programs for meeting ("attaining") them. State plans typically include strict NOx emissions permitting requirements for businesses in the states. However, power plants emit NOx from smokestacks, and prevailing winds may cause pollution to contribute to ozone levels hundreds of miles away. Many states have had trouble achieving the ozone NAAQS because they are downwind from such emissions in other states. Accordingly, the "good neighbor provision" of the Clean Air Act also requires that states reduce emissions that contribute to nonattainment in other states.[5]

Besides overseeing state plans, the Clean Air Act requires EPA to develop backstop federal programs for achieving attainment if state programs are deemed insufficient. CSAPR caps NOx emissions from much of the eastern half of the United States, particularly in states where emissions contribute to ozone nonattainment in other states.[6] An important feature is that firms must retire allowances to cover their total annual or seasonal emissions. Allowances can be traded, which results in a uniform market price that does not depend on how much those emissions contribute to ozone formation. (EPA also administers SO_2 trading programs to address cross-state pollution; these emissions caps have not been binding in recent years, and they are not the focus of this paper.) EPA finalized the CSAPR NOx trading program and set state-level emissions budgets (i.e., caps) in 2011 and updated the budgets several times since. The most recent update tightened emissions caps for 12 of the 22 states subject to NOx budgets, including Maryland, Pennsylvania, New Jersey, and New York, which are areas of focus in this paper.[7]

2.2 Policy Framework

We are interested in whether a temporally and spatially differentiated price would be more cost effective at reducing high-ozone events than a uniform price, such as the one that results from the state NOx budgets under CSAPR. This focus is motivated by the choice EPA faces: to help states achieve the ozone NAAQS, it could continue tightening NOx caps, which would increase the uniform allowance price (all else equal) or implement a price that is allowed to vary in proportion to the contribution of NOx emissions to ozone formation.

Such a differentiated price could be implemented in several ways. One approach would be to introduce trading ratios, which would allow that one ton of NOx to be worth more or less than one allowance for compliance purposes depending on when and where it was emitted. For example, suppose that one ton of NOx emitted near Baltimore, Maryland is twice as likely to cause a high-

[5] Our analysis focuses on geographically local effects of NOx emissions on ozone formation and does not model the effects of drifting over long distances, despite the negative health effects of the latter, as recognized by EPA in designing regulations. A cost-effective policy for reducing high-ozone events may involve reducing NOx emissions that would be likely to form ozone many miles and hours away. Our results nevertheless demonstrate the importance of local NOx emissions in reducing events. More carefully measuring the nonlocal effects of NOx emissions, and policies for mitigating events that they cause, is an interesting avenue for future research.

[6] The program includes Texas, Oklahoma, Kansas, Nebraska, and all states to the east except Florida and the New England states.

[7] The 12 states for which the caps were tightened are Illinois, Indiana, Kentucky, Louisiana, Maryland, Michigan, New Jersey, New York, Ohio, Pennsylvania, Virginia, and West Virginia.

ozone event at 3 pm than 6 pm. A trading ratio could require that a firm submit two allowances per ton at 3 pm but only one at 6 pm. Alternatively, EPA could replace the emissions caps with an emissions price that varies in proportion to the marginal effect on events. We abstract from further implementation details and include a brief discussion of implementation in the conclusion.

According to economic theory, a spatially or temporally differentiated price would be more cost effective at achieving attainment under two conditions: (1) the contributions of NOx emissions to nonattainment vary over space or time; and (2) the regulator can accurately predict the variation. If the first condition does not hold, the differentiated price would offer no advantage.

Fowlie and N. Muller (2019) discuss the second condition in the context of a spatially differentiated price, and the same argument applies temporally. If temporal variation, such as diurnal patterns in the marginal effect of NOx emissions, can be predicted, the regulator can create clear rules for how the price would change. However, significant prediction error would undermine the advantage of the differentiated price. For example, suppose that based on modeling analysis performed at a particular time, EPA believes that emissions contribute more to nonattainment at 3 pm than 6 pm and sets trading ratios accordingly. The resulting price would cause more emissions abatement at 3 pm than would a uniform price (holding marginal abatement costs and electric generation fixed across hours). However, EPA would have had to make assumptions about atmospheric conditions and other factors to perform its modeling analysis. Suppose, for the sake of argument, that those assumptions prove inaccurate and 3 pm and 6 pm emissions actually have the same effect. The differentiated price would cause more abatement at 3 pm than is cost-effective.

A final consideration in comparing differentiated and uniform prices is that marginal abatement costs also vary by location, time of day, and generation technology. The generation mix depends on which technologies (e.g., coal, natural gas, or renewable energy resources) the system contains and how much demand needs to be met. If it is relatively inexpensive to shift generation to cleaner-burning generators, then these costs will be relatively low. This variation will affect the cost-effectiveness of a differentiated tax relative to a uniform one (Fowlie and N. Muller (2019)).

This discussion motivates the two empirical questions we address in this paper, which inform the policy analysis that follows. First, to what extent do the effects of NOx emissions on high-ozone events vary by geography and time of day, and how accurately can those effects be predicted? Second, how do marginal abatement costs vary by geography and time of day? After answering these questions, we can assess whether a temporally differentiated price is more cost effective than a uniform price at reducing high-ozone events.

3 Data

This section describes the data used for estimation and counterfactual policy analysis. We combine data from EPA and NOAA to construct the data set used in the econometric analysis. The EPA CEMS database records hourly generation, NOx emissions, and fuel consumption at the generation-unit level for every power plant larger than 25 MW (excluding industrial and commercial cogeneration plants).

The EPA AQS database records hourly ozone concentrations at approximately 1,300 monitoring stations across the United States. We use data from 67 AQS stations in nonattainment counties in the Northeast and mid-Atlantic. We use NOAA's ISD for hourly temperature data, mapping each AQS station to its closest NOAA station.[8]

We compile monthly NOx allowance trading prices using EPA's Power Sector Progress Reports for 2015–2019, which include data collected by SNL Financial/S&P Global Market Intelligence. These prices pertain to CSAPR (2015–2019) and include both annual and seasonal allowances.

Recent literature demonstrates that local regulators strategically place monitors to facilitate compliance with air quality standards (Grainger, Schreiber, and Chang (2018), Grainger and Schreiber (2019)). Nonetheless, readings from these monitors determine counties' attainment status. We therefore rely on data from these monitors, as we are interested in assessing costs associated with EPA-defined attainment, noting that placement may bias air quality estimates.

Our choice of geographic focus is based on several factors. First, we choose states in the Eastern Interconnection, as the generator operation model we use for our instrumental variables is specific to this area.

Second, we focus on counties that failed to achieve attainment—those that did not reduce ozone concentrations sufficiently to comply with the NAAQS. Reducing high-ozone events is of greatest interest in these areas and, according to EPA's assessments, would yield the greatest health and welfare benefits.

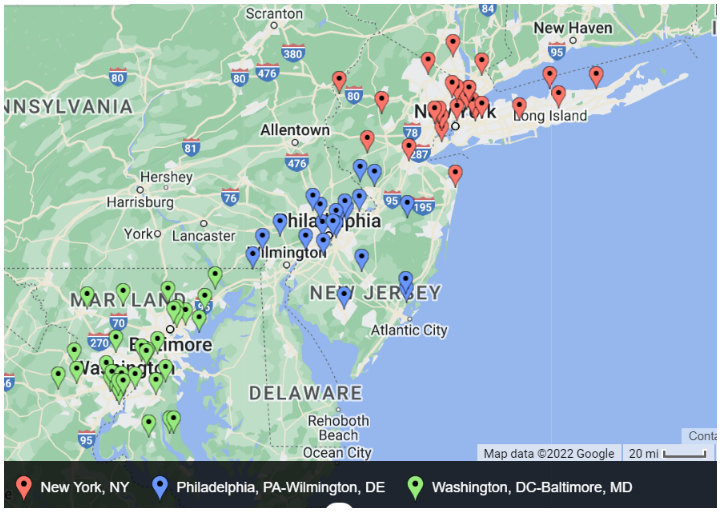
Third, we focus on the coastal mid-Atlantic and northeastern United States. Ozone pollution has been a persistent problem in this highly populated region due in part to heavy industrial activity and the eastward transport of NOx and VOCs from elsewhere.[9] Moreover, an analysis of ozone events in all nonattainment regions in the Eastern Interconnection revealed significantly greater sensitivity to NOx emissions in the northeast and mid-Atlantic, which suggests that the type of differentiated price we assess would perhaps be most effective there. Our analysis of other nonattainment regions, reported in Appendix 4, reveals a highly varied relationship between ozone concentration and local NOx emissions. This relationship across other regions, along with the effectiveness of a differentiated price, is an interesting avenue for future research.

Figure 1 shows the geographic subgroupings used in our main analysis and the location of each AQS station within a subregion. Stations are grouped geographically based on their proximity to major metropolitan locations: Washington, DC and Baltimore, Maryland; Philadelphia, Pennsylvania and Wilmington, Delaware; and New York City, New York.

[8]The average distance between an AQS station and a NOAA station is 15 miles; we exclude AQS stations that do not have a corresponding NOAA station within 25 miles.

[9]Cross-state pollution transport has been the basis for extensive litigation. For example, in February 2020, attorneys general from Connecticut, Delaware, Massachusetts, New Jersey and New York sued the US EPA for failure to address "harmful pollution blowing into our states," namely NOx and VOCs. See New Jersey vs. Wheeler, Complaint for Declaratory and Injunctive Relief, Civil Action No. 20-cv-1425, US District Court for the Southern District of New York, Filed Feb. 19, 2020.

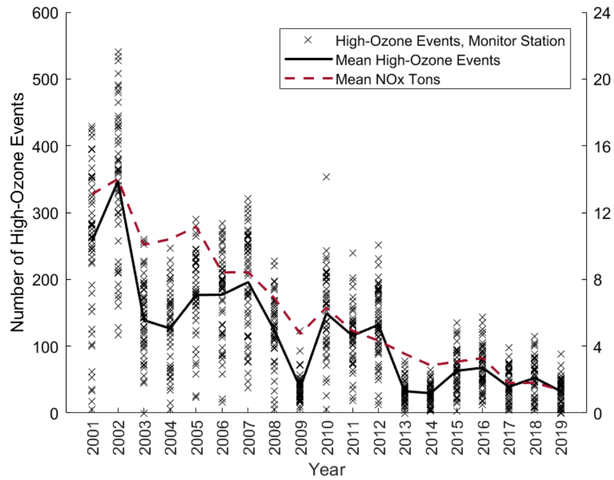
Figure 1: Geographic Groupings



Each marker represents an air monitoring station used in our analysis. We perform separate analyses for three color-coded subregions, which we define based on proximity to major metropolitan areas.

Figure 2 shows the mean number of high-ozone events (left axis) and emissions (right axis) between 2001 and 2019 across the monitors and power plants in the data. We limit our analysis to the "ozone season"—May–September—when 96 percent of all events in our sample occurred. The individual x's indicate the number of events at individual stations, revealing quite a few stations that experienced hundreds annually during the first decade. The figure also illustrates a precipitous decline in NOx emissions and events over time. However, since 2013, the number of events has remained relatively flat. Studying this region therefore allows insight into the cost of achieving additional reductions in events in an electricity system that is already characterized by relatively low NOx emissions intensity.

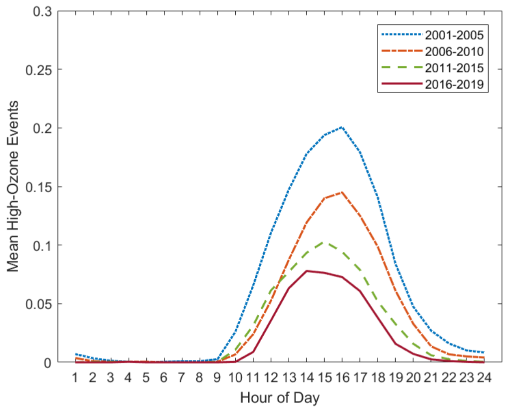
Figure 2: NOx Emissions and Occurrence of High-Ozone Events,
2001–2019



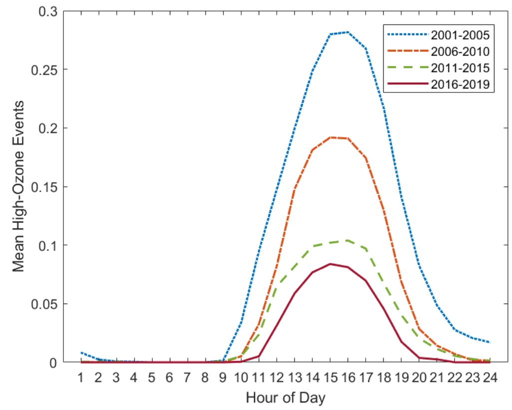
The left vertical axis shows the mean number of events across monitors (solid line) and the number at each monitor (x's). The right axis shows the average NOx emissions (tons) of plants within 100 miles of a monitor.

Figure 3 shows changes in the average frequency of high-ozone events by hour of the day for each subregion over time. The y-axis measures the mean number of events in each hour and subregion. The probability of an event exhibits a strong diurnal pattern that corresponds with sunlight and temperature. Events occur most frequently in the midafternoon and dwindle in the evening, with virtually none in the late night and early morning. Each line pertains to a different subperiod within the 19-year sample. Event occurrence roughly halved between the earlier (2001–2005, 2006–2010) and later (2011–2015, 2016–2019) subperiods. This decline continued in the southern subregions (Philadelphia-Wilmington and Washington-Baltimore). Notwithstanding the overall downward trends, even in the most recent period, events are frequent enough in all subregions to cause these areas to be in nonattainment.

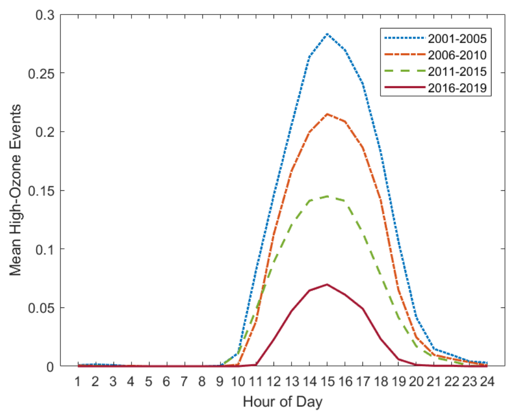
Figure 3: Mean High-Ozone Events by Hour of the Day and Subperiod



(a) NYC



(b) Phil.-Wilm.



(c) Wash.-Balt.

Each panel shows the mean number of high-ozone events by hour of day for the subregion indicated in the panel heading. Each line shows the mean across days in the indicated subperiod.

4 Estimating the Effects of NOx Emissions on Ozone Formation

The empirical analysis consists of estimating (1) the effect of NOx emissions on high-ozone events and (2) marginal abatement costs. This section discusses the estimation strategy and results pertaining to (1).

4.1 Estimation Strategy

Hypothetically, if a policy reduces NOx emissions or even the average ozone level without affecting the number of high-ozone events, it would not help an area achieve NAAQS attainment. For this reason, we aim to quantify the costs of policies that reduce the number of events. This motivates our use of an event as the dependent variable in the econometric analysis.[10]

Because we are interested in policies that affect power plant emissions, we estimate the effect of such emissions on high-ozone events. The estimating equation within each region is

$$y_{i,t} = \beta_0 + \sum_{h=1}^{24} \beta_h \mathrm{H}_h \mathrm{N}_{i,t} + \sum_{j=2}^{4} \alpha_j \mathrm{T}_{i,j} + \gamma_i + \theta_t + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t} \in \{0, 1\}$ is an indicator for whether ozone concentration exceeds 70 ppb in hour t at monitor i. The key independent variables are hour-of-day indicators (H_h) interacted with total NOx emissions from power plants within 100 miles of monitor i ($\mathrm{N}_{i,t}$). The equation includes fixed effects for quartiles of the temperature distribution ($\mathrm{T}_{i,j}$); γ_i is a station fixed effect; θ_t is a vector of fixed effects for year, month, day of the week, and hour of the day; and $\varepsilon_{i,t}$ is an error term.

The coefficients β_h are the marginal effect of emissions on a high-ozone event. We define $\mathrm{N}_{i,t}$ as the total emissions across generators within 100 miles of the monitor for simplicity. The radius is consistent with typical atmospheric conditions that cause more distant emissions to be unlikely to affect ozone levels at the monitor within the same hour. However, this definition includes two implicit assumptions. First, emissions from all plants within this radius affect ozone levels equally and within one hour. Second, emissions from power plants outside this radius do not affect ozone levels at the monitor. We have tried alternative specifications that relax these assumptions, such as by including separate variables for emissions within 25 or 50 miles or one- or two-hour lags of emissions from generators more than 100 miles away. We have also used results from the HYSPLIT model, which characterizes dispersion of air parcels in the atmosphere, to determine which generators' emissions may affect the hourly ozone reading in a particular hour. We find that these alternative methods do not improve prediction accuracy, and therefore we use Equation (1) for its relative simplicity.

In Equation (1), the coefficients on NOx emissions are identified by deviations of emissions from the corresponding hour relative to other days and after controlling for mean emissions at the monitor and during the same hour of the day, day of the week, month, and year. For example, if a generator emits more NOx on one day than it did at the same hour on the same day during the previous week, the higher emissions help identify the coefficient for that hour.

Equation (1) allows the NOx emissions coefficients to vary freely by hour. For example, the data determine whether we estimate a larger marginal effect for daytime versus nighttime. The temperature variables control for high-ozone events being more common when the temperature is high, conditional on emissions. The monitor fixed effects control for the average event probability, emissions, and temperature at the monitor. The temporal fixed effects in θ_t control for annual, monthly, day-of-week, and diurnal patterns of ozone levels, emissions, and temperature.

[10] We obtain similar results when defining the dependent variable as equal to 1 if the eight-hour moving average exceeds 70 ppb. As Appendix 3 shows, defining the dependent variable this way yields an hourly pattern that lags that of our main results but is otherwise similar. We choose to use an indicator variable based on contemporaneous ozone rather than the eight-hour average for our main analysis for ease of interpretation and because reducing hourly high-ozone events remains of interest from a public health perspective regardless of an eight-hour exceedance.

We make two remarks about Equation (1). First, this equation implicitly assumes that NOx emissions have a linear effect on the probability of a high-ozone event. As robustness checks, we have relaxed the linearity assumption by including higher-order polynomial terms in NOx emissions and adding interactions between emissions and meteorological variables, such as temperature. Such alternative specifications do not appear to reduce prediction errors appreciably.

Second, the equation does not include explicit controls for other sources of NOx emissions or VOCs or for emissions from beyond the 100-mile radius. The monitor fixed effects and θ_t control for the average levels of non-power-plant emissions for each year, month, day of the week, and hour of the day, such as diurnal patterns in vehicle emissions of NOx and VOCs. However, these variables likely do not control perfectly for other emissions sources. For example, suppose an industrial facility burns coal and consumes electricity. If it operates at an unusually high level on one day, its direct emissions of NOx will be higher than usual due to additional coal consumption. Moreover, its electricity consumption causes power plants to burn more fuel and emit more NOx than they would normally. If those power plants and the industrial facility are near the monitor, $\mathrm{N}_{i,t}$ in Equation (1) would be correlated with the omitted industrial NOx and VOC emissions, causing inconsistent estimates of the NOx coefficients.

An additional concern is emissions from upwind, nonlocal sources. Several states have filed lawsuits against EPA because these contribute to their noncompliance, attesting to the importance of NOx transport from outside of the 100-mile radius and one-hour window that we use to compute $\mathrm{N}_{i,t}$. Because of diurnal patterns in electricity demand and other factors, out-of-state emissions are also likely to be correlated with contemporaneous emissions from proximate sources.

To address the potential endogeneity of the NOx emissions variable, we instrument for $\mathrm{N}_{i,t}$. Following Johnsen, Lariviere, and Wolff (2019), the instrument is the emissions predicted from a computational model of generator operation. In a standard economic dispatch model, generators are dispatched to minimize the costs of meeting demand. We use the model from Linn and McCormack (2019), which extends the standard model by accounting for start-up and adjustment costs; they show that the model outperforms a standard model by a substantial margin.[11]

The exogenous variables in the generation model are fuel prices and the total hourly fossil fuel-fired generation for the interconnection. Fuel prices are the monthly delivered prices computed from EIA Form 923. The total generation is the average for the corresponding hour, 2005–2019. For example, for 3 pm on March 31, we compute the mean total fossil fuel-fired generation across the 15 observations of total such generation at 3 pm on March 31 for 2005–2019. Consequently, total generation in a particular hour reflects typical behavior rather than events specific to that year. This reduces the potential correlation between the instrument and omitted economic activity, such as the reduction in industrial activity during the 2008–2009 economic recession.

[11]In a standard dispatch model, each generator operates at full capacity if its marginal costs do not exceed the electricity price and does not operate if costs exceed the price. However, it is costly for thermal generators to start up after not operating for several hours or adjust their output quickly, so many generators operate at low levels even if their (static) marginal costs exceed the price. Linn and McCormack (2019) use a reduced-form strategy to approximate these costs and reproduce this behavior.

The instrument isolates variation in unit-level emissions driven by time-varying fuel prices and demand and cross-sectional variation in generator fuel type and efficiency. For example, natural gas prices were lower in 2009 than in 2008, which reduced costs of gas-fired generators compared to coal-fired generators. Therefore, the operational model predicts higher generation levels and emissions from some coal-fired power plants in 2008 than in 2009. Coal-fired generators typically have higher NOx emissions rates, so the model predicts lower NOx emissions in 2009 than 2008 because of the decrease in natural gas prices.

Moreover, the model predicts a larger emissions decline between 2008 and 2009 during hours when aggregate generation is low. When demand is high, the coal-fired generators operate even if they are more costly because they are needed to meet aggregate demand. Thus, the model yields variation in emissions across years and across hours within a year.

First-stage results (see Appendix 2) show that the emissions instrument is a strong predictor of observed emissions. The sources of variation of the inputs to the operational model help support the exclusion restriction that the instrument is uncorrelated with the error term in Equation (1). Returning to the example of the industrial facility, because we use typical hourly generation as an input, variation in electricity consumption across years is uncorrelated with the aggregate generation input in a particular hour. The underlying assumption is that variation in fuel prices across years yields emissions levels that are uncorrelated with within-year shocks to emissions from other sources. This assumption is the same as in Johnsen, Lariviere, and Wolff (2019); the main difference is that we are using a different operational model to predict each generator's emissions.

4.2 Estimation Sample Summary Statistics

Table 1 provides summary statistics for the full sample of data that include each ozone season (May–September) for 2001–2019 for 67 AQS stations. Each panel shows statistics for the subregion indicated in the panel heading.

Table 1: Ozone Regression Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
NYC					
Ozone Parts Per Billion	690,624	31.82	17.88	0.00	167.00
Ozone > 70 PPB	690,624	0.03	0.16	0.00	1.00
NOx Tons	690,624	4.83	4.95	0.25	55.23
Simulated NOx Tons	690,624	4.88	5.42	0.00	52.68
Temperature (degrees Fahrenheit)	690,624	70.35	9.59	30.02	107.96
Phil.-Wilm.					
Ozone Parts Per Billion	943,872	33.22	19.01	0.00	150.00
Ozone > 70 PPB	943,872	0.04	0.19	0.00	1.00
NOx Tons	943,872	7.20	5.82	0.34	57.06
Simulated NOx Tons	943,872	7.85	5.47	0.21	51.55
Temperature (degrees Fahrenheit)	943,872	72.49	9.74	32.00	105.08
Wash.-Balt.					
Ozone Parts Per Billion	1,097,106	32.94	19.60	0.00	158.00
Ozone > 70 PPB	1,097,106	0.04	0.19	0.00	1.00
NOx Tons	1,097,106	6.33	4.66	0.15	45.43
Simulated NOx Tons	1,097,106	7.55	3.99	0.33	39.04
Temperature (degrees Fahrenheit)	1,097,106	72.62	9.93	32.00	116.42

The table reports summary statistics of hourly observations for the subregion indicated. Ozone $>$ 70 ppb is an indicator equal to 1 if the hourly ozone concentration exceeds 70 ppb. NOx emissions are computed for power plants within 100 miles of the monitor. Simulated NOx tons is the emissions predicted by the simulation model (see text for details).

The average ozone concentration was about 32–33 ppb across subregions. The ozone level exceeded 70 ppb in approximately 4 percent of all hours in the sample. The bottom two rows of each panel show the variation of the simulated emissions and temperature, where the simulated emissions are the instrument for $\mathrm{N}_{i,t}$ in Equation (1). To identify the first stage, the simulated emissions have similar variance and range to the observed emissions.[12]

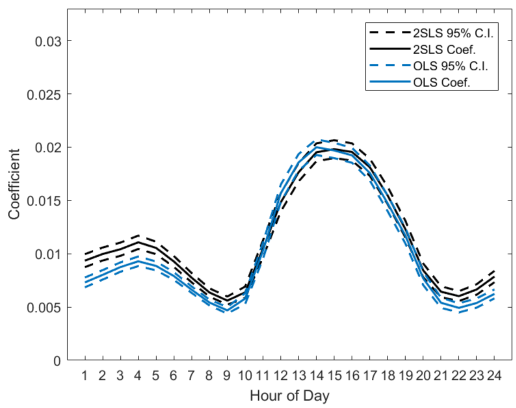
4.3 Estimation Results

Figure 4 reports hourly coefficients by subregion for ordinary least squares (OLS) and two-stage least squares (2SLS), along with 95-percent confidence intervals (standard errors are robust to heteroskedasticity). The figure illustrates a distinct diurnal pattern that matches the diurnal ozone levels in Figure 3. An additional ton of NOx emissions is statistically significantly more likely to

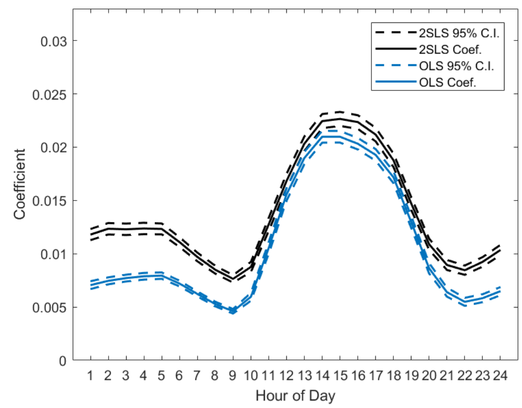
[12] The mean simulated emissions differ from the observed emissions by a few tons per hour. This difference is explained by our use of mean total fossil fuel-fired generation across 20052–2019 rather than the observed hourly generation each year. If we use the observed total generation instead, the operational model accurately predicts mean emissions, as reported in Linn and McCormack (2019).

contribute to a high-ozone event in the midafternoon than at other times of day. The pattern is intuitive because temperatures are typically highest and sunlight exposure greatest in midafternoon, both of which are conditions conducive to ozone formation. Overall, the temporal variation of the coefficients is greater than the spatial variation across subregions.

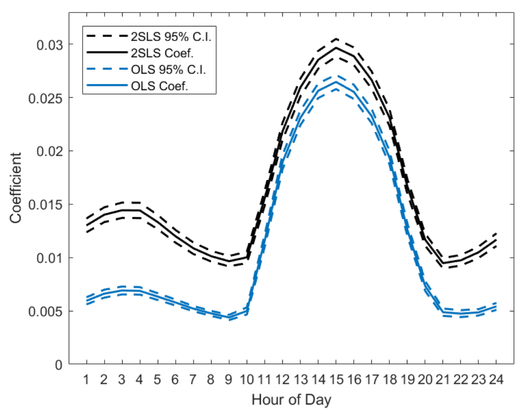
Figure 4: OLS and 2SLS Regression Results, 2001–2019



(a) NYC



(b) Phil.-Wilm.



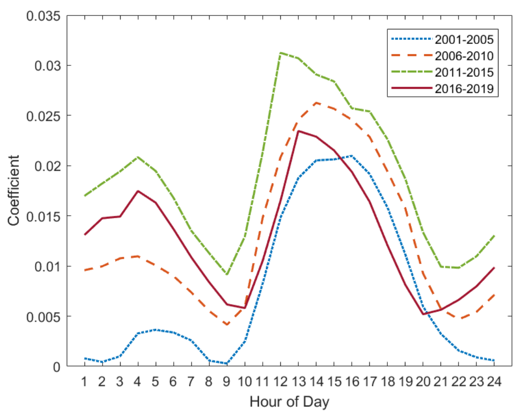
(c) Wash.-Balt.

For the subregion indicated, the figure plots the estimated coefficients on the interactions between hourly NOx emissions and a set of hour-of-day fixed effects (see Equation (1)). Dashed lines show the 95 percent confidence intervals; standard errors are robust to heteroskedasticity. The blue line reports results from estimating the equation by ordinary least squares, and the black line reports the results from instrumenting emissions with predicted emissions (see text).

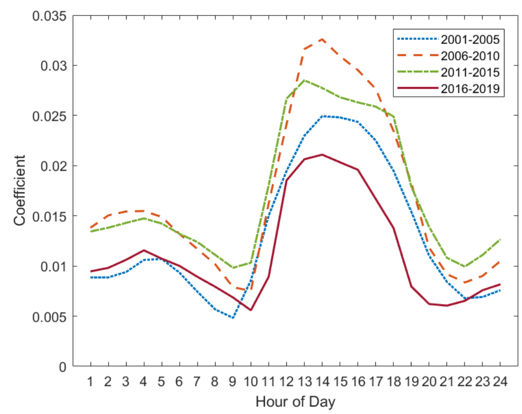
Disparity between the OLS and 2SLS coefficients would indicate that the OLS estimates could be biased by omitted variables. In principle, the bias could be negative or positive, depending on whether power plant NOx emissions are negatively or positively correlated with omitted variables. In the top two panels, the OLS estimates are larger than the 2SLS estimates, which indicates a positive correlation between emissions and omitted variables. In contrast, the bottom two panels indicate that the OLS estimates are downward biased.

Figure 5 demonstrates how the emissions coefficients change over time in each subregion. The precipitous decline in emissions from 2001 to 2019 in all subregions could cause the coefficients to become larger in magnitude if the lower NOx emissions overall increase the likelihood that ozone formation is NOx limited. However, the coefficients do not show a monotonic change. NOx sensitivity mostly increased in earlier periods (2001–2005, 2006–2010, and 2011–2015) but decreased in the most recent (2016–2019). For clarity, the figure does not include percent confidence intervals; the changes in midday coefficients are often statistically significant at the 1 percent level. The results underscore the importance of recognizing that atmospheric conditions depend on a multitude of factors that can change over time and vary widely across regions.

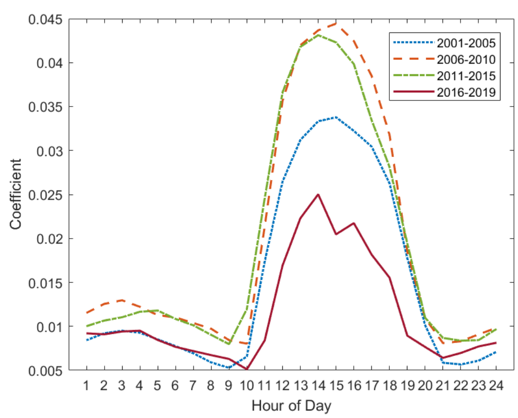
Figure 5: 2SLS Regression Results, Year-Groupings



(a) NYC



(b) Phil.-Wilm.



(c) Wash.-Balt.

The figure shows hourly coefficients for each subregion. Each line plots coefficients estimated using data from the years in the legend. All coefficients are estimated by instrumenting for NOx emissions analogously to Figure 4.

The variation of the marginal effects of emissions on high-ozone events implies that a differentiated price may be more cost effective than a uniform price at reducing events. The differentiated price should be higher during mid- and late afternoon than at other times of day.

However, as we discussed in Section 2, the advantage of a differentiated price depends on the accuracy with which one can predict temporal variation in the effect of emissions on high-ozone events. One way to assess this accuracy is to suppose that EPA predicts the temporal variation in year t using data before year t. That the coefficients vary across periods implies that if EPA uses data from one period to predict the effect of emissions in the next, the prediction is likely to be inaccurate. If this inaccuracy is sufficiently great, a differentiated price may be less cost effective than a uniform price.

5 Estimating Marginal Abatement Costs

The policies we consider in the counterfactual simulations impose emissions prices on all regulated generators. To compare the costs across counterfactual policy scenarios, we need estimates of marginal abatement costs, allowing for the possibility that these costs vary by hour of the day or subregion. This section discusses the estimation strategy and results pertaining to our estimation of short-run marginal abatement costs.

5.1 Estimation Strategy

For a generation unit facing an emissions price, we define its marginal abatement costs as the cost of reducing emissions by one ton of NOx relative to a baseline in which the price equals zero. We expect these costs to increase weakly with the level of abatement, measured in NOx tons reduced.

In the short run, firms can reduce emissions without installing capital equipment by decreasing generator output or emissions rates. For units with post-combustion controls, such as selective catalytic reduction, firms can control emissions rates by deciding whether and how to operate these controls. For other units, firms can adjust operation to reduce combustion temperatures. Linn (2008) shows that firms adjust emissions rates by up to 10 percent in response to monthly variation in allowance prices. In the long run, firms can reduce emissions by installing capital equipment that allows them to decrease emissions rates or investing in generators that use lower-emissions fuels, such as replacing coal-fired with gas-fired units or wind- or solar-powered generators.

Given these short- and long-run responses to the permit price, each firm has a short- and long-run marginal abatement cost curve, which represents the marginal costs of reducing emissions below the baseline. The short-run costs include decreased profits from producing less electricity, increased fuel costs from operating less efficiently, or increased operating costs of the emissions controls. Long-run costs include the capital costs of abatement equipment or power plant construction.

Assuming the allowance market is perfectly competitive, each unit reduces emissions until its marginal abatement costs equal the allowance price. Consequently, the aggregate marginal abatement cost curve for a region is the horizontal sum of the curves for each firm in that region.

We assume the aggregate marginal abatement cost curve is linear in abatement. The appendix shows that under this assumption, the slope of the curve is inversely proportional to the derivative of the average emissions rate with respect to the allowance price. This relationship motivates the estimating equation in which we regress the emissions rate on permit price:

$$\mathrm{E}_{i,t} = \delta_0 + \sum_{h=1}^{24} \delta_h \mathrm{H}_h p_t + \eta_i + \Xi_t + \nu_{i,t} \tag{2}$$

where $\mathrm{E}_{i,t}$ is the average hourly NOx emissions per MWh generated across regulated generators within 100 miles of station i in period t; H_h is an indicator for hour of the day; p_t is the monthly NOx allowance permit price; η_i is a station-specific fixed effect; Ξ_t is a vector of fixed effects for year, month, day of the week, and hour of the day; and $\nu_{i,t}$ is an error term. The dependent variable includes only emissions and generation of power plants in states subject to a NOx budget under CSAPR. For example, because Connecticut was excluded, a plant operator there would not adjust operations in response to a CSAPR NOx allowance price. We therefore exclude Connecticut plants from the dependent variable, even though these plants may be within the 100-mile radius of New York City. We perform a separate regression for each subregion.

By design, three features of Equation (2) are parallel to Equation (1). First, the two equations have the same unit of observation, which is an hour by monitor, and the sample includes only observations from May through September. Second, the dependent variable, $\mathrm{E}_{i,t}$, is the average emissions rate across a subset—the NAAQS-regulated portion—of the units that are used to compute NOx emissions $\mathrm{N}_{i,t}$ in Equation (1). Consequently, emissions from a common subset of the generators used to identify the effect on ozone levels (the regulated subset) are used to identify marginal abatement costs. Third, the two equations include the same set of time fixed effects to control for seasonal and diurnal patterns of generator use and emissions.[13]

The key coefficients of interest are the interactions of the hour fixed effects with the allowance price. We use monthly rather than daily permit prices because of data availability. We expect the coefficients to be negative because a higher permit price incentivizes abatement that reduces the average emissions rate. Because of the year fixed effects, the coefficients are identified by within-year permit price variation. Changes in generator use, boiler operation, and emissions controls can affect the dependent variable; all of these behaviors help identify the coefficients. Because of the year fixed effects, we interpret the coefficients as representing short-run marginal abatement cost (that is, abatement without the adoption of pollution abatement equipment). This interpretation is consistent with the construction of the counterfactuals, as we explain in the next section.

5.2 Estimation Sample Summary Statistics

Table 2 shows summary statistics for the dependent variable in Equation (2), which is the hourly average emissions rate across regulated generator units within 100 miles of the monitor. Emissions rates are greater in the southern subregions of the sample, which reflects a generation mix that is composed of more NOx-intensive (e.g. coal-burning) technologies. We limit our regression sample

[13]According to Equation (2), the emissions rate is endogenous to the allowance price. Because Equation (1) does not include the allowance price, this endogeneity is an additional argument for instrumenting for emissions. By construction, the instrument we use is uncorrelated with the allowance price.

to 2015–2019 (years following the implementation of CSAPR). These years overlap with the final subperiod used to estimate the effects of NOx emissions on ozone events.

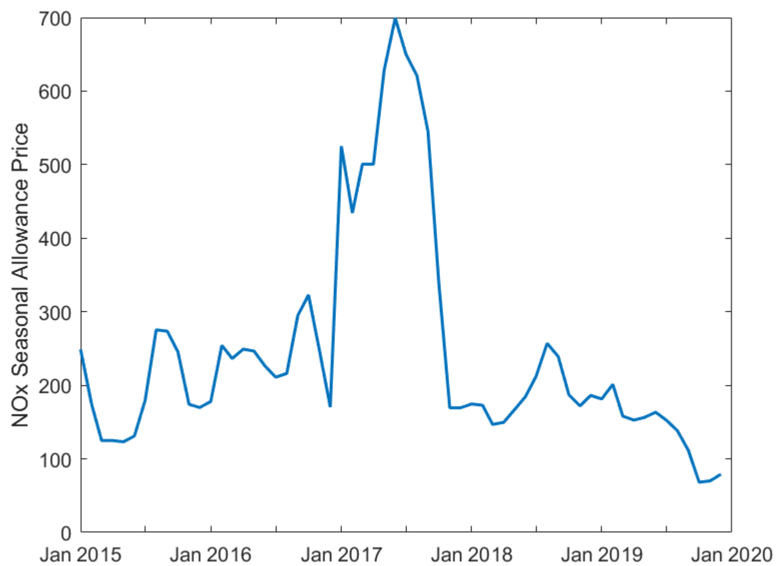
Table 2: NOx Emissions Rates (lbs. per MWh) by Subregion

Sub-Region	Obs	Mean	Std. dev.	Min	Max
NYC	331,899	0.28	0.12	0.09	1.48
Phil.-Wilm.	265,420	0.36	0.17	0.10	1.37
Wash.-Balt.	308,117	0.53	0.26	0.09	1.87

Observations are by hour and monitor.

Figure 6 shows the monthly price of an allowance of one ton of NOx emissions from January 2016 to December 2019. These permits were traded in compliance with EPA's CSAPR program, and EPA allows a limited amount of allowance banking. EPA allocates permits each year, and each permit is assigned a vintage. We use the contemporaneous vintage in the figure: prices for each calendar year reflect that year's vintage. Although this is not shown in the figure, when multiple vintages are traded at the same time, the prices for the allowances are highly correlated with one another, although earlier vintages often sell at a discount because of banking constraints.

Figure 6: Seasonal NOx Allowance Price, January 2015–December 2019

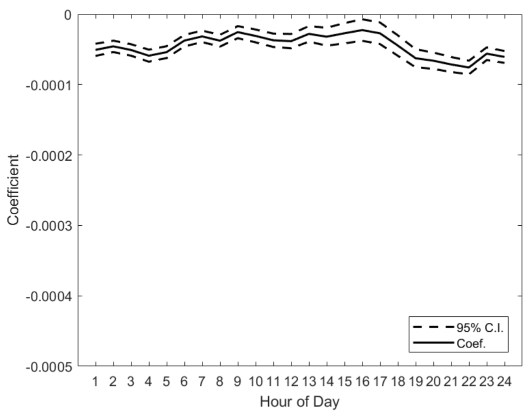


The price of a seasonal NOx allowance under CSAPR varies depending on expected demand, generation mix, and EPA's NOx allowance budgets. CSAPR budgets were tightened in 2017, leading to higher allowance prices.

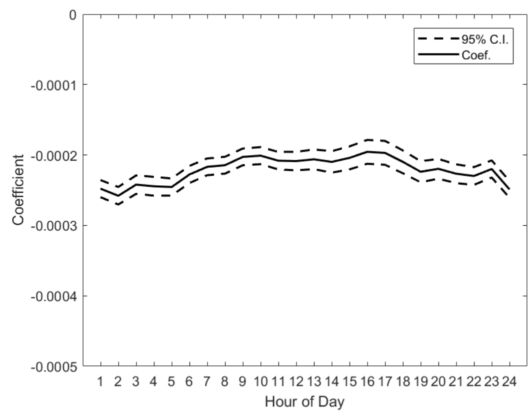
5.3 Estimation Results

Figure 7 illustrates coefficient estimates by hour of the day (δ_h from Equation (2)) for the three subregions subject to CSAPR. The coefficients are identified by within-year deviations from hour-of-day and monthly averages of permit prices and emissions rates. We interpret the coefficients as the negative reciprocal of the slope of the short-run marginal abatement cost curves, and we estimate separate coefficients for each subregion.

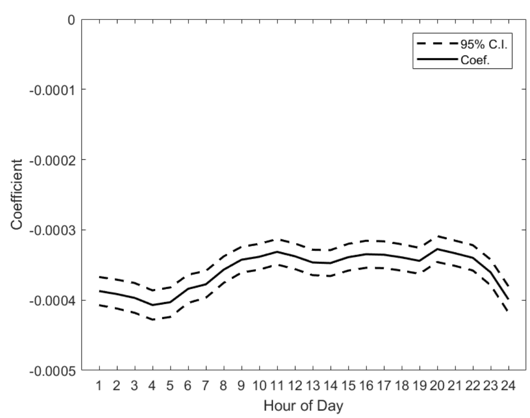
Figure 7: Marginal Abatement Cost Estimation Results



(a) NYC



(b) Phil.-Wilm.



(c) Wash.-Balt.

Each panel reports the coefficient estimates (solid lines) and 95 percent confidence intervals (dashed lines) from estimating Equation (2) for the indicated subregion. Standard errors are robust to heteroskedasticity.

For all three subregions, the interaction coefficients are nearly always statistically significant at the 1 percent level, and they are negative, as expected. Because the permit price is measured in dollars per ton of emissions and the dependent variable is measured in pounds of NOx per MWh of generation, a coefficient of -0.0002 (which is a typical estimate for the Philadelphia-Wilmington subregion) implies that a decrease of the allowance price of $100 per ton reduces the emissions rate by 0.02 pounds of NOx per MWh, which is about 6 percent of the subregion's mean emissions rate.

We interpret the negative of the reciprocal of the price–hour coefficients as the slope of the marginal abatement cost curves. The magnitudes of the coefficients decrease moving from north to south across the subregions. In other words, the curves are less steep in the southern subregions. This result may reflect greater flexibility in short-term operational changes or redispatch away from NOx-intensive generation in the southern subregions. In contrast, generators in the New York City subregion are already relatively low emitting, and reducing NOx emissions further is more costly.

Despite a weaker diurnal pattern than in Figure 4, in all three subregions, the marginal abatement cost curve appears to be less steep in the early evening than during other hours. This translates to greater abatement costs in the midafternoon, perhaps due to decrease operational flexibility (and therefore more limited means for reducing NOx emissions) as a result of greater electricity demand.

6 Policy Simulations

Having estimated the NOx–ozone relationship and marginal abatement costs, we perform counterfactual policy simulations in which we evaluate the cost-effectiveness of a differentiated NOx emissions price relative to a uniform price.

6.1 Description of Counterfactual Policy Scenarios

We simulate hypothetical policy scenarios to evaluate whether temporally or spatially differentiated emissions prices would be more cost effective than uniform prices at reducing high-ozone events between 2016 and 2019. This corresponds to the most recent period used for estimating parameters in Equation (1) and also (roughly) to the period used to estimate Equation (2).

Across the scenarios, we hold constant the average change in the probability of high-ozone events, which effectively fixes attainment status with respect to the ozone NAAQS.[14] Doing so allows us to compare the costs of policies that achieve the same reduction in events. This approach is useful for analyzing costs of achieving attainment regardless of whether attainment goals are socially optimal.

The differentiated emissions price varies by hour of the day and subregion in proportion to the marginal effect of emissions on the probability of a high-ozone event, which is estimated in Equation (1). Because the regulator must commit to the differentiated price at the beginning of the year, we construct two types of prices. The first we refer to as the *ex ante* price; it is proportional to the marginal effects estimated from the preceding (*ex ante*) period (2011–2015).

For comparison with the *ex ante* price, we define an *ex post* differentiated price that assumes perfect foresight with respect to the NOx–ozone relationship. The relationship varies according to

[14] This is not the same as holding fixed environmental damages, because two policies could cause the same probability of a high-ozone event and yet different ozone distributions. We construct the scenarios to achieve the same probability of an event because the aim of CSAPR is to facilitate attainment rather than maximize social welfare.

NOx emissions coefficients in Equation (1) estimated using *ex post* data (spanning the 2016–2019 ozone seasons). Because the relationship changes from one period to the next (see Figure 5), the *ex post* parameters produce prices that are more accurately targeted to reduce high-ozone events.[15]

Formally, the *ex ante* emissions price is defined as

$$\tau_{i,t}^{ea} \equiv \lambda_i^{ea} \beta_{i,t}^{ea} \tag{3}$$

and the *ex post* emissions price is defined as

$$\tau_{i,t}^{ep} \equiv \lambda_i^{ep} \beta_{i,t}^{ep} \tag{4}$$

where *ex ante* parameters β_i^{ea} are estimated using Equation (1) and 2011–2015 data, *ex post* parameters β_i^{ep} are estimated using Equation (1) and 2016–2019 data, and λ_i^{ea} and λ_i^{ep} are scale parameters.[16]

The third policy is a uniform emissions price, $\bar{\tau}$. To calibrate the differentiated prices, we solve for scale parameters λ_i^{ea} and λ_i^{ep} that equate reductions in expected high-ozone events in each region i:

$$\sum_t (\lambda_i^{ea} \beta_{i,t}^{ea})[\delta_{i,t} q_{i,t} \beta_{i,t}^{ep}] = \sum_t (\lambda_i^{ep} \beta_{i,t}^{ep})[\delta_{i,t} q_{i,t} \beta_{i,t}^{ep}] = \sum_t \bar{\tau}[\delta_{i,t} q_{i,t} \beta_{i,t}^{ep}] \tag{5}$$

where $q_{i,t}$ is MWh generation in region i and period t, and $\delta_{i,t} q_{i,t}$ is the change in NOx emissions resulting from a \$1 increase in the NOx price in period t. The terms inside the square brackets are the reduction in the probability of an event caused by increasing the NOx emissions price by \$1. Because we assume linear marginal abatement cost curves and a linear relationship between NOx emissions and events, the amount by which the probability of an event is reduced in period t scales linearly with the price. To mitigate potential concerns about out-of-sample extrapolation, we set $\bar{\tau} = \$100$, which is near the lower end of the prices observed (see Figure 6). Regression output from the estimation of β_i^{ea} and β_i^{ep} is presented in Appendix 2.

Next, we explain how we compute total abatement costs of each policy. The appendix shows that the slope of the marginal abatement cost curve is inversely proportional to the allowance price coefficient from Equation (2). Removing subscripts for notational convenience, total abatement cost is the integral from 0 to a of marginal abatement costs:

$$\begin{aligned} TC &= \int_{x=0}^{a} -\frac{x}{\delta q} dx \\ &= -\frac{a^2}{2\delta q} \end{aligned} \tag{6}$$

[15] Pooling observations across several years masks year-to-year variation in NOx sensitivity. To obtain more accurate estimates to inform a policy, the policymaker may wish to allow coefficients to vary by year or an even shorter time horizon or use detailed weather forecasts and air transport modeling.

[16] t indexes each hour in our sample. For ease of exposition, we use the t subscript. Note that coefficients vary only by hour-of-day h.

Total costs are proportional to the square of abatement and inversely proportional to generation and the (absolute value of the) estimated allowance price coefficient in Equation (2).

We can express total costs as a function of the allowance price rather than abatement by exploiting that firms abate emissions until marginal costs equal the allowance price. The amount of abatement achieved from price τ equals

$$a(\tau) = -\tau\delta q \tag{7}$$

Plugging Equation (7) into Equation (6) gives the total abatement costs associated with price τ:

$$TC = -\frac{1}{2}\tau^2\delta q \tag{8}$$

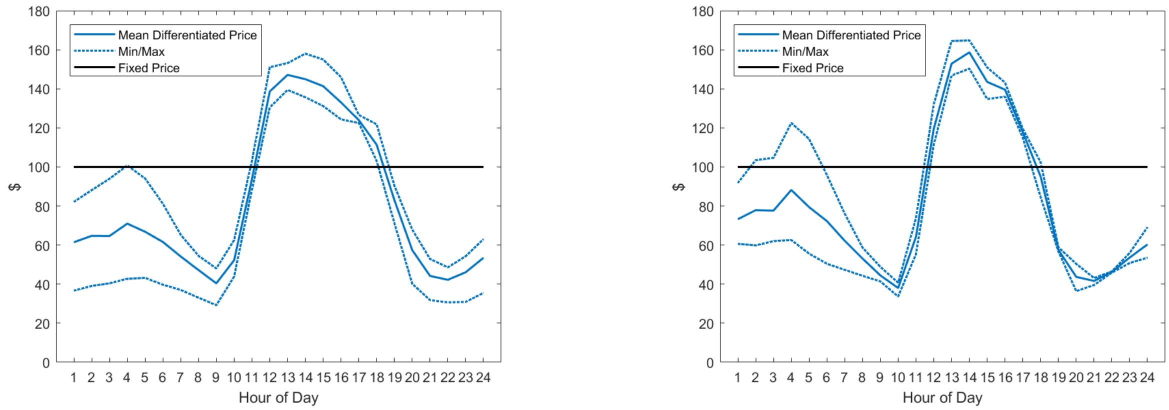
This equation allows us to compute total costs for each hour and site given the assumed allowance price, estimated δ, and generation level. Expected reductions in high-ozone events for each hour and site associated with policy τ equal $-\tau\delta q$. Cost-effectiveness is defined as total costs (summed across hours and sites) divided by the expected event reductions (summed across hours and sites).

6.2 Results

To avoid double-counting abatement costs, for each of the three subregions subject to CSAPR seasonal prices, we consider uniform or differentiated prices for the monitor in the subregion with the highest frequency of high-ozone events and exclude all other monitors. Because a generation unit may lie within 100 miles of multiple monitors, focusing on a single monitor in each subregion avoids double-counting abatement costs of the generators within 100 miles of multiple monitors.

Figure 8 compares the hour-of-day differentiated emissions prices with the uniform price of \$100. The solid line shows the mean differentiated prices by hour of the day and subregion, and the dashed lines show the minimum and maximum prices across days in the four-year analysis period. Panels (a) and (b) show the *ex ante* and *ex post* prices, respectively. In both cases, the differentiated prices are higher in the midday hours, which reflects that midday NOx emissions have larger effects on high-ozone events. On average, the differentiated prices are lower than the uniform price.

Figure 8: Mean Differentiated Price by Hour of the Day



(a) *Ex Ante* Emissions Price

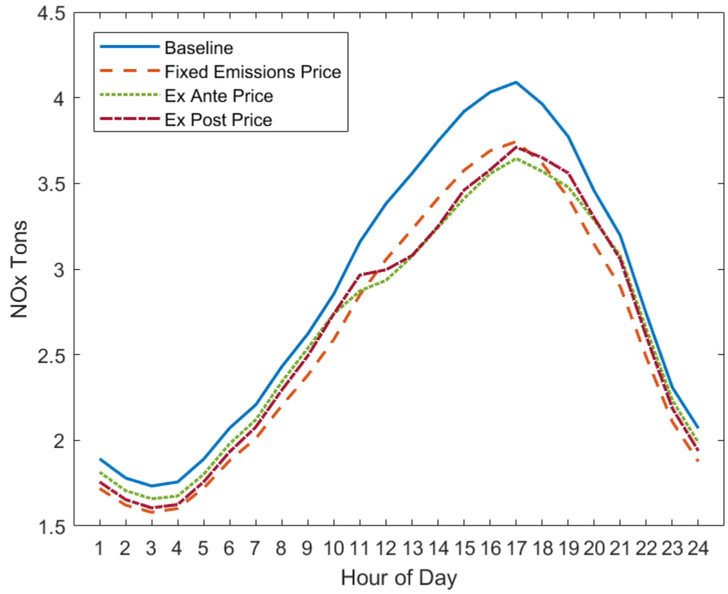
(b) *Ex Post* Emissions Price

The solid black line is the uniform emissions price of $100 per ton; the solid blue lines are the differentiated prices. Panel (a) reports differentiated prices using parameter estimates for 2011–2015 (*ex ante*), and panel (b) reports prices using estimates for 2016–2019 (*ex post*). Min/Max are the minimum and maximum prices across days.

The *ex ante* price in panel (a) reflects priors about ozone formation that are outdated; as shown in panel (b), updating those priors leads to an *ex post* price that is substantially different from the *ex ante* price. The differences between the differentiated prices in the two panels indicates that, in principle, the *ex ante* price could be less cost effective than the uniform price.

Figure 9 compares average hourly NOx emissions in the baseline (zero emissions price) with those under the uniform and differentiated prices. The uniform price causes a relatively uniform reduction in NOx emissions across all hours of the day. This is consistent with the slopes of the marginal abatement cost curves varying relatively little over the day and the uniform price not varying across hours (by assumption).

Figure 9: Average Hourly NOx Emissions Under Uniform vs.
Differentiated NOx Price

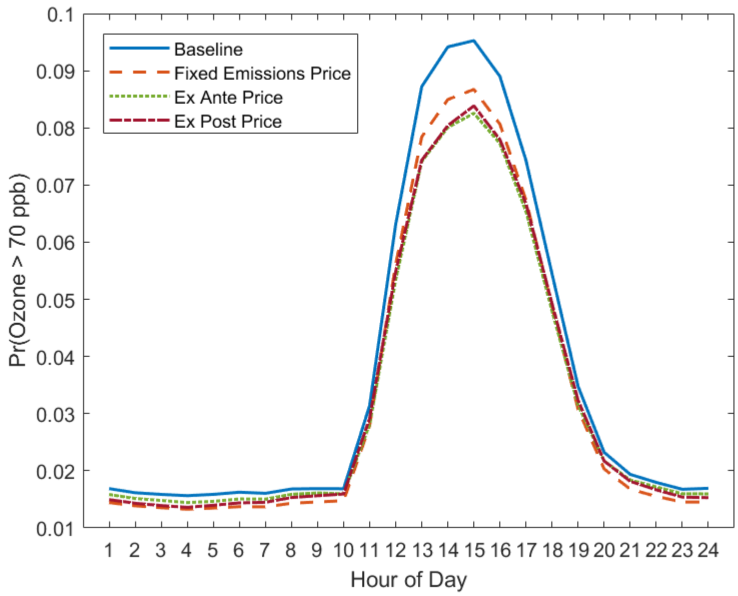


The blue curve is the average hourly emissions in the baseline scenario, which reflects an allowance price of $0. The dashed orange curve is the average hourly emissions under the uniform price scenario, and the two dotted curves are the average hourly emissions under the *ex ante* and *ex post* price scenarios.

By design, the differentiated prices reduce emissions more during the middle of the day, when NOx is most likely to contribute to high-ozone events. The changes in emissions under the *ex ante* and *ex post* prices are almost identical, although the prices differ (see Figure 8).

Figure 10 compares the resulting average decline in the probability of a high-ozone event across scenarios. The uniform price reduces the probability during all hours and by more during the middle of the day. The differentiated prices cause greater reductions in events during the middle of the day, when they are most common, than the uniform price. Analogously to Figure 9, the *ex ante* and *ex post* prices cause nearly identical changes in the probability of an event.

Figure 10: Average Probability of High-Ozone Event, Uniform vs. Differentiated NOx Price



The figure shows the average probability of high-ozone events for the baseline and three policy scenarios. Probalities are computed using the allowance prices in Figure 8 and the estimated marginal effects of emissions on ozone levels from Equation (1).

During midday hours, the differentiated prices cause larger reductions in high-ozone event probabilities than the uniform price. The situation is reversed in other hours. These results imply that overall, the differentiated prices cause less aggregate abatement because they yield greater emissions reductions when those reductions are most effective at reducing events.

Table 3 compares abatement costs across the uniform and differentiated prices. Policies are calibrated to achieve the same reduction in the expected number of high-ozone events per season. Panel (a) shows, as expected, that the differentiated prices cause less NOx abatement even though they achieve the same probability of events. By construction, costs per ton of NOx emissions reduced are equivalent under the uniform versus *ex post* price, as shown in panel (b). The *ex ante* price exhibits slightly greater costs per ton of NOx abatement due to inaccuracy of the *ex ante* parameter estimates. Nevertheless, both the *ex ante* and *ex post* prices are more cost effective than the uniform price, with the differentiated prices reducing costs by 15–21 percent.

Table 3: Cost-Effectiveness Summary

(a)

Region	Δ NOx Tons			Δ High-Ozone Events		
	Uniform	Diff. - *Ex Ante*	Diff. - *Ex Post*	Uniform	Diff. - *Ex Ante*	Diff. - *Ex Post*
NYC	123.0	106.2	100.5	1.4	1.4	1.4
Phil.-Wilm.	614.4	528.0	509.3	7.1	7.1	7.1
Wash.-Balt.	657.6	499.5	519.0	7.9	7.9	7.9

(b)

Region	Cost per NOx Ton Reduced			Cost per Expected High-Ozone Event Avoided			Pct. Savings from Differentiated Tax	
	Uniform	Diff. - *Ex Ante*	Diff. - *Ex Post*	Uniform	Diff. - *Ex Ante*	Diff. - *Ex Post*	*Ex Ante*	*Ex Post*
NYC	$50	$49	$50	$4,291	$3,667	$3,506	15%	18%
				[4276, 4306.2]	[3654.5, 3679.2]	[3493.9, 3517.2]	[0.144, 0.147]	[0.182, 0.184]
Phil.-Wilm.	$50	$49	$50	$4,298	$3,641	$3,563	15%	17%
				[4289.5, 4307.2]	[3632.8, 3649.2]	[3554.7, 3570.7]	[0.152, 0.153]	[0.17, 0.172]
Wash.-Balt.	$50	$54	$50	$4,172	$3,394	$3,293	19%	21%
				[4162.9, 4182.6]	[3385.3, 3405.1]	[3284.4, 3302.8]	[0.186, 0.187]	[0.21, 0.211]

Changes in NOx tons, changes in high-ozone events, and costs are expressed as averages per ozone season, 2016–2019. The differentiated prices are designed to reduce NOx emissions in proportion to their propensity to contribute to events. Fewer reductions are therefore required to achieve the same outcome as a uniform price (panel (a)), leading to lower overall costs (panel (b)). Bootstrapped standard errors using 1,000 draws of NOx–ozone coefficients from Equation (1) are shown in brackets.

These results differ from Fowlie and N. Muller (2019) in that the estimated emissions–ozone relationship is sufficiently accurate that the differentiated price yields cost savings. The difference is likely because we consider temporally varying prices and estimate large temporal variation in the marginal effect of NOx emissions on high-ozone events. This variation outweighs the prediction error from using *ex ante* estimates, causing the differentiated price to be more cost effective than the uniform price. However, similar to their analysis, our findings underscore the importance of accurately estimating this relationship for each subregion.

7 Conclusion and Policy Discussion

High-ozone events occur when ground-level ozone concentrations exceed the threshold EPA uses to assess attainment with Clean Air Act air quality standards. Although emissions of ozone precursors, particularly NOx, have fallen over the past few decades, these events persist in much of the United States, including in the Northeast and mid-Atlantic.

We evaluate whether temporally or spatially differentiated prices can cost-effectively reduce high-ozone events. To compare these policies with continuing the status quo of a uniform price that does not vary by hour or region, we estimate (1) the statistical relationship between NOx emissions from power generation plants and local ozone formation and (2) short-run marginal abatement costs for these generators. Unique to the literature, we estimate these relationships by geographic subregion and hour of the day to enable comparison of these policies. We then used our estimates from (1) and (2) to perform policy simulations that compare the difference in cost of achieving a fixed reduction in ozone events using a uniform price (one that does not vary by hour or region) and a differentiated price (one that does so vary).

We find rich variation over time and space in the marginal contribution of NOx to high-ozone events. NOx sensitivity exhibits strong diurnal patterns, with most ozone formation occurring midday due to atmospheric conditions (ample sunlight and high temperatures). NOx sensitivity also varies year to year, with no clear upward or downward trend over our 19-year sample, despite a steady decline in overall NOx emissions during that period. Regionally, effects are also varied, with, for example, greater NOx sensitivity in the New York City subregion as compared with the other subregions in later years of the sample.

We also estimate short-run marginal abatement costs by hour of the day and region; these negatively correlate with emissions rates of a subregion's generation mix. That is, regions with a lower NOx-intensity in generation units show a greater marginal cost of reducing NOx emissions. This result is likely due to the lower-emissions regions having less flexibility in shifting generation away from NOx-intensive units to cleaner-burning units.

The differentiated price reduces costs by 15–21 percent compared to a uniform price. The cost savings are robust to predicting the NOx–ozone relationship using historical data before implementing the differentiated price.

The cost savings from a differentiated price depend on the accuracy of the policymaker's prediction of the effect of emissions on high-ozone events. Future research may explore the extent to which additional information can improve predictions. For example, detailed weather forecasts, explicitly modeling air parcel movements over short time horizons (say, 48 hours), and incorporating variables such as real-time ambient NOx and VOC concentrations or meteorological conditions could improve accuracy of the key parameter estimates. One challenge lies in addressing ozone formation from upwind NOx emissions, which can remain in the atmosphere for hours or days, thereby producing ozone far from its source. Our modeling suggests a significant and immediate sensitivity for NOx emitted in close proximity to monitors. We show that significant reductions in ozone can be achieved when only contemporaneous NOx emissions are regulated. Additional modeling of air parcel transport would be necessary to determine both the extent to which NOx from nonlocal sources contributes to local ozone formation and the accuracy with which these emissions can be traced back to their sources. If the contribution of nonlocal NOx is low and the uncertainty with respect to its contribution great, a focus on contemporaneous and proximate NOx may be preferable. However, if NOx contributions from outside sources can be measured with sufficient certainty, the price can reflect their contribution to nonlocal ozone formation.

We end with a brief discussion of policy implementation. EPA administers annual and seasonal emissions caps in which firms must submit allowances equal to emissions; each allowance covers one ton of emissions regardless of when or where the emissions occur.

At the beginning of each year, EPA could announce trading ratios such that one ton of emissions may count for more than one allowance, depending on whether the emissions are more likely to cause high-ozone events. The likelihood could be estimated using a methodology similar to the one in this paper—for example, using ratios that are specific to hour of the day and geographic region.

An alternative to trading ratios would be to replace the annual and seasonal emissions caps with spatially and temporally varying emissions prices, although this may require a more extensive regulatory process, given that a quantity-based mechanism is already in place.

To address uncertainty in the NOx–ozone relationship arising from shifting atmospheric conditions throughout the year, EPA could announce trading ratios or set emissions prices multiple times during the ozone season based on updated information. However, it would be important for EPA to provide firms sufficient time to respond to these announced changes.

Power generators in deregulated electricity markets (such as the NYISO and PJM systems, which cover our sample) submit supply offer curves reflecting their willingness to produce electricity at a schedule of prices for each hour of the day. If plant operators are aware of dynamic prices or trading ratios that change by hour, they can adjust their offer curves accordingly. In this manner, a differentiated price or trading ratio scheme can be incorporated into existing systems to facilitate economically efficient dispatch of generation resources.

Appendix 1 Derivation of Relationship Between Marginal Abatement Costs and Derivative of Emissions Rate With Respect to Allowance Price

In this section, we show that if we assume that aggregate marginal abatement costs are linear in abatement, their slope is inversely related to the derivative of the average emissions rate with respect to allowance price. Suppressing hour and site subscripts for convenience, let $\bar{e}$ be the baseline emissions rate (when the allowance price equals \$0). Let e be the emissions rate for a positive emissions price and q be the exogenous quantity of electricity generated. Recall that abatement is the change in emissions relative to emissions if the allowance price equals \$0:

$$a \equiv -q(e - \bar{e}) \tag{9}$$

Multiplying Equation (2) by q implies $eq = \delta_0 q + \delta_1 qp$, where δ_0 includes the fixed effects and δ_1 is the coefficient on the allowance price. We assume that generators abate emissions such that marginal abatement cost m equals the allowance price. Setting baseline emissions equal to emissions at price $\bar{p} = 0$ implies

$$\begin{aligned} a &= -((\delta_0 q + \delta_1 qp) - (\delta_0 q + \delta_1 q\bar{p})) \\ &= -\delta_1 qm \\ m &= -\frac{a}{\delta_1 q} \end{aligned} \tag{10}$$

Thus, the slope of the marginal abatement cost curve is the derivative of this equation with respect to a, or $-1/\delta_1 q$. In other words, the magnitude of the allowance price coefficient in Equation (2) is inversely proportional to the slope of the curve. Because abatement is the reduction in emissions, we interpret the negative of the reciprocal of the hour–price interaction as the slope of the curve.

Note that we define abatement in tons of NOx, whereas the dependent variable in Equation (2) is the NOx emissions rate rather than the level of emissions. We can convert the change in emissions rate to abatement in tons if we assume total fossil-fuel-fired generation to be exogenous, which is commonly done in the literature (e.g., Stephen P. Holland, Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates (2016)) and seems reasonable in our context, as non-fossil-fuel generation in the subregions we analyze is largely nondispatchable and therefore cannot respond to changes in fossil-fuel-fired generation.

Appendix 2 Regression Output

Table A1 shows output from the full sample regressions. The marginal effect of NOx emissions in hour $h = 1$ (β_1 in Equation (1)) equals the NOx tons coefficient reported in the first row of the table; the marginal effect of NOx emissions in hour $h = 2, ..., 24$ ($\beta_2, ..., \beta_{24}$ in Equation (1)) equals the sum of the NOx tons coefficient and the coefficient associated with that hour's interaction term. For example, 2SLS results suggest that an increase in NOx emissions (within a 100-mile radius of the monitoring station) at 3 pm (hour 15) in New York City increases the probability that ozone will exceed 70 ppb in that hour by 1.97 percent (equal to the sum of 0.0073 and 0.0124). These effects are illustrated graphically in Figure 4.

Temperature quartile indicator variables are used as a control. Temperature effects vary by subregion. In all cases, temperatures in the highest quartile significantly increase the probability of a high-ozone event, but the magnitude of this effect varies by subregion.

Table A1: Ozone Regression Output, 2001–2019

	NYC		Phil.-Wilm.		Wash.-Balt.	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	2SLS	OLS	2SLS	OLS	2SLS
NOx Tons	0.00731***	0.00935***	0.00705***	0.0118***	0.00594***	0.0130***
	(0.000236)	(0.000311)	(0.000188)	(0.000266)	(0.000170)	(0.000330)
NOx Tons * Hour 2	0.000711***	0.000624***	0.000404**	0.000548***	0.000670***	0.00100***
	(0.000211)	(0.000215)	(0.000159)	(0.000142)	(0.000154)	(0.000143)
NOx Tons * Hour 3	0.00144***	0.00108***	0.000660***	0.000494***	0.000969***	0.00142***
	(0.000200)	(0.000211)	(0.000150)	(0.000137)	(0.000148)	(0.000142)
NOx Tons * Hour 4	0.00198***	0.00172***	0.000832***	0.000574***	0.000929***	0.00140***
	(0.000202)	(0.000210)	(0.000148)	(0.000135)	(0.000134)	(0.000135)
NOx Tons * Hour 5	0.00155***	0.00119***	0.000893***	0.000531***	0.000393***	0.000312***
	(0.000192)	(0.000199)	(0.000144)	(0.000127)	(0.000121)	(0.000116)
NOx Tons * Hour 6	0.000594***	-7.96e-05	0.000146	-0.000709***	-0.000158	-0.00102***
	(0.000182)	(0.000189)	(0.000141)	(0.000124)	(0.000114)	(0.000111)
NOx Tons * Hour 7	-0.000686***	-0.00161***	-0.000826***	-0.00210***	-0.000733***	-0.00215***
	(0.000179)	(0.000191)	(0.000141)	(0.000128)	(0.000106)	(0.000112)
NOx Tons * Hour 8	-0.00189***	-0.00299***	-0.00177***	-0.00330***	-0.00118***	-0.00289***
	(0.000181)	(0.000199)	(0.000143)	(0.000136)	(0.000109)	(0.000122)
NOx Tons * Hour 9	-0.00262***	-0.00375***	-0.00245***	-0.00416***	-0.00156***	-0.00336***
	(0.000202)	(0.000219)	(0.000149)	(0.000149)	(0.000121)	(0.000141)
NOx Tons * Hour 10	-0.00152***	-0.00297***	-0.00110***	-0.00304***	-0.000951***	-0.00300***
	(0.000286)	(0.000291)	(0.000213)	(0.000216)	(0.000166)	(0.000185)
NOx Tons * Hour 11	0.00297***	0.00110***	0.00348***	0.000955***	0.00564***	0.00255***
	(0.000396)	(0.000397)	(0.000286)	(0.000282)	(0.000287)	(0.000287)
NOx Tons * Hour 12	0.00836***	0.00547***	0.00851***	0.00503***	0.0130***	0.00881***
	(0.000424)	(0.000433)	(0.000313)	(0.000314)	(0.000337)	(0.000343)
NOx Tons * Hour 13	0.0113***	0.00829***	0.0119***	0.00853***	0.0171***	0.0129***
	(0.000416)	(0.000441)	(0.000312)	(0.000327)	(0.000345)	(0.000365)
NOx Tons * Hour 14	0.0127***	0.0102***	0.0139***	0.0106***	0.0197***	0.0155***
	(0.000400)	(0.000437)	(0.000305)	(0.000328)	(0.000345)	(0.000371)
NOx Tons * Hour 15	0.0124***	0.0105***	0.0139***	0.0109***	0.0205***	0.0167***
	(0.000397)	(0.000439)	(0.000301)	(0.000327)	(0.000341)	(0.000371)
NOx Tons * Hour 16	0.0119***	0.0102***	0.0133***	0.0106***	0.0196***	0.0159***
	(0.000388)	(0.000430)	(0.000299)	(0.000324)	(0.000339)	(0.000367)
NOx Tons * Hour 17	0.0103***	0.00877***	0.0122***	0.00938***	0.0173***	0.0136***
	(0.000389)	(0.000426)	(0.000299)	(0.000321)	(0.000336)	(0.000359)
NOx Tons * Hour 18	0.00743***	0.00612***	0.0101***	0.00697***	0.0134***	0.0101***
	(0.000400)	(0.000426)	(0.000301)	(0.000315)	(0.000326)	(0.000342)
NOx Tons * Hour 19	0.00438***	0.00295***	0.00590***	0.00289***	0.00668***	0.00366***
	(0.000393)	(0.000407)	(0.000295)	(0.000294)	(0.000294)	(0.000296)
NOx Tons * Hour 20	0.000373	-0.000916***	0.00157***	-0.000914***	0.00139***	-0.00134***
	(0.000343)	(0.000347)	(0.000265)	(0.000257)	(0.000232)	(0.000232)
NOx Tons * Hour 21	-0.00191***	-0.00291***	-0.000664***	-0.00285***	-0.00106***	-0.00354***
	(0.000282)	(0.000295)	(0.000236)	(0.000228)	(0.000176)	(0.000187)
NOx Tons * Hour 22	-0.00239***	-0.00333***	-0.00157***	-0.00334***	-0.00120***	-0.00327***
	(0.000258)	(0.000263)	(0.000216)	(0.000202)	(0.000163)	(0.000164)
NOx Tons * Hour 23	-0.00193***	-0.00270***	-0.00123***	-0.00256***	-0.00108***	-0.00252***
	(0.000250)	(0.000249)	(0.000205)	(0.000179)	(0.000144)	(0.000142)
NOx Tons * Hour 24	-0.00108***	-0.00149***	-0.000564***	-0.00145***	-0.000518***	-0.00134***
	(0.000231)	(0.000235)	(0.000203)	(0.000166)	(0.000145)	(0.000136)
Temperature Quartile 2	0.00178***	0.000899***	0.000835***	-0.00176***	-0.00351***	-0.00749***
	(0.000269)	(0.000284)	(0.000240)	(0.000269)	(0.000219)	(0.000289)
Temperature Quartile 3	-0.00179***	-0.00355***	-0.00369***	-0.00984***	-0.0105***	-0.0192***
	(0.000496)	(0.000561)	(0.000439)	(0.000533)	(0.000402)	(0.000572)
Temperature Quartile 4	0.0460***	0.0437***	0.0466***	0.0339***	0.0436***	0.0278***
	(0.000970)	(0.00118)	(0.000830)	(0.00111)	(0.000705)	(0.00107)
Constant	-0.108***	-0.0425***	-0.0350***	0.0231***	-0.0834***	-0.0223***
	(0.00415)	(0.00385)	(0.00281)	(0.00247)	(0.00439)	(0.00629)
Observations	690,624	690,624	943,872	943,872	1,097,106	1,097,106
R-squared	0.200	0.200	0.230	0.229	0.205	0.202

Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

First-stage regression output is shown in Table A2. Results suggest that our instrument—simulated NOx tons—is a strong predictor of actual NOx emissions. Our regressions have 24 instrumented variables (NOx and NOx interacted with hour of the day). This table presents first-stage coefficients for the instrumented variables.

Table A2: Ozone Regression Output, First Stage, 2001–2019

VARIABLES	(1) NYC	(2) Phil.-Wilm.	(3) Wash.-Balt.
Simulated NOx Tons	0.594***	0.702***	0.796***
	(0.00186)	(0.00167)	(0.00157)
Temperature Quartile 2	0.343***	0.383***	0.548***
	(0.00462)	(0.00495)	(0.00424)
Temperature Quartile 3	0.986***	1.060***	1.238***
	(0.00673)	(0.00618)	(0.00475)
Temperature Quartile 4	2.895***	3.067***	2.618***
	(0.0112)	(0.00950)	(0.00623)
Constant	4.007***	2.838***	0.718***
	(0.0392)	(0.0404)	(0.0527)
Observations	690,629	943,872	1,097,110
R-squared	0.841	0.856	0.885

Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Tables A3 and A4 present regression output for the *ex ante* (2011–2015) period, and Tables A5 and A6 present regression output for the *ex post* (2016–2019) period. These regression results are used to define the differentiated emissions prices, which vary by hour of the day and subregion.

Table A3: Ozone Regression Output, *Ex Ante* Period (2011–2015)

VARIABLES	(1) NYC	(2) Phil.-Wilm.	(3) Wash.-Balt.
NOx Tons	0.0170***	0.0134***	0.0100***
	(0.000885)	(0.000674)	(0.000786)
NOx Tons * Hour 2	0.00124*	0.000376	0.000641***
	(0.000699)	(0.000387)	(0.000249)
NOx Tons * Hour 3	0.00244**	0.000860**	0.00102***
	(0.000968)	(0.000356)	(0.000243)
NOx Tons * Hour 4	0.00386***	0.00130***	0.00164***
	(0.000865)	(0.000334)	(0.000247)
NOx Tons * Hour 5	0.00248***	0.000792**	0.00178***
	(0.000494)	(0.000325)	(0.000237)
NOx Tons * Hour 6	-0.000198	-0.000233	0.000825***
	(0.000477)	(0.000323)	(0.000234)
NOx Tons * Hour 7	-0.00349***	-0.00105***	9.73e-05
	(0.000481)	(0.000324)	(0.000234)
NOx Tons * Hour 8	-0.00571***	-0.00234***	-0.000995***
	(0.000498)	(0.000330)	(0.000232)
NOx Tons * Hour 9	-0.00784***	-0.00362***	-0.00204***
	(0.000589)	(0.000360)	(0.000266)
NOx Tons * Hour 10	-0.00404***	-0.00311***	0.00197***
	(0.00114)	(0.000553)	(0.000735)
NOx Tons * Hour 11	0.00435***	0.00462***	0.0145***
	(0.00169)	(0.00106)	(0.00123)
NOx Tons * Hour 12	0.0143***	0.0132***	0.0266***
	(0.00174)	(0.00122)	(0.00148)
NOx Tons * Hour 13	0.0137***	0.0151***	0.0318***
	(0.00166)	(0.00123)	(0.00158)
NOx Tons * Hour 14	0.0121***	0.0143***	0.0331***
	(0.00155)	(0.00122)	(0.00157)
NOx Tons * Hour 15	0.0114***	0.0134***	0.0323***
	(0.00150)	(0.00120)	(0.00154)
NOx Tons * Hour 16	0.00873***	0.0129***	0.0298***
	(0.00143)	(0.00117)	(0.00154)
NOx Tons * Hour 17	0.00842***	0.0124***	0.0234***
	(0.00140)	(0.00115)	(0.00150)
NOx Tons * Hour 18	0.00564***	0.0115***	0.0181***
	(0.00141)	(0.00113)	(0.00141)
NOx Tons * Hour 19	0.00170	0.00446***	0.00941***
	(0.00137)	(0.000995)	(0.00115)
NOx Tons * Hour 20	-0.00365***	0.000445	0.000956
	(0.00123)	(0.000851)	(0.000755)
NOx Tons * Hour 21	-0.00706***	-0.00263***	-0.00133**
	(0.000989)	(0.000668)	(0.000566)
NOx Tons * Hour 22	-0.00716***	-0.00350***	-0.00165***
	(0.000921)	(0.000555)	(0.000480)
NOx Tons * Hour 23	-0.00600***	-0.00234***	-0.00158***
	(0.000800)	(0.000510)	(0.000287)
NOx Tons * Hour 24	-0.00394***	-0.000771	-0.000324
	(0.000574)	(0.000521)	(0.000223)
Temperature Quartile 2	-0.00335***	-0.00404***	-0.00626***
	(0.000377)	(0.000334)	(0.000364)
Temperature Quartile 3	-0.0118***	-0.0128***	-0.0154***
	(0.000839)	(0.000738)	(0.000812)
Temperature Quartile 4	-0.00169	-0.00514***	-0.0187***
	(0.00238)	(0.00195)	(0.00196)
Constant	-0.00353***	-0.00931***	-0.0211***
	(0.00134)	(0.00214)	(0.00232)
Observations	226,117	261,464	284,238
R-squared	0.159	0.159	0.158

Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4: Ozone Regression Output, *Ex Ante* Period (2011–2015), First Stage

VARIABLES	(1) NYC	(2) Phil.-Wilm.	(3) Wash.-Balt.
Simulated NOx Tons	0.596***	0.688***	0.742***
	(0.00428)	(0.00365)	(0.00363)
Temperature Quartile 2	0.139***	0.0966***	0.279***
	(0.00531)	(0.00645)	(0.00585)
Temperature Quartile 3	0.507***	0.487***	0.695***
	(0.00845)	(0.00822)	(0.00697)
Temperature Quartile 4	2.102***	2.128***	2.157***
	(0.0164)	(0.0139)	(0.00985)
Constant	0.648***	0.155***	-1.875***
	(0.0149)	(0.0248)	(0.0283)
Observations	226,122	261,464	284,239
R-squared	0.716	0.746	0.706

Regressions have 24 instrumented variables (NOx and NOx interacted with hour of the day). Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5: Ozone Regression Output, *Ex Post* Period (2016–2019)

VARIABLES	(1) NYC	(2) Phil.-Wilm.	(3) Wash.-Balt.
NOx Tons	0.0131***	0.00946***	0.00921***
	(0.00171)	(0.000883)	(0.000874)
NOx Tons * Hour 2	0.00167**	0.000359	-0.000114
	(0.000695)	(0.000348)	(0.000473)
NOx Tons * Hour 3	0.00183***	0.00116***	0.000208
	(0.000673)	(0.000364)	(0.000480)
NOx Tons * Hour 4	0.00438***	0.00210***	0.000296
	(0.000693)	(0.000378)	(0.000491)
NOx Tons * Hour 5	0.00321***	0.00127***	-0.000760
	(0.000651)	(0.000339)	(0.000468)
NOx Tons * Hour 6	0.000580	0.000548*	-0.00155***
	(0.000638)	(0.000322)	(0.000464)
NOx Tons * Hour 7	-0.00224***	-0.000534*	-0.00202***
	(0.000617)	(0.000324)	(0.000467)
NOx Tons * Hour 8	-0.00472***	-0.00153***	-0.00248***
	(0.000687)	(0.000335)	(0.000472)
NOx Tons * Hour 9	-0.00693***	-0.00260***	-0.00292***
	(0.000751)	(0.000353)	(0.000488)
NOx Tons * Hour 10	-0.00729***	-0.00387***	-0.00409***
	(0.00106)	(0.000396)	(0.000563)
NOx Tons * Hour 11	-0.00257	-0.000524	-0.000806
	(0.00159)	(0.000955)	(0.00122)
NOx Tons * Hour 12	0.00341*	0.00907***	0.00771***
	(0.00190)	(0.00150)	(0.00181)
NOx Tons * Hour 13	0.0104***	0.0112***	0.0131***
	(0.00245)	(0.00163)	(0.00203)
NOx Tons * Hour 14	0.00980***	0.0116***	0.0158***
	(0.00241)	(0.00163)	(0.00211)
NOx Tons * Hour 15	0.00843***	0.0109***	0.0113***
	(0.00227)	(0.00160)	(0.00194)
NOx Tons * Hour 16	0.00629***	0.0101***	0.0125***
	(0.00216)	(0.00156)	(0.00193)
NOx Tons * Hour 17	0.00330	0.00724***	0.00894***
	(0.00205)	(0.00149)	(0.00181)
NOx Tons * Hour 18	-0.00103	0.00433***	0.00634***
	(0.00187)	(0.00136)	(0.00167)
NOx Tons * Hour 19	-0.00497***	-0.00150	-0.000268
	(0.00160)	(0.00103)	(0.00125)
NOx Tons * Hour 20	-0.00790***	-0.00325***	-0.00156
	(0.00134)	(0.000779)	(0.00103)
NOx Tons * Hour 21	-0.00745***	-0.00340***	-0.00279***
	(0.00126)	(0.000662)	(0.000706)
NOx Tons * Hour 22	-0.00646***	-0.00293***	-0.00224***
	(0.00113)	(0.000479)	(0.000607)
NOx Tons * Hour 23	-0.00511***	-0.00187***	-0.00149***
	(0.000868)	(0.000453)	(0.000571)
NOx Tons * Hour 24	-0.00323***	-0.00128***	-0.00107*
	(0.000633)	(0.000326)	(0.000590)
Constant	0.00941***	-0.0186***	-0.00601***
	(0.00214)	(0.00211)	(0.00153)
Observations	179,823	194,703	215,586
R-squared	0.068	0.082	0.064

Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6: Ozone Regression Output, *Ex Post* Period (2016–2019), First Stage

VARIABLES	(1) NYC	(2) Phil.-Wilm.	(3) Wash.-Balt.
Simulated NOx Tons	0.617***	0.752***	0.834***
	(0.00574)	(0.00407)	(0.00358)
Temperature Quartile 2	0.0914***	0.0554***	0.292***
	(0.00419)	(0.00476)	(0.00460)
Temperature Quartile 3	0.347***	0.281***	0.567***
	(0.00630)	(0.00585)	(0.00502)
Temperature Quartile 4	1.383***	1.239***	1.360***
	(0.0118)	(0.00898)	(0.00660)
Constant	0.137***	-0.420***	-1.082***
	(0.0138)	(0.0231)	(0.0161)
Observations	179,823	194,703	215,589
R-squared	0.716	0.769	0.708

Regressions have 24 instrumented variables (NOx and NOx interacted with hour of the day). Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A7 shows the regression results from the abatement cost estimation procedure (Equation (2)). The coefficient values are depicted graphically in Figure 7. The dependent variable in these regressions is the average hourly emissions rate, in NOx lbs. per MWh electric power output, of all generators within a 100-mile radius of each AQS monitor. The right-hand variables of interest are the NOx allowance price interacted with hour of the day.

Table A7: Emissions Rate Regression Output, Dependent Variable = lbs. NOx Emissions per MWh

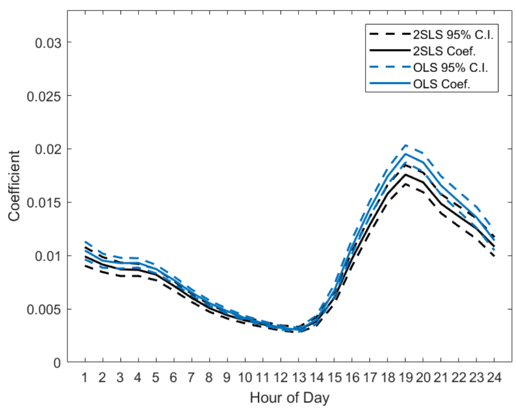
VARIABLES	(1) NYC	(2) Phil.-Wilm.	(3) Wash.-Balt.
NOx Price	-0.0000507***	-0.0002478***	-0.0003871***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 2	0.0000050	-0.0000101*	-0.0000043
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 3	-0.0000002	0.0000056	-0.0000097
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 4	-0.0000083**	0.0000034	-0.0000199*
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 5	-0.0000032	0.0000022	-0.0000159
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 6	0.0000132***	0.0000201***	0.0000032
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 7	0.0000191***	0.0000309***	0.0000096
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 8	0.0000130***	0.0000332***	0.0000305***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 9	0.0000251***	0.0000451***	0.0000446***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 10	0.0000198***	0.0000469***	0.0000488***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 11	0.0000136***	0.0000397***	0.0000559***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 12	0.0000124**	0.0000391***	0.0000495***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 13	0.0000227***	0.0000416***	0.0000407***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 14	0.0000187***	0.0000379***	0.0000398***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 15	0.0000236***	0.0000436***	0.0000482***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 16	0.0000281***	0.0000522***	0.0000524***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 17	0.0000235***	0.0000508***	0.0000517***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 18	0.0000061	0.0000381***	0.0000479***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 19	-0.0000119*	0.0000240***	0.0000430***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 20	-0.0000154***	0.0000281***	0.0000598***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 21	-0.0000208***	0.0000211***	0.0000538***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 22	-0.0000250***	0.0000179***	0.0000473***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 23	-0.0000055	0.0000279***	0.0000266***
	(0.000)	(0.000)	(0.000)
NOx Price * Hour 24	-0.0000101**	-0.0000011	-0.0000119
	(0.000)	(0.000)	(0.000)
Constant	0.2411327***	0.2511912***	0.7385380***
	(0.003)	(0.002)	(0.006)
Observations	331,899	265,420	308,117
R-squared	0.471	0.636	0.612

Fixed effects by hour of the day, day of the week, month, year, and station not shown. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

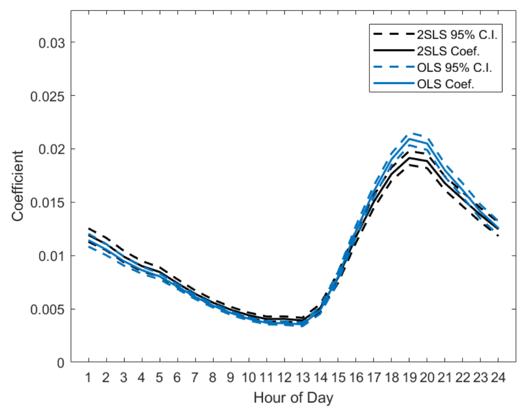
Appendix 3 Coefficient Estimates Using Alternative Dependent Variable

Figure A1 illustrates coefficient estimates when the dependent variable is defined as an indicator equal to 1 if the eight-hour moving average ozone concentration exceeds 70 ppb. Results are comparable to those shown in Figure 4, but the effect of NOx on eight-hour ozone is lagged. EPA defines attainment at the county level for each state as when the three-year average of the year's fourth-highest eight-hour moving average concentration level is no greater than 70 ppb.

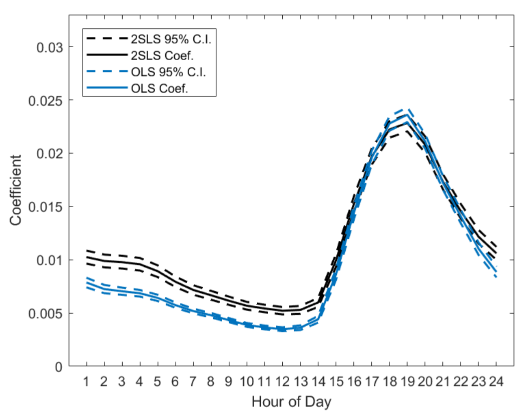
Figure A1: OLS and 2SLS Regression Results, 2001–2019, Dep. Var. = 1 if Eight-hr Moving Average Ozone Concentration > 70 ppb



(a) NYC



(b) Phil.-Wilm.



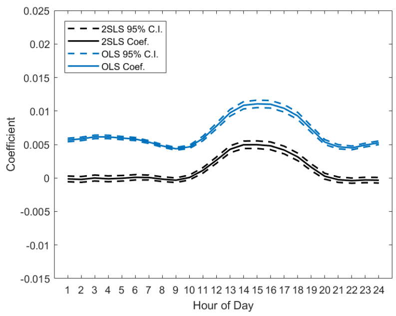
(c) Wash.-Balt.

The regressions are the same as Equation (1), except that the dependent variable uses the eight-hour moving average of the ozone level rather than the contemporaneous ozone level.

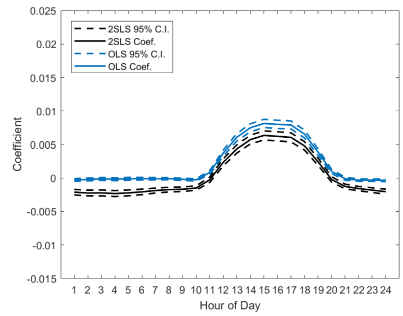
Appendix 4 NOx–Ozone Regression Results from Nonattainment Regions Outside of the Northeast and Mid-Atlantic

Figure A2 illustrates coefficient estimates for other subregions that failed to attain NAAQS standards as of 2019 but are outside of our area of focus (Northeast and mid-Atlantic). Significant interregional variation occurs in the effect of NOx on ozone emissions. These subregions exhibit significantly less sensitivity to NOx emissions relative to the Northeast and mid-Atlantic subregions.

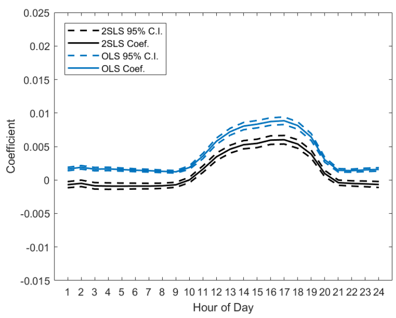
Figure A2: OLS and 2SLS Regression Results, 2001–2019, Dep. Var. = 1 if eight-hr Moving Average Ozone Concentration > 70 ppb



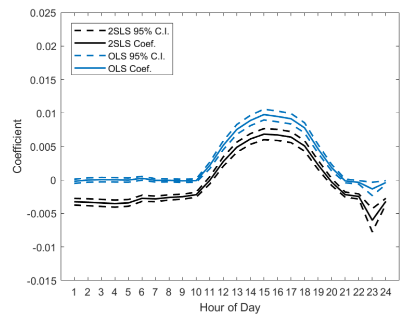
(a) Chicago, IL-Milwaukee, WI



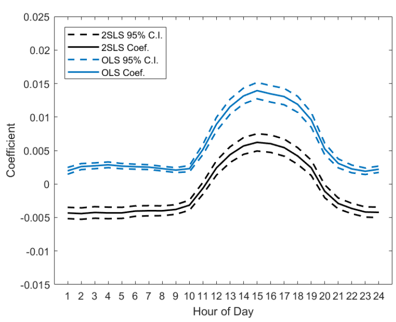
(b) Cincinnati, OH



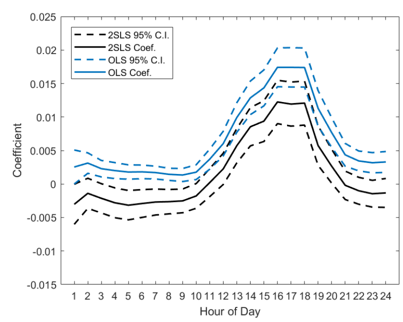
(c) Cleveland, OH-Akron, OH



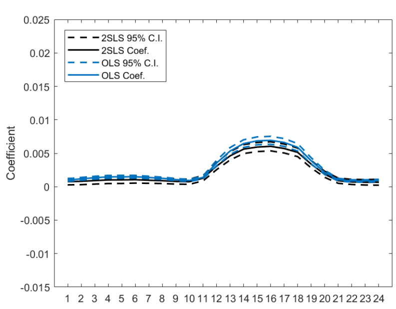
(d) Columbus, OH



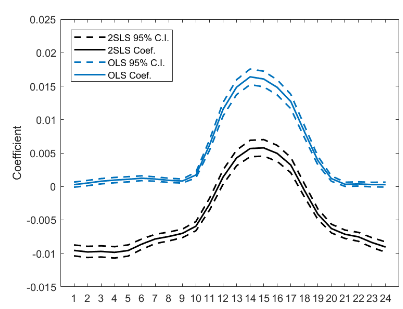
(e) Detroit, MI



(f) Eastern Lake Michigan



(g) Louisville, KY



(h) St. Louis, MO

The regressions are the same as Equation (1) but include regions that failed to attain the NAAQS as of 2019 and are outside of the Northeast and Mid-Atlantic.

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