IMPACTS OF FUEL PRICES AND REGULATIONS ON ELECTRICITY GENERATION EMISSIONS AND URBAN AIR QUALITY

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IMPACTS OF FUEL PRICES AND REGULATIONS ON ELECTRICITY GENERATION EMISSIONS AND URBAN AIR QUALITY

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

Regulatory actions and fuel price trends have decreased emissions from electricity generating units (EGUs) in the United States. The objective of this thesis is to separate the impacts of regulations and fuel prices on EGU emissions and air pollution in Atlanta and New York City (NYC) between 2006 and 2019. We used observed fuel prices, electricity demand, EGU emissions, and air pollutant concentrations to estimate what air pollutant concentrations would have been under different (counterfactual) fuel price and regulatory scenarios. By comparing the actual and counterfactual scenarios, we find that fuel prices influenced EGU dispatch, which reduced ozone and $PM_{2.5}$ in Atlanta beginning 2009 and $PM_{2.5}$ in NYC beginning 2012. Beginning 2008, installation of emissions controls due to the Clean Air Interstate Rule reduced $PM_{2.5}$ year-round but increased ozone during winter months. Coal EGU retirements due to the combined influence of the Cross-State Air Pollution Rule, Mercury and Air Toxics Standards, and other market and policy factors account for the remaining long-term reductions in $PM_{2.5}$ and ozone. Such information can be used to estimate the air quality and health benefits of past controls and aid the development of effective future emissions reductions strategies.

CHAPTER 1. INTRODUCTION

Surface air pollutants such as fine particulate matter ($PM_{2.5}$) and ozone contribute to premature mortality and other adverse health outcomes.[1] Consequently, extensive regulatory efforts in the United States have been directed towards reducing precursor emissions that form air pollution. These efforts have decreased NO_x and SO_2 emissions from fossil fuel electricity generating units (EGUs) in recent decades (Figure A1).[2] Given the large cost associated with these regulations,[3] stakeholders and policymakers are interested in the air quality improvements attributable to regulations compared to other factors that have modified pollutant levels.[4] One such factor is the decline in natural gas prices in 2008, which also reduced emissions from EGUs.[5] We aim to improve our understanding of regulatory and fuel price impacts on EGU emissions and urban air quality between 2006 and 2019.

1.1 EGU Regulations and Accountability Framework

We consider three major federal rules that have led to SO_2 and NO_x emissions reductions from EGUs between 2006 and 2019: the Clean Air Interstate Rule (CAIR), the Cross-State Air Pollution Rule (CSAPR), and the Mercury and Air Toxics Standards (MATS). CAIR was a cap-and-trade rule covering 28 Eastern states that established annual markets for NO_x (2009) and SO_2 (2010). CAIR also established a more stringent the ozone season NO_x market than the earlier NOx Budget Trading Program (NBP), effectively replacing it.[6] Federal courts remanded CAIR to the EPA in 2008,[2] but it remained in effect until it was replaced by CSAPR in 2015. Like CAIR, CSAPR established annual NO_x and SO_2 and ozone season NO_x markets, but it also created separate SO_2 trading groups for states that significantly contributed to air pollution in downwind states.[7] MATS was implemented in 2015 and required coal- and oil-fired EGUs to comply with emissions limits on certain hazardous air pollutants and mercury.[8] While not directed specifically at SO_2 or NO_x control, high cost of compliance to MATS may have caused some firms to retire coal EGUs.[9,10] Firms could comply with these policies by relying on emissions allowances, installing emissions controls, shifting electricity generation to lower emitting EGUs, or retiring polluting EGUs altogether.[2]

Attributing air quality and health effects to individual regulations is difficult due to the co-occurrence of economic, demographic, and other regulatory changes with the actions of interest. The air quality accountability chain provides a useful framework for evaluating health impacts of specific regulations by propagating impacts from regulations to emissions, from emissions to air quality, and from air quality to public health.[4,11] Henneman and coauthors[12] previously used the accountability framework to estimate the impact of EGU regulations on air quality in Atlanta between 1998 to 2013. They identified significant reductions in $PM_{2.5}$ due to decreased annual SO_2 and wintertime NO_x emissions from CAIR. However, their analysis did not consider the impact of decreasing natural gas prices separately from regulatory impacts, which could have resulted in an overestimated CAIR impact.[13]

1.2 Fuel Price Trends and EGU Emissions

Following a peak in 2008, natural gas prices decreased sharply and remained low through most of the 2010s (Figure A2). Prices declined due to many factors, including a large increase in natural gas supply from shale deposits (“shale gas boom”).[14,15] Economic literature[5,16–25] has investigated the impact of these natural gas price trends on EGU generation and capacity in the short- and long-run. In the short-run, low natural gas prices allow some natural gas combined cycle (NGCC) EGUs to generate electricity more cheaply than coal EGUs. This may cause these NGCC EGUs to serve baseload electricity demand historically served by coal EGUs.[16–22,25] In the long-run, low natural gas prices affect investment decisions that influence coal and NGCC generation capacity. Firms may invest in construction of NGCC EGUs for more economical electricity generation.[22] Similarly, firms may retire coal EGUs that were made unprofitable due to cheaper NGCC generation.[5,23,24] Therefore, cheaper natural gas prices shift electricity generation from coal EGUs to NGCC EGUs (Figure A3). Because NGCC EGUs generally emit less NO_x and much less SO_2 than coal EGUs,[20] low natural gas prices may reduce average EGU emissions rates in both the short- and long-run.

Most economic studies have focused on short- and long-run fuel price impacts on CO_2 emissions[17,19–22] rather than SO_2 or NO_x emissions;[5,16] impacts on CO_2 emissions found in these studies cannot readily be cross-applied to SO_2 or NO_x emissions. Unlike CO_2 emissions, SO_2 and NO_x emissions rates vary widely among EGUs that use the same fuel type due to different fuel compositions and installed emissions controls.[19] Therefore, investigation of fuel price impacts on SO_2 or NO_x emissions requires a unit-level approach. Johnsen and coauthors[16] used a unit-level electricity dispatch model to associate changes in coal EGU generation with changes in $PM_{2.5}$ between 2008 and 2013. They conclude that low natural gas prices due to the shale gas boom reduced short-run coal EGU generation by 28% and $PM_{2.5}$ by 2% to 6%. Linn and McCormack[5] used a unit-level model to conclude that market factors rather than regulations (primarily CSAPR) explain 82% of the reduction in NO_x EGU emissions between 2005 and 2015. These economic studies bring into question the sole attribution of EGU regulations in improving air quality without consideration of co-occurring economic conditions.

1.3 Objective and Overview

Here, we use an accountability framework to investigate the impact of both regulations and fuel price trends between 2006 to 2019 on air quality in Atlanta (ATL) and New York City (NYC), two urban regions with air quality significantly impacted by EGU emissions.[26–28] We use empirical methods[12,29] to estimate EGU emissions under scenarios in which changes to fuel prices and/or generating assets did not occur (counterfactual). Using differences between the actual (observed) and counterfactual scenarios, we estimate emissions reductions attributable to regulations and fuel price impacts. Finally, we train machine learning (ML) models to propagate estimated impacts of regulations and fuel prices on EGU emissions to impacts on air pollutant concentrations. Our study is the first to separate the coincident influence of fuel price trends and EGU regulations on observed air pollutant concentrations in this period. These estimated air quality impacts are key to understanding the health benefits of prior regulations, which can inform the development of future policies that aim to improve air quality.

CHAPTER 2. METHODS

We define three primary impacts that regulations and fuel price changes have on fossil fuel EGU emissions: 1) short-run impacts come from re-distributing electricity generation among existing EGUs (re-dispatch; on the order of weeks to months); 2) medium-run impacts come from modifications of existing EGUs, such as the installation of emissions controls (on the order of many months to years); and 3) long-run impacts come from changes to electricity generating capacity, such as the retirement or installation of an EGU (on the order of years).[17,30] We compare the actual scenario with two counterfactual scenarios: 1) a counterfactual scenario in which no short-, medium-, or long-run changes occur after 2007 (hereafter, the "total counterfactual scenario"); and 2) a counterfactual scenario in which fuel prices are fixed to 2006-level averages, but medium- and long-run changes to EGUs still occur ("short-run counterfactual scenario"). The following subchapters describe data sources and modeling approaches for actual and counterfactual EGU emissions (Chapter 2.1) and air pollutant concentrations (Chapter 2.2). Chapter 2.3 describes the estimates of uncertainty associated with counterfactual emissions and air pollutant concentrations.

2.1 Actual and Counterfactual EGU Emissions

We retrieved EGU emissions and electricity generation data measured by the Continuous Emissions Monitoring Systems (CEMS) from the Public Utility Data Liberation (PUDL) Project,[31] which provides hourly SO_2 and NO_x emissions, electricity generation, and heat rates from EGUs with greater than 25 MW nameplate capacity. We combined CEMS data with EGU characteristics data from the EPA Emissions &

Generation Resource Integrated Database (eGRID),[32] Clean Air Markets Database (CAMD),[33] and Energy Information Authority (EIA) Form-860.[34] EGU characteristics data include nameplate capacity, location, first year online, retirement year, presence of emissions controls, and the balancing authority area of each EGU. Following prior studies,[30,35] we analyzed EGU generation and emissions within balancing authority areas, regions in which a balancing authority (an entity such as a utility) manages generation and transmission of electricity to meet demand. We selected balancing authority areas that surround Atlanta (ATL) (Southern Company (SOCO)) and New York City (NYC) (PJM Interconnection (PJM), New York Independent System Operator (NYIS), and ISO New England (ISNE)) to capture regional transport of EGU emissions (Figure 1).

For the total counterfactual scenario, we follow the approach of Henneman and coauthors[12] to estimate SO_2 and NO_x EGU emissions if no changes had occurred to EGUs after 2007. We aggregate all EGUs in a region. Then, we define an average base SO_2 and NO_x emissions rate ($ER^*(d)$; in kg per MWh) that varies based on the day of year (d) using observed EGU emissions ($E(d, y)$ for year y) and electricity demand ($L(d, y)$) in 2006 and 2007 (eq. 1):

$$ER^*(d) = \frac{1}{2}\left[\frac{E(d,2006)}{L(d,2006)} + \frac{E(d,2007)}{L(d,2007)}\right] \qquad (1)$$

Total counterfactual EGU emissions ($E_{total\ cf}(d, y)$) are calculated as the product of the base ER and the total observed electricity demand ($L(d, y)$ of day of year d for year y (2006 to 2019); eq. 2):

$$E_{total\ cf}(d, y) = (ER^*(d))(L(d, y)) \quad (2)$$

For the short-run counterfactual scenario, we used an open-source dispatch model[29] to estimate EGU emissions if medium- and long-run changes to the EGU fleet had occurred but fuel prices were held constant to 2006-level averages. In brief, the dispatch model calculates the capacity, emissions rate (ER), and electricity generation cost for each EGU in a region. Generation costs are calculated from observed fuel prices,[36] generation efficiency (via heat rates), and estimated variable operations and maintenance costs (VOM). Each week, the model sorts EGUs from lowest to highest electricity generation cost ("merit order;" Figure A4). Then, using the weekly merit order, the model dispatches EGUs at or below the observed fossil fuel electricity demand for each hour of the week. Total hourly SO_2 and NO_x emissions are calculated as the sum of emissions from dispatched EGUs.

Because the base model determines available EGUs on a yearly basis, it fails to capture available EGUs that were idled for long periods because they were economically uncompetitive. These EGUs were generally coal-fired and had high ERs, so we adjusted the model to ensure that it retained these EGUs. For these EGUs, we assigned monthly fuel prices equal to average fuel prices of operating EGUs that use the same fuel. A complete list of changes we made to the model is in Appendix A.1.1.

To estimate short-run counterfactual emissions, we ran the dispatch model using observed EGU ERs, heat rates, and capacities, but we held fuel prices to 2006 averages. To preserve the heterogeneity of fuel prices observed by different EGUs that burn the same fuel type, we calculated individual counterfactual fuel prices for each EGU. We first calculated the average fuel price observed by all EGUs using natural gas, bituminous coal, or subbituminous coal for 2006 in each region ($\overline{P_j(2006)}$; in which *j* indicates fuel type). We then calculated the monthly ratio ($R_j(m, y)$ for month *m* of year *y*) of $\overline{P_j(2006)}$ and the monthly average observed fuel price for each fuel type ($\overline{P_j(m,y)}$; eq. 3):

$$R_j(m, y) = \frac{\overline{P_j(2006)}}{\overline{P_j(m, y)}} \tag{3}$$

Counterfactual fuel prices for an individual EGU *i* that uses fuel type *j* ($P_{i,\, j,short\text{-}run\ cf}(m, y)$) were calculated by scaling its observed monthly fuel prices ($P_{i,j,obs}(m,y)$) by the monthly ratios (eq. 4).

$$P_{i,j,short-run\, cf}(m, y) = (R_j(m, y))(P_{i,j,obs}(m, y)) \tag{4}$$

To correct for model biases, we also ran the dispatch model to simulate the actual scenario using observed fuel prices. We fit a least-squares linear regression between the modeled actual and observed actual emissions for each species and city. Then, we adjusted counterfactual emissions from the dispatch model with the fitted regression.

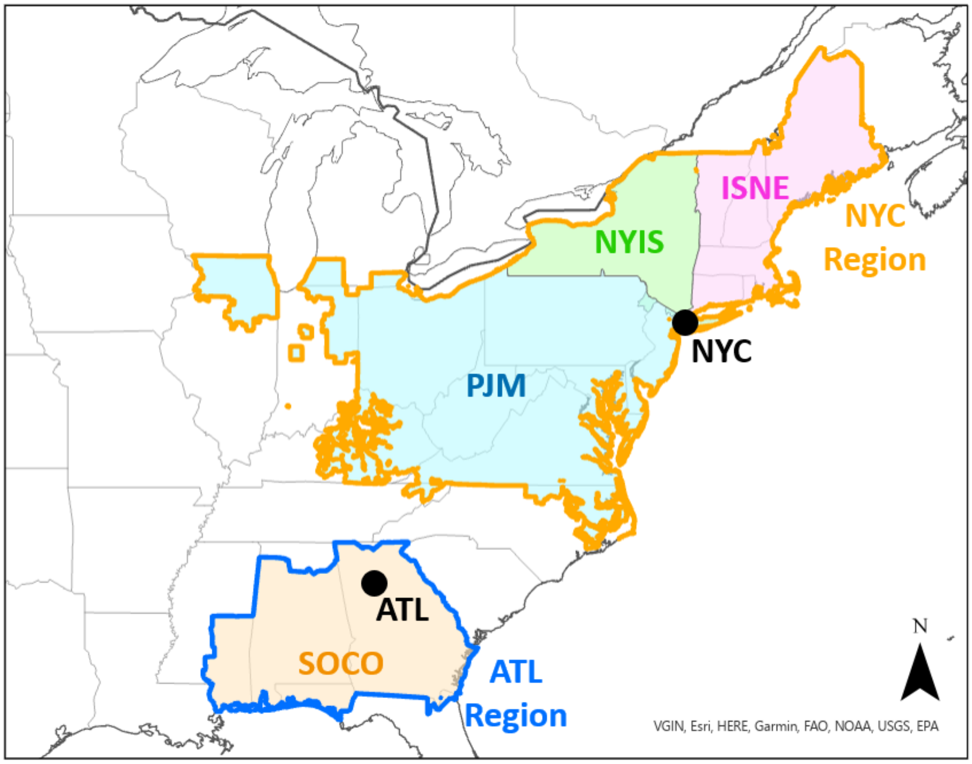

Figure 1. Boundaries of ATL and NYC regions in 2022.[37] ATL region is comprised of the Southern Company (SOCO) balancing authority area; NYC region is comprised of the PJM Interconnection (PJM), New York Independent System Operator (NYIS), and ISO New England (ISNE) balancing authority areas. Note that balancing authority area boundaries are based on producers of electricity (utility and non-utility), so boundaries may change slightly over time.

2.2 Actual and Counterfactual Air Pollutant Concentrations

We retrieved daily 8-hour maximum ozone and daily average $PM_{2.5}$ at EPA NCORE/Speciation Network sites in ATL (South Dekalb) and NYC (Bronx, Manhattan, and Queens). Ozone data were retrieved from the EPA Air Quality System (AQS) and $PM_{2.5}$ data were retrieved from the Cooperative Institute for Research in the Atmosphere (CIRA).[38]

We used the XGBoost[39] package in Python to develop relationships between air pollutant concentrations and temporal variables, meteorology, and emissions. XGBoost is a gradient boosted decision tree machine learning (ML) method capable of regression. We trained ML models separately for $PM_{2.5}$ and ozone at each site. Meteorological data were retrieved from airports near the air pollutant monitoring sites (Hartsfield-Jackson International Airport for ATL and LaGuardia International Airport for NYC). These data are from the National Centers for Environmental Information (NCEI; last access: Feb 4, 2022). We estimated mobile vehicle emissions of NO_x, SO_2, CO, $PM_{2.5}$, and NH_3 with the EPA Motor Vehicle Emission Simulator (MOVES3). Industrial and residential NO_x, SO_2, CO, $PM_{2.5}$, and NH_3 emissions were retrieved from the EPA National Emissions Inventory (NEI), from which we interpolated data between the available years. We also included day-of-year and encoded day-of-week variables to capture seasonal and weekly emissions not captured by the meteorology or emissions inventories used.

Prior to training, we held out 10% of the data as a validation set. We selected input features using prior knowledge and by variables that did not benefit model training (determined by collinearity). Hyperparameters were tuned using random and grid searches via 10-fold cross-validation on the training set.

2.3 Estimates of Uncertainty

We estimated uncertainty in the difference between the counterfactual and actual scenarios predicted from our methods to remain consistent with the methodology of prior accountability studies.[13] For total counterfactual EGU emissions, we calculated the average coefficient of variation (COV) from the calculation of $ER^*(d)$. We estimated the uncertainty of the emissions as normally distributed around the daily mean $ER^*(d)$ using the COV. For short-run counterfactual EGU emissions, we assumed that uncertainty was normally distributed around the emissions estimated from the linear regression. The standard deviation of the distributions was equal to the standard error of the slope multiplied by the unadjusted dispatch modeled emissions.

We used a Monte Carlo approach to propagate uncertainty from EGU emissions to air pollutant concentrations due to the nonlinear relationship between pollutant concentrations and emissions. To estimate the uncertainty due to the ML models, we also assigned uncertainties to emissions we did not change (mobile and “other” (residential and industrial)). Following Hanna and coauthors,[12] we assumed lognormal distributions for these emissions and used geometric standard deviations of 0.347 and 0.203 for mobile and “other” emissions, respectively.

CHAPTER 3. RESULTS AND DISCUSSION

3.1 Evaluation of Modeling Approaches

Seasonal patterns are present for total counterfactual NO_x and SO_2 ERs in both regions (Figure 2a, 2b). NO_x ERs decrease during the ozone season (-44 to -51%) due to compliance with the federal NBP or similar state-level rules (e.g., Georgia's NO_x Emissions from Electric Utility Steam Generating Units Rule). SO_2 ERs also decrease slightly during the ozone season (-9 to -10%), a likely co-benefit of certain NO_x controls (e.g., fuel switching and overfiring).

The dispatch model used for the short-run counterfactual scenario reproduces actual emissions with low bias relative to observed emissions (Normalized Mean Bias (NMB) = -13% to +9.6%; Figure 2c, 2d) and high coefficients of determination (R^2 = 0.78 to 0.99). The dispatch model performs better in the NYC region than the ATL region, which could be due to differences between the electricity market structures of the regions. EGUs in the modeled NYC region (PJM, ISNE, and NYIS) are mostly owned by independent power producers (IPPs). IPPs participate in competitive wholesale energy markets coordinated by regional transmission organizations (RTOs)/independent system operators (ISOs), through which EGUs owned by IPPs must recover their generation costs (influenced by fuel price, efficiency, and VOM).[40,41] In contrast, EGUs in the ATL region (SOCO) are owned by a regulated investor owned utility (IOU), which can pass down generation costs to customers via regulator-set retail rates.[42] This comparative lack of market pressure allows regulated IOUs more leeway to deviate from the merit order and dispatch uneconomical EGUs (e.g., self-scheduling).[43] This could also result in the sustained low bias of modeled actual emissions relative to observed emissions in 2012 and 2013 in the ATL region (Figure A5).

ML models for sites in ATL and NYC predict validation set pollutant concentrations (Figure 2e, 2f) with normalized mean errors (NMEs) ranging from 24 to 31% for $PM_{2.5}$ and 13 to 17% for ozone. Full performance metrics on both training and validation data (Table S1) show that the ML models overfit, which could be due to the low amount of data available (maximum n=4,601 for training). For NYC, we show results from the Queens site because its ML models perform the best out of the three sites. Results from other sites (Bronx and Manhattan) are shown in the Appendix and are noted if they substantially differ. Gain feature importance of the models (Figure A6) show that EGU emissions are more impactful at NYC sites than the ATL site, where mobile emissions play a larger role.

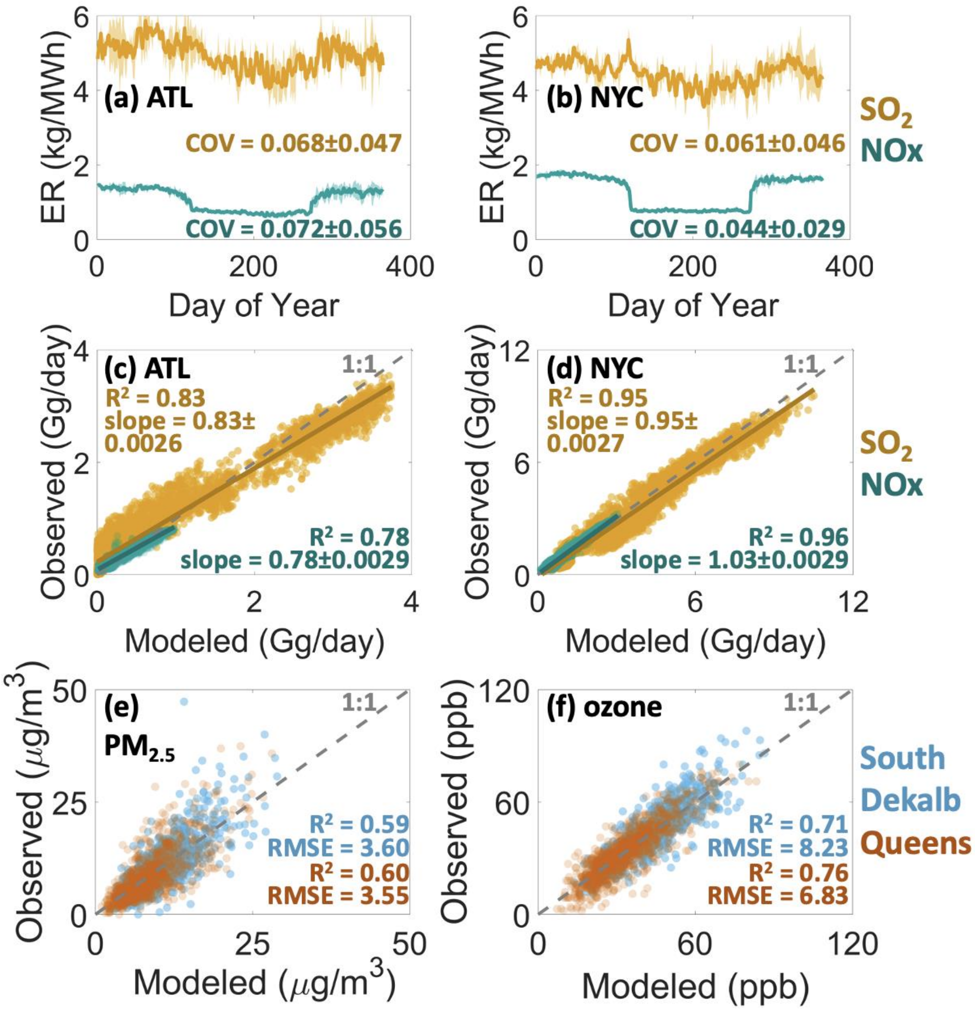

Figure 2. Evaluation of methods used to estimate counterfactual emissions and pollutant concentrations. **(a, b)** Total counterfactual SO_2 and NO_x ERs over day of year for ATL **(a)** and NYC **(b)**. Shading indicates standard deviation of the daily average. Coefficients of variation (COV) are shown (average ± standard deviation). **(c, d)** Least squares linear regression of relationship between observed and dispatch modeled actual EGU emissions for ATL **(c)** and NYC **(d)**. Coefficients of determination (R^2) and slopes of the regressions with their standard errors are shown. **(e, f)** Comparison of observed and ML-modeled daily average $PM_{2.5}$ **(e)** and 8-hour maximum ozone concentrations from the 10% validation set **(f)**. R^2 and root mean square error (RMSE) are shown. RMSE units are the same as those on the axes.

3.2 Short-Run Emissions Reductions

Short-run counterfactual emissions should be interpreted as the emissions that would occur due to a short-term return to 2006-level fuel prices at any time in the 14-year time-series. If fuel prices were fixed to 2006 levels over long periods, investment decisions would result in a different set of medium- and long-run changes than those that occurred.[5,16] Because the short-run counterfactual scenario retains actual medium- and long-run changes, we use the difference between short-run counterfactual and actual emissions (hereafter, the "short-run reduction") to estimate the impact of fuel prices on emissions through changes in the merit order. We also note that the dispatch model does not include emissions allowance prices (discussed further in Chapter 4.1), so we consider these short-run reductions to be maximal estimates of the short-run fuel price impact.

Short-run reduction trends are unique across species emitted and regions (Figure 3a-3d). In ATL, short-run reductions for SO_2 and NO_x (Figure 3a, 3c) initially follow fuel price trends (Figure 3e), in which reductions increase after the gas-to-coal price ratio decreases in 2008. This increase in short-run reductions occurs because power generation from cheaper, lower-emitting NGCC EGUs begin to displace coal EGUs in the baseload of the actual merit order. In contrast, the short-run counterfactual retains coal EGUs in the baseload (Figure A7). Beginning 2015, short-run reductions for SO_2 decrease and remain low through 2019 despite low gas-to-coal price ratios. This decrease is driven by a few highly polluting coal EGUs retiring over 2015 and 2016 during the implementation of MATS (Figure A8), which results in a large reduction in average SO_2 ERs from coal EGUs (-87% over 2015; Figure A9a). NO_x short-run reductions remain high in comparison because these retirements result in a relatively smaller decrease in average NO_x ERs (-39%; Figure A9c).

Short-run reductions in NYC are smaller than those in ATL (Figure 3b, 3d) despite similar fuel price trends and average coal EGU ERs (Figure A9). Larger short-run SO_2

reductions in 2013 are exceptions to this trend, but these reductions are likely due to temporary high model bias relative to observations (Figure A5c). Knittel and coauthors[18] conclude that differences between the response in emissions to fuel prices in the NYC and ATL regions are due to differences in electricity market structures. Firms in RTOs/ISOs invest less in NGCC capacity compared to regulated IOUs, which have a tendency to overcapitalize due to regulatory conditions.[42] This results in fewer (Figure A8c) and less efficient existing NGCC capacity in RTO/ISO regions. Indeed, the merit orders for NYC and ATL reveal that PJM (in the NYC region) has a smaller proportion of natural gas CC EGUs serving the baseload of the actual scenario after 2008 (Figure A10).

Whether short-run emissions reductions are purely beneficial depends on if they helped achieve reductions in excess of what would have been required under regulations. For example, after CAIR implementation (2009), little actual ozone season NO_x reductions occur in the NYC region until 2014. In comparison, ozone season NO_x reductions in the ATL region occur but can be mostly explained by fuel price changes. If actual reductions in the ATL region occurred beyond what was necessary under CAIR (or similar state rules in Georgia), then fuel price trends provided emissions reductions in the ATL region that could not be realized in the NYC region. Conversely, if actual emissions in the ATL region were required to decrease due to the more stringent CAIR program, then fuel price trends allowed the utility to comply without committing to more permanent solutions (controls or retirements). Had CAIR been left vacated in 2008 (as was initially done),[44] increases in natural gas prices relative to coal could have reversed these emissions reductions until future regulations were implemented.

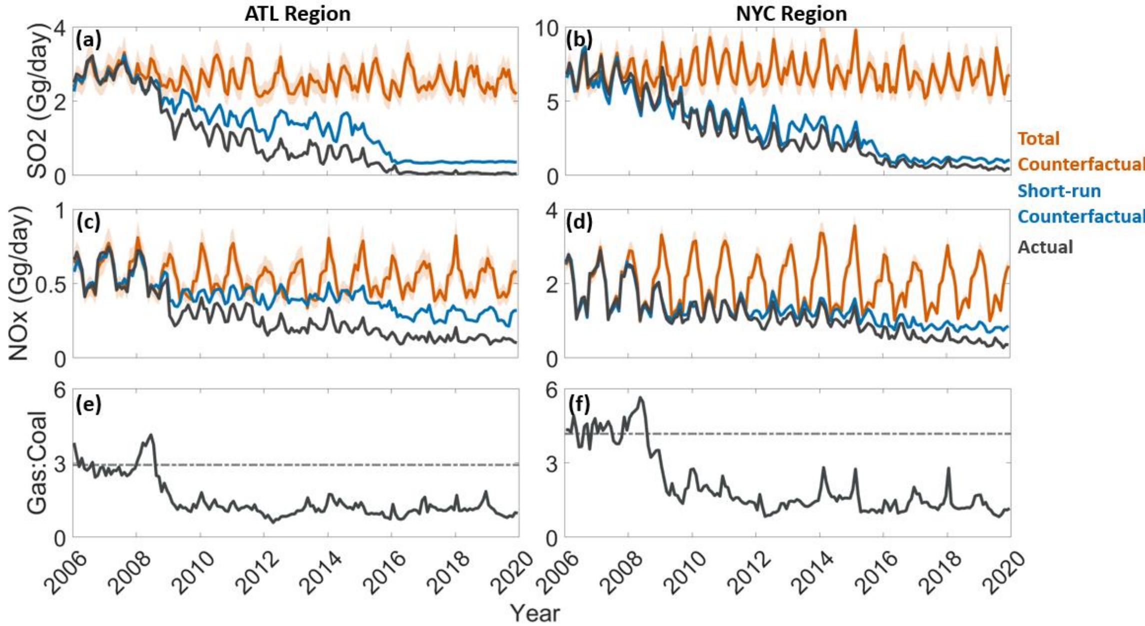

Figure 3. Actual and counterfactual EGU emissions from 2006 to 2019 for ATL region **(a, c, e)** and NYC region **(b, d, f)**. Monthly average SO_2 emissions **(a, b)**, NO_x emissions **(d, e)**, and average natural gas to coal price ratios **(e, f)** are shown. **(a-d)** shaded regions represent the 95% confidence intervals of the counterfactual emissions. **(e, f)** Dashed line indicates 2006 average.

3.3 Medium- and Long-Run Emissions Reductions

Given that short-run reductions are maximal estimates of short-run fuel price impacts, we take differences between total and short-run counterfactual emissions (hereafter, "medium-to-long-run reductions") as conservative estimates of medium- and long-run impacts on emissions. To investigate the economic and regulatory causes of medium-to-long-run reductions, we divide them by total counterfactual emissions to observe their trends relative to total emissions reductions (Figure 4). Notable trends in relative medium-to-long-run reductions occur in two distinct periods that coincide with the implementation of major federal rules: late 2007 to 2010 (CAIR) and late 2013 to 2017 (CSAPR and MATS). We fit cubic splines to the reductions in these periods to apportion the emissions reductions to their causes (final fractional emissions reductions reported in Table S2).

The earlier reduction period occurred before large changes to NGCC and coal capacity (Figure A8).[16,20,22] Therefore, we attribute the first period of emissions reductions primarily to the installation of emissions controls (Figure A11) in response to CAIR or similar state-level rules (e.g., Georgia's 2007 Multipollutant Control for Electric Utility Steam Generating Units Rule). EPA regulatory impact analysis (RIA)[6] estimated that CAIR would reduce SO_2 emissions by 45% and NO_x emissions by 41% by 2015. Our estimates attribute similar medium-run impacts to CAIR for annual SO_2 (-0.41 to -0.51) and non-ozone season NO_x (-0.30 to -0.51). However, medium-to-long-run NO_x reductions during the ozone season (-0.02 to -0.08) were lower than predicted (-25%) because actual emissions reductions were either small (NYC) or mostly explainable by short-run fuel price impacts (ATL; Figure 3).

In the latter reduction period, medium- and long-run changes further decrease SO_2 by 0.46 in ATL and 0.35 in NYC. In contrast to the CAIR period, ozone season NO_x is greatly reduced (-0.31 to -0.42) whereas non-ozone season NO_x is reduced by a smaller fraction (-0.12 to -0.14). While coal ERs again decrease (Figure A9), these decreases were driven mostly by retirements (Figure A8) instead of emissions controls (Figure A11). We find small influence of emissions controls in the NYC region on reducing coal ERs (Figure A8), but the most notable decreases in coal ERs for both regions coincide with retirements during MATS (as discussed in Chapter 3.2). Since NGCC EGUs emit less SO_2 and NO_x than coal-fired EGUs, they can be effective at meeting cap-and-trade regulatory mandates (CAIR and CSAPR) and could have also increased retirements. However, it is difficult to clearly attribute retirements to regulations because several other factors influenced retirements as well. For example, Georgia Power (in SOCO in the ATL region) attributed retirement decisions mostly to MATS and other regulations but also noted that fuel prices influenced decisions.[10] Conversely, economic studies generally attribute capacity changes mostly to fuel prices,[20,23,24,45] renewables,[17] and lower-than-expected electricity demand[5] rather than regulations. Therefore, we attribute medium-to-long-run reductions in this period to the combined influence of CSAPR, MATS, and other long-run factors on retirements.

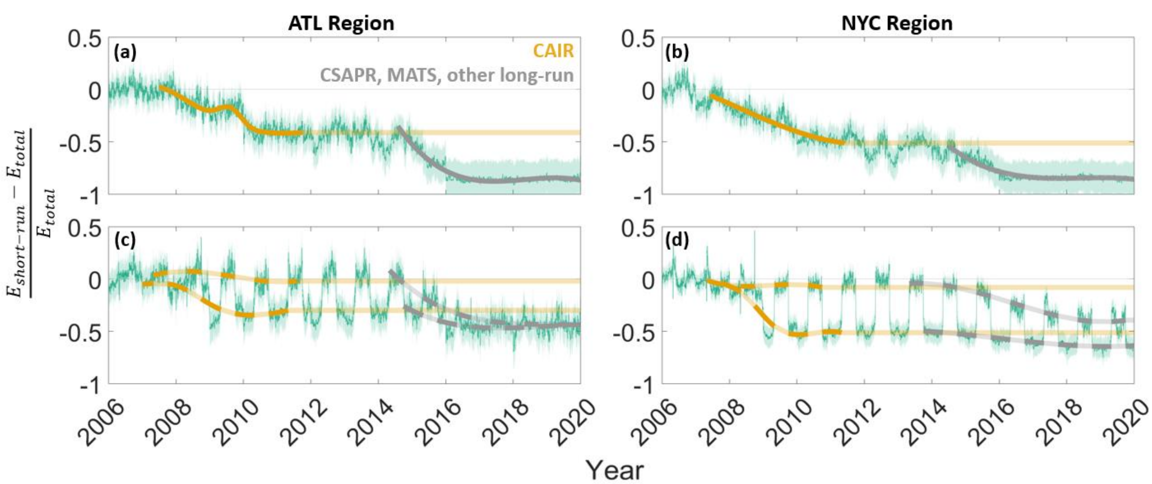

Figure 4. Daily emissions reductions from medium- and long-run EGU changes (green line) relative to total counterfactual emissions (gray horizontal line at 0) for the ATL region **(a, c)** and NYC region **(b, d)**. Reductions for SO_2 **(a, b)** and NO_x **(c, d)** are shown. Green shading indicates 95% confidence interval of emissions reductions. Yellow and gray lines are cubic splines attributable to regulatory and economic impacts, in which lines are bolded during periods in which they are fit.

3.4 Impact of Emissions Reductions on Air Pollutant Concentrations

We use emissions reductions identified in prior chapters to estimate impacts of regulations and fuel prices on air quality in ATL and NYC (Figure 5). In addition to impacts we derive from the total ("all factors together") and short-run ("short-run fuel price") counterfactual scenarios, we estimate counterfactual concentrations for two additional scenarios to identify impacts from medium- and long-run factors: 1) a scenario with no medium-run impacts from CAIR ("CAIR"); and 2) a scenario with no medium- or long-run impacts from CSAPR, MATS, or other long-run factors ("CSAPR, MATS, other long-run"). Emissions impacts from these factors are calculated from the fractional emissions reductions in Figure 3 (Appendix A.1.2). Note that the sum of individual air quality impacts may not equal the air quality impact of all factors together due to the nonlinear response of air pollutant concentrations to emissions. Time-series of counterfactual pollutant concentrations (Figure A12) and pollutant concentration impacts (Figure A13) for Bronx and Manhattan are in the Appendix.

Pollutant concentration impacts increase over time as emissions reductions increase. By 2019, all factors together decreased $PM_{2.5}$ concentrations by an annual average of -3.7 $\mu g/m^3$ (-30%) in ATL and -4.3 to -6.3 $\mu g/m^3$ (-35 to -51%) in NYC (all percentages relative to modeled total counterfactual concentrations). Ozone impacts differ among regions and sites. NO_x emissions reductions increase ozone concentrations in NYC during the non-ozone season (1.1 to 2.4 ppb (6.0 to 11%)). This wintertime increase could be caused by reduced NO_x titration of ozone and radicals.[46] Though the ATL monitor (South Dekalb) does not report 8-hour maximum ozone outside of the non-ozone season, a prior study[12] using different monitors indicates that a similar but smaller impact occurs in ATL as well. During the ozone season, NO_x emissions reductions decrease peak 8-hour average ozone in ATL (-4.0 ppb (-7.8%)). In NYC, they increase concentrations in Bronx (0.33 ppb (1.3%)) and Queens (0.47 ppb (1.9%)) but decrease concentrations in Manhattan (-1.3 ppb (-1.5%)). The heterogeneous response of ozone at NYC sites suggests that EGU emissions reductions, when considered alone, could place those sites in a transition between NO_x-saturated and NO_x-limited ozone production regimes.[47] This challenges attribution of air quality impacts from emissions impacts (discussed further in Chapter 4.1).

Short-run fuel price impacts on both $PM_{2.5}$ and ozone are large for ATL following the decrease in fuel prices until the implementation of CSAPR and MATS. After these regulations, short-run impacts still account for a large portion of NO_x emissions reductions by the end of the period (42% of total reductions). Consequently, they have a near-equivalent impact as CAIR on $PM_{2.5}$ (-1.5 and -1.6 $\mu g/m^3$). Though short-run impacts on emissions are smaller for NYC (32% of total reductions), higher importance of EGU emissions in predicting $PM_{2.5}$ (Figure A6) results in a significant reduction in $PM_{2.5}$ (-1.0 to -1.7 $\mu g/m^3$ (-10 to -15%)). These results suggest that in 2019, re-dispatch of EGUs in response to fuel prices could still notably increase $PM_{2.5}$ concentrations.

Both CAIR and CSAPR, MATS, and other long-run factors are also responsible for large $PM_{2.5}$ reductions (-1.6 to -2.0 $\mu g/m^3$ (-14 to -30%)) because of their SO_2 reductions. Though CAIR is responsible for large NO_x reductions as well, particularly in NYC, these reductions occur almost entirely outside of the ozone season. As a result, our work suggests that an observed increase in urban wintertime ozone concentrations[46] was potentially due to CAIR. In contrast, CSAPR, MATS, and long-run economic impacts reduce NO_x during the ozone season in ATL. Therefore, they reduce ozone concentrations (-2.5 ppb) and have a larger impact on $PM_{2.5}$ than CAIR by 2019.

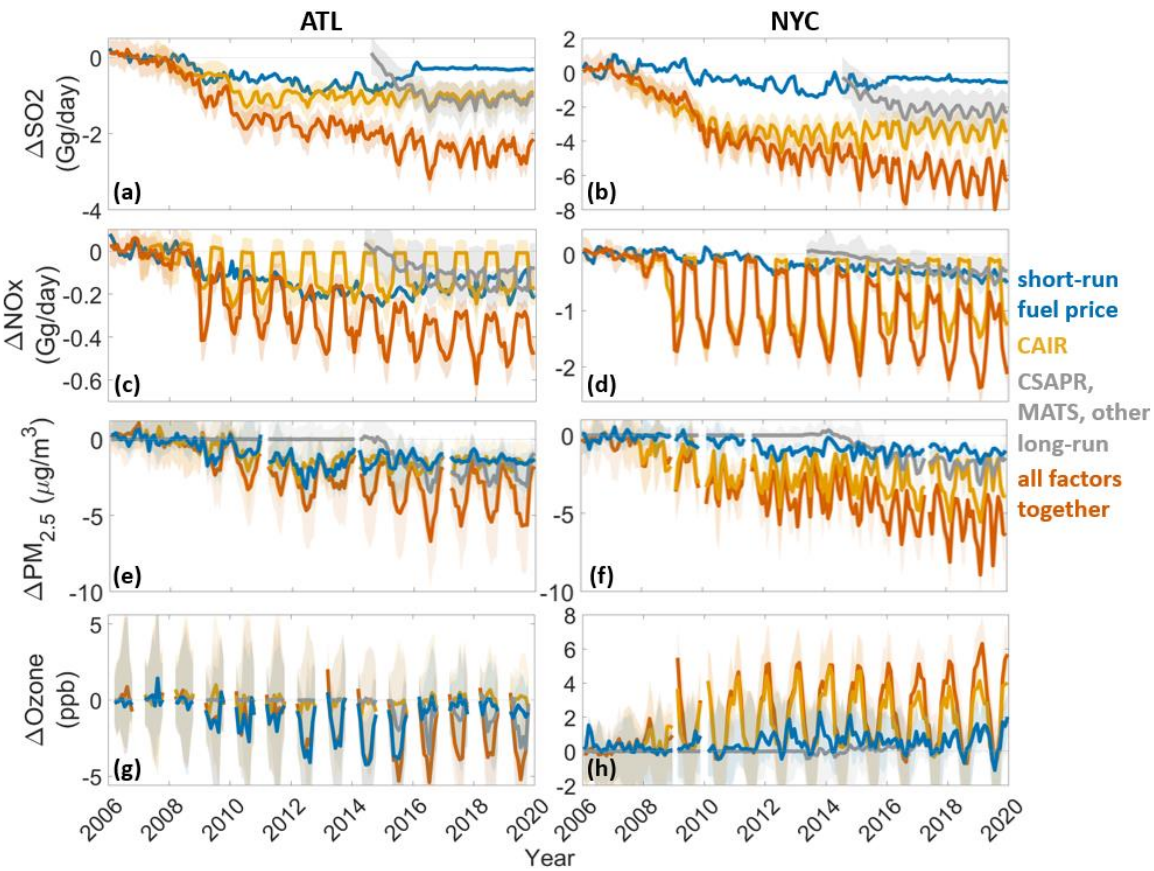

Figure 5. Change in SO_2 emissions **(a, b)**, NO_x emissions **(c, d)**, daily average $PM_{2.5}$ concentrations **(e, f)**, and daily 8-hr maximum ozone concentrations **(g, h)** due to short-run fuel price; CAIR; CSAPR, MATS, and other long-run factors; and all factors together for ATL **(a, c, e, g)** and NYC **(b, d, f, h)**. Shading is the 95% confidence interval. Gray line at 0 indicates no change.

CHAPTER 4. CONCLUSION

4.1 Limitations and Future Work

Additional uncertainties unquantified by our methods arise due to lack of fidelity in our modeling methods and difficulty separating emissions and air quality impacts into distinct factors. Here, we discuss the effect of these limitations on our estimates of air quality impacts, total counterfactual emissions, and short-run counterfactual emissions.

Nonlinear responses of ozone concentrations at NYC sites to ozone season emissions show the difficulty in attributing air quality changes to individual factors. Our counterfactual scenarios do not capture emissions reductions from mobile or residential[48] regulations between 2006 and 2019. Because ozone production regimes at Bronx and Queens may be in transition, perturbations in mobile and residential emissions could greatly affect the magnitude and sign of estimated ozone impacts, which contributes to large ozone impact uncertainties (Figure 4).

We distinguish our total counterfactual estimate that holds base year (2006 and 2007) generating assets constant from a forecast that holds economic, regulatory, and demographic conditions constant. In a forecasted scenario, medium- and long-run changes to EGU ERs would have occurred due to retirement and replacement of old EGUs[24] and changes to the efficiency of EGUs over time.[49] To better separate these impacts from our estimates, future work could employ a model that forecasts investments in generating assets based on market conditions.[5] This has the added benefit of attributing long-run emissions reductions to non-regulatory factors in the later reduction period (2013 to 2017; discussed in Chapter 3.3).

One area we did not explore was that regulations, rather than economic factors, led to emissions controls on NGCC units that contribute greatly to their low NO_x emissions. For example, NGCC EGUs with selective catalytic reduction (SCR) units emit around 90% less NO_x compared to uncontrolled NGCC EGUs.[50] Ultimately, in a counterfactual scenario without additional regulatory drivers, fuel price trends may still shift generation from coal-fired to NGCC EGUs, but the medium-to-long-run NO_x emissions impacts are primarily driven by regulations.

Our configuration of the dispatch model lacks representation of transmission capacity, scheduled EGU outages, EGU start-up costs, EGU ramping, electricity trading across balancing authority area boundaries, emissions allowances, and fuel switching between oil and natural gas. We assume that error from the lack of the former five factors is captured in the uncertainty and parameters of the linear regression between observed and dispatch modeled actual emissions (Figure 2c, 2d).[29,30] Therefore, we only discuss the lack of the two latter factors (allowances and fuel switching) in detail because they are not fully captured in the linear regression and may bias our estimated short-run counterfactual emissions. Inclusion of emissions allowance trading in our model would likely decrease estimated short-run counterfactual emissions because allowance prices impose additional costs on EGUs with high ERs. However, these costs can vary over time based on the pollutant emitted, which results in variable impacts on short-run emissions. For example, SO_2 allowance prices were near or equal to zero following the vacation and remanding of CAIR in 2008,[51,52] so our short-run SO_2 emissions estimates could be reasonable in the period between CAIR and CSAPR. In contrast, NO_x emissions caps remained binding in the early 2010s,[5] so our short-run NO_x emissions estimates may be higher than what the CAIR and CSAPR emissions allowance markets would have allowed. Another complicating factor is that a short-run decision on EGU dispatch that reduces emissions can allow firms to bank their excess emissions allowances. These banked allowances would influence future generation decisions that could increase emissions. Dispatch decisions in response to the prices and availability of emissions allowances are difficult to estimate without computational models due to heterogeneous allowance allocations, banking, and trading under different regulations (Acid Rain Program, NBP, CAIR, and CSAPR).

Some EGUs can switch between natural gas and fuel oil as their primary fuel source without needing large retrofits. These EGUs may choose to burn fuel oil if natural gas prices are relatively high or if natural gas supply is low, which occurs more often in the northeast than the southeast.[53] Though this fuel switching is a short-run behavior (because fuel switching can occur without retrofitting), the dispatch model fails to capture short-term fuel switching because it determines fuel type on an annual basis. This can result in misattribution of short-term oil-fired emissions to natural gas EGUs (or vice versa). These errors are partially captured in the linear regression between modeled and observed actual emissions (Figure 2c, 2d), but in the short-run counterfactual scenario in which gas prices are high perhaps due to lower supply, switching from gas to oil generation could occur more often. This would likely increase estimated short-run counterfactual emissions, particularly for the NYC region during wintertime.[53] Implementation of MATS, however, could discourage EGUs from switching from natural gas to oil due to additional controls required for oil-burning EGUs (defined as EGUs that generate 10% to 15% of their electricity from oil).[8]

Given all of the confounding factors impacting the linkages, future work investigating both fuel switching and emissions allowances would be valuable to further separate regulatory impacts from other contemporaneous impacts.

4.2 Conclusions

Our results suggest that re-dispatch of EGUs due to fuel price trends significantly reduced emissions and air pollutant concentrations in ATL. These impacts were largest between the implementation of CAIR (2009 to 2010) and CSAPR/MATS (2015), in which re-dispatch due to favorable fuel prices can explain all NO_x emissions reductions that coincide with the CAIR ozone season NO_x program. Retirements of highly emitting coal EGUs in 2015 and 2016 have reduced the potential for increased emissions when prices of natural gas are relatively high compared to coal, but notable short-run impacts remain for NO_x emissions and $PM_{2.5}$ concentrations in both NYC and ATL. Given the volatility of natural gas prices, policy makers should ensure that cap-and-trade NO_x programs are stringent enough to prevent potential increases in NO_x emissions[52] and $PM_{2.5}$ should natural gas prices increase.

Longer-term impacts occur primarily in two distinct periods due to the influence of emissions controls (late 2007 to 2010) and coal EGU retirements (late 2013 to 2017), which result in the largest reductions in EGU emissions and $PM_{2.5}$. We attribute installation of controls mostly to CAIR, whereas a confluence of factors contributed to coal EGU retirements. While these factors are difficult to separate, we note that large emissions reductions coincide with coal EGU retirements in response to MATS. Additionally, our results show that the seasonality of medium-to-long-run NO_x emissions reductions significantly affect air quality impacts. Because CAIR primarily reduced NO_x outside of the ozone season, it led to an increase in wintertime daily 8-hour maximum ozone. In contrast, retirements decreased NO_x during the ozone season, which resulted in ozone reductions in ATL and the Manhattan site in NYC.

This work estimated regulatory and fuel price impacts on EGU emissions and air quality between 2006 and 2019. We demonstrated how reduced-form models can capture relationships between fuel prices, electricity generation, EGU emissions, and air pollutant concentrations. As part of a larger air quality accountability study, the impacts and uncertainties estimated in this work will be propagated to impacts on public health. Collectively, these emissions, air quality, and health impacts are important for evaluating the effectiveness of past regulations and for informing future policy.

APPENDIX. SUPPLEMENTAL TEXT, FIGURES, AND TABLES

A.1 Supplemental Text

A.1.1 Changes Made to Base Dispatch Model

We forked the original repository for the dispatch model (Simple Dispatch) from Deetjen and Avezado[29] (github.com/tdeetjen/simple_dispatch). As noted in the main text (Chapter 2.1), two major changes we made were to 1) ensure idled but available coal EGUs were made available for dispatch and 2) allow observed fuel prices to be adjusted to counterfactual average fuel prices. The original publication[29] used weekly observed maximum capacity of EGUs as their maximum capacity (called "historical downtime"). Since our short-run counterfactual scenario raises natural gas-to-coal price ratios to levels unobserved after 2008 (Figure 2e, 2f in main text), this configuration of the model results in unreasonably small changes to the dispatch order. We turn the historical downtime feature off to ensure all non-retired EGUs are available at their yearly maximum observed capacity.

Similar to how the model is unable to capture available but idled coal EGUs, it may not be able to fully capture the maximum generating capacity of coal EGUs in years with low natural gas-to-coal price ratios. Therefore, for coal EGUs, we use the maximum observed capacity over all years (2006-2019) instead of the maximum yearly observed capacity. We note that this prevents the model from capturing periods where EGUs undergo maintenance. However, we run the actual scenario through the configured dispatch model (Figure 1c, 1d) to capture errors that may result from this.

The edited model used for this thesis is available on GitHub (https://github.com/ericjmei/simple_dispatch_total_emissions).

A.1.2 Counterfactual Scenarios Used for Air Quality Impacts

Table A3 shows the emissions impacts included in all scenarios shown in Figure 5 in the main text. Short-run emissions impacts ($I_{short\text{-}run}(d)$) are calculated from the daily difference between short-run counterfactual ($E_{short\text{-}run}(d)$) and actual emissions ($E_{actual}(d)$) (eq. S1):

$$I_{short-run}(d) = E_{short-run}(d) - E_{actual}(d) \tag{S1}$$

Emissions impacts from all factors together ($I_{total}(d)$) are calculated from the difference between total counterfactual and actual emissions (eq. S2):

$$I_{total}(d) = E_{total}(d) - E_{actual}(d) \tag{S2}$$

Emissions impacts from CAIR ($I_{CAIR}(d)$) are calculated by multiplying the spline fits ($f_{CAIR}(d)$) (Chapter 3.3) by the difference between short-run and total counterfactual emissions (eq. S3):

$$I_{CAIR}(d) = f_{CAIR}(d)(E_{total}(d) - E_{short-run}(d)) \tag{S3}$$

Emissions impacts from CSAPR, MATS, and other long-run factors ($I_{other}(d)$) are calculated by multiplying spline fits by the difference between short-run and total counterfactual emissions and subtracting CAIR impacts (eq. S4):

$$I_{other}(d) = f_{other}(d)\big(E_{total}(d) - E_{short-run}(d)\big) - I_{CAIR}(d) \qquad \text{(S4)}$$

Uncertainty for all emissions reductions is assumed to be Gaussian. Uncertainty of impacts from short-run fuel price changes and all factors together are equal in magnitude to uncertainty from short-run and total counterfactual emissions, respectively. We propagate uncertainty to CAIR and CSAPR, MATS, and other long-run factors from estimates of short-run and total counterfactual emissions (Chapter 2.3 in the main text) using their daily standard deviation ($s_E(d)$) (eq. S5, S6):

$$s_{CAIR}(d) = \sqrt{(s_{short-run}(d))^2 + (s_{total}(d))^2} \qquad \text{(S5)}$$

$$s_{other}(d) = \sqrt{(s_{short-run}(d))^2 + (s_{total}(d))^2 + (s_{CAIR}(d))^2} \qquad \text{(S6)}$$

A.2 Supplemental Figures

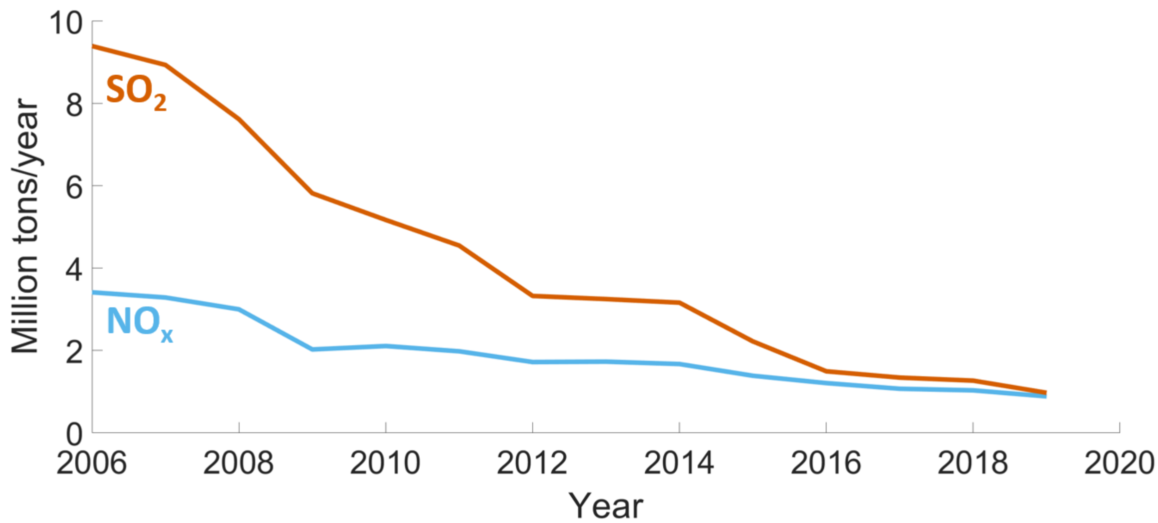

Figure A1. Annual SO_2 (red line) and NO_x (blue line) EGU emissions.[54]

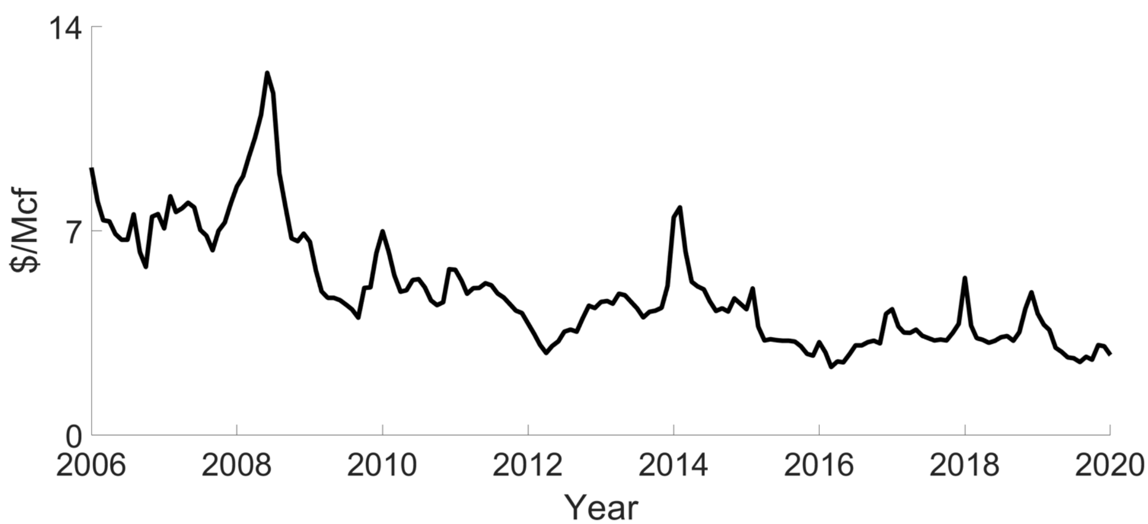

Figure A2. Monthly average nominal natural gas prices in the US.[55]

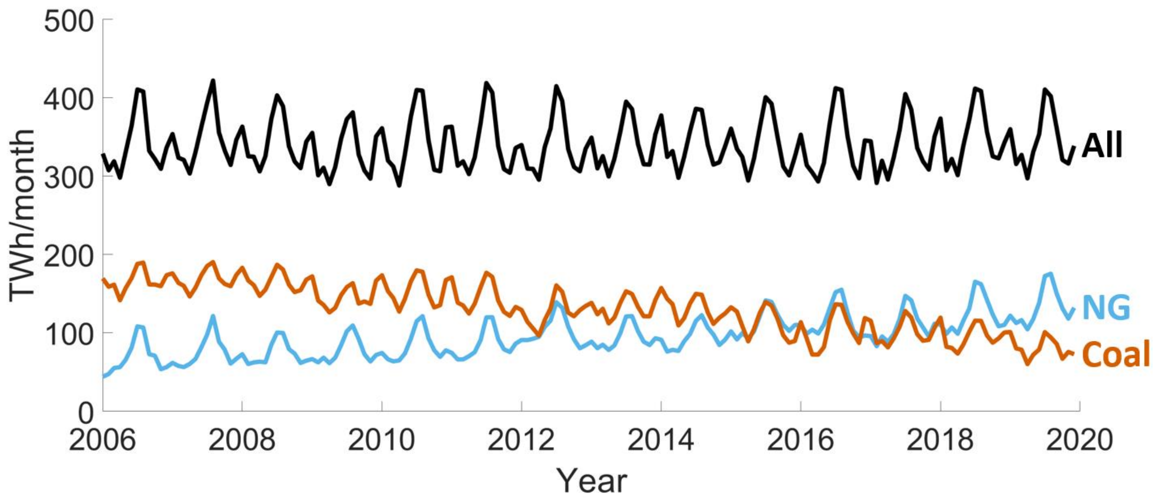

Figure A3. Monthly electricity generation from all sources ("All"), natural gas ("NG"), and coal ("Coal").[56]

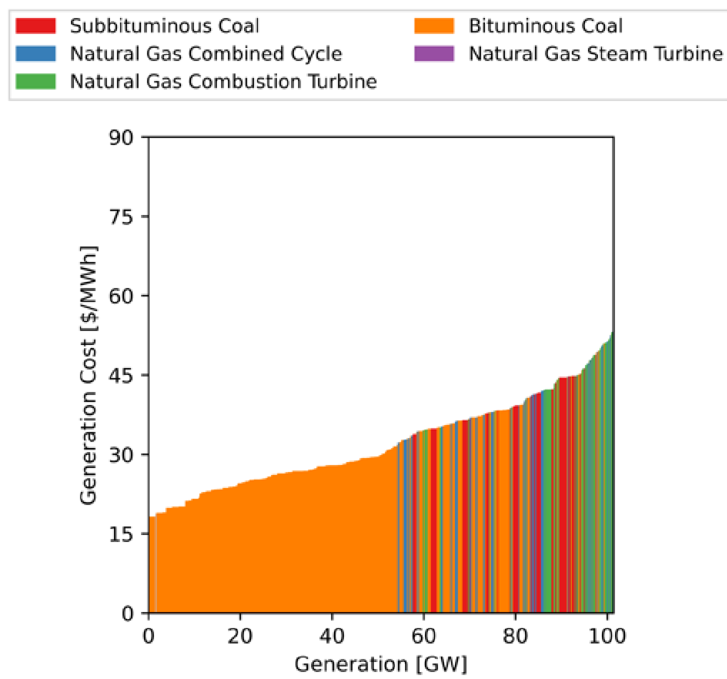

Figure A4. Merit order for fossil fuel demand in PJM during the first week of August, 2011. Each EGU is represented as a bar, in which the width of the bar is the maximum observed capacity of the EGU. See Deetjen and Avezado (2019)[29] for further details regarding the merit order.

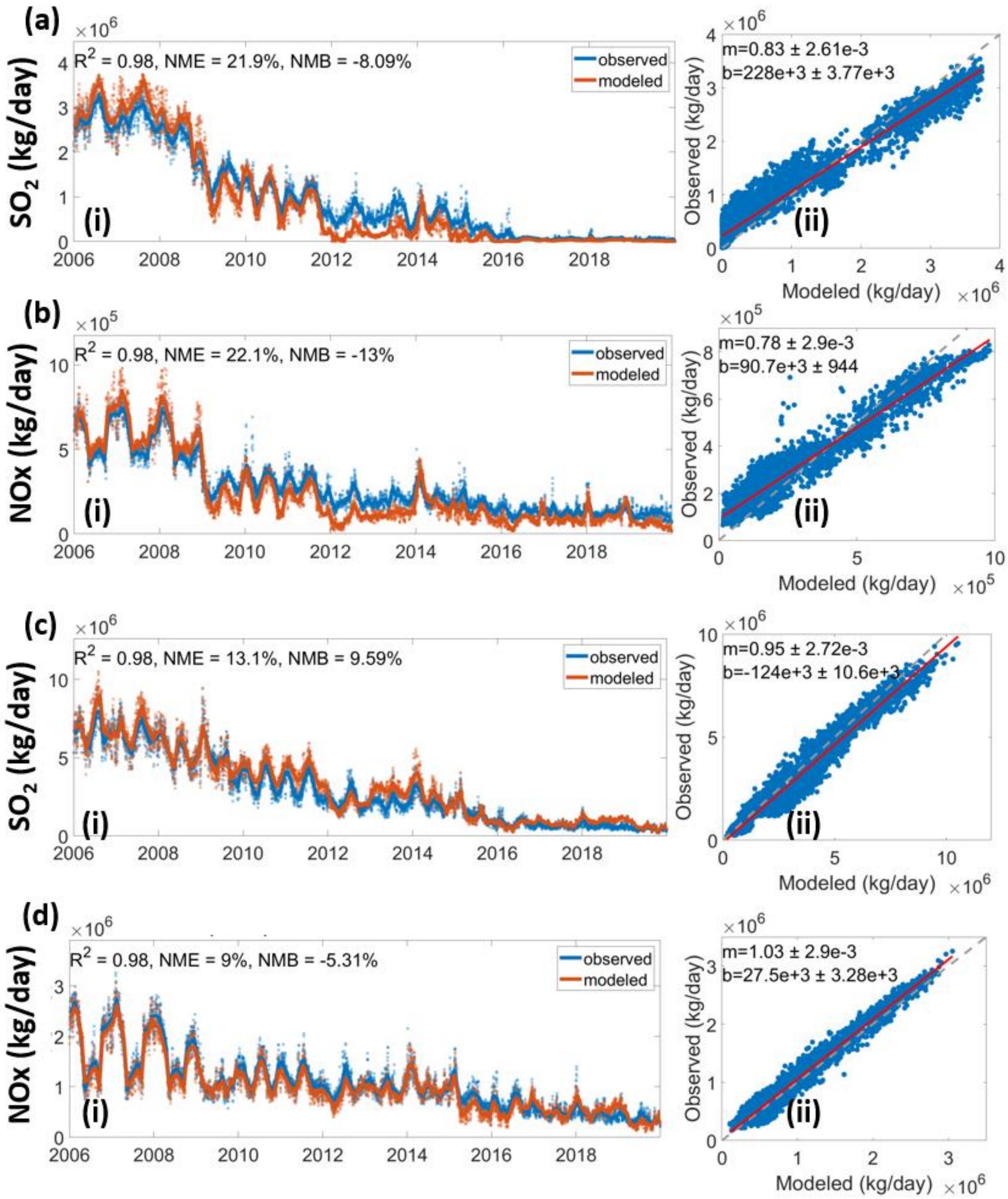

Figure A5. Comparison of observed and dispatch modeled actual SO2 (a, c) and NOx (b, d) emissions in the ATL region (a, b) and NYC region (c, d). (i) Time-series of observed and modeled emissions. Points are total daily emissions; lines are daily values binned to monthly averages. Coefficients of variation (R^2; note that this is different than the coefficient of determination shown in the main text), normalized mean errors (NME), and normalized mean biases (NMB) are shown. (ii) Scatterplots of daily emissions with least squares linear regression in red. One-to-one line shown as dashed gray line. Slopes (*m*) and intercepts (*b*) of linear regression are shown along with their standard errors.

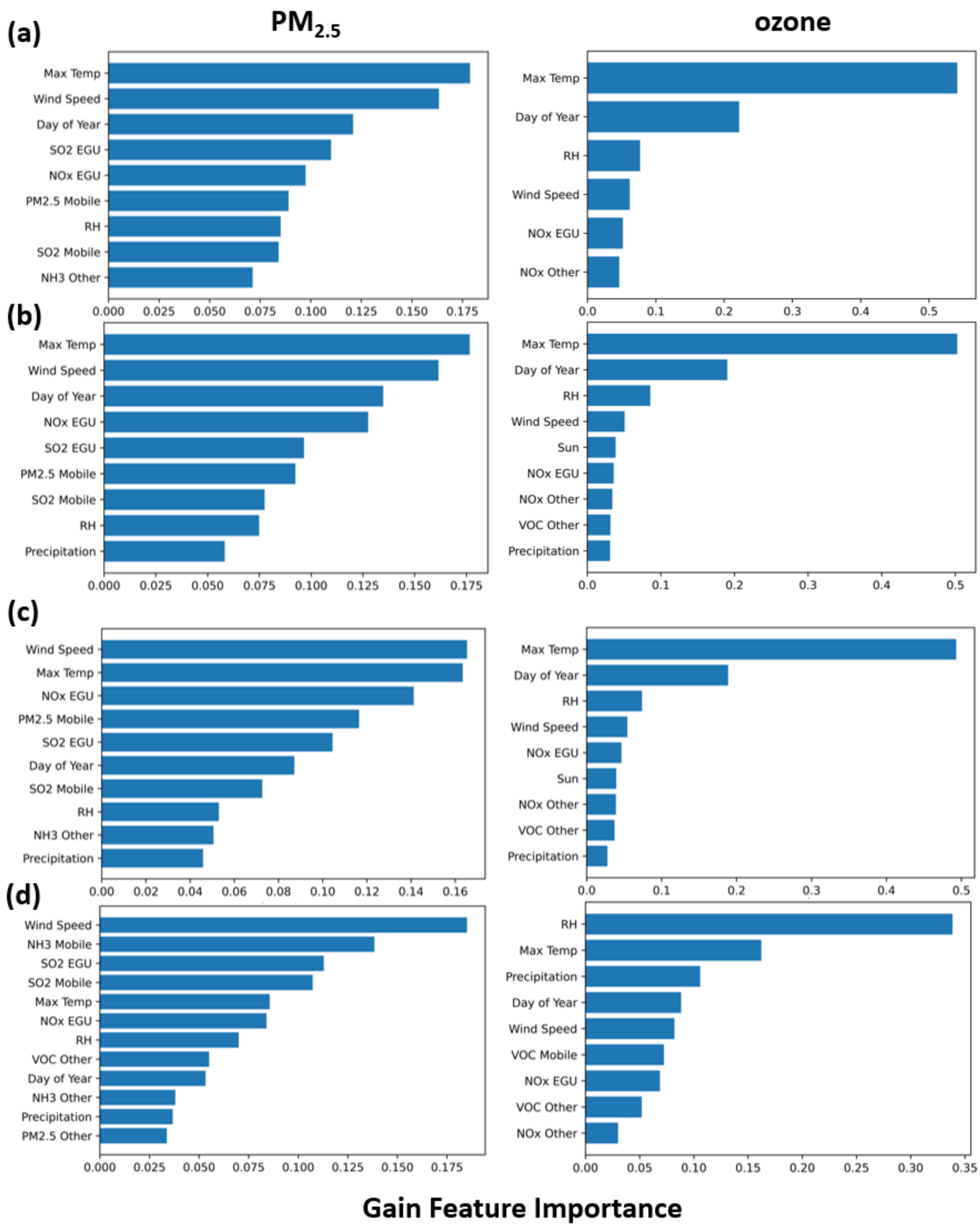

Figure A6. Gain feature importance of ML models for PM2.5 (left) and ozone (right) at Bronx (a), Manhattan (b), Queens (c), and South Dekalb (d).

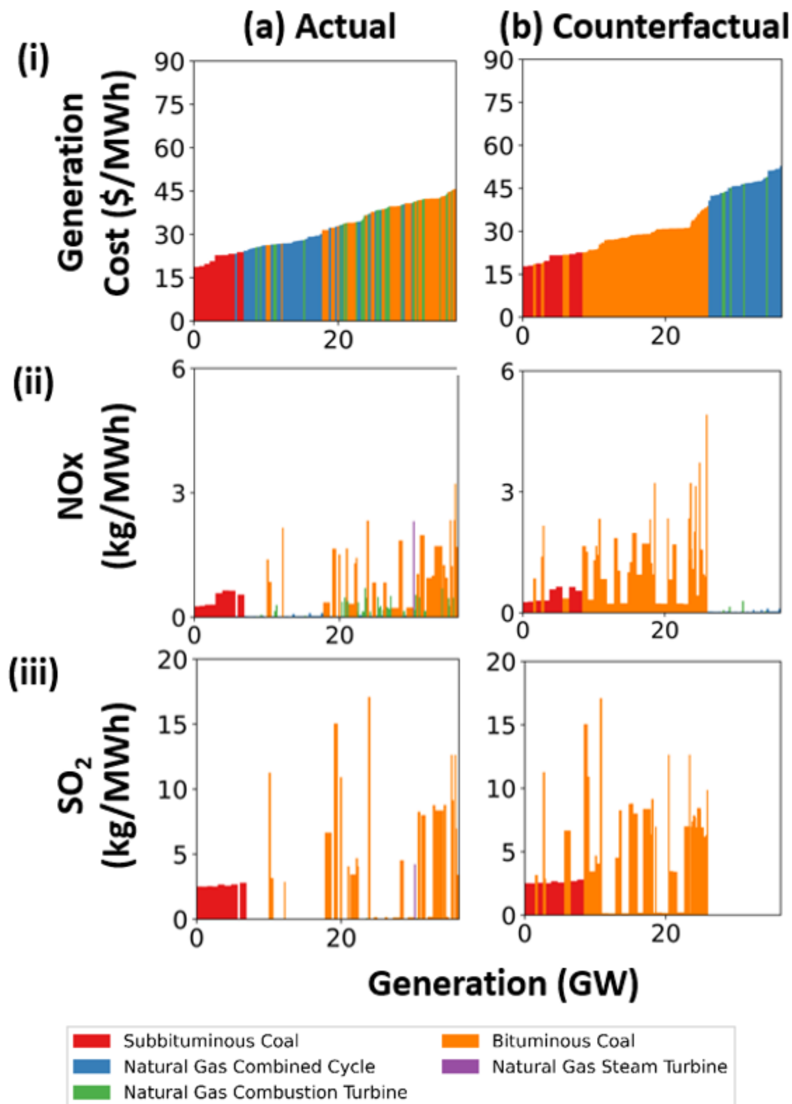

Figure A7. Merit orders (i) with associated emissions rates for NOx (ii) and SO2 (iii) in the actual (a) and counterfactual (b) scenarios in the ATL region in the first week of August in 2009.

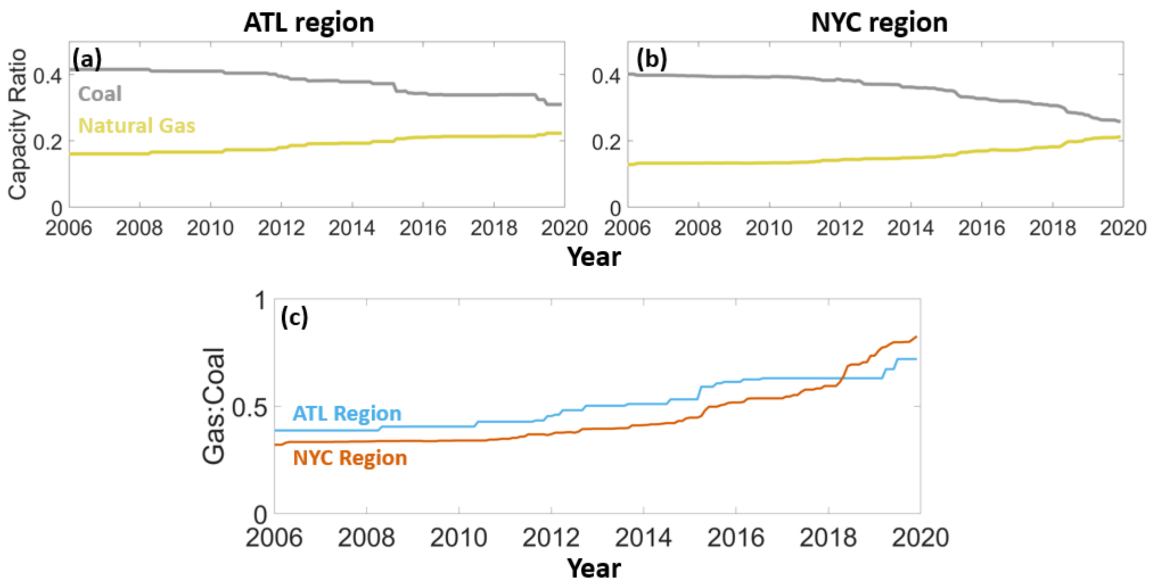

Figure A8. Capacity trends of natural gas combined cycle and coal EGUs. Ratio of installed natural gas combined cycle and coal capacity to total fossil generation capacity for the ATL region (a) and NYC region (b). (c) Ratio of natural gas combined cycle capacity to coal capacity.

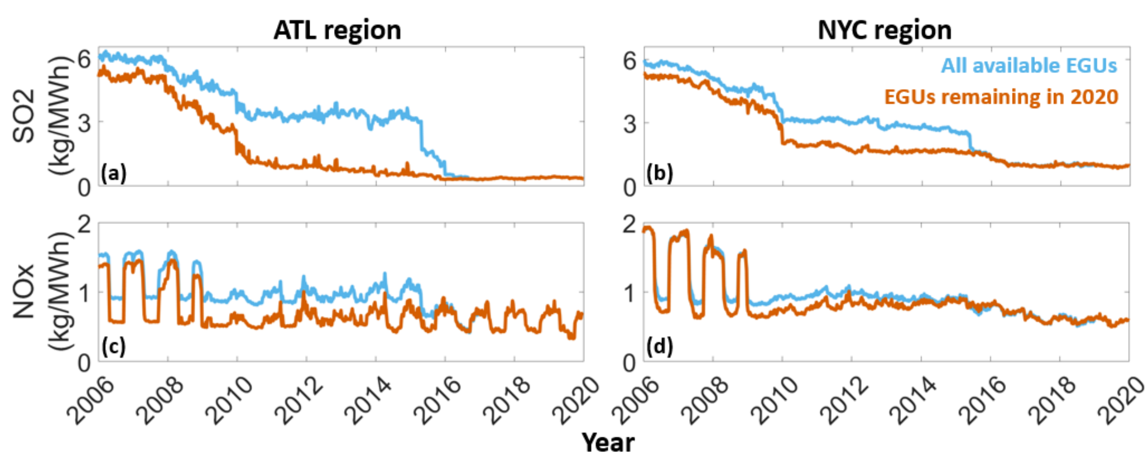

Figure A9. Average emissions rate (ER) trends of coal EGUs of SO2 (a, b) and NOx (c, d) for ATL (a, c) and NYC (b, d) regions. Blue line shows average ERs of available coal EGUs at any given time, and orange line shows average ERs of only coal EGUs that still remain by the end of the period. Average ERs were calculated by weighting individual EGU ERs by their maximum capacities.

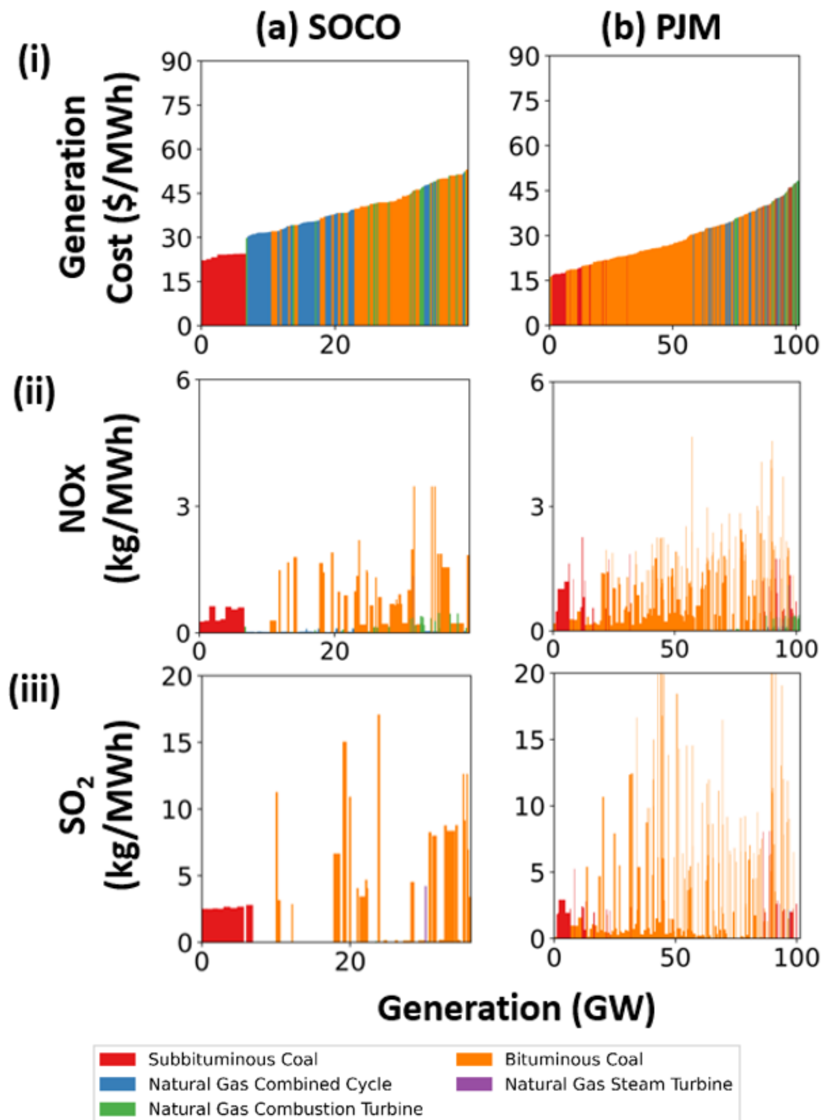

Figure A10. Merit orders (i) with associated emissions rates for NOx (ii) and SO2 (iii) in the actual scenario for SOCO (ATL region) (a) and PJM (part of the NYC region) (b) in the first week of August 2010.

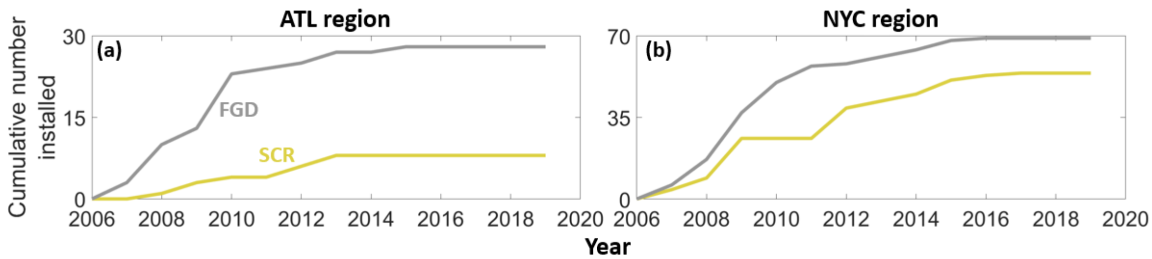

Figure A11. Cumulative number of EGUs on which emissions controls (FGD = Flue Gas Desulfurization, SCR = Selective Catalytic Reduction) were installed for the ATL region (a) and NYC region (b).

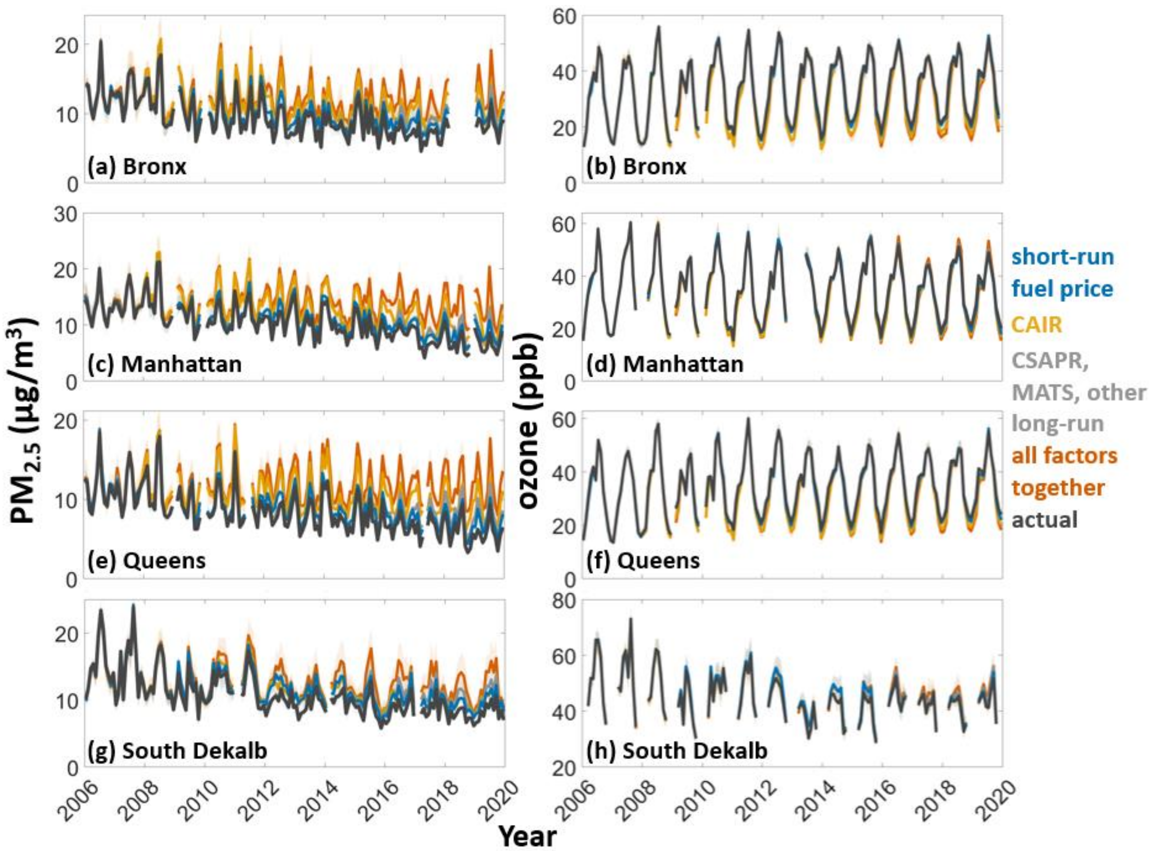

Figure A12. Daily average PM2.5 concentrations (a, b, e, g), and daily 8-hr maximum ozone concentrations (c, d, f, h) for actual and counterfactual scenarios in Bronx (a, b), Manhattan (c, d), Queens (e, f), and South Dekalb (g, h). Shading is the 95% confidence interval.

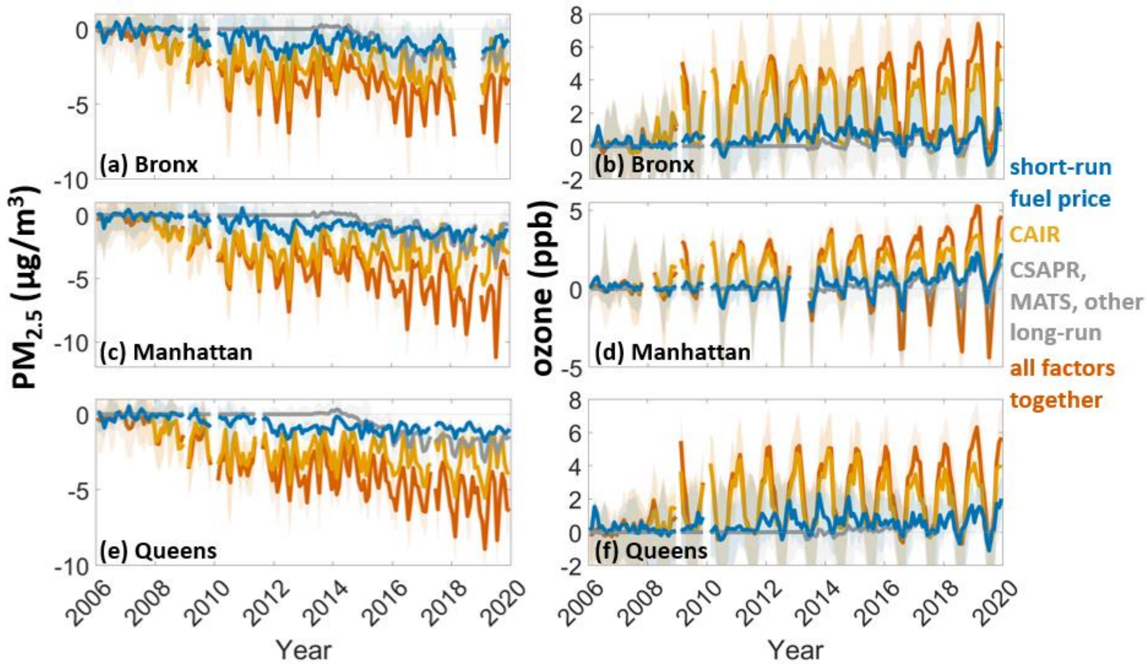

Figure A13. Change in daily average PM2.5 concentrations (a, b, e), and daily 8-hr maximum ozone concentrations (c, d, f) due to impacts for Bronx (a, b), Manhattan (c, d), and Queens (e, f) in NYC. Shading is the 95% confidence interval. Gray line at 0 indicates no change.

A.3 Supplemental Tables

Table A1. Performance of ML models

		Test		Train	
		R^2	RMSE	R^2	RMSE
Bronx	PM2.5	0.58	4.16	0.82	2.75
	ozone	0.78	6.92	0.85	5.66
Manhattan	PM2.5	0.55	3.99	0.76	3.14
	ozone	0.75	7.87	0.87	5.60
Queens	PM2.5	0.60	3.55	0.76	2.80
	ozone	0.76	6.83	0.86	5.60
South Dekalb	PM2.5	0.59	3.60	0.74	2.86
	ozone	0.71	8.23	0.86	5.50

Table A2a. Fractional medium- and long-run SO2 emissions reductions

	ATL	NYC
CAIR	-0.41	-0.51
CSAPR, MATS, other long-run	-0.46	-0.35
Total	-0.87	-0.86

Table A2b. Fractional medium- and long-run NOx emissions reductions

	ATL		NYC	
	Ozone season	Non-ozone season	Ozone season	Non-ozone season
CAIR	-0.02	-0.30	-0.08	-0.51
CSAPR, MATS, other long-run	-0.42	-0.14	-0.31	-0.12
Total	-0.44	-0.44	-0.39	-0.64

Table A3. Emissions included in various scenarios

	Emissions included			
Scenario	Actual	Short-run	CAIR	CSAPR, MATS, other long-run
Short-run	x	x		
CAIR	x		x	
CSAPR, MATS, other long-run	x			x
All factors together	x	x	x	x

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