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

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**Abstract**

This paper studies the firm's short-run strategic response to unexpected shocks in environmental regulation. Our theoretical model suggests that firms strategically reduce their environmental compliance effort when regulatory stringency declines in the short run. We focus on coal-fired power plants in the United States, and use the EPA's furlough during the 2018 – 19 federal government shutdown as a natural experiment to test our theory. We use two high frequency data sets to measure the pollution: EPA AMPD data set provides daily $SO_2$ and $NO_x$ emissions, and NASA satellite based aerosol optical depth (AOD) data indicates the daily PM concentration with fine resolution. Our empirical results imply that during the government shutdown, EPA's furlough causes a negative shock on regulation stringency, and coal-fired power plants significantly increase their PM emissions. On average, the local AOD surrounding the coal-fired power plants is raised by 15.43% during the EPA's furlough by temporally turning off PM pollution control devices. There is no significant change in $SO_2$ and $NO_x$, because these two pollutants are under continuous monitoring, so EPA's furlough has small effect on the stringency of $SO_2$ and $NO_x$ regulation.

**Key words:** government shutdown, air pollution, coal-fired power plant, aerosol optical depth

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# 1 Introduction

Firms coordinate their technological capability and managerial strategies in response to regulatory schemes, especially the regulations tasked with environmental protection. For example, firms adjust their emission, employment, capital stock and other characteristics responding to EPA's county non-attainment designation (Greenstone, 2002; Curtis, 2018; Gibson, 2019). Most of the studies explain these effects in the long-run through three channels primarily: (i) Firms change their emission and abatement strategies given the technology. Gibson (2019) finds firms may substitute emissions from a plant in non-attainment county to another plant in attainment county. (ii) Firms uses new abatement technologies. Zhou et al. (2020) shows firms may upgrade their abatement technologies to reduce emissions after the implement of EPA's 33/50 program. (iii) Firms manage their environmental initiatives and investment to pursue a lenient regulatory burden. Decker (2002) and Li and Khanna (2018) show that regulator tends to allocate its inspection resources according to firm's environmental managerial strategies.

Firms also make quick responses in the event of an *unanticipated* temporary modification in carrying out the enforcement actions. This unanticipated interruption typically occurs within a short time span, resulting from exogenous reasons and leading to changes in the stringency of the regulations. For instance, to address the emergency circumstances of hurricane, the U.S. Environmental Protection Agency (EPA) waived requirements for certain programs and issued no action assurances for facilities in impacted regions, with these waivers and no action assurances expired after a short period.[1] Besides of natural disasters, lapses in appropriation is another typical scenario where the regulations can be interrupted. The lapses in appropriation is often caused by government shutdown, when most enforcement activities are no longer required and most of the employees will also be furloughed. As a consequence of these temporary policy modifications, the environmental regulation becomes lenient, offering opportunities for polluting firms not complying with the policy without being penalized.

This paper focuses on unanticipated and temporary changes in environmental regulations, and we test whether and to what extent as well as by what means firms respond to such changes within a short period of time. When facing such an unexpected and brief change in regulatory enforcement, firms can not easily and quickly adjust their abatement technology and

[1]EPA archived the response to Hurricane Michael, Florence, Harvey, Irma, and Maria at here: https://www.epa.gov/hurricane-response

environmental investment because the period is too brief for a firm to alter them. It means that, in contrast to the long run effects as we discussed above, any effects in the short-run stem from the changes in firm's emissions and abatement strategies.Moreover, Zou (2018) shows that firms are able to strategically change their emission and abatement behaviors on a daily basis. Then the remaining question becomes whether the firms take strategic changes immediately in emissions and abatement behaviors in response to the regulation shocks. Our study aims to answer that question by revealing the short-run effect of regulation shocks on firms' emissions and abatement behaviors.

We focus on the 2018–19 federal government shutdown, and ask an empirical question of whether and to what extent this shutdown causes coal-fired power plant to emit more pollutants. 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 the history. Among many other impacts, the impact on environmental regulation is thought to be significant because federal EPA employees do not carry out any duties such as pollution inspection and monitoring during federal government shutdown.[2] According to the EPA contingency plan for shutdown both before (September 25, 2018) and during (December 31, 2018) the 2018 – 2019 shutdown, the shutdown activities were accomplished within only 4 hours, leaving the total number of agency employees from more than 14,000 to less than 1,000.[3] Out of the retained employees during the shutdown, no one were necessary to perform activities necessarily implied by law. This EPA's furlough provides us an exogenously short-run shock in environmental regulation, allowing us to use this most recent U.S. federal government shutdown as a natural experiment to study firms' short-run strategic behavior.

We implement an empirical strategy suggested by the theory proposed by Maxwell and Decker (2006), in which a representative firm choosing its environmental effort in pollution abatement to minimize the overall cost of emissions including expected violation penalties and the cost of the environmental effort it devoted. The model indicates that a negative shock in regulation stringency increases the probability of being inspected by the regulator, so that the firm will invest more environmental effort to reduce the probability of triggering the pollution violation, and at the same time to reduce its emission level.

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

[3] EPA Contingency Plan for Government Shutdown: https://www.epa.gov/lapse/us-epa-contingency-plans-event-government-shutdown

We implement a difference-in-difference framework to bound the causal role of the 2018–2019 United States federal government shutdown effect on coal-fired power plants' emissions. The treated group is coal-fired power plants' emissions in 2018-19, the year when the government shutdown took place. Because the government shutdown is a universal effect to all coal-fired power plants in United States, there is no clearly defined control group available for estimating the counterfactual. We use the average emissions of the same coal-fired power plant at same dates during the previous 5 years, which are 2013-14, 2014-15, 2015-16, 2016-17, and 2017-18, as the counterfactual of its own 2018-19 emissions. Our empirical results provide evidence that during the government shutdown, coal-fired power plants temporally turned off their pollution control device for particulate matters abatement and significantly increased their PM emissions, which is consistent to our theory. However, we do not find any significant changes in coal-fired power plants' $SO_2$ and $NO_x$ emissions. It is because both $SO_2$ and $NO_x$ emissions of coal-fired power plants are monitored continuously, so that the absence of EPA inspections have negligible effect on the level of regulation stringency. Therefore, coal-fired power plants do not change their emissions and abatement behaviors regarding to $SO_2$ and $NO_x$.

The time span poses a particularly challenging problem for the study because high frequency data are often very scarce. To overcome this empirical difficulty, we use several high frequency data sets including EPA's Air Markets Program Data (AMPD), satellite based NASA MODIS Aerosol Data (AOD), Parameter-elevation Regressions on Independent Slopes Model Data (PRISM), and National Centers for Environmental Prediction -U.S. Department of Energy Reanalysis II Data (NCEPRII). Our empirical analysis focuses on the most polluting industry in U.S., the coal fired electricity industry, and AMPD data provides power plants' daily emission 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 provides daily particulate matters concentration of the surrounding area of power plants. PRISM data and NCEPRII data provide daily weather information. We describe the details of these data sets in the data part of section 3.

The paper proceeds as follows. In section 2, we present the theoretical model showing the regulation shocks affecting firm's environmental effort in pollution abatement as well as emission levels. In section 3 we present our empirical model identifications and data details. In section

4 we reports the baseline empirical results. In section 5 we check the robustness of baseline results using placebo tests. We conclude our paper in the last section.

## 2 Theoretical Framework

We build a simple model with similar setting as Maxwell and Decker (2006) to understand firm's emission level and abatement approach in response to the regulation. In the model, we assume a representative firm making decision in choosing their *environmental effort*, measured by amount of investment in pollution abatement technology and management. The environmental effort tends to lower both the probability of triggering a environmental violation and emission level. We assume that in the short-run (i) the firm takes the probability of receiving regulator's inspections and the violation penalties as given; and (ii) the firm is not able to change its characteristics such as abatement technologies. The firm's objective is to minimize the expected cost due to emissions, which is the summation of expected penalties of being inspected with violation and the cost of environmental efforts invested in the pollution abatement management.

Consider the model within a short-run time span $t \in [1, T]$. A firm chooses its environmental effort $x_t$ at time $t$, implying that the probability of environmental compliance is $p(x_t) \in [0, 1]$. $p(x_t)$ is increasing along with $x_t$ at a decreasing rate (an increasing and concave function of $x_t$). $1 - p(x_t)$ is the probability of violation. The cost of environmental effort is $g(\theta_t, x_t)$. $\theta_t$ is the firm's characteristics at time $t$, and $g(\theta_t, x_t)$ is an increasing and convex function of $x_t$. Let $m_t \in [0, 1]$ be the probability that firm will receive inspection from the regulator at time $t$, and $f_t$ be the penalty if violations are found during each inspection. We define a shock of environmental regulation as an exogenous changes in $m_t$. At each time $t$, the firm's objective function is to minimize the expected total cost of environmental regulation:

$$\min_{x} E(C_t) = (1 - p(x_t))m_t f_t + g(\theta_t, x_t). \tag{1}$$

Recall that we assume regulator is not able to strategically change inspection choices and violation penalties in response to firm's environmental performance in the short-run period, and firm can not strategically change their characteristics. We assume that $m_t$, $f_t$ and $\theta_t$ are exogenous and taken by firm as given. Firm will choose the optimal $x_t^* = x^*(m_t, f_t, \theta_t)$ to minimize the expected cost of emissions, due to the first order condition:

$$m_t f_t \frac{\partial p(x_t^*)}{\partial x_t^*} = \frac{\partial g(\theta_t, x_t^*)}{\partial x_t^*}. \tag{2}$$

The optimal compliance effort $x^*(m_t, f_t, \theta_t)$ increases in both the likelihood of being inspected ($m_t$) and penalty if any ($f_t$).

Finally, we assume that firm's emission $e(\theta_t, x_t)$ at time $t$ depends on firm's characteristics $\theta_t$ and compliance effort $x_t$. $e(\theta_t, x_t)$ is a decreasing function of $x_t$. In addition, $\frac{\partial e(\theta_t, x^*(m_t, f_t, \theta_t))}{\partial m_t} < 0$, implying that in short-run period, a negative shock in environmental regulation decreases firm's compliance effort and increases emission.

# 3 Empirical Model

## 3.1 Identification

During the government shutdown, there is a negative shock on $m_t$, because there is no inspection from EPA federal office. Our model implies that a negative change in $m_t$ decreases the coal-fired power plants' compliance effort $x_t^*$, and increases their emissions $e(\theta_t, x_t^*)$. We target coal-fired power plants, one of the most polluted sector, to test the following hypothesis:

**Hypothesis:** During the days when the U.S. federal government shut down, coal-fired power plants increase their air pollutant emissions.

The EPA's furlough timeline was slightly different from the official shutdown period, as the EPA used its available fund to keep the regular operations for one additional week after the shutdown, and reopened on the Monday after the weekend when the federal government announced the end of shutdown. This makes the EPA employee furlough start from December 29, 2018 to January 27, 2019, 30 days in total, which was the time when the coal-fired power plants made reactions to the EPA furlough.

Since the federal government shutdown is a universal event for all the plants, we do not have a comparable sector serving as a valid counterfactual measurement. However, we could use the emissions from the same group of power plants, but from different points of time to serve as their own counterfactual measurements. The underlying assumption is that the daily trend of emissions from power plants do not vary dramatically year by year. However, using a single past year is likely subject to some randomly occurred while unobserved events, so we use the previous 5 years data to smooth out any abnormal event if any. To be specific, we are using 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) as counterfactual measurements. For simplicity, in the following sections, we call December 29–January 27 the *furlough days*; 2018–19 the *shutdown year*; and 2013–14, 2014–15, 2015–16, 2016–17, 2017–18 the *previous 5 years.*

We compare emission outcomes before and after the furlough days, between the shutdown year and previous 5 years in a difference-in-differences framework. The time horizon of our data is set on a daily basis from October 22 to January 27, including 61 days prior to the EPA's furlough and 30 furlough days. The model reads:

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

where $i$ is the plant-year index, $j$ is the year index, and $t$ is the date index. $Y_{it}$ is the daily emissions. $D_{ijt}$ is the shutdown dummy with $D_{ijt} = 1$ if the observation is in the time period from December 29, 2018 to January 27, 2019, and $D_{ijt} = 0$ otherwise. $X_{ijt}$ is vector of the time-variant covariates including daily weather factors and electricity generation.

In addition to $X_{ijt}$, a series of fixed effects are included to ensure that the remaining variations in the outcome variables are solely due to the EPA's furlough, allowing us to isolate $\beta$ as the causal impacts of furlough on the outcome variable. The plant fixed effect captures the time invariant plant specific characteristics. Weekdays fixed effect captures the potential difference coming from the variations in electricity demand or other social economic activities across weekdays. Date fixed effect is the time fixed effect, capturing the average time trend on daily basis across different years. Year fixed effect captures both the differences across years and the intercept difference between treated group and control group. In addition, our model includes the interaction term, $\text{Plant}_i \times \text{Weeks}_t$, to allow plants having their own time trend on a weekly basis. The definition of week is based on 2018–19, from Monday to Sunday.[4] There are in total 23 weeks, but the last week only contains one day.

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

### 3.2 Data

We create a plant-by-day data set that includes coal-fired power plants in the continental United States. Compiled from multiple data sources, each power plant has daily information on air emissions, operational data, and surrounding PM concentration and weather.

The list of coal-fired power plants is extracted from the U.S. Energy Information Administration (EIA).[5] As of April 2019, 303 out of total 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, using coal as the only fuel source.

We obtain the daily emissions and operational data from the EPA's Air Market Program Data (AMPD) under the program of Clear Air Markets. The AMPD provides extensive daily data of any 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 $CO_2$. The daily emission data is recorded by a continuous emission monitoring system and a flow monitoring system installed in each coal-fired unit, which is required by EPA federal regulation code.[6] 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, each year from 2013 to 2019. Finally, for the sake of robustness check, we extended our data for another 57 days after the EPA returned to the active enforcement.

Another primary outcome variable of interest is PM concentration surrounding each power plant. 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: $PM_{2.5}$ (size $< 2.5\mu m$) and $PM_{10}$ (size $< 10\mu m$) (Liu et al., 2004; Donkelaar et al., 2016). Higher AOD indicates worse air quality, and therefore higher PM pollution. Following Zhang et al. (2020)'s method, we define the PM concentration outcome as a weighted average AOD in a circular area of 3 kilometers radius around each power plant.

We control for weather variables of daily precipitation, daily temperature, daily dew point, and wind speed, because they vary with air emission and output of power plants. First, it

[5] https://www.eia.gov/electricity/data/browser/

[6] 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).

accounts for the correlations between weather conditions and the electricity production. Second, weather variables affect coal condition, such as the moisture level of the coal, which further affects the heat content and emissions (Chandralal et al., 2014). Third, the weather variables are critical confounders between the strong association between AOD and PM (Kumar et al., 2007; Foster et al., 2009; Zhang et al., 2020).

We collected the daily precipitation, daily temperature, and daily dew point data from Parameter – elevation Regressions on Independent Slopes Model (PRISM), a spatial climate database.[7] PRISM has a spatial resolution at 4 $km^2$ grid, which is comparable with the AOD data. Similar approach is used to calculate the daily value of these variables for the 3km circular area around each coal-fired power plant. We extract the daily wind data from National Centers for Environmental Prediction (NCEP)-U.S. Department of Energy (DOE) Reanalysis II (NCEPRII).[8] The data is at resolution of 2.5 degree in latitude and longitude. We assign wind speed value to each power plants depending on which 2.5 degree square the power plant is located.

Table 1 summarizes all of the variables in our data by year. We observe a declining trend on average $SO_2$, $NO_x$ and $CO_2$ emissions. AOD is in general declining, but rise back in 2018-19. The electricity production and heat input decreases from 2013-14 to 2015-16, and rise back and stay stable from 2016-17 to 2018-19. The weather variables except wind speed show large variations across years, which is consistent to the national weather pattern.[9]

# 4 Results

## 4.1 Evaluating identifying assumptions

Our key identifying assumption is that the emissions in the previous 5 years provide an appropriate counterfactual of the trend that the emission in the shutdown year would have had if there were no government shutdown. A significant advantage of our study design is that, it is plausible to assume emissions in the shutdown year and previous 5 years are similar in both levels and trends over the same month-day after controlling electricity generation, given there are 197 out of 203 plants that we observe over both the shutdown year and all/some of the

[7] http://prism.oregonstate.edu
[8] https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html
[9] https://www.ncdc.noaa.gov/cag/national/time-series

previous 5 years.

Though there is no agreed-upon method to test the common trends assumption, following a recent wisdom, we run the following regression to provide a suggestive evidence for the common trends assumption:

$$Y_{ijt} = \alpha X_{ijt} + \text{Plant}_i \times \text{Weeks}_t + \text{Year}_j + \text{Weekdays}_{jt} + \text{Date}_t + \text{Date}_t \times \text{Group}_j + \epsilon_{ijt}, \quad (4)$$

where $\text{Group}_j$ is the group fixed effect. $\text{Group}_j = \textit{Treated}$ if the observation is from the shutdown year, and $\text{Group}_j = \textit{Control}$ otherwise. The interaction term $\text{Date}_t \times \text{Group}_j$ captures the daily difference between treated group and control group. We run equation 4 on a pre-shutdown period (October 22 – December 28), and plot the estimations of $\text{Date}_t \times \text{Group}_j$ for every single day with 95% confidence interval. The standard error is clustered at plant level.

Figure 1, 2 and 3 plot the differences in $SO_2$, $NO_x$ and AOD respectively between treated group and control group on each single day during the pre-shutdown period. In order to make equation 4 be identified, we need to set a reference level for each of the fixed effects as well as the interaction terms $\text{Date}_t \times \text{Group}_j$. Let the reference level of interaction term be $\text{Date}_{t_0} \times \text{Group}_j$, where $t_0$ is an arbitrary date. Then $\text{Year}_j + \text{Date}_{t_0} \times \text{Group}_j$ becomes the intercept difference between treated group and control group, because the group index is nested into the year index. By defining the reference level of interaction terms with different arbitrary date $t_0$, the regression estimates different interception differences. The common trend is supported as long as there exist a reference level with an arbitrary date so that after taking away the corresponding estimated interception difference, there is no remaining difference between treated group and control group. We use different reference levels in Figure 1, 2 and 3.

We find that for each of these three pollutants every day during the pre-shutdown period, although the joint F tests are always significant due to the long time horizon, for every individual day, the treated group is always not significantly different from the control group. These results support the common trends assumption and validate the reliability of any causal relationship we found in the following analysis.

## 4.2 Main results

Table 2 reports effects of the shutdown on daily $SO_2$, $NO_x$ and AOD. The column (1) to (3) consider the full sample with a relative long pre-shutdown window (October 22 – December 28, 61 days), and column (4) to (6) shorten the pre-shutdown period to the similar length as the shutdown period (December 1 – December 28, 28 days). The shorter time frame of pre-shutdown is conducted as a sensitive analysis as relate to the validity of common trends assumption. Because this shorter pre-shutdown window is short to permit and enhance the validity of the common trends assumption, also long enough to serve as a pre-treatment window.

Additionally, sample sizes are smaller in the AOD regressions in column (3) and (6) because AOD values are usually missing in winter season because of either heavy clouds, snow cover, or high surface reflectance (Xiao et al., 2017). This would not be a concern to our analysis since our sample spans from October 22 to January 27, overlapping with the winter season, and thus the missing AOD value is a random and exogenous issue to the AOD measurement. For each regression, we report standard errors both without and with clustering by plant.

Table 2 shows that our findings are indifferent when using different pre-shutdown periods. We find weak evidence in the change of daily $SO_2$ emission, as shown in column (1) and (4) that the shutdown coefficient is positive significant only when the standard error is not clustered. Besides, we do not find any significant change in daily $NO_x$ emissions, as shown in column (2) and (4). In comparison, the results in column (3) and (6) show that the daily AOD surrounding the plants significantly increased by about 0.018 – 0.022, which is on average 15.43% – 19.53% above the counterfactual (as if there is no regulation shock).[10]

Thus, our results suggest that during the government shutdown, the coal-fired power plants significantly increases their particulate matter emissions due to the EPA's furlough. The results of $SO_2$ and $NO_x$ are not surprising, because they are continuously monitored. The insignificant results suggest that thanks to the continuous monitoring device, the temporally absence of EPA inspections does not affect the regulation stringency on $SO_2$ and $NO_x$ emissions, so that the their emission levels stay the same. In comparison, there is not such a device in power plants to monitor PM emissions, so the regulation stringency of this unmonitored pollutant can be affected by the inspections from the regulators. Therefore, the missing EPA inspections

[10] This value is calculated as the difference between the observed AOD and the average treatment effect.

causes plants to strategically reduce their compliance effort and increase their particulate matter emissions, so that we detect a significant raise in local AOD due to the EPA's furlough.

In conclusion, the empirical results support the theory that when there is a shock weakening regulation stringency, plants tend to take advantage of the less strict regulation to lower their compliance efforts and emit more pollution.

### 4.3 Robustness check

Our main results identified a significant increase in particulate matter emissions due to the EPA's furlough. The findings may fail if there was an unconsidered incident happening around the time of the EPA's furlough contributed to coal-fired power plants' emissions, considering the following two cases: (i) an unconsidered incident occurred during the time of EPA's furlough and increased coal-fired power plants' emissions; (ii) an unconsidered incident occurred prior to the time of EPA's furlough and reduced the coal-fired power plants' emissions, suggestion a violation of the common trends assumption necessary for identification.

Below, we present results using the same identification framework as in equation 3, in which we either include a post-furlough period to detect the case (i) or artificially assign a placebo "EPA furlough" before the true EPA furlough to detect the case (ii). This robustness analyses rule out the two possibilities and do not lead us to alter our findings in the main analysis.

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

We could run into two scenarios if there was an incident during the furlough that contributes to the emission: First, an incident spanned from the EPA's furlough to some point during the post-furlough; second, this incident was nested in the time frame of the EPA's furlough. To test the first possibility, we extend our sample to March 25, bringing 57 days after furlough days.[11] We test if there is any difference between treated and control group after the EPA returned to the regular enforcement in relation to the pre-furlough group difference. An insignificant difference (insignificant coefficient of the post-furlough dummy) not only rules out any incident that spanned from the furlough to some point during the post-furlough, but also rules out any lagged effects if any. Table 5 reports the estimation results with post-furlough dummy for both full sample and the subsample with short time horizon. The results are insensitive to different

[11] March 24 for 2015 – 2016 data because of the leap year.

samples. We do not find any significant effect on the post period of EPA's furlough, suggesting there is not such an incident failing our main results, and thus supporting the finding that the increased AOD is solely driven by the EPA's furlough. In addition, such result is consistent to our theory that the plants restore their compliance effort and emissions immediately after the regulation shock ends.

If our baseline results are driven by an unconsidered incident without lagged effect and nested in the time frame of EPA's furlough, we are not able to test it, because the same year counterfactual is not available. However, such incident must have a national-wide effect on all United States coal-fired power plants. Since we do not find any major incident happened nationally related to power plants during EPA's furlough period, we believe such case to be highly unlikely.

***Robustness check 2: ruling out incident prior to the EPA's furlough***

The possibility that there is an unconsidered incident prior to the EPA furlough can be ruled out if the pre-shutdown period common trend assumption is valid. We show some evidence of the pre-shutdown period common trend in the previous section. Here, we do additional placebo test to in further make sure that there is no unconsidered incident during the pre-shutdown period that falsify our findings.

First, we take the subset of the full sample in the pre-shutdown period, from November 22 to December 28, and assign a pre-shutdown placebo treatment from December 1 to December 28. The estimation results of the placebo treatment is reported in Table 6, column (1) to (3). For all pollutants, the pre-shutdown placebo treatment coefficients are insignificant. We also test the same pre-shutdown placebo treatment in the full sample. In the model, we include both the true shutdown treatment and post-shutdown placebo treatment. The estimation results are reported in Table 6, column (4) to (6). Again, none of pre-shutdown and post-shutdown placebo treatment coefficients are significant. Second, we again use the pre-shutdown period data, both from the full sample and the subsample with shorter time horizon. We assign multiple placebo treatments during the pre-shutdown period, which are mostly defined on weekly basis. Table 7 reports the estimation results. The first three columns are based on the pre-shutdown data of the subsample with shorter time horizon, and the last three columns are based on the pre-shutdown data of the full sample. We find none of these placebo treatments has significant coefficient.

These tests suggest that there is no significant difference between the shutdown year time trend and previous years average time trend before the shutdown, and it is unlikely to falsify our main results due to an unconsidered incident during the pre-shutdown period.

## 5 Explaining Emission Effects of Shutdown

A further development of this analysis is to examine by what means coal-fired power plants are able to increase their unmonitored emissions when the federal government shutdown. In practice, the coal-fired power plants may reduce their compliance efforts by taking three strategic actions. First, they tend to switch to cheaper but more polluting grades of coal in the absence of strict enforcement, because the unit price varies greatly across different types of coal.[12] Although it is implausible to assume power plants to switch to a different coal provider from another coal mining region in such short period, but it is still possible for them to get lower grades coal from same coal provider, because coal grades are not only different across coal mining regions in U.S., but also varies within the same region.[13] The second strategic action power plants might take is to start running a unit with lower efficiency. The low efficiency units are used to be unprofitable to operate because they have higher production cost. The lower risk of federal inspections and penalties during the shutdown reduces the expected emission cost, which is a part of total production cost. Therefore, running these low efficiency units is more likely to generate profit. The third strategic action is to temporarily turn off pollution control devices as a cost saving measure.[14]

In the following text, we disentangle and test the three strategic actions separately. The estimation is based on the identification framework in equation 3, with different model spec-

[12] According to EIA website, 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, unit price varies with the heat and sulfur content of the coal.

[13] 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)

[14] According to https://www.eia.gov/electricity/annual/html/epa_09_04.html, average operation and maintenance costs of scrubber is \$2.15 per megawatthour in 2017. We can do some calculation: for example, in January 2017, the net generation from 359 coal-fired power plants is 115,332 thousand megawatthour, so the associated cost-saving for one day on average is: \$2.15 * (115,330,000/359plants/30days) = \$22,645.

ifications for each of the three strategic action. The results are reported in Table 3 (the full sample) and Table 4 (the short time horizon), both with the standard errors clustered at plant level. The results remain insensitive across different samples.

First, we test whether coal-fired power plants switched to lower grade coal, using daily $CO_2$ emissions as the outcome variable. $CO_2$ emission is neither regulated nor subject to any pollution control devices, 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. We do not find significant changes in daily $CO_2$ emissions, shown in column (2) of Tables 3 and 4. This suggest that the increased AOD as we found in the main analysis was not led by switching grades of coal.

Then, to test whether coal-fired power plants started to operate their lower efficiency units temporarily, we use daily electricity production as outcome variable. We include weather, heat input, steam production, and $CO_2$ emissions as controls. According to energy conversion, heat input should equal to the summation of electric energy produced, steam energy produced, and energy loss. So conditioning on heat input and steam production, the lower electricity production means higher heat loss, therefore implies lower efficiency.[15] We control the $CO_2$ emissions because coal type affects the heat rate (Walsh et al., 2015). Since for same heat content, different coal types have different $CO_2$ emissions, holding heat input and $CO_2$ constant excludes the coal type variation. Reported in column (1) in Tables 3 and 4, we show that conditioning on heat input and $CO_2$ emissions, there is no significant change in the daily electricity production during the shutdown period, which implies that the plants do not operate at lower production efficiency in these days. In another words, the increased AOD during the EPA's furlough was not due to switching to lower efficiency units.

Finally, we test whether coal-fired power plants temporarily turn off pollution control devices. We use daily $SO_2$, $NO_x$, and AOD as outcome variables. Our control variables include the daily heat input and $CO_2$ emissions, which allows us to simultaneously exclude the effects of changing production efficiency and coal type, thus identifying the changes in pollution control. Both daily $SO_2$ and $NO_x$ emissions do not change, suggesting there is no change in pollution control input with respect to $SO_2$ and $NO_x$. These results are consistent to the baseline results,

[15] Since steam production efficiency is also affected by the overall production efficiency, we estimate a lower bound for efficiency loss.

suggesting that we find insignificant change in daily $SO_2$ and $NO_x$ emissions in baseline results because nothing happens through all three mechanisms that may affect daily $SO_2$ and $NO_x$ emissions.

However, We find a significant increasing in AOD during the shutdown with the same magnitude as the baseline results. Because the changes in pollution control mechanism raise AOD at same level as the AOD increasing in the main results, all the AOD changes are coming from the pollution control mechanism. These statistical evidences show that coal-fired power plants temporarily turn off the particulate matter pollution control devices during the EPA furlough.

# 6 Conclusion

Understanding polluters' behavior in response to any changes in regulatory scheme is essential for designing environmental policies. A central focus of the literature has been examining the long run impact of environmental regulation on firms' behavior through various mechanisms. There is yet not an emphasis on firms' responses in the event of an unanticipated and temporary modification in environmental regulatory stringency. Using a theoretical model, we demonstrate that for short-run period, a negative shock in environmental regulation stringency will make firms immediately reduce their effort in pollution abatement, and as a result, plants increase their emissions in order to minimize total emission cost.

We exploit the 2018–19 government shutdown, and assess whether this temporary interruption in environmental regulation causes increases in coal-fired power plants emissions. We use a difference-in-differences framework to identify the causal relationship between the EPA's furlough and the increases in emissions. We define our treated group as every coal-fired power plant's emissions in 2018-19, the year when government shutdown took place. We use the emissions from the same plant on the same date from previous 5 years as the counterfactual. We use two high frequency data set to measure these emissions: EPA AMPD data set provides coal-fired power plants' daily $SO_2$ and $NO_x$ emissions, and the satellite based aerosol optical depth (AOD) data from NASA indicates the local PM concentration from coal-fired power plants PM emissions. Our empirical results implies that during the government shutdown, coal-fired power plants significantly increase their PM emissions and raise the local AOD, which is consistent to the theory. On average, the local AOD within 3km surrounding the coal-fired power plants is raised by 15.43% because of EPA's furlough during government shutdown. However, there is no significant change in $SO_2$ and $NO_x$. Although it seems to be contradicted to our theory, it is not surprising. We believe insignificance is because these two pollutants are under continuous monitoring, so that the absence of EPA inspections has very small effect on the stringency level of $SO_2$ and $NO_x$ regulation. Therefore, coal-fired power plants do not change their emissions and abatement behaviors regarding to $SO_2$ and $NO_x$ because of EPA's furlough.

This paper contributes to the environmental regulation literature by filling the gap of studying the short-run effect of environmental regulation shocks. We provide evidence that loosing the regulation stringency will immediately causes firms to increase their emissions at daily basis. Our results suggest that EPA inspections play an important role in regulating firm's emissions. We also show that without considering the monitoring cost, the continuous monitoring system seems to be a very effective way of pollution regulation. Another contribution of this paper is its novel application of satellite based air quality data. There are several papers exploring the satellite based air quality data, but it is still relatively new in the economic research. Most of the previous studies find some relationship between AOD and environmental policies, but none of them use AOD to actually detect the emissions from a particular pollution source. Another paper of us, Zhang et al. (2020), use AOD data to detect the point source emissions from shale gas industry. This paper also use AOD data and successfully measure the changes in point source emissions from coal-fired power plants.

## Table 1: Descriptive Statistics

| | 2013-14 | 2014-15 | 2015-16 | 2016-17 | 2017-18 | 2018-19 | Full Sample |
|---|---|---|---|---|---|---|---|
| $SO_2$ (tons) | 24.2637 | 19.9044 | 14.1759 | 14.0553 | 14.1111 | 13.9624 | 16.9137 |
| | (39.1076) | (35.8647) | (22.4849) | (19.4454) | (20.2046) | (21.2217) | (28.2134) |
| $NO_x$ (tons) | 15.9075 | 13.8532 | 11.1687 | 11.7995 | 11.2345 | 11.1412 | 12.5922 |
| | (17.2749) | (15.5208) | (12.5850) | (13.0558) | (11.8005) | (11.7257) | (14.0176) |
| AOD | 0.1281 | 0.1235 | 0.1111 | 0.1146 | 0.1120 | 0.1197 | 0.1180 |
| | (0.1506) | (0.1240) | (0.1201) | (0.1393) | (0.1198) | (0.1408) | (0.1330) |
| $CO_2$(1000 tons) | 17626.1374 | 16198.3180 | 13706.0265 | 15541.9582 | 15458.6365 | 15662.2706 | 15731.7688 |
| | (15112.2997) | (13796.3559) | (12474.9668) | (13736.2448) | (13412.0796) | (13605.6617) | (13783.8914) |
| Electricity Productions (GWH) | 17.0647 | 15.6763 | 13.0472 | 14.8966 | 14.8581 | 15.0859 | 15.1389 |
| | (15.6340) | (14.2244) | (12.7424) | (14.1046) | (13.8832) | (13.9693) | (14.1946) |
| Steam Prodiction (1000 lbs.) | 4450.3207 | 3949.7323 | 3627.0441 | 3677.0374 | 3834.0095 | 3451.2717 | 3843.9745 |
| | (18470.1188) | (17535.6550) | (14191.8825) | (14117.9891) | (15238.5919) | (14176.5329) | (15796.8510) |
| Heat Input (1000 mmBtu) | 170.0676 | 156.3668 | 132.6772 | 150.1145 | 149.5302 | 151.3600 | 151.9984 |
| | (143.6520) | (131.6558) | 118.6296 | 130.6641 | (127.5920) | (129.5645) | (131.1914) |
| Precipitation (mm) | 2.0016 | 1.8867 | 2.8105 | 1.9193 | 2.1358 | 2.8500 | 2.2577 |
| | (6.4248) | (5.6563) | (8.8509) | (5.6107) | (6.5245) | (7.6026) | (6.8678) |
| Temperature (Celsius) | 0.8056 | 1.9111 | 4.7673 | 4.7824 | 2.4577 | 1.9828 | 2.7496 |
| | (8.6757) | (8.3304) | (8.0075) | (8.5111) | (8.4761) | (7.8655) | (8.4565) |
| Dew Point Temperature (Celsius) | $-5.0677$ | $-3.9645$ | $-1.0567$ | $-1.3668$ | $-3.7089$ | $-2.5792$ | $-3.0000$ |
| | (8.5967) | (8.3412) | (8.4337) | (8.6497) | (8.7986) | (8.0267) | (8.6017) |
| Wind Speed (m/s) | 5.5047 | 5.2665 | 5.5879 | 5.6941 | 5.4858 | 5.1938 | 5.4551 |
| | (2.8289) | (2.7241) | (2.9687) | (2.9384) | (2.8068) | (2.8060) | (2.8506) |
| Number of Plants[1] | 200 | 202 | 203 | 200 | 198 | 197 | 204 |
| Number of Observations ($SO_2$ & $NO_x$ Regressions) | 29,282 | 28,641 | 27,031 | 26,596 | 26,431 | 26,017 | 163,998 |
| Number of Observations (AOD Regressions) | 6,052 | 5,726 | 6,135 | 6,819 | 6,121 | 4,706 | 35,559 |

*Different numbers of plants is because of the missing observations.*

Figure 1: $SO_2$ common trend plot for pre-shutdown period, Dec. 4th is the reference date

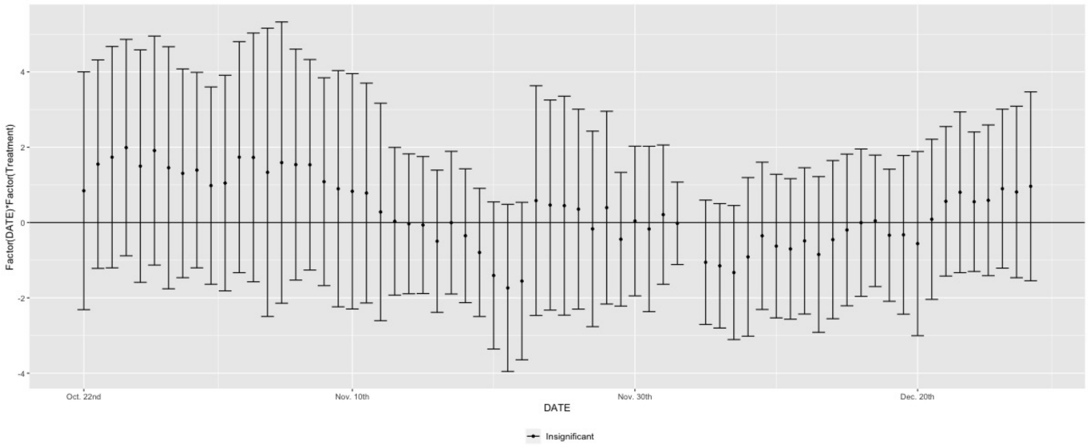


Figure 2: $NO_x$ common trend plot for pre-shutdown period, Nov. 3rd is the reference date

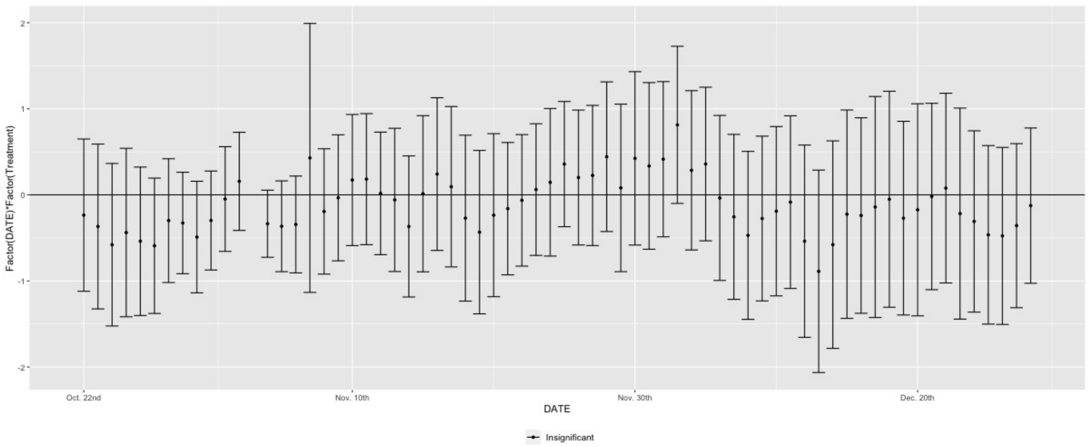


Figure 3: AOD common trend plot for pre-shutdown period, Nov. 2nd is the reference date

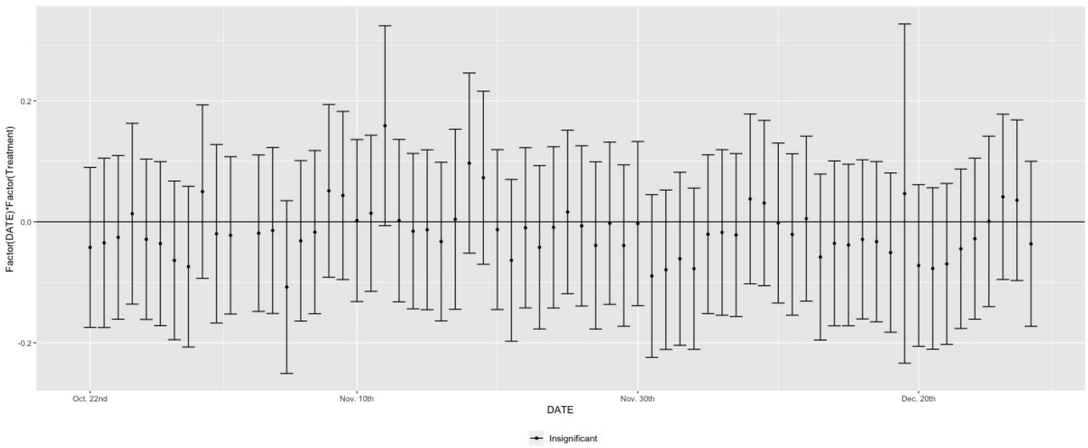

Table 2: Main results, with standard errors not clustered and clustered at plant level

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | *Full Sample* | | | *Short Sample* | | |
| | SO2 (tons) | NOX (tons) | AOD | SO2 (tons) | NOX (tons) | AOD |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| shutdown | 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)** |
| ppt | −0.007 | −0.005 | −0.0005 | −0.001 | −0.001 | −0.0002 |
| | (0.007) | (0.003)* | (0.0002)*** | (0.010) | (0.004) | (0.0002) |
| | (0.005) | (0.003) | (0.0001)*** | (0.008) | (0.003) | (0.0002) |
| tmean | −0.035 | −0.038 | −0.004 | −0.065 | −0.023 | −0.006 |
| | (0.020)* | (0.007)*** | (0.0003)*** | (0.027)** | (0.010)** | (0.0004)*** |
| | (0.046) | (0.024) | (0.0004)*** | (0.040) | (0.020) | (0.001)*** |
| tdmean | 0.028 | 0.019 | 0.003 | 0.050 | 0.007 | 0.004 |
| | (0.018) | (0.007)*** | (0.0003)*** | (0.025)** | (0.009) | (0.0004)*** |
| | (0.025) | (0.027) | (0.0003)*** | (0.027)* | (0.020) | (0.0004)*** |
| Wind | −0.010 | −0.003 | −0.003 | −0.030 | −0.001 | −0.004 |
| | (0.018) | (0.007) | (0.0003)*** | (0.024) | (0.009) | (0.0004)*** |
| | (0.020) | (0.008) | (0.0003)*** | (0.021) | (0.010) | (0.0005)*** |
| k_MWH | 1.149 | 0.754 | 0.0003 | 1.118 | 0.759 | 0.0002 |
| | (0.008)*** | (0.003)*** | (0.0001)** | (0.011)*** | (0.004)*** | (0.0002) |
| | (0.186)*** | (0.049)*** | (0.0002)* | (0.172)*** | (0.050)*** | (0.0002) |
| SLOAD..1000.lbs. | 0.0002 | 0.0001 | 0.00000 | 0.0002 | 0.0001 | −0.000 |
| | (0.00001)*** | (0.00000)*** | (0.00000) | (0.00001)*** | (0.00000)*** | (0.00000) |
| | (0.0001)*** | (0.00001)*** | (0.00000) | (0.0001)** | (0.00001)*** | (0.00000) |
| factor(Year)2014 | −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)** |
| factor(Year)2015 | −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)** |
| factor(Year)2016 | −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)*** |
| factor(Year)2017 | −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) |
| factor(Year)2018 | −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)*** |
| factor(weekday)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)* |
| factor(weekday)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) |
| factor(weekday)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)*** |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| Year FE & 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 two standard error, the first is the standard error without clustering, the second is the standard error with clustering at plant level.*

*For the first three columns, sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17 and 2017-18;*

*and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).*

*For the last three columns, sample is from Dec. 1st to Feb. 24th, each year of 2013-14, 2014-15, 2015-16, 2016-17 and 2017-18.*

Table 3: Test the different mechanisms, long sample.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | k_MWH | CO2 (tons) | SO2 (tons) | NOX (tons) | AOD |
| | (1) | (2) | (3) | (4) | (5) |
| shutdown | −0.0591 | 24.9647 | 0.3214 | 0.0868 | 0.0181** |
| | (0.0458) | (17.0567) | (0.5170) | (0.2006) | (0.0076) |
| ppt | 0.0004 | −0.0545 | −0.0065 | −0.0048 | −0.0005*** |
| | (0.0007) | (0.2503) | (0.0052) | (0.0032) | (0.0001) |
| tmean | 0.0025 | 0.2710 | −0.0323 | −0.0346 | −0.0036*** |
| | (0.0033) | (0.9660) | (0.0459) | (0.0233) | (0.0004) |
| tdmean | −0.0063** | 1.6192** | 0.0167 | 0.0168 | 0.0031*** |
| | (0.0026) | (0.7567) | (0.0234) | (0.0260) | (0.0003) |
| Wind | −0.0014 | −1.6051** | −0.0085 | −0.0036 | −0.0033*** |
| | (0.0016) | (0.7794) | (0.0198) | (0.0075) | (0.0003) |
| SLOAD..1000.lbs. | −0.0001*** | | | | |
| | (0.000002) | | | | |
| heat | 0.0894*** | 104.1469*** | −0.0873 | 0.0908*** | −0.0001 |
| | (0.0082) | (0.1893) | (0.1454) | (0.0349) | (0.0004) |
| CO2_MASS..tons. | 0.0002* | | 0.0020 | −0.0001 | 0.000001 |
| | (0.0001) | | (0.0013) | (0.0003) | (0.000004) |
| factor(Year)2014 | −0.0081 | −7.1912 | −2.3800*** | −0.7482** | −0.0016 |
| | (0.0705) | (16.3295) | (0.7786) | (0.3044) | (0.0027) |
| factor(Year)2015 | −0.1714** | −3.7202 | −5.2575*** | −1.6702*** | −0.0162*** |
| | (0.0729) | (15.9189) | (0.9212) | (0.3690) | (0.0035) |
| factor(Year)2016 | −0.1325* | 17.2385 | −7.2308*** | −2.3574*** | −0.0044 |
| | (0.0797) | (24.4226) | (1.7902) | (0.4325) | (0.0034) |
| factor(Year)2017 | −0.1098 | 10.4224 | −7.3046*** | −2.9962*** | −0.0110*** |
| | (0.0847) | (26.2125) | (1.7232) | (0.5063) | (0.0032) |
| factor(Year)2018 | −0.1271 | −2.7263 | −7.2878*** | −3.3433*** | −0.0128*** |
| | (0.0964) | (31.7673) | (1.6273) | (0.6779) | (0.0036) |
| factor(weekday)Monday | −0.0110* | 2.5151 | −0.0648 | 0.0454 | 0.0023 |
| | (0.0060) | (2.5475) | (0.0820) | (0.0382) | (0.0027) |
| factor(weekday)Saturday | −0.0253*** | 3.5415 | −0.0930 | −0.0795*** | 0.0023 |
| | (0.0066) | (2.4446) | (0.0950) | (0.0295) | (0.0026) |
| factor(weekday)Sunday | −0.0594*** | 8.2751* | −0.2135** | −0.0670 | 0.0017 |
| | (0.0095) | (4.5321) | (0.1011) | (0.0450) | (0.0027) |
| factor(weekday)Thursday | −0.0038 | −1.5017 | 0.0433 | 0.0426 | 0.0044 |
| | (0.0047) | (1.8706) | (0.0498) | (0.0264) | (0.0029) |
| factor(weekday)Tuesday | −0.0032 | 0.7578 | 0.0196 | 0.0168 | 0.0081*** |
| | (0.0057) | (2.2079) | (0.0758) | (0.0391) | (0.0025) |
| factor(weekday)Wednesday | 0.0068 | −1.7239 | 0.0441 | 0.0355 | 0.0035 |
| | (0.0052) | (2.3948) | (0.0636) | (0.0277) | (0.0028) |
| Year FE | Y | Y | Y | Y | Y |
| Week FE×Plant FE | Y | Y | Y | Y | Y |
| Date FE | Y | Y | Y | Y | Y |
| Observations | 104,282 | 104,282 | 104,282 | 104,282 | 24,310 |
| $R^2$ | 0.9957 | 0.9996 | 0.7143 | 0.8497 | 0.2450 |
| Adjusted $R^2$ | 0.9956 | 0.9995 | 0.7059 | 0.8453 | 0.1511 |
| Residual Std. Error | 0.9504 (df = 101321) | 297.8518 (df = 101323) | 15.0874 (df = 101322) | 5.5955 (df = 101322) | 0.1018 (df = 21621) |

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

*Long sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17 and 2017-18; and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).*

*Standard error is clustered at plant level.*

Table 4: Test the different mechanisms, short sample.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | k_MWH | CO2 (tons) | SO2 (tons) | NOX (tons) | AOD |
| | (1) | (2) | (3) | (4) | (5) |
| shutdown | −0.0287 | 8.4695 | 0.7135 | 0.1606 | 0.0224** |
| | (0.0445) | (21.9723) | (0.5273) | (0.1945) | (0.0092) |
| ppt | −0.0002 | 0.2266 | −0.0014 | −0.0016 | −0.0002 |
| | (0.0009) | (0.4086) | (0.0081) | (0.0033) | (0.0002) |
| tmean | 0.0047 | 1.3461 | −0.0627 | −0.0183 | −0.0060*** |
| | (0.0037) | (1.2908) | (0.0397) | (0.0193) | (0.0006) |
| tdmean | −0.0074** | 0.8215 | 0.0379 | 0.0038 | 0.0040*** |
| | (0.0029) | (1.0062) | (0.0257) | (0.0196) | (0.0004) |
| Wind | −0.0009 | −1.3668 | −0.0278 | −0.0018 | −0.0039*** |
| | (0.0021) | (0.8747) | (0.0207) | (0.0096) | (0.0005) |
| SLOAD..1000.lbs. | −0.0001*** | | | | |
| | (0.000002) | | | | |
| heat | 0.0898*** | 104.1330*** | −0.1314 | 0.0821** | 0.0003 |
| | (0.0077) | (0.1968) | (0.1432) | (0.0339) | (0.0006) |
| CO2_MASS..tons. | 0.0001* | | 0.0024* | −0.00001 | −0.000002 |
| | (0.0001) | | (0.0013) | (0.0003) | (0.00001) |
| factor(Year)2014 | −0.0191 | −3.6156 | −2.9502*** | −0.8759** | −0.0079** |
| | (0.0825) | (19.6408) | (0.8841) | (0.3697) | (0.0040) |
| factor(Year)2015 | −0.1429* | 4.0980 | −5.4299*** | −1.6103*** | −0.0107** |
| | (0.0768) | (18.9690) | (1.0097) | (0.3867) | (0.0043) |
| factor(Year)2016 | −0.1305 | 16.2779 | −7.5493*** | −2.3119*** | −0.0107*** |
| | (0.0836) | (24.8426) | (1.9060) | (0.4631) | (0.0041) |
| factor(Year)2017 | −0.0903 | −6.5325 | −7.3870*** | −3.0501*** | −0.0019 |
| | (0.0906) | (26.2219) | (1.8730) | (0.5426) | (0.0045) |
| factor(Year)2018 | −0.1455 | 12.7860 | −7.9961*** | −3.4195*** | −0.0158*** |
| | (0.1006) | (43.2329) | (2.0154) | (0.6422) | (0.0054) |
| factor(weekday)Monday | −0.0126 | 0.8867 | −0.0515 | 0.0532 | 0.0088* |
| | (0.0083) | (2.4839) | (0.1044) | (0.0480) | (0.0045) |
| factor(weekday)Saturday | −0.0238*** | 1.5181 | −0.1334 | −0.0854** | 0.0027 |
| | (0.0081) | (1.6582) | (0.0939) | (0.0360) | (0.0046) |
| factor(weekday)Sunday | −0.0578*** | 5.1999* | −0.3111*** | −0.0647 | 0.0097*** |
| | (0.0108) | (2.9756) | (0.1083) | (0.0475) | (0.0037) |
| factor(weekday)Thursday | −0.0013 | −3.9938 | 0.1457** | 0.0769** | 0.0029 |
| | (0.0053) | (2.5923) | (0.0706) | (0.0322) | (0.0037) |
| factor(weekday)Tuesday | −0.0008 | −0.6459 | 0.1062 | 0.0392 | 0.0028 |
| | (0.0076) | (2.2945) | (0.0954) | (0.0469) | (0.0036) |
| factor(weekday)Wednesday | 0.0050 | −4.5665* | 0.1184 | 0.0382 | 0.0062 |
| | (0.0068) | (2.7475) | (0.0828) | (0.0385) | (0.0050) |
| Year FE | Y | Y | Y | Y | Y |
| Week FE×Plant FE | Y | Y | Y | Y | Y |
| Date FE | Y | Y | Y | Y | Y |
| Observations | 63,528 | 63,528 | 63,528 | 63,528 | 11,274 |
| $R^2$ | 0.9957 | 0.9995 | 0.7011 | 0.8503 | 0.3077 |
| Adjusted $R^2$ | 0.9956 | 0.9995 | 0.6919 | 0.8456 | 0.1887 |
| Residual Std. Error | 0.9799 (df = 61622) | 316.0176 (df = 61624) | 15.6874 (df = 61623) | 5.7173 (df = 61623) | 0.0954 (df = 9620) |

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

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

Table 5: Robustness check, including post shutdown period

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | *Long Sample* | | | *Short Sample* | | |
| | SO2 (tons) | NOX (tons) | AOD | SO2 (tons) | NOX (tons) | AOD |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| shutdown | 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 | −0.364 | 0.281 | 0.006 | −0.572 | 0.221 | 0.013 |
| | (0.556) | (0.259) | (0.007) | (0.531) | (0.258) | (0.008) |
| ppt | −0.008 | −0.003 | −0.0004*** | −0.005 | −0.001 | −0.001*** |
| | (0.006) | (0.003) | (0.0001) | (0.008) | (0.003) | (0.0002) |
| tmean | −0.054** | −0.019 | −0.003*** | −0.088*** | −0.020 | −0.006*** |
| | (0.026) | (0.014) | (0.0004) | (0.028) | (0.015) | (0.001) |
| tdmean | 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 | −0.013 | −0.008 | −0.004*** | −0.019 | −0.017** | −0.004*** |
| | (0.019) | (0.007) | (0.0004) | (0.022) | (0.008) | (0.001) |
| k_MWH | 1.172*** | 0.751*** | 0.0004** | 1.136*** | 0.747*** | 0.0002 |
| | (0.205) | (0.050) | (0.0001) | (0.189) | (0.050) | (0.0002) |
| SLOAD..1000.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) |
| factor(Year)2014 | −2.757*** | −0.934*** | −0.006* | −3.088*** | −1.154*** | −0.017*** |
| | (0.761) | (0.296) | (0.003) | (0.883) | (0.363) | (0.005) |
| factor(Year)2015 | −5.066*** | −1.655*** | −0.017*** | −5.152*** | −1.636*** | −0.015*** |
| | (0.868) | (0.331) | (0.004) | (0.935) | (0.347) | (0.005) |
| factor(Year)2016 | −7.286*** | −2.363*** | −0.014*** | −7.423*** | −2.450*** | −0.018*** |
| | (1.751) | (0.413) | (0.004) | (1.828) | (0.426) | (0.005) |
| factor(Year)2017 | −7.111*** | −2.829*** | −0.017*** | −7.358*** | −3.048*** | −0.006 |
| | (1.702) | (0.489) | (0.003) | (1.815) | (0.507) | (0.005) |
| factor(Year)2018 | −7.286*** | −3.293*** | −0.017*** | −7.830*** | −3.469*** | −0.020*** |
| | (1.616) | (0.682) | (0.004) | (1.944) | (0.647) | (0.006) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| Year FE | Y | Y | Y | Y | Y | Y |
| Week FE×Plant FE | Y | Y | Y | Y | Y | Y |
| Date 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, sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17 and 2017-18; and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).*
*For the last three columns, sample is from Dec. 1st to Feb. 24th, each year of 2013-14, 2014-15, 2015-16, 2016-17 and 2017-18.*
*Standard error is clustered at plant level.*

Table 6: Placebo test, placebo shutdown is from Dec. 1st to Dec. 28th.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | SO2 (tons) | NOX (tons) | AOD | SO2 (tons) | NOX (tons) | AOD |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Placebo shutdown | −0.726 | −0.059 | −0.011* | −0.617 | −0.125 | −0.007 |
| | (0.785) | (0.278) | (0.006) | (0.707) | (0.266) | (0.006) |
| Shutdown | | | | 0.869 | 0.128 | 0.022** |
| | | | | (0.569) | (0.201) | (0.009) |
| Post | | | | −0.013 | 0.352 | 0.010 |
| | | | | (0.490) | (0.265) | (0.008) |
| ppt | −0.007 | −0.003 | −0.001*** | −0.008 | −0.003 | −0.0004*** |
| | (0.005) | (0.004) | (0.0002) | (0.006) | (0.003) | (0.0001) |
| tmean | 0.005 | −0.054* | −0.003*** | −0.052* | −0.019 | −0.003*** |
| | (0.063) | (0.030) | (0.0004) | (0.027) | (0.014) | (0.0004) |
| tdmean | 0.007 | 0.023 | 0.003*** | 0.034** | 0.010 | 0.003*** |
| | (0.035) | (0.032) | (0.0004) | (0.017) | (0.016) | (0.0003) |
| Wind | −0.011 | −0.004 | −0.003*** | −0.013 | −0.008 | −0.004*** |
| | (0.024) | (0.009) | (0.0004) | (0.019) | (0.007) | (0.0004) |
| k_MWH | 1.168*** | 0.753*** | 0.0002 | 1.172*** | 0.751*** | 0.0004** |
| | (0.183) | (0.049) | (0.0002) | (0.205) | (0.050) | (0.0001) |
| SLOAD..1000.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) |
| factor(Year)2014 | −2.212*** | −0.496 | −0.003 | −2.757*** | −0.934*** | −0.006* |
| | (0.822) | (0.325) | (0.003) | (0.761) | (0.296) | (0.003) |
| factor(Year)2015 | −5.160*** | −1.677*** | −0.026*** | −5.069*** | −1.656*** | −0.017*** |
| | (0.901) | (0.384) | (0.004) | (0.870) | (0.331) | (0.004) |
| factor(Year)2016 | −7.202*** | −2.307*** | −0.007* | −7.290*** | −2.363*** | −0.014*** |
| | (1.768) | (0.436) | (0.004) | (1.754) | (0.412) | (0.004) |
| factor(Year)2017 | −7.327*** | −2.908*** | −0.020*** | −7.113*** | −2.829*** | −0.017*** |
| | (1.690) | (0.528) | (0.004) | (1.703) | (0.489) | (0.003) |
| factor(Year)2018 | −6.834*** | −3.226*** | −0.012*** | −7.020*** | −3.239*** | −0.014*** |
| | (1.384) | (0.750) | (0.004) | (1.446) | (0.714) | (0.004) |
| factor(weekday)Monday | 0.041 | 0.082* | 0.004 | −0.040 | 0.053* | 0.001 |
| | (0.090) | (0.050) | (0.003) | (0.065) | (0.030) | (0.003) |
| factor(weekday)Saturday | −0.031 | −0.064* | 0.003 | −0.051 | −0.079*** | −0.002 |
| | (0.121) | (0.037) | (0.003) | (0.105) | (0.027) | (0.003) |
| factor(weekday)Sunday | 0.014 | −0.032 | 0.003 | −0.114 | −0.034 | −0.002 |
| | (0.117) | (0.057) | (0.003) | (0.137) | (0.044) | (0.003) |
| factor(weekday)Thursday | 0.077 | 0.027 | 0.007* | 0.081 | 0.052** | −0.0002 |
| | (0.061) | (0.035) | (0.004) | (0.061) | (0.024) | (0.003) |
| factor(weekday)Tuesday | 0.050 | 0.011 | 0.011*** | −0.003 | 0.021 | 0.005** |
| | (0.090) | (0.046) | (0.003) | (0.063) | (0.028) | (0.003) |
| factor(weekday)Wednesday | 0.031 | 0.006 | 0.005 | 0.018 | 0.025 | 0.001 |
| | (0.068) | (0.035) | (0.004) | (0.063) | (0.025) | (0.003) |
| Year FE | Y | Y | Y | Y | Y | Y |
| Week FE×Plant FE | Y | Y | Y | Y | Y | Y |
| Date FE | Y | Y | Y | Y | Y | Y |
| Observations | 71,011 | 71,011 | 18,659 | 163,998 | 163,998 | 35,559 |
| $R^2$ | 0.718 | 0.847 | 0.228 | 0.696 | 0.843 | 0.245 |
| Adjusted $R^2$ | 0.709 | 0.842 | 0.135 | 0.687 | 0.839 | 0.145 |
| Residual Std. Error | 14.848 (df = 68893) | 5.600 (df = 68893) | 0.104 (df = 16661) | 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, sample is from Oct. 22nd to Dec. 28th, each year of 2013-14, 2014-15, 2015-16, 2016-17 and 2017-18.*
*For the last three columns, sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17 and 2017-18;*
*and from Oct. 22nd to Mar. 24th, 2015-16 (because of the leap year).*
*Standard error is clustered at plant level.*

Table 7: Placebo test, placebo shutdown is set for every weeks before government shutdown

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | *Short Sample* | | | *Long Sample* | | |
| | SO2 (tons) | NOX (tons) | AOD | SO2 (tons) | NOX (tons) | AOD |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Placebo shutdown: Oct. 22nd - Oct. 28th | | | | 0.485 | −0.409 | −0.015 |
| | | | | (0.595) | (0.327) | (0.022) |
| Placebo shutdown: Oct. 29nd - Nov. 4th | | | | 0.319 | −0.195 | 0.010 |
| | | | | (0.361) | (0.214) | (0.023) |
| Placebo shutdown: Nov. 5th - Nov. 11th | | | | 0.091 | 0.002 | 0.022 |
| | | | | (0.500) | (0.303) | (0.022) |
| Placebo shutdown: Nov. 12th - Nov. 18th | | | | −1.171 | −0.022 | 0.028 |
| | | | | (1.028) | (0.349) | (0.023) |
| Placebo shutdown: Nov. 19th - Nov. 25th | | | | −1.661* | −0.022 | 0.004 |
| | | | | (0.958) | (0.339) | (0.021) |
| Placebo shutdown: Nov. 26th - Nov. 30th | | | | −1.044 | 0.304 | 0.004 |
| | | | | (0.917) | (0.335) | (0.022) |
| Placebo shutdown: 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 shutdown: 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 shutdown: 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 shutdown: 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) |
| ppt | 0.004 | 0.005 | −0.0005* | −0.007 | −0.003 | −0.001*** |
| | (0.010) | (0.004) | (0.0003) | (0.005) | (0.004) | (0.0002) |
| tmean | −0.012 | −0.044 | −0.005*** | 0.001 | −0.053* | −0.002*** |
| | (0.062) | (0.029) | (0.001) | (0.061) | (0.030) | (0.0004) |
| tdmean | 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 | −0.046 | 0.007 | −0.005*** | −0.014 | −0.005 | −0.003*** |
| | (0.032) | (0.017) | (0.001) | (0.024) | (0.009) | (0.0004) |
| k_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) |
| SLOAD..1000.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) |
| factor(Year)2014 | −3.079*** | −0.314 | −0.026*** | −2.210*** | −0.497 | −0.004 |
| | (1.058) | (0.450) | (0.007) | (0.823) | (0.325) | (0.003) |
| factor(Year)2015 | −5.647*** | −1.624*** | −0.035*** | −5.155*** | −1.679*** | −0.027*** |
| | (1.085) | (0.432) | (0.007) | (0.899) | (0.385) | (0.004) |
| factor(Year)2016 | −7.977*** | −2.253*** | −0.013** | −7.195*** | −2.310*** | −0.008** |
| | (1.911) | (0.499) | (0.006) | (1.765) | (0.436) | (0.004) |
| factor(Year)2017 | −7.850*** | −2.967*** | −0.017*** | −7.319*** | −2.911*** | −0.021*** |
| | (1.930) | (0.613) | (0.007) | (1.687) | (0.528) | (0.004) |
| factor(Year)2018 | −6.939*** | −3.116*** | −0.022 | −6.316*** | −3.167*** | −0.019 |
| | (1.641) | (0.731) | (0.021) | (1.287) | (0.802) | (0.021) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| factor(weekday)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) |
| Year FE | Y | Y | Y | Y | Y | Y |
| Week FE×Plant FE | Y | Y | Y | Y | Y | Y |
| Date 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, sample is from Dec. 1st to Dec. 28th, each year of 2013-14, 2014-15, 2015-16, 2016-17 and 2017-18. The reference date is Dec. 28th.*
*For the last three columns, sample is from Oct. 22nd to Mar. 25th, each year of 2013-14, 2014-15, 2016-17 and 2017-18;*
*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.*

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