Firm Behavior under Unanticipated Change in Regulation: Power Plant Emissions during the 2018-2019 Federal Government Shutdown*

Ruohao Zhang[a,b,†], Huan Li[c], Neha Khanna[d]

[a] *Kellogg School of Management, Northwestern University, Evanston, IL*

[b] *Pritzker School of Law, Northwestern University, Evanston, IL*

[c] *Department of Economics, North Carolina A&T State University, Greensboro, NC*

[d] *Department of Economics, Binghamton University, Binghamton, NY*

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Abstract

We show that firms strategically reduce their compliance effort when regulatory stringency unexpectedly declines in short run. We analyze daily air emissions from coal-fired power plants in the United States, using the Environmental Protection Agency's furlough during the 2018 – 19 federal government shutdown as a natural experiment. Using an engineering-based approach we confirm that coal-fired power plants increased daily particulate matter emissions during the furlough of Federal employees by temporarily reducing end-of-pipe pollution control. At the same time, consistent with our expectations, there is no detectable increase in daily emissions of SO_2 and NO_X during the furlough, because they are continuously monitored and the furlough did not represent a change in regulation stringency for these pollutants.

Key words: government shutdown, strategic behavior, air pollution, power plant, aerosol optical depth, furlough, regulation, PM, SO_2, NO_X

JEL codes: D22 H41 Q52 Q53

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† Corresponding author: Ruohao Zhang: ruohao.zhang@kellogg.northwestern.edu; Address: 2001 Sheridan Rd, Evanston, IL 60208. Huan Li: hli1@ncat.edu. Neha Khanna, Email: nkhanna@binghamton.edu.

1 Introduction

We analyze firm responses to unanticipated and temporary changes in environmental regulation which may change unexpectedly in the short-term for exogenous reasons. For instance, the United States Environmental Protection Agency (EPA) typically issues No Action Assurances waiving specific regulations during emergencies caused by natural disasters such as hurricanes.[1] Lapses in appropriation is another scenario where the stringency and enforcement of regulations can be interrupted. Associated with government shutdowns, lapses in appropriations result in the furlough of employees and a temporary halt in enforcement activities. As a consequence of these temporary policy modifications, regulation becomes less stringent, offering opportunities for firms to be temporarily non-compliant with regulatory policy without the threat of being penalized.

A large literature has studied firms' responses to environmental regulation (Carlson et al., 2000; Greenstone, 2002; Curtis, 2020; Gibson, 2019; Calel, 2020; Zhou et al., 2020). In most cases, firms respond with adopting off–the–shelf pollution control technologies. For example, when the EPA started the Acid Rain Program in 1995, a cap–and–trade program to reduce SO_2 emissions from fossil–fueled power plants, the installation of scrubbers at electricity generating units increased by 50% between 1995 and 2002 (Chan et al., 2018). Similar findings have been reported under the NO_X Budget Trading Program, which also regulates stationary sources of emissions since 1999 (Linn, 2008; Fowlie, 2010). Technological innovation is another response to environmental regulation. For example, Calel (2020) finds that the European Union's Emission Trading System encouraged firms to innovate low–carbon technologies, but had little effect on the adoption of existing abatement technologies.[2] In addition to technological responses, firms often initiate environmental management plans in reaction to (anticipated) changes in regulation. These self–motivated compliance efforts typically include decentralized and voluntary self–regulation plans aimed at improving environmental performance and eventually lowering the likelihood of being inspected or penalized for poor performance (Khanna and Damon, 1999; Li and Khanna, 2018).

Different from long term adaptation, in the short run firms rely exclusively on existing

[1]For example, to minimize problems with the supply of gasoline due to Hurricane Florence in 2018, EPA waived the federal requirements for the Reid vapor pressure test (a standard measure of the volatility of liquid fuels) for fuel sold in designated areas in North Carolina, South Carolina, Georgia, and Virginia. Archived responses to Hurricane Ida, Laura, Michael, Florence, Harvey, Irma, and Maria are available at: https://www.epa.gov/hurricane-response.

[2]This is in line with the Porter Hypothesis: strict environmental regulation motivates firms to innovate, which ultimately improves firm competitiveness and profitability (Porter and Van der Linde, 1995). Similar findings have been reported in several other studies (Jaffe and Palmer, 1997; Popp, 2006; Arimura et al., 2007; Johnstone et al., 2010; Lanoie et al., 2011; Taylor, 2012). Popp (2019) provides a comprehensive review of environmental policy and innovation.

technologies and operation methods to comply with changes in regulation or regulation stringency. Zou (2021) shows that firms are able to strategically change their emissions on a daily basis in response to planned changes in EPA's monitoring of particulate matter concentrations. The question that remains unanswered is whether firms make strategic short–term changes in emissions and abatement behaviors in response to unanticipated regulation shocks. We focus on the 2018–19 U.S. federal government shutdown, and ask the empirical question whether and to what extent coal–fired power plants, among the most highly regulated entities in the U.S., emitted more pollutants during the shutdown. The 2018–19 federal government shutdown lasted from midnight on December 22, 2018, through January 25, 2019, in total 35 days, making it the longest federal government shutdown in U.S. history. Among many other impacts, we expect the impact on environmental quality to be significant because federal EPA employees did not carry out any duties during the shutdown, including pollution inspection and monitoring.[3] According to the EPA contingency plan both before (September 25, 2018) and during (December 31, 2018) the 2018–19 shutdown, the shutdown activities were accomplished within only 4 hours, shrinking the total number of active agency employees from more than 14,000 to less than 1,000; roughly 95% of Agency staff were furloughed.[4] None of the employees retained during the shutdown were engaged in inspection and enforcement activities. Thus, the EPA's furlough during the most recent U.S. federal government shutdown provides an exogenous short–run shock in environmental regulation, allowing us to study firms' short–run strategic behavior in response to an unanticipated and temporary change in regulation stringency.

Our empirical strategy is motivated by a theoretical model based on Maxwell and Decker (2006) in which a representative firm chooses its environmental effort to minimize the overall cost of emissions, which is determined as the sum of the expected violation penalties and the cost of environmental effort. The model indicates that a negative shock that weakens the stringency of regulation reduces the probability of being inspected by the regulator. Firms invest less environmental effort and release higher emissions in response to the lower probability of being inspected and triggering a pollution violation.

We implement a difference–in–differences framework to estimate the causal impact of the 2018–19 U.S. federal government shutdown and the subsequent furlough of federal EPA employees on coal–fired power plants' emissions. Because the government shutdown applied universally to all coal–fired power plants in the U.S., there is no clearly defined

[3] https://epa.gov/sites/production/files/2018-12/documents/agency_shutdown_faqs_12282018.pdf

[4] U.S. EPA Contingency Plan for Government Shutdown: https://www.epa.gov/sites/production/files/2018-12/documents/epa_contingency_plan_december_18_2018_508.pdf. Two other agencies that were severely affected is the National Science Foundation (99% employee furloughed) and NASA (95% employee furloughed). Unlike the NSF and NASA, the EPA undertakes inspection and enforcement actions.

contemporaneous control group available for estimating the counterfactual. Hence, we use emissions from the same coal–fired power plants on the same dates during the previous 5 years, 2013–14, 2014–15, 2015–16, 2016–17, and 2017–18, to generate the counterfactual 2018–19 emissions.

The short time span of the shutdown (EPA furlough) treatment poses a particularly challenging problem for our study because most emissions data are reported on an annual or monthly basis. To overcome this empirical difficulty, we use several high frequency data sources including the EPA's Air Markets Program Data (AMPD) and satellite–based Aerosol Optical Depth (AOD). AMPD provides daily power plant emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_X), carbon dioxide (CO_2), daily heat input and daily electricity and steam production. The satellite–based AOD data correlate with daily particulate matter concentration in the areas surrounding power plants.

We focus on SO_2, NO_X, and particulate matter emissions and test whether the government shutdown caused empirically detectable changes in their emissions. We expect that the shutdown had a heterogeneous effect on the regulation stringency of these pollutants. Specifically, SO_2 and NO_X are continuously monitored via devices at individual generating units at each plant under the Acid Rain Program and NO_X Budget Trading Program. Hence, the temporary furlough of federal EPA inspectors had no appreciable effect on the stringency with which these two pollutants are regulated and plants had a negligible incentive to strategically reduce the emissions of these pollutants during the furlough. In contrast, fine particulate matter emissions are not continuously monitored on-site at individual plants. Instead, the EPA monitors the ambient concentrations of PM_{10} and $PM_{2.5}$ at roughly 1,200 monitoring sites across the country. These monitors use filters and require manual operation including routine field sample collection Zou (2021). In addition, EPA inspectors may visit individual polluters for on-site stack tests. Hence, the furlough of EPA employees represents a tangible reduction in the stringency of particulate matter regulation and enforcement. This hiatus in enforcement related activities during the furlough offered plants the opportunity to strategically reduce their compliance effort and increase their particulate matter emissions. Consistent with out expectations, our empirical results provide evidence that during the government shutdown, coal-fired power plants temporarily reduced end-of-pipe particulate matter pollution control during the government shutdown, significantly increasing their PM emissions. However, we find no evidence of the increase in SO_2 and NO_X emissions during the government shutdown.

The paper proceeds as follows. In section 2, we present the theoretical model outlining how regulation shocks affect a firm's environmental effort in pollution abatement as well as its emission levels. In section 3 we present our empirical identification strategy and data details. Section 4 describes our data. Section 5 reports the baseline empirical results and assesses the robustness of these results. In section 6, we identify the factors driving our results. We conclude our paper in section 7.

2 Conceptual Motivation

We consider a setting similar to Maxwell and Decker (2006) to model a firm's response to changes in regulation. We assume a representative firm chooses its *compliance effort* to minimize the expected cost of compliance, which is the summation of expected penalties from being inspected with violation and the cost of compliance efforts. Compliance effort lowers the probability of triggering a violation. We assume that in the short–run (i) firms take the probability of being inspected and the associated violation penalties as determined by the regulator and exogenous to their contemporaneous compliance behavior;[5] and (ii) firms are not able to change their long–run characteristics by adopting new compliance or production technologies and managerial skills.

Consider that a firm chooses its compliance effort x, such that the probability of compliance is $p(x) \in [0, 1]$. $p(x)$ increases with x at a decreasing rate (an increasing and concave function of x). $1 - p(x)$ is the probability of violation. The cost of compliance effort is $g(x; \theta)$. θ is the firm's characteristics, and $g(\theta, x)$ is an increasing and convex function of x. Let $m \in [0, 1]$ be the probability that the firm will be inspected by the regulator, and f be the penalty if violations are found during the inspection. We define a shock in regulation as an exogenous change in m. We assume the regulator is not able to strategically change inspection probabilities and violation penalties in response to the firm's compliance performance in the short-run, and the firm cannot strategically change its characteristics. That is, we assume that m, f and θ are exogenous and taken as given by the firm.

The firm's objective is to choose its compliance effort so as to minimize the expected total cost of regulation:

$$\underset{x}{min}\ E(C) = (1 - p(x))mf + g(\theta, x) \tag{1}$$

The firm chooses the optimal compliance effort $x^* = x^*(m, f, \theta)$ according to the first order condition:

$$mf \frac{\partial p(x^*)}{\partial x^*} = \frac{\partial g(\theta, x^*)}{\partial x^*}, \tag{2}$$

where the marginal benefit of the firm's compliance effort, represented by the expected reduction in violation penalties (left-hand side of the equation 2) equals the marginal cost of increasing compliance (right-hand side of the equation 2). The optimal compliance

[5] Examples include OSHA inspections on workplace safety or EPA inspections on pollution abatement.

effort $x^*(m, f, \theta)$ increases in both the likelihood of being inspected (m) and the violation penalty (f), since they each increase the marginal benefit of compliance effort.[6]

3 Power Plant Emissions during the Federal Government Shutdown

Our theoretical framework implies that firms strategically change their compliance effort when faced unanticipated lenience in environmental regulation. We test the empirical validity of this implication by examining power plant emissions during the 2018–19 federal government shutdown. In the U.S., power plant emissions are regulated under the Clean Air Act (CAA), which is enforced by the U.S. EPA and local environmental authorities via on–site inspections, continuous on–site monitoring, and other strategies. During the 2018–19 federal government shutdown, the EPA adopted its contingency plan to furlough about 95% of federal employees, thereby suspending inspection activities. Therefore, the EPA furlough had the effect of exogenously lowering the environmental regulation burden in the short–run, and offers a natural experiment to examine firms' response to the unanticipated shocks in regulation.

To apply the theoretical framework to the federal government shutdown, consider a power plant with emissions level $e(x;\theta)$, where θ and x denote the plant's characteristics and compliance effort, respectively. Emissions are negatively associated with compliance effort, i.e., $e(x;\theta)$ is a decreasing function of x, and a negative shock in environmental regulation (i.e., a decrease in the probability of being inspected) decreases the firm's compliance effort and increases its emissions. That is, $\frac{\partial e(x^*(m_t, f_t, \theta);\theta)}{\partial m_t} < 0$.[7] This property leads to our testable hypothesis: *During the U.S. federal government shutdown (EPA furlough), coal-fired power plants increased their air emissions.*

3.1 Power plant emissions under the Clean Air Act

The CAA has played a critical role in improving air quality in the U.S. since it was first enforced by the EPA in 1970. Under the CAA, the EPA established national ambient air quality standards (NAAQS) for six criteria pollutants (PM, O_3, SO_2, NO_X, CO, and lead), and requires states to take enforceable actions to meet the air quality standards. Over nearly 50 years, the combined emissions of these six common pollutants dropped by 77% (https://www.epa.gov/air-trends). This progress is partly attributed to the Clean Air Act Amendment (CAAA) in 1990. This amendment introduced a cap on the total

[6] See proof in Appendix A.1.

[7] We remain agnostic about the curvature of $e(\theta; x)$.

amount of SO_2 and NO_X emissions that can be emitted by power plants nationwide. Under such cap–and–trade programs, power plants have incentives to increase abatement when their abatement cost is less than the market price of allowances. Given the stringent air regulations that the power plants face, any interruption or relaxation of the CAA enforcement by the EPA would encourage power plants to raise emissions in order to seize immediate albeit temporary benefits.

3.2 Empirical identification

The timeline for the EPA's furlough was slightly different from the official shutdown period, as the EPA used its available funds to maintain regular operations for one additional week, and reopened on the Monday after the weekend when the federal government announced the end of the shutdown. Thus the EPA employee furlough extended from December 29, 2018, to January 27, 2019, 30 days in total, which was the time period during which coal-fired power plants experienced an unanticipated decrease in regulation stringency.

Since the federal government shutdown was a universal event for all power plants, there is no obvious contemporaneous counterfactual measurement. Instead, we use emissions from the same group of power plants, but from different points in time to generate their own counterfactual measurements. The underlying assumption is that, conditional on observable confounders, the daily trend in power plant emissions does not vary dramatically year by year. However, a single past year of data might deviate from the trend in the shutdown year due to randomly occurring though unobserved events, so we use the previous 5 years data to smooth out any abnormalities. To be specific, we use the average emissions on the same month-day (December 29–January 27) from the previous 5 years (2013–14, 2014–15, 2015–16, 2016–17, 2017–18) to obtain counterfactual measurements. For simplicity, we refer to December 29–January 27 in every year of our data as the furlough days; 2018–19 as the shutdown year; and 2013–14, 2014–15, 2015–16, 2016–17, 2017–18 as the previous 5 years.

We compare emission outcomes before and during the furlough days, between the shutdown year and the previous 5 years in a difference-in-differences framework. In our full sample, we use data on a daily frequency from October 22 to January 27, giving us 14 weeks in total including 68 days prior to the EPA's furlough and 30 furlough days. We do not acquire data from earlier dates before October 22 because: earlier months are associated with different seasonal patterns in both air pollution and electricity usage that may weaken the validity of our model.[8] Our benchmark model reads as follows:

[8]For example, Zhang et al. (2021a) find a strong seasonal pattern in particulate matter pollution.

$$Y_{ijt} = \alpha X_{ijt} + \beta D_{ijt} + \text{Plant}_i \times \text{Weeks}_t + \text{Year}_j + \text{Weekdays}_{jt} + \text{Date}_t + \text{Plant}_i + \epsilon_{ijt}. \quad (3)$$

where i is the plant index, j is the year index, and t is the date index (month–day of each year). Y_{ijt} is daily emissions. D_{ijt} is the shutdown dummy with $D_{ijt} = 1$ if the observation falls between December 29, 2018 and January 27, 2019, and $D_{ijt} = 0$ otherwise. X_{ijt} is vector of the time–varying covariates including daily weather variables and electricity and steam generation.[9]

In addition to X_{ijt}, we include a series of fixed effects to ensure that the remaining variation in the outcome variables is solely due to the EPA's furlough, allowing us to isolate β as the causal impact of the furlough on the outcome variable. The plant fixed effect (Plant_i) captures time invariant plant specific characteristics. The days of week fixed effect (Weekdays_{jt}) captures the variation in electricity demand or other social economic activities across the days of the week.[10] The date (month-day of each year) fixed effect (Date_t) is the time fixed effect, capturing the average time trend on a daily basis across different years. The year fixed effect (Year_j) captures both the differences across years and the intercept difference between the treated group and the control group. In addition, our model includes a plant-by-week fixed effect ($\text{Plant}_i \times \text{Weeks}_t$), allowing a plant-specific time trend on a weekly basis. The definition of week is based on 2018–19, from Monday to Sunday.[11]

4 Data

4.1 Data description

We create a plant–by–day data set that includes coal-fired power plants in the continental U.S. Compiled from multiple data sources for each power plant, we obtain daily information on air emissions, aerosol concentration surrounding each power plant, operational information, and weather.

The list of coal–fired power plants is extracted from the U.S. Energy Information Administration (EIA), including the Annual Electric Generator Report (EIA-860); the Monthly Update to Annual Electric Generator Report (EIA-860M); and the Power Plant Operation Report (EIA-923) (https://www.eia.gov/electricity/data/browser/). As of

[9] We use the level of emissions instead of natural log because the engineering relationship between emissions and is expected to be linear.

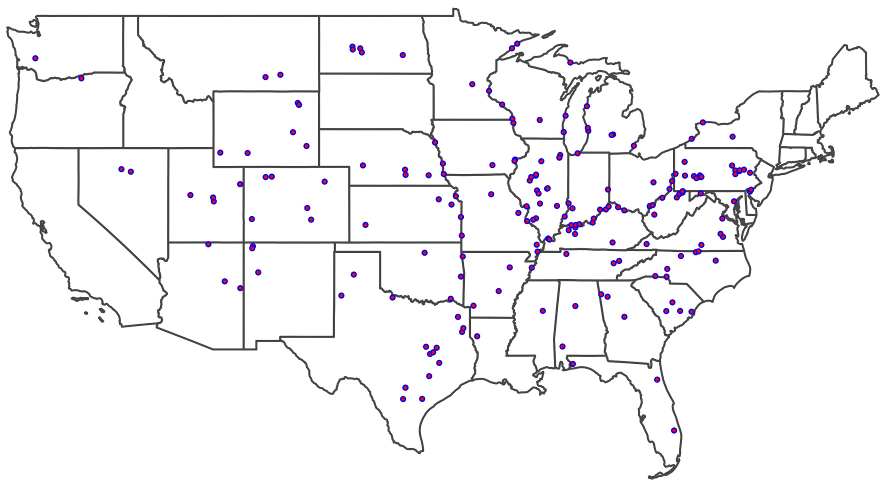
[10] Electricity demand is generally lower on weekends than it is on the weekdays because many businesses are closed and less electricity is demanded for lighting and electronic equipment.

[11] The starting date of our sample, October 22, 2018, is a Monday.

April 2019, 303 out of 9,047 power plants in the lower 48 states use coal as their primary fuel source, out of which 233 are pure coal-fired power plants, with coal as the only fuel source.[12]

We obtain daily emissions and operational data from the EPA's Air Market Program Data (AMPD) under the Clear Air Markets program. The AMPD provides extensive daily data on power plants with capacity greater than 25 megawatts. The data we collect includes electricity generation, steam production, heat input, as well as air emissions of SO_2, NO_X, and CO_2.[13] The daily emission data for SO_2 and NO_X are recorded by a continuous emission monitoring system and a flow monitoring system installed in each coal–fired unit, as required by EPA federal regulation code.[14] We were able to obtain data for 204 out of the 233 coal–fired power plants over our study period: October 22 to January 27, of the shutdown year (2018–2019) and the previous five years (2013–2014; 2014–2015; 2015–2016; 2016–2017; 2017–2018). Figure 1 shows the location of the power plants in our sample.

Figure 1: Location of coal-fired power plants



Another primary outcome variable of interest is the concentration of aerosols surrounding each power plant, as it correlates with fine particulate matter emission from

[12] Although the number of coal–fired power plants is relatively small, they usually have very high capacity. In 2019, coal accounts for 23.4% of the total electricity generation in U.S., which is the second–largest source for electricity after natural gas.

[13] We do not use CO_2 as our primary outcome variables because CO_2 emissions are not currently subject to regulation. However, we use CO_2 emissions and heat input to identify the mechanism underlying the effects of the government shutdown on the three targeted pollutants. See section 6.

[14] https://www.ecfr.gov/, see title 40, chapter I, subchapter C, part 75.10. Not all coal-fired power plants are required to install the continuous emission monitoring system (title 40, chapter I, subchapter C, part 75.2).

the power plants. We take advantage of NASA's satellite based measurements of AOD, a high-frequency and high resolution measure retrieved by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's satellites. The literature has shown that AOD is a good predictor of PM of different sizes: $PM_{2.5}$ (diameter $< 2.5 \mu m$) and PM_{10} (diameter $< 10 \mu m$) (Liu et al., 2004; Donkelaar et al., 2016).[15] Higher AOD indicates higher PM pollution.[16] Following Zhang et al. (2021b), we measure the aerosol concentration as an area–weighted average AOD in a circular area of 3 km radius around each power plant.

Our data also includes daily measurements for the following weather variables: precipitation, temperature, dew point, and wind speed. These variables are included as control variables in our regression model because they account for the correlation between weather conditions and electricity production. Weather may also affect the moisture level of coal, which further affects the heat content and thus emissions (Chandralal et al., 2014). Finally, the weather variables are included in order to remove any confounding effects of weather on aerosol concentration and weather (Kumar et al., 2007; Foster et al., 2009; Zhang et al., 2021b).

We collect the daily precipitation, temperature, and dew point data from Parameter–elevation Regressions on Independent Slopes Model (PRISM), a spatial climate database (http://prism.oregonstate.edu). PRISM data are available at a spatial grid of 4 km^2, which is comparable with the spatial resolution of the AOD data. We extract daily wind data from the National Centers for Environmental Prediction (NCEP)-U.S. Department of Energy (DOE) Reanalysis II (NCEPRII) (https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html). These data are at a resolution of 2.5 degree in latitude and longitude. We assign wind speed and direction to each power plant depending on the 2.5 degree square the power plant is located in.

Table 1 summarizes all of the key variables by year in the first 6 columns, and for the whole sample in the last column.[17] On average, we observe a declining trend in SO_2, NO_X and CO_2 emissions. AOD is also declining, though it rises in 2018-19. Electricity production and heat input decrease from 2013–14 to 2015–16, but rise back and stay stable from 2016–17 to 2018–19. Except for wind speed, the weather variables

[15] AOD, or aerosol optical depth, measures the degree to which aerosols prevent transmission of light by absorption or scattering of light through the entire vertical column of atmosphere from ground to satellite sensors. AOD is a unit–less measure.

[16] When using AOD to predict $PM_{2.5}$, there is a slight downward bias when the AOD/$PM_{2.5}$ concentration is high (Fowlie et al., 2019).

[17] The number of AOD observations (N=35,559) is much smaller than the number of observations for other pollutants (N=163,998). This is because the accuracy of the AOD measurement can be affected by cloud and snow covers, and MODIS excludes all unreliable AOD observations. We also conduct event studies using the short sample, and find that there are no significant group differences during the pre–treatment period for all three pollutants.

Table 1: Descriptive Statistics

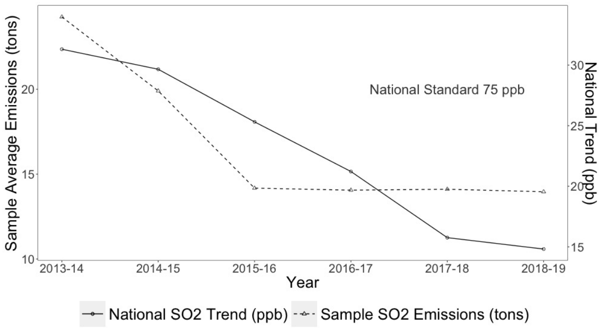
	Subsample by Year						Full Sample
	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2013-19
SO_2 (tons)	24.26	19.90	14.18	14.06	14.11	13.96	16.91
	(39.11)	(35.86)	(22.48)	(19.45)	(20.20)	(21.22)	(28.21)
NO_x (tons)	15.91	13.85	11.17	11.80	11.23	11.14	12.59
	(17.27)	(15.52)	(12.59)	(13.06)	(11.80)	(11.73)	(14.02)
AOD (unitless)	0.13	0.12	0.11	0.11	0.11	0.12	0.12
	(0.15)	(0.12)	(0.12)	(0.14)	(0.12)	(0.14)	(0.13)
CO_2 (1,000 tons)	17.63	16.20	13.71	15.54	15.46	15.66	15.73
	(15.11)	(13.80)	(12.47)	(13.74)	(13.41)	(13.61)	(13.78)
Electricity Production (gWh)	17.06	15.68	13.05	14.90	14.86	15.09	15.14
	(15.63)	(14.22)	(12.74)	(14.10)	(13.88)	(13.97)	(14.19)
Steam Production (10^6 lbs.)	4.45	3.95	3.63	3.68	3.83	3.45	3.84
	(18.47)	(17.54)	(14.19)	(14.12)	(15.24)	(14.18)	(15.80)
Heat Input (10^3 mmBtu)	170.07	156.37	132.68	150.11	149.53	151.36	151.99
	(143.65)	(131.66)	(118.63)	(130.66)	(127.59)	(129.56)	(131.19)
Precipitation (mm)	2.00	1.89	2.81	1.92	2.14	2.85	2.26
	(6.42)	(5.66)	(8.85)	(5.61)	(6.52)	(7.60)	(6.87)
Temperature (°C)	0.81	1.91	4.77	4.78	2.46	1.98	2.75
	(8.68)	(8.33)	(8.01)	(8.51)	(8.48)	(7.87)	(8.46)
Dew Point (°C)	−5.07	−3.96	−1.06	−1.37	−3.71	−2.58	−3.00
	(8.57)	(8.34)	(8.43)	(8.65)	(8.80)	(8.03)	(8.60)
Wind Speed (m/s)	5.50	5.27	5.59	5.69	5.49	5.19	5.46
	(2.83)	(2.72)	(2.97)	(2.94)	(2.81)	(2.81)	(2.86)
Number of Plants	200	202	203	200	198	197	204
Number of Observations (SO_2 & NO_x Sample)	29,282	28,641	27,031	26,596	26,431	26,017	163,998
Number of Observations (AOD Sample)	6,052	5,726	6,135	6,819	6,121	4,706	35,559

Note: The first five columns report the summary statistics for plant-by-day observations in each single year. The last column reports the summary statistics for plant-by-day observations for whole sample including all years. The reported number is the mean, with the standard deviation in parenthesis.

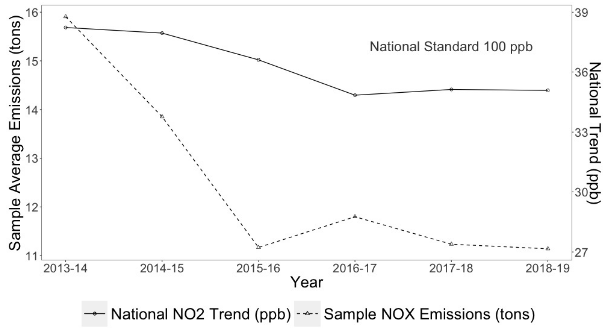
vary substantially across years but are consistent with the national weather pattern (https://www.ncdc.noaa.gov/ca-g/national/time-series). Figure 2 shows the sample average annual trends for SO_2, NO_X and AOD, and compares them with the national trend for the corresponding pollutant concentrations.[18]

[18]Sample data is for 2013–14, 2014–15, 2015–16, 2016–17 and 2017–18. National data is for 2013, 2014, 2015, 2016, 2017 and 2018.

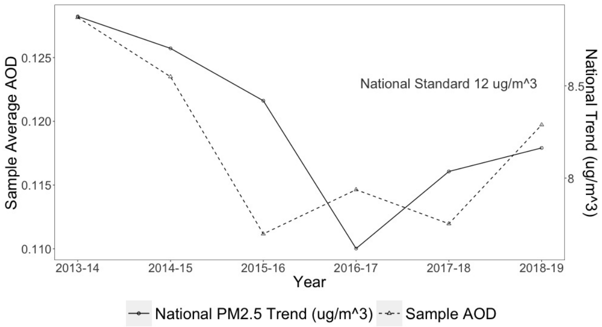
Figure 2: Trends in air pollution



(a) SO_2 annual trend



(b) NO_x annual trend



(c) $PM_{2.5}$/AOD annual trend

5 Results

5.1 Evaluating the identifying assumptions: event studies

Our key identifying assumption is that the emissions in the previous 5 years provide an appropriate counterfactual for emissions in the shutdown year as if there were no government shutdown. Given that we observe 197 out of 204 power plants in every year of our sample, an advantage of our study design is that it is plausible to assume emissions in the shutdown year (treatment group) and the previous 5 years (control group) are similar in both levels and trends over the same month–day after controlling for electricity generation and other confounders.

Following recent wisdom, we use event studies to provide evidence regarding the validity of our control group and the underlying assumption of a common trend. Specifically, we estimate the conditional weekly average differences between the shutdown year and the previous 5 years throughout our sample period using the following regression:

$$\begin{aligned} Y_{ijt} = \alpha X_{ijt} + \text{Plant}_i \times \text{Weeks}_t + \text{Year}_j + \text{Weekdays}_{jt} + \text{Date}_t \\ + \sum_{k \neq 9} (\lambda_k \times 1[\text{Group}_j = \textit{Treated}] \times 1[\text{Weeks}_t = k]) + \epsilon_{ijt}. \end{aligned} \tag{4}$$

In the regression, i, j, t and X_{ijt} have the same definitions as in Equation 3. We first estimate equation 4 using our full sample, so k is a sequence of integers between 1 and 14, as we have 14 weeks in the full sample. The shutdown treatment starts from the 10th week (the week that ends on December 30). Following the conventional design of event study analysis, we set the week before treatment, the 9th week, as the reference week (in the summation term, $k \neq 9$). The coefficient of the interaction term $[\text{Group}_j = \textit{Treated}] \times 1[\text{Weeks}_t = k]$, λ_k, captures the weekly average differences in daily emissions between the treatment group (the shutdown year) and the control group (the previous 5 years) in week k, conditional on the control variables and the fixed effects. An insignificant λ_k suggests that after accounting for the intercept difference and other observable differences, there is no additional weekly average difference in the daily outcome variable between the treatment and control groups in week k. To visualize the weekly average differences in daily SO_2, NO_X, and AOD between the two groups, we plot λ_k in Figures 3a, 3b, and 3c, along with the 95% confidence interval. Standard errors are clustered at the plant level.

The event study results using full sample in Figure 3) support our choice of the previous years as a credible control group: most of the group differences are statistically insignificant during the pre-treatment periods. The only exceptions are found in the case of AOD where two out of the nine pre-treatment group differences are significant. Other than that, the results show a weak and insignificant pattern of increased SO_2 emissions due to the lockdown; no pattern for NO_X emissions; and a strong and significant pattern of increased AOD after the lockdown. These results are in line with our expectation since particulate matter emissions experienced the largest reduction in regulation stringency reduction.

To avoid potential bias induced by the two pre-treatment weeks with significant group differences for AOD in the following analysis, we consider an alternative short sample starting from December 1.[19] The shorter sample also mitigates potential issues of seasonality in the data.[20].

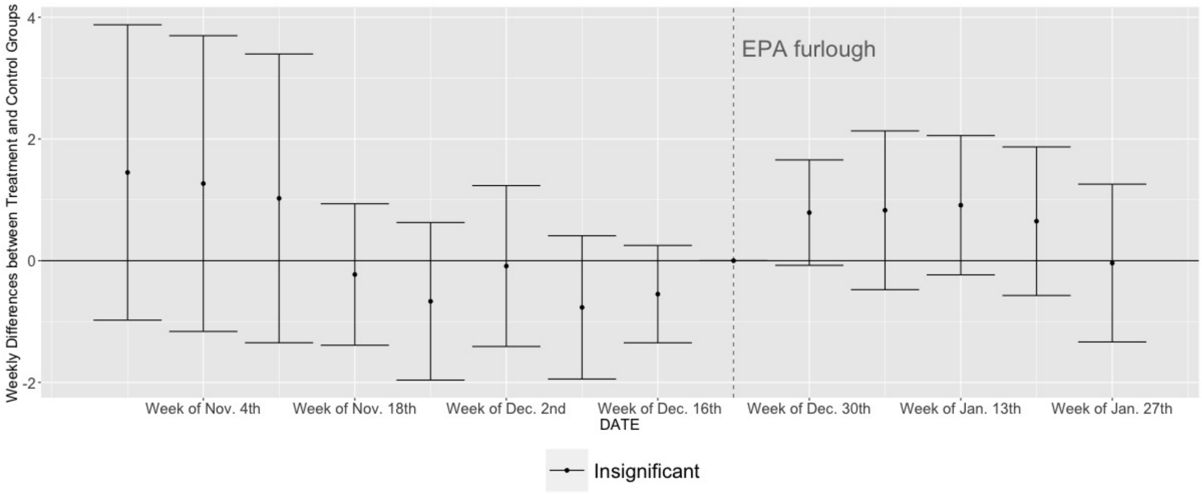
5.2 Main results

Table 2 reports the causal effects of the EPA furlough on daily SO_2, NO_X and AOD using both the full and short samples. For each regression, we report unclustered standard errors along with standard errors that are clustered at either the plant or the state level to account for potential correlations between observations within the plant or state group. At best, we find weak evidence of an increase in daily SO_2 emissions during the

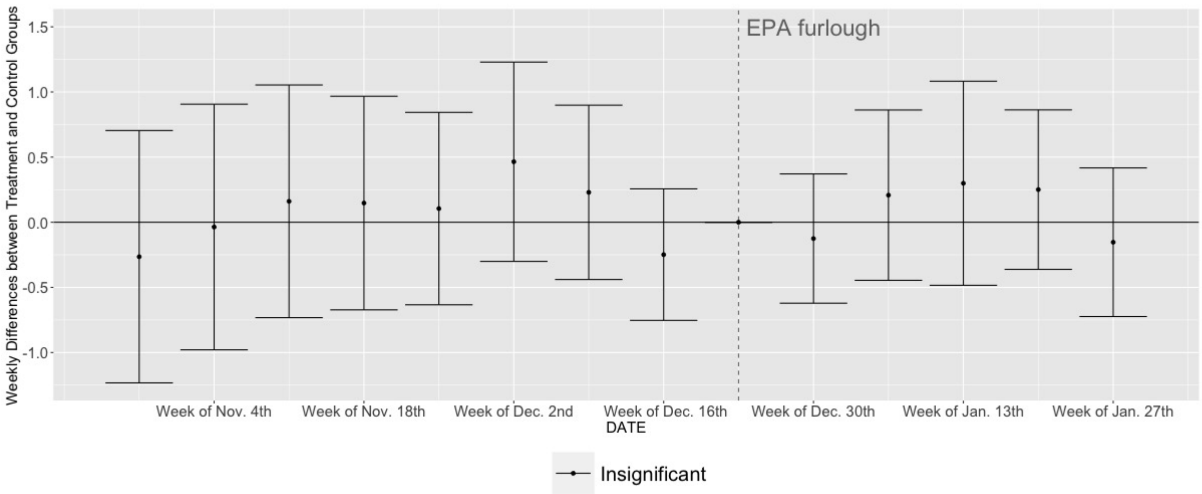
[19]The short sample uses the same week labels as the full sample. It consists of 9 weeks, starting from the 6th week that only have its last 2 days (December 1 and December 2).

[20]The event study analysis using the short sample is provided in Appendix Figure A1

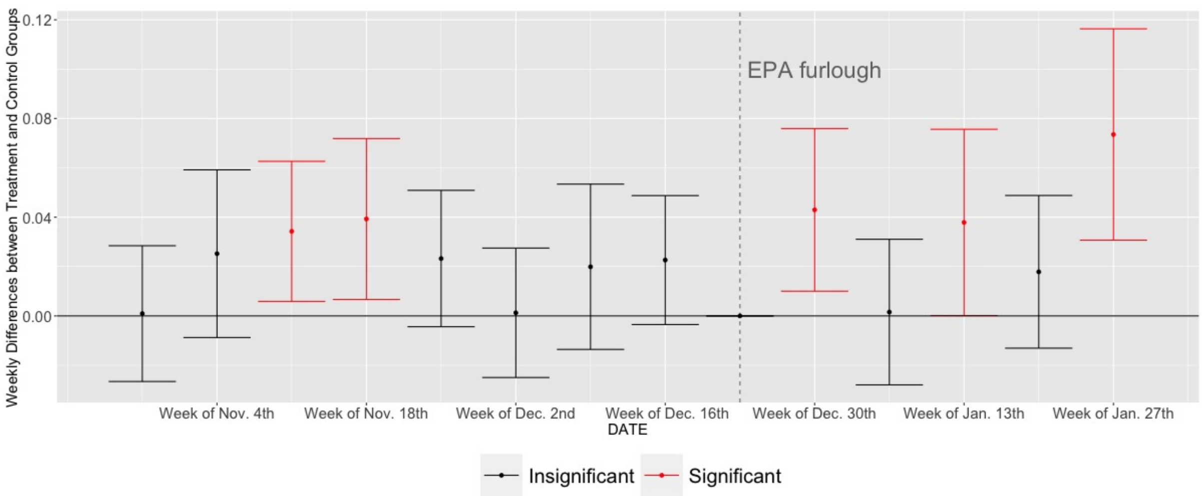
Figure 3: Event Study, Full Sample



(a) SO_2 Emissions



(b) NO_X Emissions



(c) AOD Concentration

Table 2: Results: main analysis

	Full Sample			Short Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	SO_2 (tons)	NO_X (tons)	AOD (unitless)	SO_2 (tons)	NO_X (tons)	AOD (unitless)
EPA Furlough	0.445	0.094	0.018	0.774	0.156	0.022
	(0.278)	(0.104)	(0.005)***	(0.344)**	(0.126)	(0.006)***
	(0.550)	(0.207)	(0.008)**	(0.533)	(0.201)	(0.009)**
	(0.521)	(0.250)	(0.008)**	(0.479)	(0.230)	(0.010)**
Control Variables						
Weather, Electricity						
& Steam Production	Y	Y	Y	Y	Y	Y
Fixed Effects						
Year, Date, Weekdays	Y	Y	Y	Y	Y	Y
Week × Plant						
Adjusted R^2	0.707	0.843	0.151	0.693	0.845	0.189
Sample Size	104,282	104,282	24,310	63,528	63,528	11,274

Note: The full sample consists of the pre-furlough period from October 22 to December 28 and the furlough period from December 29 to January 27 of the shutdown year and the previous 5 years. The short sample consists of the shorter pre-fought period from December 1 to December 28 and the furlough period from December 29 to January 27, in the shutdown year and the previous 5 years. We report three standard errors for each coefficient: the first is the standard error without clustering, while the second and the third standard errors are clustered at the plant and the state level, respectively. The full results are reported in Appendix Table A1. Significance level: *** p< .01, ** p<.05, * p<.1.

shutdown: the estimated coefficient is statistically significant only when the standard errors are not clustered in the short sample shown in column (4). Similarly, we do not detect a statistically significant change in daily NO_X emissions as shown in columns (3) and (5), although the coefficients on the EPA furlough dummy variable are positive. In contrast, the results in columns (3) and (6) show that the daily AOD surrounding the plants significantly increased by about 0.018 – 0.022, which is 15.43% – 19.53% above the counterfactual on average (as if there was no regulation shock).[21] Thus, our results suggest that during the government shutdown, coal–fired power plants significantly increased their particulate matter emissions due to the EPA's furlough. Although daily plant emissions of SO_2 and NO_X also appear to be relatively higher during the shutdown, representing a 2.63% – 4.58% increase for SO_2 and a 0.75% – 1.24% increase for NO_X (compared to sample average), these effects are not statistically significant. These results are consistent with our hypothesis as well as the event study analysis reported in subsection 5.1.

The negligible effects of the EPA furlough on SO_2 and NO_X emissions might be driven by two factors. The first factor is related to the SO_2 and NO_X trading programs, which were unaffected by the government shutdown so that the abatement incentive provided by the trading programs remained in place.Second, under the CAA SO_2 and NO_X emissions are measured by a Continuous Emissions Monitoring System (CEMS), which operates 24 hours a day and is usually installed in an exhaust system or smoke stack through which

[21]This value is calculated as a percentage: (observed AOD - counterfactual AOD)/counterfactual AOD. The conterfactural AOD is the estimated AOD as if there is no EPA furlough during the true EPA furlough period.

the majority of a plant's air emissions pass (U.S. General Accounting Office, 1990). Such plant–level continuous monitoring was unaffected by the furlough of EPA employees. Therefore, the shutdown did not affect the regulation stringency for SO_2 and NO_X to the same extent as particulate matter, and plants had a lower incentive to strategically increase their SO_2 and NO_X emissions.

In addition to inspections and enforcement actions, the EPA also designates counties as being in attainment or not with the NAAQS. The designation is made annually and non-attainment has significant implications for local governments that must file State Implementation Plans outlining strategies to reduce the concentrations of the violating pollutants, including source–specific requirements. Thus non–attainment counties face additional scrutiny compared to attainment counties (Henderson, 1996). To assess whether county non–attainment status plays a role in the change in emissions during the furlough, we re–estimate our benchmark model after separating plants into two groups based on the attainment designation of the county in which they are located. We obtain the annual attainment status for counties where the coal–fire power plants are located from the EPA Greenbook (`https://www.epa.gov/green-book`). We designate a county as being in non–attainment when at least one criteria pollutant fails to meet the corresponding NAAQS, either wholly or partially. We have 26 plants located in non–attainment counties and 152 plants located in attainment counties. The remaining 26 plants are not used for this part of the analysis because their counties switch attainment status at least once between 2013 and 2019. In the regression model, we include two treatment effects associated with the shutdown: one for plants in non-attainment counties and the other for plants in attainment counties.[22]

As shown in Tables 3, the strategic response of plants in non–attainment counties is either absent or sufficiently muted so that there is no detectable change in the emissions of all three pollutants during the furlough. In contrast, it appears that the increase in AOD reported in Table 2 is driven by the response of plants located in attainment counties.

5.3 Robustness checks

The causal interpretation of our findings may be challenged if there was a contemporaneous incident around the time of the EPA's furlough that contributed to coal–fired power plants' emissions. Consider the following two cases: (i) an unrelated incident occurred during the EPA's furlough that increased coal–fired power plants' emissions in

[22]We also estimate an alternative model with the EPA furlough dummy and the interaction between the EPA furlough and a non-attainment dummy. The results are shown in Appendix Table A3. Since we have very few plants in non-attainment counties, the model does not have enough power to reject the null hypothesis that there is no difference in the effect of EPA furlough due to county attainment status.

Table 3: Additional results: Attainment vs non-attainment counties

	Full Sample			Short Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	SO2 (tons)	NOX (tons)	AOD	SO2 (tons)	NOX (tons)	AOD
EPA Furlough	−7.066	0.422	0.078	−6.618	0.501	0.087
(Non-attainment Counties)	(6.783)	(1.323)	(0.054)	(6.435)	(1.276)	(0.055)
EPA Furlough	1.255	0.188	0.010	1.758	0.268	0.015**
(Attainment Counties)	(1.049)	(0.239)	(0.007)	(1.393)	(0.271)	(0.007)
Control Variables						
Weather, Weekdays,						
Electricity & Steam Prod.	Y	Y	Y	Y	Y	Y
Fixed Effects						
Year FE, Date F.E.,						
Week × Plant F.E.	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.684	0.840	0.161	0.677	0.842	0.213
Sample Size	91,508	91,508	21,245	55,738	55,738	9,785

Note: In this sample, there are 26 plants in non-attainment counties, and 152 plants in attainment counties. The full sample consists of the shorter pre-furlough period from October 22 to December 28 and the furlough period from December 29 to January 27, each year in the shutdown year and the previous 5 years. The short sample consists of the pre-fought period from December 1 to December 28 and the furough period from December 29 to January 27, in the shutdown year and the previous 5 years. All the regressions include the following control variables: weather, electricity and steam production; and fixed effects: year FE, date FE, weekdays, week × plant FE. The standard errors are clustered at the plant level. The full results are reported in Appendix Table A2. Significance level: *** p< .01, ** p<.05, * p<.1.

2018–2019; (ii) an unrelated incident occurred in the weeks preceding the furlough that reduced coal–fired power plants' emissions, violating the common trends assumption necessary for identification.

To account for these possibilities, we include a post–furlough period to detect the case (i) and artificially assign a placebo "EPA furlough" in 2018 before the true EPA furlough to detect the case (ii).

Robustness check 1: ruling out incidents during the EPA's furlough

Conditional on the results of our event study analysis, there still remain two plausible scenarios that do not violate the common trend assumption, but through which an incident contemporaneous with the furlough may contribute to emissions: first, an unrelated incident that extended from the EPA's furlough to some point after the furlough; second, an incident that was nested within the time frame of the EPA's furlough. To test the first possibility, we extend our sample to March 25, including an additional 57 days after the furlough officially ended.[23] We test for a difference between the treatment and control group after the EPA returned to regular enforcement relative to the pre–furlough group

[23] The exception is 2016 which is a leap year: the data are extended to March 24 rather than March 25.

difference. Failure to detect a difference (insignificant coefficient on the post-furlough dummy) not only rules out any incident that extended from the furlough to some point during the post-furlough period, it also rules out any lagged effects from the furlough. Table 4 reports the results with a post-furlough dummy for both the full sample and the subsample with the shorter pre–furlough time horizon. Regardless of the outcome pollutant or analysis sample, we do not find any significant effect during the post furlough period.[24] Furthermore, the coefficients on the furlough period dummy are similar in sign, significance and magnitude to those reported in our benchmark results in Table 2. Not only does this finding support our empirical conclusion that the increase in AOD is driven by the EPA's furlough, it is also consistent with our theory that plants restore their compliance effort and emissions immediately after the regulation shock ends.

If our baseline results are driven by a contemporaneous incident without a lagged effect and nested within the time frame of the EPA's furlough, we are not able to disentangle it from the furlough treatment, because there is no appropriate contemporaneous same year counterfactual. However, the incident must have a nation–wide effect on all U.S. coal–fired power plants. Since we do not find any reports of a national event or policy change related to power plants during the EPA's furlough period, we believe this case is highly unlikely.

Table 4: Robustness check: including post EPA furlough period

	Full Sample			Short Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	SO_2 (tons)	NO_X (tons)	AOD (unitless)	SO_2 (tons)	NO_X (tons)	AOD (unitless)
EPA Furlough	0.521	0.058	0.018**	0.819	0.123	0.021**
	(0.543)	(0.201)	(0.008)	(0.547)	(0.196)	(0.009)
Post EPA Furlough	−0.364	0.281	0.006	−0.572	0.221	0.013
	(0.556)	(0.259)	(0.007)	(0.531)	(0.258)	(0.008)
Adjusted R^2	0.687	0.839	0.145	0.679	0.845	0.173
Sample Size	163,998	163,998	35,559	93,796	93,796	15,988

Note: The full sample consists of the pre-furlough period from October 22 to December 28; the furlough period from December 29 to January 27; and the post-furlough period from January 28 to March 25, of the shutdown year and the previous 5 years. The short sample consists of the shorter pre-fought period from December 1 to December 28; the furlough period from December 29 to January 27; and the post-furlough period from January 28 to March 25, in the shutdown year and the previous 5 years. All the regressions include the following control variables: weather, electricity and steam production; and fixed effects: year FE, date FE, weekdays, week × plant FE. The standard errors are clustered at the plant level. The full results are reported in Appendix Table A4. Significance level: *** p< .01, ** p<.05, * p<.1.

[24]The magnitude of post furlough coefficients in Table 4 are also much smaller than the furlough coefficients except NO_X.

Robustness check 2: ruling out an incident in 2018 prior to the EPA's furlough

The possibility that there is a confounding incident in 2018 prior to the EPA furlough can be ruled out if the pre–shutdown period weekly trends in that year is statistically similar to the weekly trend in the previous years. We report some evidence in favor of this in Figures 3 and A1. Here, we report the results from an additional placebo test to bolster the case that there is no incident during the pre–shutdown period that falsifies our findings.

First, we take the subset of the full sample in the pre–shutdown period, from October 22 to December 28, and assign a pre–shutdown placebo treatment from December 1 to December 28. The results of the placebo treatment are reported in Table 5, columns (1) to (3). For all pollutants, the coefficient on the pre–shutdown placebo treatment are generally insignificant; the only exception for the placebo treatment is the coefficient on AOD which is negative and significant at 10%. In Appendix Table A5 column (3b), we re–estimate the model for AOD after excluding observations from the two pre–treatment weeks in November with significantly higher AOD (see Figure 3c) and we confirm that the coefficient on the placebo treatment is driven by these anomalous observations. We also test the same pre–shutdown placebo treatment in an extended model where we additionally include both the true shutdown treatment and post–shutdown placebo treatment. The results are reported in Table 5, columns (4) to (6). Again, none of the pre–shutdown and post–shutdown placebo treatment coefficients are statistically significant.

Table 5: Placebo test: placebo EPA furlough from December 1 to December 28, 2018

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
	SO_2 (tons)	NO_X (tons)	AOD (unitless)	SO_2 (tons)	NO_X (tons)	AOD (unitless)
Placebo EPA Furlough	−0.726	−0.059	−0.011*	−0.617	−0.125	−0.007
	(0.785)	(0.278)	(0.006)	(0.707)	(0.266)	(0.006)
EPA Furlough				0.869	0.128	0.022**
				(0.569)	(0.201)	(0.009)
Post EPA Furlough				−0.013	0.352	0.010
				(0.490)	(0.265)	(0.008)
Adjusted R^2	0.687	0.839	0.145	0.679	0.845	0.173
Sample Size	71,011	71,011	18,659	163,998	163,998	35,559

Note: The sample for columns (1) – (3) consists of a pre-furlough period from October 22 to November 30 and a placebo furlough period from December 1 to December 28, in each year from 2013 to 2018. The sample for columns (4) – (6) consists of the pre–furlough period from October 22 to December 28; the furlough period from December 29 to January 27; and the post-furlough period from January 28 to March 25, each year of the shutdown year and the previous 5 years. All the regressions include the following control variables: weather, electricity and steam production; and fixed effects: year FE, date FE, weekdays, week × plant FE. The standard errors are clustered at the plant level. The full results are reported in Appendix Table A5. Significance level: *** p< .01, ** p<.05, * p<.1.

Second, we again use the pre–shutdown period data, from both the full sample and

Table 6: Robustness check: placebo furlough in every week before the true EPA furlough

	Full Sample			Short Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	SO_2 (tons)	NO_X (tons)	AOD (unitless)	SO_2 (tons)	NO_X (tons)	AOD (unitless)
Placebo EPA furlough:	0.485	−0.409	−0.015			
Oct. 22nd - Oct. 28th	(0.595)	(0.327)	(0.022)			
Placebo EPA furlough:	0.319	−0.195	0.010			
Oct. 29nd - Nov. 4th	(0.361)	(0.214)	(0.023)			
Placebo EPA furlough:	0.091	0.002	0.022			
Nov. 5th - Nov. 11th	(0.500)	(0.303)	(0.022)			
Placebo EPA furlough:	−1.171	−0.022	0.028			
Nov. 12th - Nov. 18th	(1.028)	(0.349)	(0.023)			
Placebo EPA furlough:	−1.661*	−0.022	0.004			
Nov. 19th - Nov. 25th	(0.958)	(0.339)	(0.021)			
Placebo EPA furlough:	−1.044	0.304	0.004			
Nov. 26th - Nov. 30th	(0.917)	(0.335)	(0.022)			
Placebo EPA furlough:	−1.592	0.297	−0.039*	−1.525*	0.291	−0.034
Dec. 1st - Dec. 7th	(1.232)	(0.365)	(0.023)	(0.822)	(0.340)	(0.021)
Placebo EPA furlough:	−1.711	−0.406	0.019	−1.641*	−0.408	0.013
Dec. 8th - Dec. 14th	(1.335)	(0.415)	(0.021)	(0.848)	(0.369)	(0.023)
Placebo EPA furlough:	−1.279	−0.137	−0.012	−1.250*	−0.078	−0.014
Dec. 15th - Dec. 21st	(1.182)	(0.479)	(0.025)	(0.690)	(0.384)	(0.024)
Placebo EPA furlough:	−0.348	−0.243	0.007	−0.329	−0.247	−0.003
Dec. 22nd - Dec. 28th	(1.102)	(0.426)	(0.022)	(0.482)	(0.305)	(0.021)
Adjusted R^2	0.709	0.842	0.137	0.681	0.844	0.150
Sample Size	71,011	71,011	18,659	30,257	30,257	5,623

Note: The sample for columns (1) – (3) consists of the pre-treatment period of the full sample from October 22 to December 28, each year in the shutdown year and the previous 5 years. The sample for columns (4) – (6) consists of the pre-treatment period of the short sample from December 1 to December 28, each year in the shutdown year and the previous 5 years. The standard errors are clustered at the plant level. The full results are reported in Appendix Table A6. Significance level: *** p< .01, ** p<.05, * p<.1.

the short sample and assign multiple placebo treatments during the pre–shutdown period, which are mostly defined on a weekly basis. Table 6 reports the results: none of these placebo treatments has a statistically significant coefficient at the 5% or lower level of significance, and only four coefficients in the SO_2 models have negative coefficients that are significant at the 10% level.[25] On the whole, these results do not support a confounding event in the pre–furlough period.

[25]This is another way to obtain suggestive evidence on the pre–treatment common trend assumption, and it reaffirms our findings from the event study analysis.

6 Explaining the Change in Emission During the Furlough

Having established a causal link between the EPA furlough and the statistically significant increase in aerosol concentration (AOD) around coal–fired power plants along with negligible changes in SO_2 and NO_X emissions, we next examine the channels through which coal–fired power plants were able to increase their unmonitored emissions during the federal government shutdown. In practice, coal–fired power plants can adjust their compliance efforts by modifying pollution control methods during the pre–combustion, in–combustion, or/and post–combustion phases. During pre–combustion, power plants may switch to cheaper but more polluting grades of coal in the absence of strict enforcement, because the unit price of coal varies across coal types and grades within type (Taylor, 2012).[26] Although it is implausible to assume power plants switch to different coal providers from another coal mining region in such a short period, it is possible for plants to acquire lower grade coal from the same coal providers, because coal grades are not only different across coal mining regions in the U.S., they also vary within the same region.[27] In addition, according to the EIA (https://www.eia.gov/coal/data/browser/, by mine/plant data), coal-fired power plants routinely acquire coal of different grades from multiple providers at same time, which also makes it easy to temporally switch the coal grade. During the in–combustion phase, power plants might operate units with lower efficiency. The low efficiency units are typically less profitable to operate because they are subject to higher emission cost and therefore higher production costs. However, the lower risk of federal inspections and penalties during the shutdown reduced the expected emission cost. The third strategic action is to temporarily reduce post-combustion end-of-pipe pollution control as a cost saving measure.[28]

[26] According to the EIA, the national average unit price per short ton is \$59.43 for bituminous and \$13.64 for subbituminous (https://www.eia.gov/energyexplained/coal/prices-and-outlook.php) Within coal types, the unit price varies with the heat and sulfur content of the coal.

[27] For example, in Western Montana low-sulfur subbituminous coal has 0.39 lbs/MBTU sulfur content and 18.56 MBTU per short ton heat content whereas mid-sulfur subbituminous coal has 0.80 lbs/MBTU sulfur content and 17.05 MBTU per short ton heat content. Switching to coal from a different region or from bituminous to subbituminous coal can result in even greater changes in sulfur and heat contents (EIA, 2018)

[28] According to EPA's Clean Air Markets Division (EPA Clean Air Markets Division, 2013), there are two post-combustion retrofit NO_x control technologies for existing coal units: selective catalytic reduction (SCR) and selective non-catalytic reduction. The Flue Gas Desulfurization post-combustion control technology for SO_2 includes wet and dry flue gas desulfurization. The control techonology for PM includes pulse-jet fabric filter and electrostatic precipitator upgrade adjustment. EPA Clean Air Markets Division (2013) also includes the captial, fixed and variable operational and maintenance costs for each control technology. For instance, using a 275 MW unit as example, NO_x's SCR capital cost is about 71.64 $\$/kW$; fixed operation and maintenance cost is approximately 1.04 $\$/kW$ per year; variable operational and maintenance cost is approximately 0.13 $\$/MWh$.

Table 7: Potential mechanisms

	Full Sample		
	(1)	(2)	(3)
	CO_2 (10^3 tons)	Electricity Prod. (10^3 MWH)	AOD (unitless)
EPA Furlough	0.025	−0.059	0.018**
	(0.017)	(0.046)	(0.008)
Adjusted R^2	0.999	0.996	0.151
Sample Size	104,282	104,282	24,310
	Short Sample		
	CO_2 (10^3 tons)	Electricity Prod. (10^3 MWH)	AOD (unitless)
EPA Furlough	0.009	−0.029	0.022**
	(0.000)	(0.045)	(0.009)
Adjusted R^2	0.999	0.996	0.189
Sample Size	63,528	63,528	11,274

Note: The full sample consists of the pre-furlough period from October 22 to December 28; the furlough period from December 29 to January 27; and the post-furlough period from January 28 to March 25, each year in the shutdown year and the previous 5 years. The short sample consists of the pre-fought period from December 1 to December 28; the furlough period from December 29 to January 27; and the post-furlough period from January 28 to March 25, each year in the shutdown year and the previous 5 years. All the regressions include the following control variables: weather, heat input; and fixed effects: year FE, date FE, weekdays, week × plant FE. Additional control variables: column (2) includes steam production, column (3) – (5) include CO_2 emissions. The standard errors are clustered at the plant level. The full results are reported in Appendix Tables A7 and A8. Significance level: *** p< .01, ** p<.05, * p<.1.

In the following, we empirically disentangle these three strategic actions. We use the same identification framework as in equation 3, with different model specifications for each of the three strategic actions. The results are reported in Table 7, including the results using the full sample and short pre-treatment time horizon, both with the standard errors clustered at plant level. The results are insensitive to the choice of samples.

First, we test whether coal-fired power plants switched to lower grade coal using daily CO_2 emissions as the outcome variable. CO_2 is neither regulated nor subject to any end-of-pipe pollution control, thus, conditioning on weather and heat input ensures that the variation in CO_2 emission is solely driven by burning different grades of coal, not production efficiency or pollution control.[29] We do not find significant changes in daily CO_2 emissions during the furlough, as shown in column (2) in both panels of Tables 7. This suggests that the increase in particulate matter emissions reported in the main analysis was not due to switching coal grades.

Then, to test whether coal-fired power plants temporarily operated their lower effi-

[29]A more direct test on fuel switching would require daily plant-level fuel data. However, these data are not publicly available.

ciency units, we use daily electricity production as the outcome variable. We include weather, heat input, steam production, and CO_2 emissions as controls. In keeping with the first law of thermodynamics, heat input should equal the summation of electric energy produced, steam energy produced, and energy loss. So conditioning on heat input and steam production, lower electricity production means higher heat loss, and therefore lower efficiency. We include CO_2 emissions as a control variable because the heat rate of a power plant (heat input per net kWh electricity generated) is affected by the type and grade of coal used (Walsh et al., 2015). Since for same heat content, different coal types have different CO_2 emissions, holding heat input and CO_2 constant accounts for coal type variation. As reported in column (2) of Table 7, conditioning on heat input and CO_2 emissions, there is no significant change in daily electricity production during the furlough period. This implies that the increase in particulate matter emissions during the EPA's furlough was not due to the operation of lower efficiency units.

Finally, we test whether coal-fired power plants temporarily reduced end-of-pipe pollution control. We use daily AOD as outcome variable.[30] Our control variables include the daily heat input and CO_2 emissions, which allows us to simultaneously account for the effects of changing production efficiency and coal type, thus identifying the changes in end-of-pipe pollution control.

We find a significant increase in AOD during the furlough, similar in magnitude to the baseline results. The comparable magnitude of the increase in AOD reported in Table 2 versus Table 7 suggests that the AOD changes are almost entirely explained via the pollution control mechanism.

7 Discussion and Conclusion

Understanding firm behavior in response to changes in regulatory policy is essential for designing public policies. A central focus of the literature is the long–run impact of regulation on firm behavior. There is scant emphasis on firm responses in the event of an unanticipated and temporary modification in regulation. Using a simple conceptual framework, we demonstrate that firms react strategically even to a temporary, short–run change in environmental regulatory stringency, by immediately reducing their pollution abatement effort in order to minimize their total emission cost.

Following this conceptual framework, we exploit the 2018–19 federal government shutdown as a natural experiment, and assess whether this temporary interruption in the enforcement of environmental regulation caused increases in daily emissions of regu-

[30]We also analyze SO_2 and NO_X emissions and, as expected, we do not find any evidence of a change in end-of-pipe pollution control. See Appendix Tables A7 and A8 for the full results.

lated pollutants from coal-fired power plants. We focus on the universe of coal-fired power plants that were operating during the shutdown, and use emissions from the same plant on the same date from the previous 5 years to obtain the counterfactual. Using a difference-in-differences model, we find that the aerosol concentration (measured by satellite–retrieved AOD data) surrounding the coal-fired power plants increased significantly during the EPA's furlough. In contrast with the counterfactual (as if there was no government shutdown), the aerosol concentration within a 3 km radium circular area surrounding coal-fired power plants was higher by 0.018 − 0.022, on average. This is a large increase compared to the average AOD for the U.S. of 0.1 to 0.15,[31] and it is almost five times higher than the increase in aerosol concentrations in the vicinity of unconventional shale gas wells in Pennsylvania reported by Zhang et al. (2021b). We confirm that the increase in aerosol concentration occurred because plants temporarily reduced end-of-pipe pollution abatement. At the same time, there was no change in SO_2 and NO_X emissions both of which are continuously monitored under emissions trading programs and did not experience any appreciable change in regulation stringency.

This paper fills a gap in the regulation literature by isolating the short–run effect of a temporary interruption in regulation. We provide evidence that unexpectedly lowering the stringency of environmental regulation even temporarily elicits a strategic response from polluting firms that immediately lower their environmental effort and increase their daily emissions. Conversely, once regulation stringency is restored, firm emissions are correspondingly lowered. Given the association between air pollution and health outcomes (Dominici et al., 2006; Atkinson et al., 2014), our findings raise concerns regarding the potential health implications from even a temporary and short–term change in environmental regulation, not only due to a federal government shutdown, but due to any unusual interruption that may weaken environmental enforcement. As a unique example, during the COVID-19 pandemic, the EPA has relaxed its enforcement of several CAA regulations (https://www.epa.gov/sites/production/files/2020-03/documents/oecamemooncovid19implications.pdf), which may increase the emissions of particulate matter. Using the coefficients reported in Zhang et al. (2021b), we estimate that the 0.018–0.022 increase in AOD translates to an increase by $PM_{2.5}$ concentrations of about 0.118–0.144 $\mu g/m^3$.[32] Sadly, Wu et al. (2020) finds that an increase of only 1 $\mu g/m^3$ in $PM_{2.5}$ is associated with an 8% increase in the COVID-19 death rate, making the health implications even more prominent and acute. Our results suggest that EPA inspections play an important role in regulating firm emissions, and that monitoring costs

[31] According to the Global Monitoring Laboratory within NOAA, a value of 0.01 corresponds to an extremely clean atmosphere, and a value of 0.4 would correspond to a very hazy condition.

[32] This assumes that the relationship between the increase in AOD and $PM_{2.5}$ identified by Zhang et al. (2021b) for Pennsylvania can be generalized for the entire U.S.

aside, a continuous emission monitoring system can be an effective tool for pollution regulation.

A Appendix: For online publication

A.1 Comparative Statistics

Taking the partial derivative of equation 2 with respect to m_t yields

$$f\frac{\partial p(x^*)}{\partial x^*} + mf\frac{\partial^2 p(x^*)}{\partial x^{*2}}\frac{\partial x^*}{\partial m} = \frac{\partial^2 g(x^*;\theta)}{\partial x^{*2}}\frac{\partial x^*}{\partial m}, \tag{A1}$$

$$\frac{\partial x^*}{\partial m} = \frac{f\frac{\partial p(x^*)}{\partial x^*}}{\frac{\partial^2 g(x^*;\theta)}{\partial x^{*2}} - mf\frac{\partial^2 p(x^*)}{\partial x^{*2}}} \tag{A2}$$

Because $\frac{\partial^2 g(x^*;\theta)}{\partial x^{*2}} > 0$, $\frac{\partial^2 p(x^*)}{\partial x^{*2}} < 0$ and $\frac{\partial p(x^*)}{\partial x^*} > 0$; we have $\frac{\partial x^*}{\partial m} > 0$. Similarly, the partial derivative of equation 2 with respect to f gives

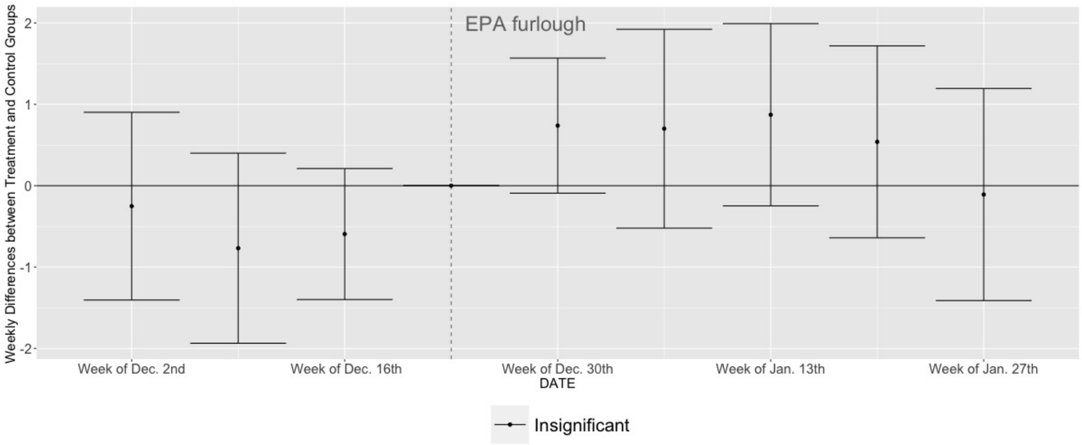
$$m\frac{\partial p(x^*)}{\partial x^*} + mf\frac{\partial^2 p(x^*)}{\partial x^{*2}}\frac{\partial x^*}{\partial f} = \frac{\partial^2 g(x^*;\theta)}{\partial x^{*2}}\frac{\partial x^*}{\partial f}, \tag{A3}$$

$$\frac{\partial x^*}{\partial f} = \frac{m\frac{\partial p(x^*)}{\partial x^*}}{\frac{\partial^2 g(x^*;\theta)}{\partial x^{*2}} - mf\frac{\partial^2 p(x^*)}{\partial x^{*2}}} \tag{A4}$$

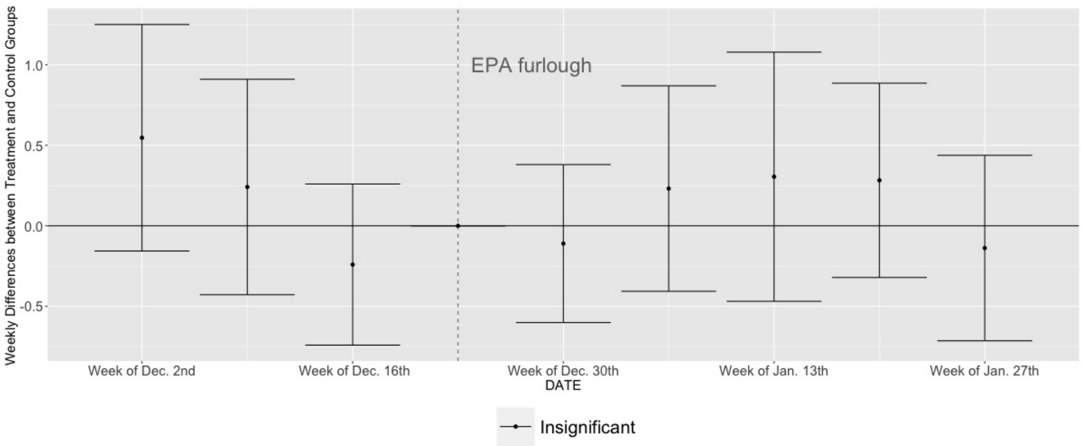
Because $\frac{\partial^2 g(x^*;\theta)}{\partial x^{*2}} > 0$, $\frac{\partial^2 p(x^*)}{\partial x^{*2}} < 0$ and $\frac{\partial p(x^*)}{\partial x^*} > 0$; we have $\frac{\partial x^*}{\partial f} > 0$.

A.2 Event Study using the Short Sample

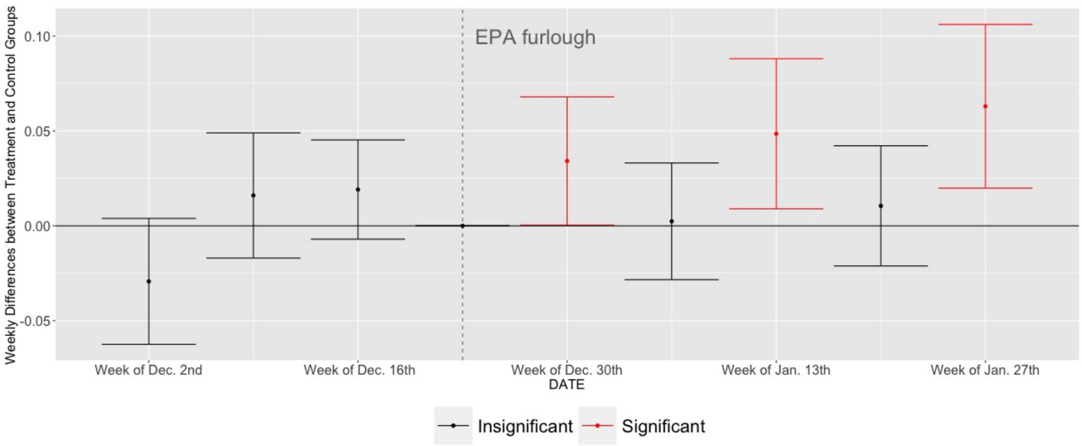
Figure A1: Event Study, Short Sample



(a) SO_2 Emissions



(b) NO_X Emissions



(c) AOD Concentration

A.3 Tables

Table A1: Main results

	Dependent variable:					
	Full Sample			*Short Sample*		
	SO2 (tons)	NOX (tons)	AOD	SO2 (tons)	NOX (tons)	AOD
	(1)	(2)	(3)	(4)	(5)	(6)
EPA Furlough	0.445	0.094	0.018	0.774	0.156	0.022
	(0.278)	(0.104)	(0.005)***	(0.344)**	(0.126)	(0.006)***
	(0.550)	(0.207)	(0.008)**	(0.533)	(0.201)	(0.009)**
	(0.521)	(0.250)	(0.008)**	(0.479)	(0.230)	(0.010)**
Precipitation	−0.007	−0.005	−0.001	−0.001	−0.001	−0.000
	(0.007)	(0.003)*	(0.000)***	(0.010)	(0.004)	(0.000)
	(0.005)	(0.003)	(0.000)***	(0.008)	(0.003)	(0.000)
	(0.005)	(0.003)	(0.000)***	(0.008)	(0.004)	(0.000)
Temperature	−0.035	−0.038	−0.004	−0.065	−0.023	−0.006
	(0.020)*	(0.007)***	(0.000)***	(0.027)**	(0.010)**	(0.000)***
	(0.046)	(0.024)	(0.000)***	(0.040)	(0.020)	(0.001)***
	(0.042)	(0.025)	(0.001)***	(0.043)	(0.021)	(0.001)***
Dew Point	0.028	0.019	0.003	0.050	0.007	0.004
	(0.018)	(0.007)***	(0.000)***	(0.025)**	(0.009)	(0.000)***
	(0.025)	(0.027)	(0.000)***	(0.027)*	(0.020)	(0.000)***
	(0.028)	(0.027)	(0.001)***	(0.035)	(0.020)	(0.000)***
Wind Speed	−0.010	−0.003	−0.003	−0.030	−0.001	−0.004
	(0.018)	(0.007)	(0.000)***	(0.024)	(0.009)	(0.000)***
	(0.020)	(0.008)	(0.000)***	(0.021)	(0.010)	(0.001)***
	(0.023)	(0.010)	(0.001)***	(0.025)	(0.012)	(0.001)***
Electricity Prod. (10^3 MWH)	1.149	0.754	0.000	1.118	0.759	0.000
	(0.008)***	(0.003)***	(0.000)**	(0.011)***	(0.004)***	(0.000)
	(0.186)***	(0.049)***	(0.000)*	(0.172)***	(0.050)***	(0.000)
	(0.190)***	(0.064)***	(0.000)*	(0.179)***	(0.066)***	(0.000)
Steam Prod. (10^3 lbs.)	0.000	0.000	0.000	0.000	0.000	−0.000
	(0.000)***	(0.000)***	(0.000)	(0.000)***	(0.000)***	(0.000)
	(0.000)***	(0.000)***	(0.000)	(0.000)**	(0.000)***	(0.000)
	(0.000)***	(0.000)***	(0.000)	(0.000)**	(0.000)***	(0.000)
Year 2014-15	−2.372	−0.766	−0.002	−2.927	−0.885	−0.008
	(0.160)***	(0.060)***	(0.002)	(0.215)***	(0.079)***	(0.003)**
	(0.764)***	(0.301)**	(0.003)	(0.870)***	(0.372)**	(0.004)**
	(0.862)***	(0.235)***	(0.003)	(0.984)***	(0.305)***	(0.004)*
Year 2015-16	−5.051	−1.596	−0.016	−5.248	−1.545	−0.011
	(0.166)***	(0.062)***	(0.003)***	(0.222)***	(0.081)***	(0.004)***
	(0.895)***	(0.364)***	(0.003)***	(0.985)***	(0.379)***	(0.004)**
	(0.741)***	(0.392)***	(0.005)***	(0.785)***	(0.423)***	(0.004)**
Year 2016-17	−7.031	−2.299	−0.004	−7.356	−2.238	−0.011
	(0.166)***	(0.062)***	(0.002)*	(0.218)***	(0.080)***	(0.004)***
	(1.792)***	(0.430)***	(0.003)	(1.907)***	(0.454)***	(0.004)***
	(1.302)***	(0.522)***	(0.004)	(1.399)***	(0.599)***	(0.003)***
Year 2017-18	−7.144***	−2.957***	−0.011***	−7.291***	−3.009***	−0.002
	(0.164)***	(0.061)***	(0.002)***	(0.217)***	(0.079)***	(0.003)
	(1.720)***	(0.507)***	(0.003)***	(1.867)***	(0.539)***	(0.005)
	(1.268)***	(0.631)***	(0.005)**	(1.369)***	(0.706)***	(0.006)
Year 2018-19	−7.133***	−3.279***	−0.013***	−7.796***	−3.334***	−0.016***
	(0.188)***	(0.070)***	(0.003)***	(0.283)***	(0.104)***	(0.004)***
	(1.610)***	(0.689)***	(0.004)***	(2.004)***	(0.643)***	(0.005)***
	(1.257)***	(0.850)***	(0.005)**	(1.587)***	(0.838)***	(0.006)**
Monday	−0.046	0.052	0.002	−0.036	0.064	0.009
	(0.177)	(0.066)	(0.003)	(0.236)	(0.086)	(0.004)**
	(0.084)	(0.039)	(0.003)	(0.107)	(0.049)	(0.005)*
	(0.073)	(0.042)	(0.004)	(0.101)	(0.052)	(0.006)
Saturday	−0.054	−0.073	0.002	−0.101	−0.074	0.003
	(0.177)	(0.066)	(0.003)	(0.236)	(0.086)	(0.004)
	(0.094)	(0.030)	(0.003)	(0.096)	(0.035)**	(0.005)
	(0.098)	(0.035)**	(0.003)	(0.113)	(0.039)*	(0.004)
Sunday	−0.125	−0.041	0.002	−0.232	−0.031	0.010
	(0.177)	(0.066)	(0.003)	(0.237)	(0.087)	(0.004)**
	(0.104)	(0.046)	(0.003)	(0.113)**	(0.049)	(0.004)***
	(0.116)	(0.039)	(0.004)	(0.151)	(0.044)	(0.006)*
Thursday	0.044	0.048	0.004	0.137	0.081	0.003
	(0.177)	(0.066)	(0.003)	(0.237)	(0.087)	(0.004)
	(0.050)	(0.027)*	(0.003)	(0.071)*	(0.032)**	(0.004)
	(0.049)	(0.022)**	(0.005)	(0.064)**	(0.026)***	(0.006)
Tuesday	0.024	0.022	0.008	0.104	0.043	0.003
	(0.177)	(0.066)	(0.003)***	(0.235)	(0.086)	(0.004)
	(0.076)	(0.038)	(0.003)***	(0.097)	(0.046)	(0.004)
	(0.082)	(0.037)	(0.004)**	(0.097)	(0.041)	(0.004)
Wednesday	0.033	0.033	0.004	0.101	0.038	0.006
	(0.177)	(0.066)	(0.003)	(0.237)	(0.087)	(0.004)
	(0.064)	(0.027)	(0.003)	(0.082)	(0.038)	(0.005)
	(0.064)	(0.028)	(0.003)	(0.074)	(0.033)	(0.006)
Date FE	Y	Y	Y	Y	Y	Y
Week FE×Plant FE	Y	Y	Y	Y	Y	Y
Observations	104,282	104,282	24,310	63,528	63,528	11,274
R^2	0.716	0.848	0.245	0.702	0.850	0.308
Adjusted R^2	0.707	0.843	0.151	0.693	0.845	0.189
Residual Std. Error	15.048 (df = 101322)	5.633 (df = 101322)	0.102 (df = 21621)	15.656 (df = 61623)	5.732 (df = 61623)	0.095 (df = 9620)

Note: *p<0.1; **p<0.05; ***p<0.01

Each coefficient has three standard errors: without clustering, clustering at plant level, clustering at state level.
For the first three columns, the sample is from Oct. 22nd to Mar. 25th for 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19;
and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).
In the last three columns, the sample is from Dec. 1st to Feb. 24th of each year 2013-14, 2014-15, 2015-16, 2016-17, 2017-18 and 2018-19.

Table A2: Additional results: comparison between coal fired power plants in Clean Air Act attainment counties (152 plants) and non-attainment counties (26 plants)

	Dependent variable:					
	Full Sample			*Short Sample*		
	SO2(tons)	NOX(tons)	AOD	SO2(tons)	NOX(tons)	AOD
	(1)	(2)	(3)	(4)	(5)	(6)
EPA Furlough × Attainment	1.255	0.188	0.010	1.758	0.268	0.015^{**}
	(1.049)	(0.239)	(0.007)	(1.393)	(0.271)	(0.007)
EPA Furlough × Non-attainment	−7.066	0.422	0.078	−6.618	0.501	0.087
	(6.783)	(1.323)	(0.054)	(6.435)	(1.276)	(0.055)
Precipitation	−0.002	−0.005	-0.000^{***}	0.002	−0.001	−0.000
	(0.005)	(0.004)	(0.000)	(0.009)	(0.004)	(0.000)
Temperature	−0.020	−0.035	-0.004^{***}	−0.046	−0.019	-0.006^{***}
	(0.056)	(0.026)	(0.000)	(0.050)	(0.022)	(0.001)
Dew Point	0.010	0.021	0.003^{***}	0.024	0.009	0.004^{***}
	(0.030)	(0.029)	(0.000)	(0.031)	(0.022)	(0.000)
Wind Speed	−0.015	−0.003	-0.003^{***}	-0.039^{**}	−0.006	-0.004^{***}
	(0.018)	(0.008)	(0.000)	(0.018)	(0.010)	(0.001)
Electricity Prod. (10^3 MWH)	1.207^{***}	0.788^{***}	0.000^{**}	1.159^{***}	0.796^{***}	0.000^{*}
	(0.218)	(0.057)	(0.000)	(0.198)	(0.060)	(0.000)
Steam Prod. (10^3 lbs.)	0.000^{***}	0.000^{***}	0.000	0.000^{**}	0.000^{***}	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2014-15	-2.132^{***}	-0.896^{***}	−0.004	-2.621^{***}	-1.011^{***}	-0.010^{***}
	(0.782)	(0.312)	(0.003)	(0.788)	(0.391)	(0.004)
Year 2015-16	-5.148^{***}	-1.802^{***}	-0.017^{***}	-5.419^{***}	-1.778^{***}	-0.011^{***}
	(0.977)	(0.399)	(0.004)	(1.074)	(0.412)	(0.004)
Year 2016-17	-7.310^{***}	-2.491^{***}	-0.007^{*}	-7.741^{***}	-2.433^{***}	-0.012^{***}
	(1.988)	(0.475)	(0.004)	(2.132)	(0.497)	(0.004)
Year 2017-18	-7.910^{***}	-3.289^{***}	-0.012^{***}	-8.103^{***}	-3.324^{***}	−0.005
	(1.947)	(0.567)	(0.003)	(2.115)	(0.600)	(0.005)
Year 2018-19	-7.721^{***}	-3.754^{***}	-0.014^{***}	-8.592^{***}	-3.828^{***}	-0.019^{***}
	(1.758)	(0.759)	(0.004)	(2.215)	(0.693)	(0.004)
Monday	−0.039	0.055	0.0004	0.011	0.083^{*}	0.006
	(0.087)	(0.035)	(0.003)	(0.105)	(0.047)	(0.005)
Saturday	−0.048	-0.072^{**}	0.003	−0.100	-0.066^{*}	0.003
	(0.102)	(0.032)	(0.003)	(0.098)	(0.039)	(0.005)
Sunday	−0.137	−0.038	0.001	-0.251^{**}	−0.023	0.009^{**}
	(0.104)	(0.048)	(0.003)	(0.102)	(0.052)	(0.004)
Thursday	0.002	0.054^{*}	0.004	0.086	0.090^{**}	−0.002
	(0.051)	(0.028)	(0.003)	(0.069)	(0.035)	(0.004)
Tuesday	0.027	0.012	0.008^{***}	0.108	0.036	0.0003
	(0.085)	(0.035)	(0.003)	(0.106)	(0.041)	(0.004)
Wednesday	0.007	0.028	0.003	0.057	0.038	0.002
	(0.070)	(0.028)	(0.003)	(0.084)	(0.037)	(0.004)
Date FE	Y	Y	Y	Y	Y	Y
Week FE × Plant FE	Y	Y	Y	Y	Y	Y
Observations	91,508	91,508	21,245	55,738	55,738	9,785
R^2	0.693	0.845	0.254	0.687	0.847	0.329
Adjusted R^2	0.684	0.840	0.161	0.677	0.842	0.213
Residual Std. Error	15.239 (df = 88911)	5.728 (df = 88911)	0.099 (df = 18894)	15.724 (df = 54066)	5.814 (df = 54066)	0.091 (df = 8344)

Note: *p<0.1; **p<0.05; ***p<0.01
Sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19;
and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).
Standard error is clustered at plant level.

Table A3: Additional results: comparison between coal fired power plants in Clean Air Act attainment counties (152 plants) and non-attainment counties (26 plants), alternative model with interactions

	Dependent variable:					
	Full Sample			*Short Sample*		
	SO2(tons)	NOX(tons)	AOD	SO2(tons)	NOX(tons)	AOD
	(1)	(2)	(3)	(4)	(5)	(6)
EPA Furlough	1.255	0.188	0.010	1.758	0.268	0.015**
	(1.049)	(0.239)	(0.007)	(1.393)	(0.271)	(0.007)
EPA Furlough × Non-attainment	−8.321	0.234	0.068	−8.376	0.233	0.072
	(7.677)	(1.432)	(0.053)	(7.699)	(1.431)	(0.054)
Precipitation	−0.002	−0.005	−0.000***	0.002	−0.001	−0.0001
	(0.005)	(0.004)	(0.000)	(0.009)	(0.004)	(0.000)
Temperature	−0.020	−0.035	−0.004***	−0.046	−0.019	−0.006***
	(0.056)	(0.026)	(0.000)	(0.050)	(0.022)	(0.001)
Dew Point	0.010	0.021	0.003***	0.024	0.009	0.004***
	(0.030)	(0.029)	(0.000)	(0.031)	(0.022)	(0.000)
Wind Speed	−0.015	−0.003	−0.003***	−0.039**	−0.006	−0.004***
	(0.018)	(0.008)	(0.000)	(0.018)	(0.010)	(0.001)
Electricity Prod. (10^3 MWH)	1.207***	0.788***	0.000**	1.159***	0.796***	0.000*
	(0.218)	(0.057)	(0.000)	(0.198)	(0.060)	(0.000)
Steam Prod. (10^3 lbs.)	0.000***	0.000***	0.000	0.000**	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
Year 2014-15	−2.132***	−0.896***	−0.004	−2.621***	−1.011***	−0.010***
	(0.782)	(0.312)	(0.003)	(0.788)	(0.391)	(0.004)
Year 2015-16	−5.148***	−1.802***	−0.017***	−5.419***	−1.778***	−0.011***
	(0.977)	(0.399)	(0.004)	(1.074)	(0.412)	(0.004)
Year 2016-17	−7.310***	−2.491***	−0.007*	−7.741***	−2.433***	−0.012***
	(1.988)	(0.475)	(0.004)	(2.132)	(0.497)	(0.004)
Year 2017-18	−7.910***	−3.289***	−0.012***	−8.103***	−3.324***	−0.005
	(1.947)	(0.567)	(0.003)	(2.115)	(0.600)	(0.005)
Year 2018-19	−7.721***	−3.754***	−0.014***	−8.592***	−3.828***	−0.019***
	(1.758)	(0.759)	(0.004)	(2.215)	(0.693)	(0.004)
Monday	−0.039	0.055	0.0004	0.011	0.083*	0.006
	(0.087)	(0.035)	(0.003)	(0.105)	(0.047)	(0.005)
Saturday	−0.048	−0.072**	0.003	−0.100	−0.066*	0.003
	(0.102)	(0.032)	(0.003)	(0.098)	(0.039)	(0.005)
Sunday	−0.137	−0.038	0.001	−0.251**	−0.023	0.009**
	(0.104)	(0.048)	(0.003)	(0.102)	(0.052)	(0.004)
Thursday	0.002	0.054*	0.004	0.086	0.090**	−0.002
	(0.051)	(0.028)	(0.003)	(0.069)	(0.035)	(0.004)
Tuesday	0.027	0.012	0.008***	0.108	0.036	0.0003
	(0.085)	(0.035)	(0.003)	(0.106)	(0.041)	(0.004)
Wednesday	0.007	0.028	0.003	0.057	0.038	0.002
	(0.070)	(0.028)	(0.003)	(0.084)	(0.037)	(0.004)
Date FE	Y	Y	Y	Y	Y	Y
Week FE × Plant FE	Y	Y	Y	Y	Y	Y
Observations	91,508	91,508	21,245	55,738	55,738	9,785
R^2	0.693	0.845	0.254	0.687	0.847	0.329
Adjusted R^2	0.684	0.840	0.161	0.677	0.842	0.213
Residual Std. Error	15.239 (df = 88911)	5.728 (df = 88911)	0.099 (df = 18894)	15.724 (df = 54066)	5.814 (df = 54066)	0.091 (df = 8344)

Note: *p<0.1; **p<0.05; ***p<0.01
Sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19; and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).
Standard error is clustered at plant level.

Table A4: Robustness check, including post EPA furlough period

	Dependent variable:					
	Full Sample			*Short Sample*		
	SO2 (tons)	NOX (tons)	AOD	SO2 (tons)	NOX (tons)	AOD
	(1)	(2)	(3)	(4)	(5)	(6)
EPA Furlough	0.521	0.058	0.018**	0.819	0.123	0.021**
	(0.543)	(0.201)	(0.008)	(0.547)	(0.196)	(0.009)
Post EPA Furlough	−0.364	0.281	0.006	−0.572	0.221	0.013
	(0.556)	(0.259)	(0.007)	(0.531)	(0.258)	(0.008)
Precipitation	−0.008	−0.003	−0.000***	−0.005	−0.001	−0.001***
	(0.006)	(0.003)	(0.000)	(0.008)	(0.003)	(0.000)
Temperature	−0.054**	−0.019	−0.003***	−0.088***	−0.020	−0.006***
	(0.026)	(0.014)	(0.000)	(0.028)	(0.015)	(0.001)
Dew Point	0.035**	0.011	0.003***	0.058**	0.011	0.004***
	(0.017)	(0.016)	(0.0003)	(0.027)	(0.013)	(0.0004)
Wind Speed	−0.013	−0.008	−0.004***	−0.019	−0.017**	−0.004***
	(0.019)	(0.007)	(0.000)	(0.022)	(0.008)	(0.001)
Electricity Prod. (10^3 MWH)	1.172***	0.751***	0.000**	1.136***	0.747***	0.0002
	(0.205)	(0.050)	(0.000)	(0.189)	(0.050)	(0.0002)
Steam Prod. (10^3 lbs.)	0.000***	0.000***	−0.000	0.000**	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2014-15	−2.757***	−0.934***	−0.006*	−3.088***	−1.154***	−0.017***
	(0.761)	(0.296)	(0.003)	(0.883)	(0.363)	(0.005)
Year 2015-16	−5.066***	−1.655***	−0.017***	−5.152***	−1.636***	−0.015***
	(0.868)	(0.331)	(0.004)	(0.935)	(0.347)	(0.005)
Year 2016-17	−7.286***	−2.363***	−0.014***	−7.423***	−2.450***	−0.018***
	(1.751)	(0.413)	(0.004)	(1.828)	(0.426)	(0.005)
Year 2017-18	−7.111***	−2.829***	−0.017***	−7.358***	−3.048***	−0.006
	(1.702)	(0.489)	(0.003)	(1.815)	(0.507)	(0.005)
Year 2018-19	−7.286***	−3.293***	−0.017***	−7.830***	−3.469***	−0.020***
	(1.616)	(0.682)	(0.004)	(1.944)	(0.647)	(0.006)
Monday	−0.040	0.053*	0.001	0.034	0.066	0.006
	(0.065)	(0.030)	(0.003)	(0.077)	(0.041)	(0.004)
Saturday	−0.054	−0.079***	−0.002	−0.098	−0.091***	−0.005
	(0.104)	(0.027)	(0.003)	(0.104)	(0.032)	(0.004)
Sunday	−0.115	−0.034	−0.002	−0.177	−0.043	0.010***
	(0.136)	(0.044)	(0.003)	(0.140)	(0.052)	(0.003)
Thursday	0.080	0.052**	−0.0001	0.153*	0.075**	−0.0004
	(0.061)	(0.024)	(0.003)	(0.080)	(0.031)	(0.004)
Tuesday	−0.003	0.021	0.005**	0.120	0.026	0.004
	(0.063)	(0.028)	(0.003)	(0.087)	(0.037)	(0.004)
Wednesday	0.018	0.025	0.001	0.100	−0.004	0.003
	(0.064)	(0.025)	(0.003)	(0.083)	(0.035)	(0.004)
Date FE	Y	Y	Y	Y	Y	Y
Week FE×Plant FE	Y	Y	Y	Y	Y	Y
Observations	163,998	163,998	35,559	93,796	93,796	15,988
R^2	0.696	0.843	0.245	0.689	0.849	0.295
Adjusted R^2	0.687	0.839	0.145	0.679	0.845	0.173
Residual Std. Error	15.780 (df = 159355)	5.627 (df = 159355)	0.123 (df = 31392)	16.211 (df = 91049)	5.668 (df = 91049)	0.111 (df = 13627)

Note: *p<0.1; **p<0.05; ***p<0.01
For the first three columns, the sample is from Oct. 22nd to Mar. 25th for 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19; and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).
For the last three columns, the sample is from Dec. 1st to Feb. 24th of each year 2013-14, 2014-15, 2015-16, 2016-17 2017-18 and 2018-19.
Standard error is clustered at plant level.

Table A5: Placebo test, placebo EPA furlough is from December 1 to 28, 2018

	Dependent variable:						
	Pre-Furlough Placebo Only				*Full Sample*		
	SO2 (tons)	NOX (tons)	AOD	AOD	SO2 (tons)	NOX (tons)	AOD
	(1)	(2)	(3a)	(3b)	(4)	(5)	(6)
Placebo EPA Furlough	−0.726	−0.059	−0.011*	−0.003	−0.617	−0.125	−0.007
	(0.785)	(0.278)	(0.006)	(0.006)	(0.707)	(0.266)	(0.006)
EPA Furlough					0.869	0.128	0.022**
					(0.569)	(0.201)	(0.009)
Post EPA Furlough					−0.013	0.352	0.010
					(0.490)	(0.265)	(0.008)
Precipitation	−0.007	−0.003	−0.001***	−0.001***	−0.008	−0.003	−0.000***
	(0.005)	(0.004)	(0.000)	(0.000)	(0.006)	(0.003)	(0.000)
Temperature	0.005	−0.054*	−0.003***	−0.002***	−0.052*	−0.019	−0.003***
	(0.063)	(0.030)	(0.000)	(0.001)	(0.027)	(0.014)	(0.000)
Dew Point	0.007	0.023	0.003***	0.003***	0.034**	0.010	0.003***
	(0.035)	(0.032)	(0.000)	(0.000)	(0.017)	(0.016)	(0.000)
Wind Speed	−0.011	−0.004	−0.003***	−0.004***	−0.013	−0.008	−0.004***
	(0.024)	(0.009)	(0.000)	(0.000)	(0.019)	(0.007)	(0.000)
Electricity Prod. (10^3 MWH)	1.168***	0.753***	0.000	0.000	1.172***	0.751***	0.0004**
	(0.183)	(0.049)	(0.000)	(0.000)	(0.205)	(0.050)	(0.000)
Steam Prod. (10^3 lbs.)	0.000***	0.000***	−0.000	−0.000**	0.000***	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2014-15	−2.212***	−0.496	−0.003	−0.016***	−2.757***	−0.934***	−0.006*
	(0.822)	(0.325)	(0.003)	(0.004)	(0.761)	(0.296)	(0.003)
Year 2015-16	−5.160***	−1.677***	−0.026***	−0.039***	−5.069***	−1.656***	−0.017***
	(0.901)	(0.384)	(0.004)	(0.005)	(0.870)	(0.331)	(0.004)
Year 2016-17	−7.202***	−2.307***	−0.007*	−0.011**	−7.290***	−2.363***	−0.014***
	(1.768)	(0.436)	(0.004)	(0.004)	(1.754)	(0.412)	(0.004)
Year 2017-18	−7.327***	−2.908***	−0.020***	−0.032***	−7.113***	−2.829***	−0.017***
	(1.690)	(0.528)	(0.004)	(0.005)	(1.703)	(0.489)	(0.003)
Year 2018-19	−6.834***	−3.226***	−0.012***	−0.027***	−7.020***	−3.239***	−0.014***
	(1.384)	(0.750)	(0.004)	(0.005)	(1.446)	(0.714)	(0.004)
Monday	0.041	0.082*	0.004	0.004	−0.040	0.053*	0.001
	(0.090)	(0.050)	(0.003)	(0.004)	(0.065)	(0.030)	(0.003)
Saturday	−0.031	−0.064*	0.003	0.006*	−0.051	−0.079***	−0.002
	(0.121)	(0.037)	(0.003)	(0.004)	(0.105)	(0.027)	(0.003)
Sunday	0.014	−0.032	0.003	0.004	−0.114	−0.034	−0.002
	(0.117)	(0.057)	(0.003)	(0.004)	(0.137)	(0.044)	(0.003)
Thursday	0.077	0.027	0.007*	0.016***	0.081	0.052**	−0.0002
	(0.061)	(0.035)	(0.004)	(0.005)	(0.061)	(0.024)	(0.003)
Tuesday	0.050	0.011	0.011***	0.009**	−0.003	0.021	0.005**
	(0.090)	(0.046)	(0.003)	(0.004)	(0.063)	(0.028)	(0.003)
Wednesday	0.031	0.006	0.005	0.011**	0.018	0.025	0.001
	(0.068)	(0.035)	(0.004)	(0.005)	(0.063)	(0.025)	(0.003)
Date FE	Y	Y	Y	Y	Y	Y	Y
Week FE×Plant FE	Y	Y	Y	Y	Y	Y	Y
Observations	71,011	71,011	18,659	13,990	163,998	163,998	35,559
R^2	0.718	0.847	0.228	0.227	0.696	0.843	0.245
Adjusted R^2	0.709	0.842	0.135	0.128	0.687	0.839	0.145
Residual Std. Error	14.848 (df = 68893)	5.600 (df = 68893)	0.104 (df = 16661)	0.105 (df = 12406)	15.780 (df = 159354)	5.627 (df = 159354)	0.123 (df = 31391)

Note: *p<0.1; **p<0.05; ***p<0.01
For the first three columns, the sample is from Oct. 22nd to Dec. 28th for 2013-14, 2014-15, 2015-16, 2016-17, 2017-18 and 2018-19.
For the fourth column, the sample is from Oct. 22nd to Dec. 28th but exclude two anomalous weeks in November (see Figure 3c) for 2013-14, 2014-15, 2015-16, 2016-17, 2017-18 and 2018-19.
For the last three columns, the sample is from Oct. 22nd to Mar. 25th of each year 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19;
and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).
Standard error is clustered at plant level.

Table A6: Placebo test, placebo EPA furlough is set for every week before the EPA furlough

	Dependent variable:					
	Short Sample			*Full Sample*		
	SO2 (tons)	NOX (tons)	AOD	SO2 (tons)	NOX (tons)	AOD
	(1)	(2)	(3)	(4)	(5)	(6)
Placebo EPA Furlough: Oct. 22nd - Oct. 28th				0.485	−0.409	−0.015
				(0.595)	(0.327)	(0.022)
Placebo EPA Furlough: Oct. 29nd - Nov. 4th				0.319	−0.195	0.010
				(0.361)	(0.214)	(0.023)
Placebo EPA Furlough: Nov. 5th - Nov. 11th				0.091	0.002	0.022
				(0.500)	(0.303)	(0.022)
Placebo EPA Furlough: Nov. 12th - Nov. 18th				−1.171	−0.022	0.028
				(1.028)	(0.349)	(0.023)
Placebo EPA Furlough: Nov. 19th - Nov. 25th				−1.661*	−0.022	0.004
				(0.958)	(0.339)	(0.021)
Placebo EPA Furlough: Nov. 26th - Nov. 30th				−1.044	0.304	0.004
				(0.917)	(0.335)	(0.022)
Placebo EPA Furlough: Dec. 1st - Dec. 7th	−1.525*	0.291	−0.034	−1.592	0.297	−0.039*
	(0.822)	(0.340)	(0.021)	(1.232)	(0.365)	(0.023)
Placebo EPA Furlough: Dec. 8th - Dec. 14th	−1.641*	−0.408	0.013	−1.711	−0.406	0.019
	(0.848)	(0.369)	(0.023)	(1.335)	(0.415)	(0.021)
Placebo EPA Furlough: Dec. 15th - Dec. 21st	−1.250*	−0.078	−0.014	−1.279	−0.137	−0.012
	(0.690)	(0.384)	(0.024)	(1.182)	(0.479)	(0.025)
Placebo EPA Furlough: Dec. 22nd - Dec. 28th	−0.329	−0.247	−0.003	−0.348	−0.243	0.007
	(0.482)	(0.305)	(0.021)	(1.102)	(0.426)	(0.022)
Precipitation	0.004	0.005	−0.0005*	−0.007	−0.003	−0.001***
	(0.010)	(0.004)	(0.0003)	(0.005)	(0.004)	(0.0002)
Temperature	−0.012	−0.044	−0.005***	0.001	−0.053*	−0.002***
	(0.062)	(0.029)	(0.001)	(0.061)	(0.030)	(0.0004)
Dew Point	0.014	0.0003	0.004***	0.011	0.023	0.003***
	(0.045)	(0.028)	(0.001)	(0.033)	(0.032)	(0.0004)
Wind Speed	−0.046	0.007	−0.005***	−0.014	−0.005	−0.003***
	(0.032)	(0.017)	(0.001)	(0.024)	(0.009)	(0.0004)
Electricity Prod. (10^3 MWH)	1.130***	0.763***	0.0001	1.170***	0.752***	0.0002
	(0.154)	(0.050)	(0.0003)	(0.184)	(0.049)	(0.0002)
Steam Prod. (10^3 lbs.)	0.0002***	0.0001***	−0.00000*	0.0002***	0.0001***	−0.00000
	(0.0001)	(0.00001)	(0.00000)	(0.0001)	(0.00001)	(0.00000)
Year 2014-15	−3.079***	−0.314	−0.026***	−2.210***	−0.497	−0.004
	(1.058)	(0.450)	(0.007)	(0.823)	(0.325)	(0.003)
Year 2015-16	−5.647***	−1.624***	−0.035***	−5.155***	−1.679***	−0.027***
	(1.085)	(0.432)	(0.007)	(0.899)	(0.385)	(0.004)
Year 2016-17	−7.977***	−2.253***	−0.013**	−7.195***	−2.310***	−0.008**
	(1.911)	(0.499)	(0.006)	(1.765)	(0.436)	(0.004)
Year 2017-18	−7.850***	−2.967***	−0.017***	−7.319***	−2.911***	−0.021***
	(1.930)	(0.613)	(0.007)	(1.687)	(0.528)	(0.004)
Year 2018-19	−6.939***	−3.116***	−0.022	−6.316***	−3.167***	−0.019
	(1.641)	(0.731)	(0.021)	(1.287)	(0.802)	(0.021)
Monday	0.201	0.149*	0.018**	0.044	0.082	0.004
	(0.149)	(0.082)	(0.007)	(0.090)	(0.050)	(0.003)
Saturday	−0.095	−0.038	0.007	−0.039	−0.057	0.003
	(0.156)	(0.058)	(0.006)	(0.118)	(0.038)	(0.003)
Sunday	−0.008	0.019	0.020***	0.006	−0.026	0.003
	(0.165)	(0.077)	(0.006)	(0.115)	(0.058)	(0.003)
Thursday	0.332***	0.071	0.010	0.081	0.026	0.007**
	(0.117)	(0.054)	(0.006)	(0.062)	(0.035)	(0.004)
Tuesday	0.282*	0.044	0.006	0.052	0.011	0.011***
	(0.144)	(0.074)	(0.005)	(0.090)	(0.046)	(0.003)
Wednesday	0.209*	−0.009	0.012	0.031	0.008	0.005
	(0.108)	(0.067)	(0.009)	(0.068)	(0.035)	(0.004)
Date FE	Y	Y	Y	Y	Y	Y
Week FE×Plant FE	Y	Y	Y	Y	Y	Y
Observations	30,257	30,257	5,623	71,011	71,011	18,659
R^2	0.692	0.849	0.296	0.718	0.847	0.230
Adjusted R^2	0.681	0.844	0.150	0.709	0.842	0.137
Residual Std. Error	15.872 (df = 29191)	5.764 (df = 29191)	0.097 (df = 4658)	14.847 (df = 68884)	5.599 (df = 68884)	0.104 (df = 16652)

Note: *p<0.1; **p<0.05; ***p<0.01
For the first three columns, the sample is from Dec. 1st to Dec. 28th for 2013-14, 2014-15, 2015-16, 2016-17, 2017-18 and 2018-19. The reference date is Dec. 28th.
For the last three columns, the sample is from Oct. 22nd to Mar. 25th of each year 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19;
and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year). The reference date is Nov. 1st.
Standard error is clustered at plant level.

Table A7: Potential mechanisms, full sample.

	Dependent variable:				
	Electricity Prod. (10^3 MWH)	CO2 (10^3 tons)	SO2 (tons)	NOX (tons)	AOD
	(1)	(2)	(3)	(4)	(5)
EPA Furlough	−0.059	0.025	0.321	0.087	0.018**
	(0.046)	(0.017)	(0.517)	(0.201)	(0.008)
Precipitation	0.000	−0.000	−0.006	−0.005	−0.001***
	(0.001)	(0.000)	(0.005)	(0.003)	(0.000)
Temperature	0.003	0.000	−0.032	−0.035	−0.004***
	(0.003)	(0.001)	(0.046)	(0.023)	(0.000)
Dew Point	−0.006**	0.002**	0.017	0.017	0.003***
	(0.003)	(0.001)	(0.023)	(0.026)	(0.000)
Wind Speed	−0.001	−0.002**	−0.009	−0.004	−0.003***
	(0.002)	(0.001)	(0.020)	(0.008)	(0.000)
Steam Prod. (10^3 lbs.)	−0.000***				
	(0.000)				
Heat Input (10^3 mmBtu)	0.089***	0.104***	−0.087	0.091***	−0.000
	(0.008)	(0.002)	(0.145)	(0.035)	(0.000)
CO2 (10^3 tons)	0.152*		2.000	−0.097	0.001
	(0.081)		(1.329)	(0.319)	(0.004)
Year 2014-15	−0.008	−0.007	−2.380***	−0.748**	−0.002
	(0.070)	(0.016)	(0.779)	(0.304)	(0.003)
Year 2015-16	−0.171**	−0.004	−5.258***	−1.670***	−0.016***
	(0.073)	(0.016)	(0.921)	(0.369)	(0.003)
Year 2016-17	−0.132*	0.017	−7.231***	−2.357***	−0.004
	(0.080)	(0.024)	(1.790)	(0.432)	(0.003)
Year 2017-18	−0.110	0.010	−7.305***	−2.996***	−0.011***
	(0.085)	(0.026)	(1.723)	(0.506)	(0.003)
Year 2018-19	−0.127	−0.003	−7.288***	−3.343***	−0.013***
	(0.096)	(0.032)	(1.627)	(0.678)	(0.004)
Monday	−0.011*	0.003	−0.065	0.045	0.002
	(0.006)	(0.003)	(0.082)	(0.038)	(0.003)
Saturday	−0.025***	0.004	−0.093	−0.080***	0.002
	(0.007)	(0.002)	(0.095)	(0.030)	(0.003)
Sunday	−0.059***	0.008*	−0.213**	−0.067	0.002
	(0.009)	(0.005)	(0.101)	(0.045)	(0.003)
Thursday	−0.004	−0.002	0.043	0.043	0.004
	(0.005)	(0.002)	(0.050)	(0.026)	(0.003)
Tuesday	−0.003	0.001	0.020	0.017	0.008***
	(0.006)	(0.002)	(0.076)	(0.039)	(0.003)
Wednesday	0.007	−0.001	0.044	0.035	0.004
	(0.005)	(0.001)	(0.064)	(0.028)	(0.003)
Date FE	Y	Y	Y	Y	Y
Week FE×Plant FE	Y	Y	Y	Y	Y
Observations	104,282	104,282	104,282	104,282	24,310
R^2	0.996	1.000	0.714	0.850	0.245
Adjusted R^2	0.996	1.000	0.706	0.845	0.151
Residual Std. Error	0.950 (df = 101321)	0.298 (df = 101323)	15.087 (df = 101322)	5.595 (df = 101322)	0.102 (df = 21621)

Note: *p<0.1; **p<0.05; ***p<0.01
Long sample is from Oct. 22nd to Mar. 25th for 2013-14, 2014-15, 2016-17, 2017-18 and 2018-19;
and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).
Standard error is clustered at plant level.

Table A8: Potential mechanisms, short sample.

	Dependent variable:				
	Electricity Prod. (10^3 MWH)	CO2 (tons)	SO2 (10^3 tons)	NOX (tons)	AOD
	(1)	(2)	(3)	(4)	(5)
EPA Furlough	−0.029	0.009	0.713	0.161	0.022**
	(0.044)	(0.022)	(0.527)	(0.194)	(0.009)
Precipitation	−0.000	0.000	−0.001	−0.002	−0.000
	(0.001)	(0.000)	(0.008)	(0.003)	(0.000)
Temperature	0.005	0.001	−0.063	−0.018	−0.006***
	(0.004)	(0.001)	(0.040)	(0.019)	(0.001)
Dew Point	−0.007**	0.001	0.038	0.004	0.004***
	(0.003)	(0.001)	(0.026)	(0.020)	(0.000)
Wind Speed	−0.001	−0.001	−0.028	−0.002	−0.004***
	(0.002)	(0.001)	(0.021)	(0.010)	(0.001)
Steam Prod. (10^3 lbs.)	−0.000***				
	(0.000)				
Heat Input (10^3 mmBtu)	0.090***	0.104***	−0.131	0.082**	0.000
	(0.008)	(0.000)	(0.143)	(0.034)	(0.001)
CO2 (10^3 tons)	0.149*		2.393*	−0.011	−0.002
	(0.076)		(1.384)	(0.313)	(0.006)
Year 2014-15	−0.019	−0.004	−2.950***	−0.876**	−0.008**
	(0.083)	(0.020)	(0.884)	(0.370)	(0.004)
Year 2015-16	−0.143*	0.004	−5.430***	−1.610***	−0.011**
	(0.077)	(0.019)	(1.010)	(0.387)	(0.004)
Year 2016-17	−0.131	0.016	−7.549***	−2.312***	−0.011***
	(0.084)	(0.025)	(1.906)	(0.463)	(0.004)
Year 2017-18	−0.090	−0.007	−7.387***	−3.050***	−0.002
	(0.091)	(0.026)	(1.873)	(0.543)	(0.005)
Year 2018-19	−0.146	0.013	−7.996***	−3.420***	−0.016***
	(0.101)	(0.043)	(2.015)	(0.642)	(0.005)
Monday	−0.013	0.001	−0.052	0.053	0.009*
	(0.008)	(0.002)	(0.104)	(0.048)	(0.005)
Saturday	−0.024***	0.002	−0.133	−0.085**	0.003
	(0.008)	(0.002)	(0.094)	(0.036)	(0.005)
Sunday	−0.058***	0.005*	−0.311***	−0.065	0.010***
	(0.011)	(0.003)	(0.108)	(0.047)	(0.004)
Thursday	−0.001	−0.004	0.146**	0.077**	0.003
	(0.005)	(0.003)	(0.071)	(0.032)	(0.004)
Tuesday	−0.001	−0.001	0.106	0.039	0.003
	(0.008)	(0.002)	(0.095)	(0.047)	(0.004)
Wednesday	0.005	−0.005*	0.118	0.038	0.006
	(0.007)	(0.003)	(0.083)	(0.038)	(0.005)
Date FE	Y	Y	Y	Y	Y
Week FE×Plant FE	Y	Y	Y	Y	Y
Observations	63,528	63,528	63,528	63,528	11,274
R^2	0.996	1.000	0.701	0.850	0.308
Adjusted R^2	0.996	1.000	0.692	0.846	0.189
Residual Std. Error	0.980 (df = 61622)	0.316 (df = 61624)	15.687 (df = 61623)	5.717 (df = 61623)	0.095 (df = 9620)

Note: *p<0.1; **p<0.05; ***p<0.01

Short sample is from Dec. 1st to Feb. 24th for 2013-14, 2014-15, 2015-16, 2016-17, 2017-18 and 2018-19.
Standard error is clustered at plant level.

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