Go with the Wind: Polluters' Strategic Response to Monitoring*

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June 9, 2025

Abstract

I investigate the strategic behavior of polluters in the US. Under the Clean Air Act, air quality monitor data determine whether an area meets environmental standards. Because wind carries pollution, monitors detect more pollution from upwind sources and less from downwind sources. This disparity incentivizes polluters to emit less when they are upwind of a monitor, and more when they are downwind. I identify such strategic behavior among US coal-fired power plants, finding that a one-standard-deviation increase in favorable wind direction—when wind blows pollutants away from monitors—leads to a 0.8% (172 lbs) and 0.4% (54 lbs) increase in sulfur dioxide (SO_2) and nitrogen dioxide (NO_x) emissions, respectively. At the same time, fuel input remains unchanged, but the emission rate rises, suggesting that power plants temporarily turn off pollution control equipment. Additionally, the increase is more pronounced when power plants are in a non-attainment county, located in the same state as the monitor, or surrounded by fewer nearby polluters. These findings suggest that polluters facing stricter regulatory pressure are more likely to respond strategically when conditions are favorable.

*I am grateful to Tatyana Deryugina, Julian Reif, David Molitor, and George Deltas for invaluable guidance and support. This paper has also benefited from comments and suggestions by Adam Osman, Ben Marx, Russell Weinstein, Eliza Forsythe, Alex Bartik, Andrew Hultgren, Akshaya Jha, and seminar participants at the Applied Micro Research Lunch and the Program in Environmental and Resource Economics seminar for helpful comments and suggestions. All errors are my own.

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1 Introduction

Environmental regulation in the United States has traditionally been implemented through a federalist framework. Under the US Clean Air Act, the federal government sets the National Ambient Air Quality Standards (NAAQS), whereas state and local governments monitor air pollution levels to enforce those standards. Despite the theoretical efficiencies of federalism noted by Oates (1972), this decentralized structure may also create opportunities for local governments or polluters—who prioritize maximizing local economic growth or profits—to evade compliance through strategic responses (Grainger and Schreiber, 2019; Zou, 2021; Mu et al., 2021; Morehouse and Rubin, 2021). Understanding these behaviors is crucial for balancing local monitoring with consistent and effective enforcement of environmental regulations.

Polluters may have an incentive to strategically adjust emissions based on their likelihood of being detected by air quality monitors for two reasons. First, emission control is costly—not only due to installation expenses, but also because ongoing costs for electricity, water, and steam often exceed the annual depreciation of the equipment (Wu et al., 2015). Additionally, air pollutants can travel long distances with the wind (Schlenker and Walker, 2016; Deryugina et al., 2019; Jia and Ku, 2019; Anderson, 2020; Borgschulte et al., 2022), influencing the likelihood that emissions will be detected by local monitoring stations. As a result, firms are less likely to bear the costs of pollution control when wind conditions disperse emissions away from monitors, but they are more likely to reduce emissions when the wind increases their chances of being detected.

In this paper, I study how polluters strategically adjust emissions based on their chances of increasing measured air pollution in the area. Specifically, I identify short-term strategic emissions adjustments in response to wind direction among coal-fired power plants[1]. I find that a one-standard-deviation increase in favorable wind direction (i.e., when the wind blows pollutants away from monitors) leads to a 0.8% and 0.4% increase in sulfur dioxide (SO_2) and nitrogen dioxide (NO_x) emissions, respectively. This corresponds to an average increase of 172 lbs of SO_2 and 54 lbs of NO_x. In contrast, no such strategic response is observed for their cleaner counter-

[1] Coal-fired power plants have historically accounted for a substantial share of air pollution in the U.S. From 1997 to 2017, they were responsible for 90% of SO_2 emissions and 76% of NO_x emissions from the U.S. electric power industry. Their emissions include particles, mercury, and acid gases such as sulfur dioxide. The U.S. Environmental Protection Agency has implemented multiple regulations to control power plant emissions, including the Acid Rain Program, the Mercury and Air Toxics Standards (MATS), and the Clean Power Plan.

parts, natural gas power plants. These results are robust to various weather controls, fixed effects, radius definitions, and alternative ways of measuring the relative wind direction between power plants and monitors. Given that monitoring stations are often placed in relatively cleaner areas (Grainger and Schreiber, 2019), my estimates may be lower than the actual effects.

I also examine which polluters strategically adjust emissions. The EPA determines whether counties—rather than individual polluters—meet air quality standards by using monitoring data to classify them as "attainment" or "non-attainment" based on comparisons with the NAAQS. State and local governments are responsible for enforcing these standards and may face regulatory consequences for non-compliance. To explore whether polluters under direct regulatory enforcement strategically emit more when conditions are favorable, I compare power plants based on whether they are located in the same state as their nearest monitor or in a different state. I find that strategic behavior is more pronounced when a power plant and its nearest monitor are within the same state. Quantitatively, when restricting the sample to power plants located within the same state, a one-standard-deviation increase in favorable wind direction raises the estimated level of disguised pollution from 0.8% to 1.19% for SO_2 and from 0.4% to 1% for NO_x. In contrast, the effect is not statistically significant when the nearest monitor is in a different state, suggesting that polluters do not strategically adjust emissions if the monitor lacks direct authority. Similarly, polluters in non-attainment counties exhibit stronger strategic behavior, suggesting that stricter regulatory pressure increases incentives to manipulate emissions. I also find that polluters in low-polluter-density areas are more likely to engage in strategic behavior, likely because emissions are easier to trace to a specific source, giving them a stronger incentive to exploit favorable wind conditions when possible. In contrast, power plants in attainment counties and those in denser industrial areas exhibit weaker or no strategic response. These findings highlight how regulatory enforcement and monitoring structures shape firms' incentives to manipulate emissions under favorable conditions.

I then examine the underlying mechanisms through which power plants increase emissions on days with favorable wind conditions. I find that favorable wind direction has no significant effect on fuel input or electricity generation. However, the emission rate for SO_2 and NO_x (pollution emitted per unit of fuel burned) follows the same strategic pattern, suggesting that the observed increase in emissions is, at least partly, driven by power plants partially turning off pollution control equipment. In contrast, there is no significant effect on the CO_2 emission rate, as power plants typically are not required to have specific emission control equipment for CO_2. Quantitatively, a one-standard-deviation increase in favorable wind direction raises the SO_2 emission rate by 0.003 lbs/mmBtu and the NO_x rate by 0.0004 lbs/mmBtu, which accounts for approximately 128% of the total increase in SO_2 emissions and 62% of the total increase in NO_x emissions. [2]. This indicates that the increase in emission rates is the primary driver of the overall rise in emissions.

This paper contributes to the current literature in two main ways. First, it adds to the discussion on the gaps between regulation enforcement and actual pollution abatement (Ghanem and Zhang, 2014; Greenstone et al., 2022; Oliva, 2015; Reynaert, 2021). There is emerging literature on agents' strategic responses to environmental regulations. For example, Zou (2021) documents increases in polluting activities during unmonitored times. Agarwal et al. (2023) provide evidence that firms increase SO_2 emission levels after sunset under the cover of darkness. This paper contributes to this stream of literature by showing that even with a nationwide automated monitoring systems, strategic behaviors could still occur. Most previous studies focus on firms' responses to regular events, while I provide evidence that plants also react to less predictable changes, such as shifts in wind direction. My estimates are roughly half the magnitude of those reported by Zou (2021) in percentage terms, suggesting either that firms respond less strongly or that fewer firms engage in strategic behavior when events are less predictable.These wind patterns are likely overlooked by the federally regulators, who implicitly assume data from ambient air quality monitors are representative of the local region.

Second, this paper contributes to the increasingly important literature on wind directions and environmental justice. Minority, low-income, and indigenous populations are more likely to reside downwind of the pollution source, often bearing a disproportionate burden of environmental harms and adverse health outcomes[3]. Previous research on wind direction and power plants typically focus on the long-run effects. For example, Heblich et al. (2021) provide evidence that historical pollution and prevailing winds induce neighborhood sorting and make eastern downwind suburbs notably poorer. Morehouse and Rubin (2021) show that decision-makers disproportionately sited power plants to reduce counties' downwind pollution exposure. By contrast, I focus on short-run effects of wind direction and find that power

[2] These percentages are calculated using the mean heat input: $77,552.85 \times 0.003/172 = 135\%$ for SO_2 and $77,552.85 \times 0.0004/54 = 57\%$ for NO_x.

[3] https://www.epa.gov/power-sector/power-plants-and-neighboring-communities

plants increase pollution when they are downwind of monitoring stations. Using simulations from the Intervention Model for Air Pollution (InMAP), I find suggestive evidence that the extra emissions from strategic pollution disproportionately affect counties with a higher Black population share. Given that the black population are more exposed to pollution (Tessum et al., 2021; Banzhaf and Walsh, 2008) and the negative health effect is larger for them (Alexander and Currie, 2017; Gillingham and Huang, 2021), this strategic emission may exacerbate environmental injustice and health disparities.

The rest of the paper is organized as follows. Section 2 provides a brief background on air quality monitoring and power plants in the US. Section 3 outlines a conceptual framework for understanding how wind directions can affect pollution emissions. Section 4 describes the data and provides summary statistics. Section 5 introduces the empirical strategy in detail. Section 6 presents the main results. Section 7 covers robustness checks. Section 8 concludes.

2 Background

2.1 Ambient Air Quality Monitoring

In the United States, environmental regulation historically follows a federalist approach. Under the Clean Air Act (CAA), the Environmental Protection Agency (EPA) is responsible for setting safety standards in the form of maximum concentration levels for outdoor air pollution. These are the National Ambient Air Quality Standards (NAAQS), which regulate six criteria pollutants: particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), lead (Pb), and carbon monoxide (CO). Local governments coordinate plans and monitor air quality to ensure these standards are met within their jurisdictions. This sparse network of monitoring sites measures local air quality across the US. Among these monitoring networks, the NCore network plays a critical role in providing consistent multi-pollutant air quality measurements. Established in 2011, NCore monitors are designed to track key pollutants, including SO_2, NO_2, and $PM_{2.5}$, which are major emissions from power plants. The NCore network's primary objectives include timely public air quality reporting, supporting long-term health assessments for NAAQS reviews, and ensuring compliance by establishing attainment and non-attainment areas through NAAQS comparisons.

The EPA evaluates data from these monitoring sites to classify counties as either *attainment* or *non-attainment*. Counties labeled as non-attainment face significantly higher regulatory costs, impacting both state and local governments as well as industries within these areas. States with non-attainment counties must formulate a State Implementation Plan, outlining specific regulations to bring these regions into compliance. These regulations often include the adoption of advanced pollution control technologies and the imposition of strict emission limits on existing industries. Furthermore, new industrial projects in non-attainment areas must implement the "lowest achievable emission rate" technology, regardless of cost.

2.2 Power Plants

In the US, fossil fuels are the most common fuel type for electricity production and coal-fired power plants are a leading source of air pollution: coal combustion is the largest single source of sulfur dioxide (SO_2) emissions and the second largest source of nitrogen oxides (NO_x)[4]. It also produces significantly more greenhouse gases, such as carbon dioxide (CO_2).

To reduce emissions from power plants, various programs have been implemented, including the Acid Rain Program (ARP), Mercury and Air Toxics Standards (MATS), and the Cross-State Air Pollution Rule (CSAPR). These programs have significantly reduced SO_2 and NO_x emissions from power plants over the past several decades. From 1995 to 2022, average emissions of SO_2 and NO_x from power plants fall by over 90 percent (Figure 1).

3 Conceptual Framework

To motivate my empirical analysis, I present a conceptual framework that helps rationalize how wind directions can affect firms' behaviors. I assume a power plant's production function is Q(K), where K represents capital. Production has declining returns to scale, i.e., $Q_K > 0$ and $Q_{KK} < 0$.

Producing output Q also generates emissions E as a by-product. Emissions increase with Q. These emissions can be reduced by employing emissions control technologies at cost C.[5] The final emission level is therefore a continuously differentiable

[4] SO_2 and NO_x contribute to the formation of fine particulate matter (PM). NO_x emissions also lead to the formation of ground-level ozone.

[5] Since the installation of emission control equipment is mandatory for power plants in the US, we ignore the already incurred fixed installation costs. Therefore, the cost C here represents only the marginal cost of operation and maintenance, which is continuous.

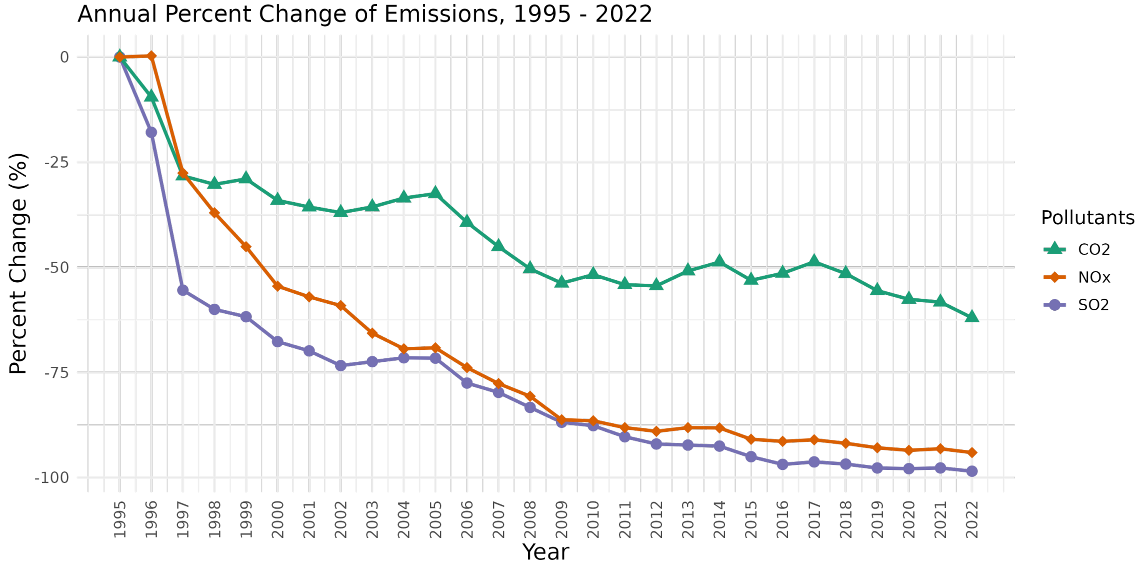


Figure 1. Annual Percent Reduction in Power Plant Emissions Relative to 1995 (1995-2022). Source: Clean Air Markets Program Data

function $E(Q, C)$. I assume that $E_Q > 0$, $E_{QQ} < 0$, $E_C < 0$, and $E_{CC} > 0$.

The readings of nearby pollution monitors are denoted by $R(E, W)$, where E represents the emission from the power plant, and W is the relative wind direction. An increase in emissions E from the nearby power plant would lead to higher readings R; thus, $R_E > 0$. A larger W represents more favorable wind directions (i.e., the wind is blowing from the monitors to the plant, causing pollutants to be blown away from the monitor), so that $R_W < 0$. If the readings of the monitor exceed the standards, the plant bears a cost of s, reflecting the consequences of stringent regulations, such as the need to adopt advanced pollution control technologies and comply with more rigorous emission limits.

Given this setup, the firm chooses its capital input for production and emission control input to maximize its profit. Formally, it solves the problem:

$$\max_{K,C} \ \pi = p \times Q(K) - r \times K - v \times C - s \times R(E(Q, C), W)$$

where p represents the market output price, r represents the capital price, v represents the cost of operating the emission control equipment, and s represents the cost of higher pollution levels. The first-order conditions for the firm's profit maximization problem are therefore:

$$\frac{\partial \pi}{\partial K} = p \times Q_K - r - s \times R_E \times E_Q \times Q_K = 0$$
$$\frac{\partial \pi}{\partial C} = -v - s \times R_E \times E_c = 0$$

Applying the implicit function theorem, I derive

$$\frac{\partial K}{\partial W} = -\frac{s \times F_{EW} \times E_Q \times Q_K}{s \times F_E \times E_Q \times Q_{KK} - p \times Q_{KK}}$$
$$\frac{\partial C}{\partial W} = -\frac{F_{EW} \times E_C}{F_E \times E_{CC}}.$$

Since $F_E > 0, F_{EW} < 0, E_C > 0$, and $E_{CC} < 0$, it follows $\frac{\partial C}{\partial W} < 0$. This implies that when the wind comes from a more favorable direction W (i.e., W increases), the firm would decrease emission control input C, and thus emissions would increase.

4 Data

The data used in the paper come from three main sources: pollution emission data from the Continuous Emission Monitoring Systems (CEMS), EPA monitor characteristics from the EPA's Air Quality System (AQS), and weather data from ECMWF Reanalysis v5 (ERA5). The linkage and further details are described below.

Pollution Emission Data CEMS are the set of equipment used to measure the concentration or emission rate of gases or particulate matter. These systems function by analyzing pollutants and converting these measurements into results that comply with emission standards, using computer programs. I obtain the CEMS data from the EPA's Clean Air Markets Program Data, which provides detailed emissions information at the unit-hourly level for each facility. Under the Clean Air Markets Division's regulatory programs, power plants are required to install CEMS that automatically measure and upload hourly end-of-pipe emission data to the government. This allows the government to monitor emissions and detect any violations of the prescribed standards. I use unit-daily CEMS data includes emissions of SO_2 and NO_x, spanning from 2011 to 2022. I then match this data with the power sector data crosswalk[6] to obtain the latitude and longitude of each power plant.

[6]https://www.epa.gov/power-sector/power-sector-data-crosswalk. Accessed Feb 2, 2024.

Air Quality Monitors To determine the relative locations of coal-fired power plants and nearby air quality monitors, I obtain data from the EPA's Air Quality System (AQS) for the years 2011 to 2022. The AQS annual summary files include the latitude and longitude of each monitoring site, along with the years during which each site was established and operational. I match daily emission data from each power plant with the nearest active NCore monitoring sites[7]. For each plant-monitor pair, I calculate the distance and relative direction based on their geographic coordinates to assess how emissions disperse under varying wind conditions.

Weather Temperature, precipitation, wind direction and wind speed data are obtained from the ERA5 reanalysis database. ERA5 data are reported on a 0.25×0.25 degrees grid ($\approx 27km \times 27km$). I construct plant-level daily weather data by matching each coal-fired power plant with its nearest weather grid based on its latitude and longitude. Specifically, wind direction and wind speed are construct using the East-West wind vector (u-wind) and the North-South wind vector (v-wind) provided in the database[8] Wind direction is defined as the direction the wind is blowing *from*.

Construction of the Downwind Index I construct a continuous variable indicating the relative wind direction of a power plant and nearest monitors for each day, using a three-step procedure. First, I measured the direction of each power plant relative to the nearest NCore air quality monitor, by using an angle called "azimuth" ranging from 0°to 360°.[9] Second, I construct the wind vector azimuth, defined as where the wind blows *towards*. This is calculated by subtracting 180° from the direction where the wind blows *from*, as defined in Section 4, Weather[10]. Third, I generate

[7]The NCore network is a federally managed multipollutant monitoring system designed to collect high-quality measurements for tracking air quality trends and ensuring compliance with the NAAQS. More details can be found at: https://www.epa.gov/amtic/ncore-monitoring-network. Accessed Feb 15, 2025/.

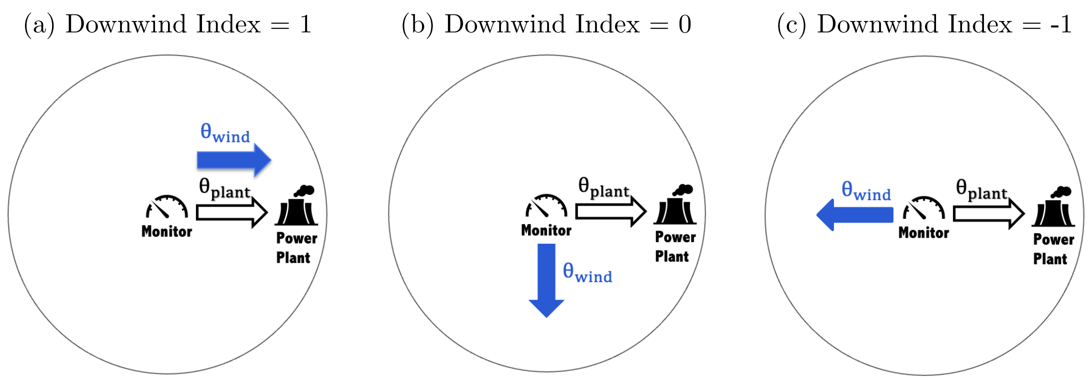
[8]Note that wind directions and speed are computed from the zonal (u) and meridional (v) wind components. Since these are vectors and cannot be averaged or interpolated numerically, I first average the u and v components and then derive the wind speed and direction from the resulting vector.

[9]The azimuth from point B (the power plant) to point A (the monitors) is the angle formed by the vector $\vec{AB}$ on a horizontal plane, with north as the 0°reference point. Moving clockwise in a 360-degree circle, azimuths of 90°, 180°, or 270°indicate that B is due East, South, or West of A, respectively.

[10]For example, a wind *blowing from* due West is calculated as a wind with a direction of 270°. I subtract 180°from the 270°and get a 90°wind direction; I add 360°if the subtraction used by the conversion results in a negative value. Similar to the azimuth for the power plant and monitoring station, a wind vector azimuth of 90°, 180°, or 270°means that a wind *blows towards due East*, *due*

the relative wind direction indicator using the cosine of the difference between the direction from a monitor to a power plant (θ_{plant}) and the wind direction, defined as the direction toward which the wind blows (θ_{wind}). Formally, the Downwind Index is defined as $\cos(|\ \theta_{plant} - \theta_{wind}\ |)$. Intuitively, this index equals 1 when the wind blows exactly from the monitor to the power plant, indicating that the plant is strictly downwind of the monitor; it equals 0 when the plant is perpendicular to the wind direction; and it equals -1 when the plant is strictly upwind of the monitor. Panels (a), (b), and (c) in Figure 2 show cases where the index equals 1, 0, and -1, respectively.

Figure 2. Downwind Index Illustration



Notes: This figure illustrates the Downwind Index, calculated as $\cos(|\ \theta_{plant} - \theta_{wind}\ |)$. (a) A Downwind Index of 1 indicates that the power plant is directly downwind of the monitor, meaning the wind is blowing from the power plant towards the monitor. (b) A Downwind Index of 0 represents a perpendicular orientation, where the wind direction is perpendicular to the vector pointing from the power plant to the monitor. (c) A Downwind Index of -1 denotes that the power plant is directly upwind of the monitor, meaning the wind is blowing from the power plant towards the monitor.

Summary Statistics Table 1 presents summary statistics for the main estimation sample, which includes plant-day observations from 2011 to 2022 for coal-fired power plants in the contiguous U.S. The average downwind index is -0.03 with a standard deviation of 0.72, indicating that there is substantial variation in wind direction. Coal-fired power plants also have much higher emissions and emission rates compared to gas-fired power plants.[11]

Figure A1 shows the spatial distribution of coal-fired and gas-fired power plants in the U.S., while Figure A2 displays the mean downwind index for each county. The fact that most indices are centered around 0 confirms that wind direction varies

South, or *due West*, respectively.

[11]Full summary statistics for gas-fired power plants are in Table A1.

considerably within counties; if values were consistently near 1 or -1, it would suggest stable wind patterns, potentially introducing bias into the analysis.

Table 1. Summary Statistics

Variables	N	Mean	St. Dev.	Min	Max
Emissions					
SO_2 (lbs)	686,194	23,188.68	41,933.32	0.00	1,636,826.00
NO_x (lbs)	720,253	10,350.71	11,347.70	0.00	345,728.00
CO_2 (short tons)	680,392	7,969.82	5,880.96	0.00	37,978.00
Heat Input (mmBtu)	720,253	75,623.63	55,655.18	0.00	370,153.10
Gross Load (MWh)	684,009	9,161.66	5,590.50	0.00	35,084.00
SO_2 Rate (lbs/mmBtu)	686,122	0.36	0.72	0.00	219.60
NO_x Rate (lbs/mmBtu)	720,253	0.17	0.21	0.00	92.88
CO_2 Rate (tons/mmBtu)	680,320	0.10	0.02	0.00	1.21
Weather					
Precipitation (mm)	720,253	3.04	6.88	0.00	420.89
Mean Temperature (°C)	720,253	14.04	11.04	−31.42	37.67
Wind Direction Towards (degrees)	720,253	158.94	110.12	0.00	360.00
Wind Speed (m/s)	720,253	2.73	1.54	0.00	16.11
Location Relative to Monitor					
Distance (miles)	720,253	32.79	15.42	3.77	59.91
Direction (degrees)	720,253	161.55	104.87	1.33	359.10
Downwind Index	720,253	−0.03	0.72	−1.00	1.00
Same State (0/1)	720,253	0.79	0.41	0.00	1.00

Notes: This table reports the summary statistics for coal-fired power plants in my sample. Direction is the degree of a vector pointing from the monitor to the power plant, and the downwind index is defined as in Section 4, Construction of the Downwind Index.

5 Empirical Strategy

My objective is to identify plants' strategic behavior under more or less favorable conditions. Specifically, I study the effect of wind patterns on plant emissions. My identification assumption is that conditional on high dimensional location and time-fixed effects and other atmospheric controls, wind direction is unrelated to other determinants of a plant's pollution emissions. The primary estimation equation is:

$$E_{it} = \beta \times \text{Downwind Index}_{it} + \mathbf{X}_{it}\gamma + \mu_i + \eta_{sm} + \lambda_{my} + \epsilon_{it} \tag{1}$$

where

$$\text{Downwind Index}_{it} = \cos\left(\mid \theta_{\text{plant}_i} - \theta_{\text{wind}_{it}} \mid\right) \tag{2}$$

where E_{it} is the outcome variable, representing the daily emissions (including SO_2 and NO_x) from plant i on date t; Downwind Index$_{it}$ is a continuous index ranging from -1 to 1 for plant i on date t, as defined in Section 4. $\theta_{\text{plant}_{iy}}$ is the vector pointing from a monitor to a nearby power plant i in year y,[12] and $\theta_{\text{wind}_{it}}$ i is the direction that the wind is blowing *toward* at plant i on date t. I expect $\beta > 0$ because when polluters are downwind of a nearby air quality monitor (i.e., Downwind Index$_{it} > 0$), they have an incentive to emit more since their pollution is less likely to be detected; vice versa, when they are upwind of a nearby monitor (i.e., Downwind Index$_{it} < 0$), they are more likely to emit less to avoid regulatory scrutiny.

μ_i represents plant fixed effects, capturing plant-specific characteristics; η_{sm} represents state-by-month fixed effects, controlling for seasonal variations in electricity demand and wind directions; λ_{sy} represents state-by-year fixed effects, capturing state-level regulations and emission trends. $\mathbf{X}_{it}$ represents a flexible set of daily weather controls, including temperature categorized into 10 bins, precipitation categorized into 4 bins, and wind speed in quartiles. The coefficient of interest, β, captures the average change in E_{it} on downwind days, conditional on weather, plant, and date fixed effects. The sample is restricted to coal-fired power plants from 2011 to 2022. Standard errors are clustered at the plant level.

6 Results

6.1 Main Effects

I first examine whether coal-fired power plant strategically increase emissions on days with favorable wind directions (i.e, when the wind blows pollutants away from nearby monitors). Table 2 presents the results from estimating Equation (1) using facility-level panel data from 2011 to 2022 with different fixed effects. Panel A shows the result for SO_2, and Panel B shows the result for NO_x. All the coefficients are positive and statistically significant, suggesting that favorable wind direction increase coal-fired power plant emissions. Quantitatively, a one-standard-deviation increase in the downwind index leads to a 0.8% increase in SO_2 emissions[13] and a 0.4% increase in

[12] I only include operating monitors in year y, so the location of the monitor is updated yearly.

[13] This is calculated using the standard deviation for the downwind index: $0.71 \times 244.88/23189 = 0.8\%$

NO_x emissions.[14] This corresponds to an average increase of 172 lbs of SO_2 and 54 lbs of NO_x. These effects are statistically significant across various fixed effects specifications.

In contrast, Table A2 presents results for natural gas power plants, which serve as a placebo test. Unlike coal-fired power plants, natural gas plants are cleaner and subject to less regulatory pressure, meaning they have little incentive to manipulate emissions based on wind direction. Consistent with this expectation, the results show no statistically significant change in emissions for natural gas plants in response to wind direction.

Table 2. Effect of Wind Directions on Pollution Emissions

	(1)	(2)	(3)	(4)
Panel A: SO_2				
Downwind Index	244.88**	188.91**	190.70**	241.65**
	(96.618)	(80.402)	(75.214)	(103.78)
DV mean (lbs)	23,189	23,189	23,189	23,189
R^2	0.66	0.67	0.72	0.66
Observations	686,194	686,194	686,194	686,194
Panel B: NO_x				
Downwind Index	57.94**	41.14**	47.22*	52.87*
	(24.82)	(18.51)	(24.52)	(27.02)
DV mean (lbs)	10,351	10,351	10,351	10,351
R^2	0.71	0.73	0.77	0.70
Observations	720,253	720,253	720,253	720,253
Facility FE	Yes		Yes	Yes
State-month FE	Yes			
Month-year FE	Yes	Yes		
Facility-month FE		Yes		
State-month-year FE			Yes	
Month FE				Yes
Year Fe				Yes

Notes: This table reports the regression results using equation (1) with varying fixed effects. The dependent variable is the emissions for power plant unit i on date t. Controls include fixed effects, as well as a flexible function of temperature, precipitation, and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

[14] Calculated as $0.71 \times 57.94/10351 = 0.4\%$

6.2 Mechanism

Turning Off Emission Control Equipment The combustion of fuels inevitably generates air pollution. To mitigate this, the U.S. government has implemented various policies that either mandate or incentivize industrial firms, particularly coal-fired power plants, to upgrade their boiler technologies and improve fuel standards. However, even with these advancements, exhaust gases can still contain pollutant levels that exceed regulatory limits. To address this, environmental regulators require polluting firms to install end-of-pipe pollutant scrubbers (see Figure A4 for an example), which are designed to significantly reduce the concentration of pollutants in emissions.

In addition to the initial installation costs, the operation of these scrubbers entails substantial variable costs, including labor and materials. The marginal cost of operating scrubbers is estimated to be between \$84 and \$265 per ton of SO_2 removed (Stoerk, 2018). Because these end-of-pipe scrubbers are typically stand-alone equipment that can be switched on and off during production, firms are incentivized to turn off the scrubbers under certain conditions to save on operating costs. When scrubbers are turned off, the untreated exhaust gases result in higher emissions compared to when pollutant removal processes are active. For example, Karplus and Wu (2023) shows that environmental inspections prompt power plants to operate their existing scrubbers, resulting in a decrease in SO_2 during the onsite period.

To investigate whether the observed increase in emissions is (at least partly) due to power plants turning off pollution control equipment to reduce costs, I estimate the emission rate (pollution emitted per unit of fuel burned) using Equation (1). As shown in Table 3, the emission rates of SO_2 and NO_x both increase when power plants are relatively downwind of a nearby monitor, suggesting that power plants may be partially turning off their emission control equipment to save costs.

As a placebo test, I also examine changes in the CO_2 emission rate. Unlike SO_2 and NO_x, emission control technology for CO_2 is less widely used, so power plants cannot alter its CO_2 emission rate in the short term. As a result, the emission-to-heat input ratio for CO_2 remains relatively stable. Consistent with this, Table 3 shows no statistically significant change in the CO_2 emission rate.

Table 3. Effect of Wind Directions on Emission Rates

	(1) SO2 rate	(2) NOx rate	(3) CO2 rate
Downwind Index	0.004**	0.0006**	0.00002
	(0.002)	(0.0002)	(0.00003)
Facility FE	Yes	Yes	Yes
State-month FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
DV Mean	0.36 lbs/mmBtu	0.17 lbs/mmBtu	0.10 tons/mmBtu
R^2	0.54	0.42	0.86
Observations	686,122	720,253	680,320

Notes: This table reports the regression results using equation (1). The dependent variable is input or output in log form in unit i on date t. Controls include facility, state-by-month and state-by-year fixed effects, as well as a flexible function of temperatures, precipitation and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Increasing Output Besides turning off emission control equipment, emissions may also increase as a result of higher output. To examine whether the increase in pollution is driven by increased output, I estimate the difference using Equation (1) for a power plant's input and output separately. As shown in Table 4, the estimates for heat input, gross load (i.e., electricity generated), steam load and CO_2 emissions are all positive but not statistically significant. This suggests that changes in input and output do not account for much of the observed increase in emissions.

Table 4. Effect of Wind Directions on Output and Input

	(1) Heat Input	(2) Gross Load	(3) Steam Load	(4) CO2
Downwind Index	50.01	2.725	39.59	5.409
	(88.04)	(9.838)	(23.58)	(9.753)
Facility FE	Yes	Yes	Yes	Yes
State-month FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes
DV Mean	75,623	9,001	8,787	7,970
R^2	0.92	0.90	0.92	0.92
Observations	720,253	625,139	95,069	680,392

Notes: This table reports the regression results using equation (1). The dependent variable is average input or output per hour in log form in plant i on date t. Controls include facility-by-month and date fixed effects, as well as a flexible function of temperatures, precipitation, wind speed, dew points. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

6.3 Regulatory Pressure

Understanding the underlying nature of strategic behavior is essential for assessing how regulatory and monitoring structures influence polluters' actions. A natural starting point is a county's regulatory and monitoring status. In this section, I conduct a heterogeneity analysis by splitting the sample based on three key factors: (1) whether the polluter and monitor are in the same state, subjecting the polluter to direct regulatory oversight; (2) whether the polluter is in a non-attainment county; and (3) whether the polluter operates in a low-polluter-density area.

Same-state Local governments monitor air pollution to demonstrate compliance with National Ambient Air Quality Standards (NAAQS) set by the federal government. They coordinate plans and oversee air quality to ensure these standards are met within their jurisdictions. When a power plant is downwind of an in-state monitor, regulators have less incentive to enforce strict pollution controls since the pollution is carried away. Conversely, when a power plant is upwind of a monitor within the same state, its emissions are more likely to be detected, giving local governments stronger incentives to enforce reductions. As a result, power plants may be more cautious and reduce emissions to avoid regulatory scrutiny. However, when a power plant's nearest monitor is in a different state, local regulators lack the authority to enforce pollution controls, making strategic emission adjustments less likely.

To examine whether polluters under direct regulatory enforcement strategically emit more when conditions are favorable, I compare power plants based on whether their nearest monitor is in the same state or a different state. As shown in columns (1) and (2) of Table 5, when the power plant and monitor are in the same state (76% of the data), the level of disguised pollution increases from 0.8% to 1.19% for SO_2 and from 0.4% to 1% for NO_x. In contrast, the effect is not statistically significant when they are in different states, suggesting that polluters do not strategically adjust emissions if the nearby monitor has no direct authority.

Table 5. Effect of Wind Directions on Pollution Emissions - Same vs. Different State

	Same State		Different State	
	(1)	(2)	(3)	(4)
	SO2	NOx	SO2	NOx
Downwind Index	306.82***	74.164***	51.812	-14.232
	(116.38)	(27.117)	(114.18)	(31.738)
DV Mean (lbs)	25,197	10,650	16,109	9,258
R^2	0.67	0.72	0.50	0.63
Observations	534,537	565,539	151,657	154,714
Facility FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes

Notes: This table reports the regression results using equation (1). The dependent variable is the emission in unit i on date t. Controls include facility, state-by-year and state-by-month fixed effects, as well as a flexible function of temperatures, precipitation and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Non-attainment Status A non-attainment status results in substantial regulatory costs for both local governments and polluters. Polluters in non-attainment jurisdictions face much stricter regulations, including more frequent inspections and higher fines (Blundell et al., 2020). These penalties have been shown to cause significant losses in firm productivity (Greenstone et al., 2012).

The cost of compliance with non-attainment status has also led to strategic behavior. For example, Mu et al. (2021) find that local governments strategically turn off their air quality monitors to avoid regulatory costs, with this practice being more prevalent in non-attainment areas. Similarly, Zou (2021) find that pollution gaps tend to emerge in counties that have experienced non-attainment designation. When a power plant operates in a non-attainment county, it faces stricter regulations and greater pressure to comply. Consequently, when an opportunity arises to engage in strategic behavior to reduce costs, firms may take advantage of it whenever possible.

To examine how strategic responses vary by non-attainment status, I split the sample into attainment and non-attainment counties. Table 6 shows that the response is stronger in non-attainment counties. A one-standard-deviation increase in the relevant variable raises SO_2 emissions by 249.23 lbs and NO_x emissions by 59.24 lbs. In attainment counties, the effect is smaller and less statistically significant, with SO_2 significant only at the 0.1 level and NO_x not statistically significant.

Table 6. Effect of Wind Directions on Pollution Emissions - Nonattainment vs. Attainment Counties

	Nonattainment Counties		Attainment Counties	
	(1)	(2)	(3)	(4)
	SO2	NOx	SO2	NOx
Downwind Index	351.03***	83.427**	187.95*	36.143
	(126.88)	(33.724)	(95.026)	(31.896)
DV Mean (lbs)	30,678	10,988	15,753	9,751
R^2	0.68	0.69	0.60	0.75
Observations	341,849	349,455	344,345	370,798
Facility FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes

Notes: This table reports the regression results using equation (1). The dependent variable is the emission in unit i on date t. Controls include facility, state-by-year and state-by-month fixed effects, as well as a flexible function of temperatures, precipitation and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Polluter Density Air pollution can travel long distances, making it difficult to pinpoint the source of emissions when multiple polluters operate nearby. In such cases, regulators may struggle to attribute changes in air quality to a specific firm, reducing the likelihood of enforcement actions. However, in areas with only one major polluter, it is easier to assign responsibility for pollution levels. As a result, firms in less industrially dense areas may have a stronger incentive to exploit favorable wind conditions. On days with a favorable wind direction, these firms can emit more without immediate regulatory consequences. In contrast, on days with an unfavorable wind direction, they face greater pressure to maintain lower emissions to avoid detection.

To test this hypothesis, I divide the sample into counties with fewer polluters (below the median) and counties with more polluters (above the median). As shown in Table 7, polluters in less industrially dense counties (48% of the data) exhibit stronger strategic behavior. When the number of polluters is below the median, disguised pollution increases from 0.8% to 1.7% for SO_2 and from 0.4% to 0.67% for NO_x. In contrast, counties with more polluters (52% of the data) show no significant strategic response. This suggests that polluters in less industrially dense areas are more likely to exploit favorable wind conditions, as they face greater regulatory pressure on days without such conditions.

Table 7. Effect of Wind Directions on Pollution Emissions - Fewer vs. More Polluters

	Fewer Polluters		More Polluters	
	(1) SO2	(2) NOx	(3) SO2	(4) NOx
Downwind Index	420.36**	89.373**	90.554	34.800
	(170.58)	(34.907)	(89.318)	(33.364)
DV Mean (lbs)	17,963	9,512	28,065	11,110
R^2	0.62	0.75	0.67	0.68
Observations	331,249	342,394	354,945	377,859
Facility FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes

Notes: This table reports the regression results using equation (1). The dependent variable is the emission in unit i on date t. Controls include facility, state-by-year and state-by-month fixed effects, as well as a flexible function of temperatures, precipitation and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

6.4 Environmental Justice

In the previous section, I showed that polluters strategically respond to monitoring. However, directly linking these estimates to environmental justice is challenging because, while power plants increase emissions under favorable conditions, it is unclear how this emission gap affects different geographical regions and demographic groups. To address this, I turn to simulations from the Intervention Model for Air Pollution (InMAP),[15] which models how emissions of SO_2 and NO_x are transported across the U.S. (Tessum et al., 2017).

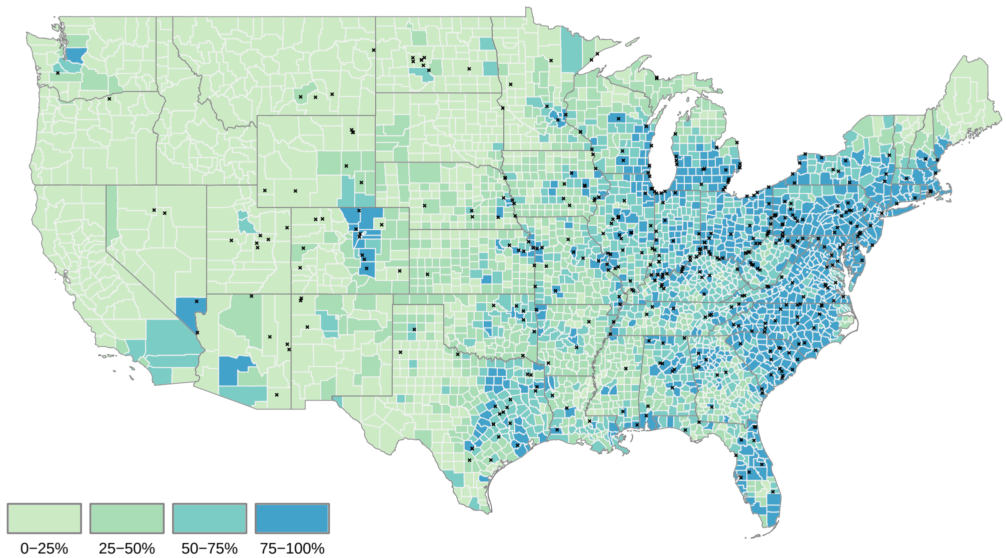
[15] The InMAP model is available for download from `https://github.com/spatialmodel/inmap/releases/tag/v1.9.6`. The evaluation data used in my estimation is from Tessum et al. (2019).

Since InMAP requires annual emission inputs, I construct plant-specific estimates of the total excess emissions attributable to strategic behavior. I follow a two-step procedure. First, for each power plant, I use wind direction data to compute a downwind-weighted total over the year, where fully downwind days contribute the most and fully upwind days contribute nothing.[16] This proxies how often a plant faces favorable monitoring conditions throughout the year. Second, I multiply this downwind-weighted total by the estimated increase in emissions on favorable days, as derived from the earlier heterogeneity analysis. For instance, a plant in a non-attainment county is estimated to emit an additional 351.09 lbs of SO_2 on a fully favorable day. If its annual downwind-weighted total is 90, the resulting annual excess emission input to InMAP is $351.09 \times 90 = 31,598$ lbs. I then simulate pollutant transport and population exposure using InMAP for each power plant and aggregate the results to examine how this excess pollution is distributed across counties in the U.S.

Figure 3 presents a map of the increase in PM2.5 resulting from a one-standard-deviation rise in the downwind index over one year. Figure A3 shows the distribution of SO_2 and NO_x,which closely resemble the $PM_{2.5}$ patterns, as they are influenced by the same atmospheric conditions (e.g., wind, temperature).

[16]Specifically, I use strictly upwind days (with a downwind index of 1) as the baseline, assuming no strategic emissions occur under these conditions. I then assign a weight of 1 to days with perpendicular wind direction (index = 0), and a weight of 2 to fully downwind days (index = 1), reflecting the increasing likelihood of strategic emissions as wind direction shifts toward the monitor.

Figure 3. Increases in $PM_{2.5}$ Induced by Strategic Emissions

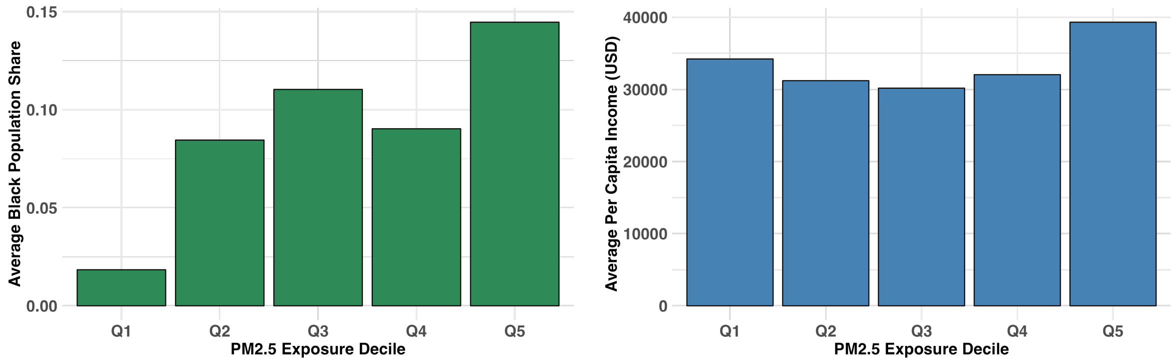


Notes: This map illustrates the distribution of pollutants simulated using InMAP models. The black crosses represent the locations of coal-fired power plants. The colors indicate the concentration quantiles (0–25%, 25–50%, 50–75%, 75–100%), with darker colors representing higher air pollutant concentrations.

Next, I calculate the mean Black population share and per capita income in counties grouped by $PM_{2.5}$ increase quintiles. Figure 4 provides suggestive evidence that extra emissions from strategic pollution disproportionately affect counties with a higher Black population share, although the relationship with income is less clear. Given that Black populations are more exposed to pollution (Tessum et al., 2021; Banzhaf and Walsh, 2008) and experience greater negative health effects (Alexander and Currie, 2017; Gillingham and Huang, 2021), this strategic emission behavior may exacerbate environmental injustice and health disparities.

Figure 4. Demographic Characteristics by $PM_{2.5}$ Exposure Increase Deciles

(a) $BlackShare$ (b) $Income$

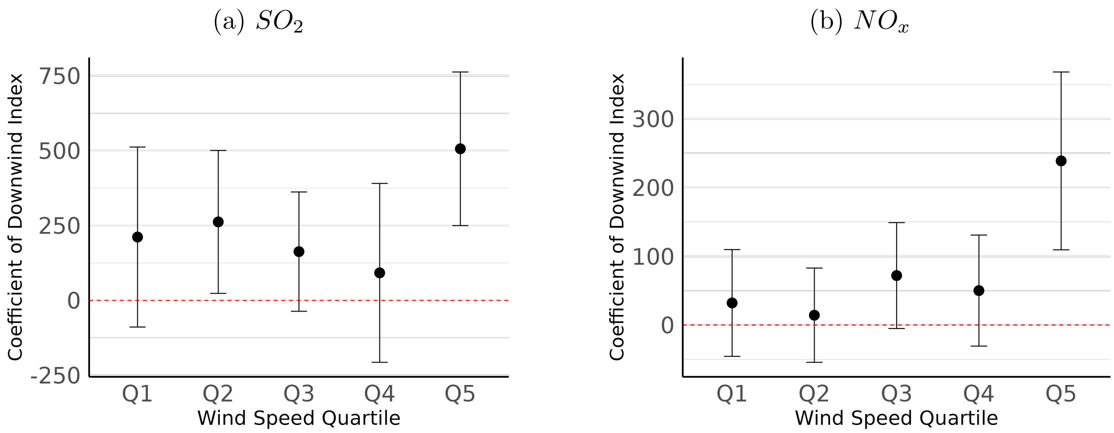


6.5 The Role of Wind Speed

Air pollutants are transported by wind, and higher wind speeds allow them to travel further. Therefore, on days with higher wind speeds, if a power plant is downwind of a monitor, more pollutants are carried away from the monitor. Conversely, if a power plant is upwind, more pollutants are likely to reach the monitor, increasing the measured air pollution in the area.

To test whether strategic behavior in power plant emissions is more pronounced at higher wind speeds, I divided the data into five parts based on wind speed quintiles and estimated Equation 1 separately for each quintile. As shown in 5, for both SO_2 and NO_x, the effects are primarily driven by days with wind speeds in the highest quintile. At very low wind speeds, pollutants tend to remain localized, limiting firms' ability to take advantage of wind direction. At higher wind speeds, pollutants disperse more quickly, allowing firms to confidently manipulate emissions while minimizing regulatory risk.

Figure 5. Heterogeneity across Wind Speed



Notes: This figure reports the heterogeneity of the estimates for four different subsamples, each including only days that fall within a specific wind speed quartile. The magnitude of the emission gap is largest when the sample is limited to days with high wind speeds.

7 Robustness Checks

I conduct several additional analyses to check the robustness of the baseline results. First, I check the robustness of the baseline results with respect to (1) different definitions of downwind direction, (2) different distance thresholds for sample selection, (3) different comparison regions, and (4) different sets of fixed effects or weather controls. Then, I conduct a placebo test using randomly assigned downwind days.

7.1 Alternative Specifications

In the main specification, downwind index is a continuous variable, defined as the cosine of power plant's relative direction to the monitors and the direction wind blows to: $cos(\mid \theta_{plant} - \theta_{wind} \mid)$, with details provided in Section 4. In this section, I create a binary variable indicating whether a power plant is downwind of nearby monitors. This variable is equal to one if $\mid \theta_{plant} - \theta_{wind} \mid < 45°$ and zero otherwise, as illustrated by the yellow region in Figure 6. Similarly, I generate a binary variable for being upwind of nearby monitors. To do this, I create a vector pointing from the power plant to the monitor $\theta_{monitor}$, and the upwind dummy is equal to one if $\mid \theta_{plant} - \theta_{wind} \mid < 45°$ and zero otherwise, as shown by the pink region in Figure 6.

Then I estimate the following equation:

$$E_{it} = \beta_1 \times \text{Downwind}_{it} + \beta_2 \times \text{Upwind}_{it} + \mathbf{X}_{it}\gamma + \mu_i + \eta_{sm} + \lambda_{sy} + \epsilon_{it} \tag{3}$$

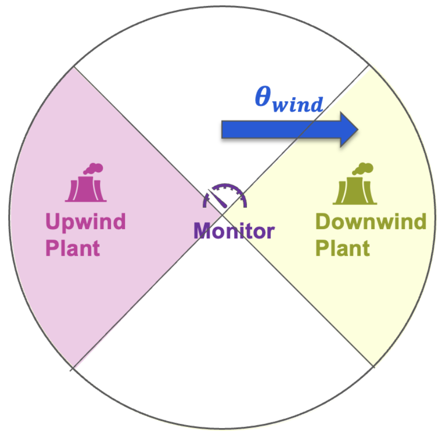


Figure 6. Definition of Binary Downwind and Upwind Indicators

Notes: This figure illustrates the creation of binary variables that indicate whether a power plant is downwind or upwind of nearby monitors on a certain day. The downwind variable is equal to one if the angular difference between the direction from the monitor to the power plant (θ_{plant}) and the wind direction (θ_{wind}) is less than 45° ($\mid \theta_{plant} - \theta_{wind} \mid < 45°$), as shown by the yellow region. Similarly, the upwind variable is set to one if the angular difference between the direction from the power plant to the monitor (θ_{monitor}) and the wind direction (θ_{wind}) is less than 45° ($\mid \theta_{monitor} - \theta_{wind} \mid < 45°$), as illustrated by the pink region.

As shown in Table 8, the estimates based on alternative definitions are similar to the main results: power plants strategically emit less when they are upwind and more when they are downwind of nearby monitors. This implies that the main specification is robust to different definitions of upwind and downwind directions.

Table 8. Robustness to Binary Downwind and Upwind

	SO2			NOx		
	(1)	(2)	(3)	(4)	(5)	(6)
Binary Upwind	-229.27**	-277.62**		-87.665**	-106.55**	
	(105.60)	(117.91)		(36.863)	(42.665)	
Binary Downwind	147.35		226.68	57.941		88.217*
	(131.18)		(139.40)	(42.941)		(47.689)
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DV mean (lbs)	22,701	22,701	22,701	10,809	10,809	10,809
R^2	0.65	0.65	0.65	0.71	0.71	0.71
Observations	753,752	753,752	753,752	787,811	787,811	787,811

Notes: This table reports the regression results using Equation (3). The dependent variable is the emission for unit i on date t. Controls include facility, state-by-month, and state-by-year fixed effects, as well as flexible functions of temperature, precipitation, and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Furthermore, I use a 60-mile radius to identify nearby monitors in the main specification. To test the robustness of this choice, I estimate the model using alternative distance thresholds of 20, 40, 60, 80, 100, and 120 miles.Table 9 demonstrates robustness across different radii and suggests a potential inverted U-shaped pattern in the estimated coefficients. At very short distances (e.g., 20 miles), the strategic effect is not statistically significant, likely because emissions are close enough to affect monitor readings regardless of wind direction. As the radius increases, the coefficients rise, peaking around 60–80 miles, and then decline slightly. This decline is likely due to the monitor being too far away, such that polluters no longer perceive it as a meaningful regulatory constraint and are therefore less likely to respond strategically.

Table 9. Robustness to Different Radii

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SO_2						
Downwind Index	21.644	232.30*	244.88**	234.73***	192.60***	131.75**
	(53.19)	(136.80)	(96.62)	(81.00)	(70.30)	(62.23)
DV mean (lbs)	12,649	21,038	23,189	22,266	23,272	22261
R^2	0.82	0.73	0.66	0.66	0.69	0.67
Observations	173,647	434,066	686,194	913,356	1,108,249	1,298,994
Panel B: NO_X						
Downwind Index	20.883	55.641**	57.943**	67.934**	77.223***	49.641*
	(19.70)	(27.97)	(24.82)	(28.89)	(28.37)	(27.85)
DV mean (lbs)	6,683	9,698	10,351	10,718	11,198	11,400
R^2	0.79	0.72	0.71	0.71	0.72	0.70
Observations	185,945	459,876	720,253	970,145	1,190,632	1,389,857
Radii (miles)	20	40	60	80	100	120
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
State-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the regression results using Equation (1) with varying distance thresholds of 20 miles, 40 miles, 60 miles, 80 miles, 100 miles, and 120 miles. The dependent variable is the emission for unit i on date t. Controls include facility, state-by-month and month-by-year fixed effects, as well as flexible functions of temperature, precipitation and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Lastly, to test the robustness of the model specification, I estimate regressions using different estimation methods and various weather controls. Table 10 presents the results when the emission variable is modeled in three different forms beyond in levels: log,[17] log(y+1), and Poisson. Table 11 shows the results with different types of weather controls. The findings are consistent across these alternative specifications, suggesting that the main estimates are robust to different modeling choices and variations in weather controls.

[17] In this case, observations with zero emissions are excluded, which is equivalent to focusing only on power plants that are operating on a certain day.

Table 10. Robustness to Different Outcome

	SO2			NOx		
	(1)	(2)	(3)	(4)	(5)	(6)
Downwind Index	0.83*	0.80*	0.008**	0.40*	0.37*	0.004**
	(0.45)	(0.46)	(0.004)	(0.22)	(0.22)	(0.002)
Outcome	log(y)	log(y+1)	Poisson	log(y)	log(y+1)	Poisson
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DV Mean	52,214	54,943	49,675	19,414	19,452	19,013
R^2	0.85	0.85		0.87	0.86	
Observations	751,120	753,752	753,752	787,645	787,811	787,811

Notes: This table reports the regression results using Equation (1) with different outcome: log, log(y+1), and Poisson. Coefficient estimates and standard errors are multiplied by 100 to represent effects in percentage points. Controls include facility, state-by-month, and state-by-year fixed effects, as well as flexible functions of temperature, precipitation, and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Robustness to Different Forms Weather Controls

	SO2			NOx		
	(1)	(2)	(3)	(4)	(5)	(6)
Downwind Index	242.22***	217.54**	232.89***	75.95**	64.49*	74.50**
	(89.28)	(90.34)	(88.83)	(33.11)	(33.50)	(33.67)
Forms of Weather Controls	Bin	Linear	No	Bin	Linear	No
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
DV mean (lbs)	22,701	22,701	22,701	10,809	10,809	10,809
R^2	0.65	0.65	0.65	0.71	0.71	0.71
Observations	753,752	753,752	753,752	787,811	787,811	787,811

Notes: This table reports the regression results using Equation (1) with different forms of weather controls: bins, linear controls, and no weather controls. The dependent variable is emissions in log form for unit i on date t. Coefficient estimates and standard errors are multiplied by 100 to represent effects in percentage points. Controls include facility, state-by-month, and state-by-year fixed effects, as well as flexible functions of temperature, precipitation, and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

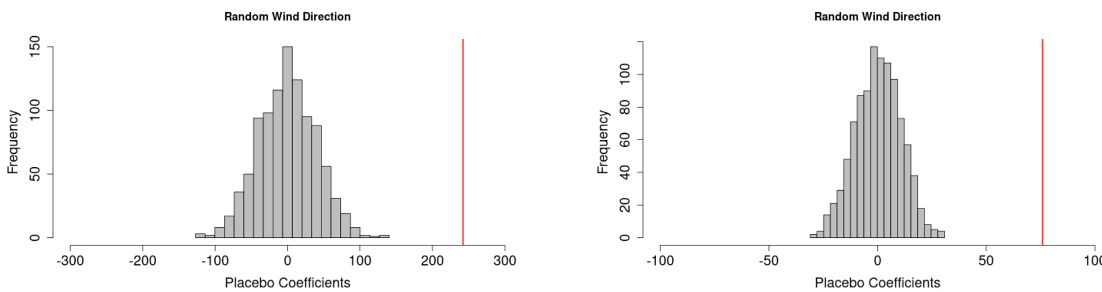
7.2 Placebo Test

I conduct a placebo test based on random wind directions. I repeat the process 1000 times for each pollutant and plot the distributions of the estimated coefficients

(Figure 7). In both panels, the placebo coefficients are small, centered around zero, and significantly different from the baseline estimates (represented by the red solid line on the right). This figure provides further evidence of the validity of the empirical strategy and confirms that it is indeed the actual wind direction that leads to a significant increase in emissions.

Figure 7. Placebo Tests

(a) SO_2 (b) NO_X



Notes: This figure plots the placebo test based on randomly generated wind directions. In the placebo test, I repeat the practice 1000 times and plot the distribution of the estimated coefficients. The red solid line at the right is the baseline estimate using equation (1).

8 Conclusion

Based on the location of coal-fired power plants, air quality monitors, and wind patterns between 2011 and 2022, I find strong empirical evidence that local polluters strategically adjust their end-of-pipe emissions in response to wind direction and wind speed. Specifically, polluters emit more pollution when they are downwind of nearby monitors, especially on days with high wind speeds or when the monitor is located within the same state. This emission gap is robust to various definitions of downwind and upwind, as well as different model specifications. This finding provides new evidence of local strategic behavior that could undermine the effectiveness of environmental regulations and lead to inefficiencies under decentralized management.

This study is not without its limitations. First, because my sample is limited to power plants in the U.S., I cannot examine whether similar strategic behavior occurs in other polluting industries. Second, my findings do not directly address the broader question of whether current environmental regulations are appropriately calibrated. There is an inherent trade-off between pollution abatement efforts and economic growth, and it is possible that strategic polluting behavior could have some cost-saving benefits if few people live downwind of a power plant (Li, 2025), resulting in lower abatement costs with minimal adverse health effects. However, this possibility requires further investigation. Third, it remains unclear who is driving this strategic behavior—the local government or the polluter. The observed emission gap could result from polluters adjusting emissions to avoid detection, or it could reflect leniency from local governments that know increased emissions will not impact their monitoring data.

Despite these limitations, this paper makes several contributions. First, it enriches the literature on the gap between regulatory enforcement and actual pollution abatement by examining a previously overlooked factor: the short-term impact of wind direction on plant emissions. Building on prior research on strategic responses (Zou, 2021; Mu et al., 2021; Agarwal et al., 2023; Grainger and Schreiber, 2019; Morehouse and Rubin, 2021; He et al., 2020), these findings more broadly emphasize the importance for regulators to be cautious and aware of potential strategic responses to regulation.

Second, this paper contributes to the field of environmental justice. A broad literature demonstrates the correlation or causation between pollution exposure and income (Carson et al., 1997; Banzhaf and Walsh, 2008; Banzhaf et al., 2019). Furthermore, Grainger and Schreiber (2019) find that low-income neighborhoods are also less likely to be monitored. My findings extend this literature by demonstrating that low-income groups may be disproportionately affected on downwind days. When these communities are located downwind and not properly monitored, they are less likely to receive regulatory attention—even when ambient pollution levels exceed federal standards.

Under the Clean Air Act, in situ monitoring data is considered the gold standard for compliance. As the federal government establishes standards and local governments monitor their own pollution levels, this federalist framework empowers local authorities to strategically respond to regulations. Existing literature suggests that utilizing remote sensing data or mobile monitors could enhance the current monitoring system (Grainger and Schreiber, 2019; Zou, 2021). Moreover, incorporating CEMS data into compliance assessments can further reduce strategic behavior, improve the comprehensiveness of the monitoring system, and more effectively protect human health, especially in low-income communities.

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A Appendix Tables and Figures

Appendix Table A1. Summary Statistics for Natural Gas Power Plants

Variables	N	Mean	St. Dev.	Min	Max
Emissions					
SO_2 (lbs)	1,205,642	1,321.73	9,544.26	0.00	319,554
NO_x (lbs)	1,304,092	1,198.79	2,997.58	0.00	96,726
CO_2 (short tons)	1,201,090	2,228.04	1,222.53	0.00	21,606.00
Heat Input (mmBtu)	1,304,092	34,115.23	17,790.67	0.00	364,471.20
Gross Load (MWh)	1,664,562	2,395.61	2,330.18	0.00	17,706.00
SO_2 Rate (lbs/mmBtu)	1,205,642	0.04	0.29	0.00	5.93
NO_X Rate (lbs/mmBtu)	1,304,092	0.04	0.08	0.00	5.47
CO_2 Rate (lbs/mmBtu)	1,201,090	0.06	0.03	0.00	9.69
Weather					
Precipitation (mm)	1,304,092	2.81	6.86	0.00	204.07
Temperature (°C)	1,304,092	17.24	10.02	−30.58	40.54
Wind Direction (degrees)	1,304,092	161.67	110.52	0.0002	360.00
Wind Speed (m/s)	1,304,092	2.50	1.45	0.004	15.04
Relative Locations					
Distance (km)	1,304,092	42.29	27.93	2,601.11	99,777.41
Direction (degrees)	1,304,092	170.11	108.56	0.61	359.67
Downwind Index	1,304,092	−0.04	0.72	−1.00	1.00
Same State (0/1)	1,304,092	0.88	0.32	0	1

Notes: This table reports the summary statistics for gas-fired power plants in my sample. Direction is the degree of a vector pointing from the monitor to the power plant, and the downwind index is defined as in Section 4, Construction of the Downwind Index.

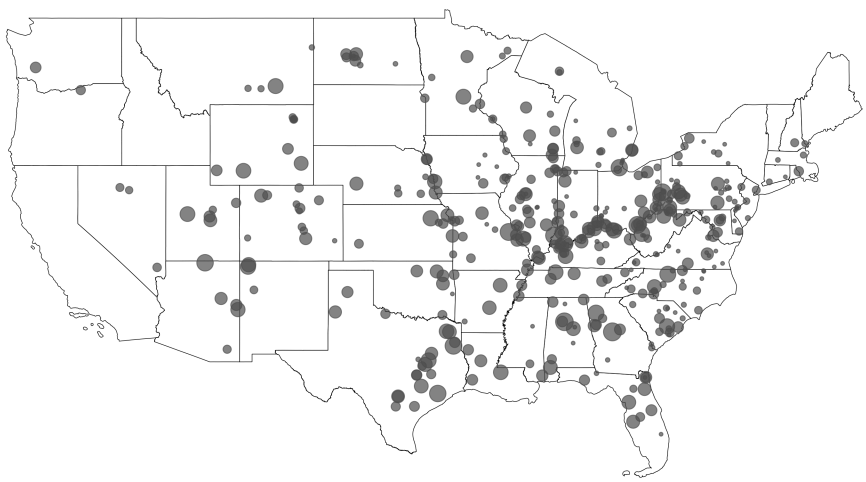
Appendix Table A2. Effect of Wind Directions on Pollution Emissions for Natrual Gas Power Plants

	(1)	(2)	(3)
Panel A: SO_2			
Downwind Index	19.796	18.140	35.98
	(29.075)	(21.791)	(39.103)
DV mean (lbs)	1,322	1,322	1,322
R^2	0.51	0.73	0.49
Observations	1,205,642	1,205,642	1,205,642
Panel B: NO_X			
Downwind Index	7.1081	7.0474	8.2121
	(5.1320)	(4.3483)	(6.4237)
DV mean (lbs)	1,199	1,199	1,199
R^2	0.72	0.76	0.72
Observations	1,304,092	1,304,092	1,304,092
Facility FE	Yes	Yes	Yes
State-Month FE	Yes	Yes	
Month-year FE	Yes		Yes
State-year FE		Yes	

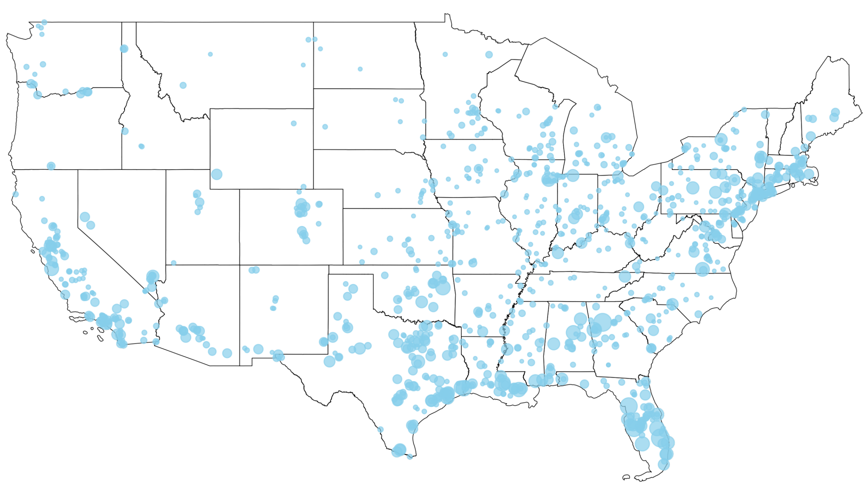
Notes: This table reports regression results based on equation (1) for natural gas power plants, with varying fixed effects. The dependent variable is the logarithm of emissions for power plant unit i on date t. Controls include fixed effects and a flexible function of temperature, precipitation, and wind speed. Standard errors are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Figure A1. Distribution of Power Plants in the US

(a) Coal-fired Power Plants



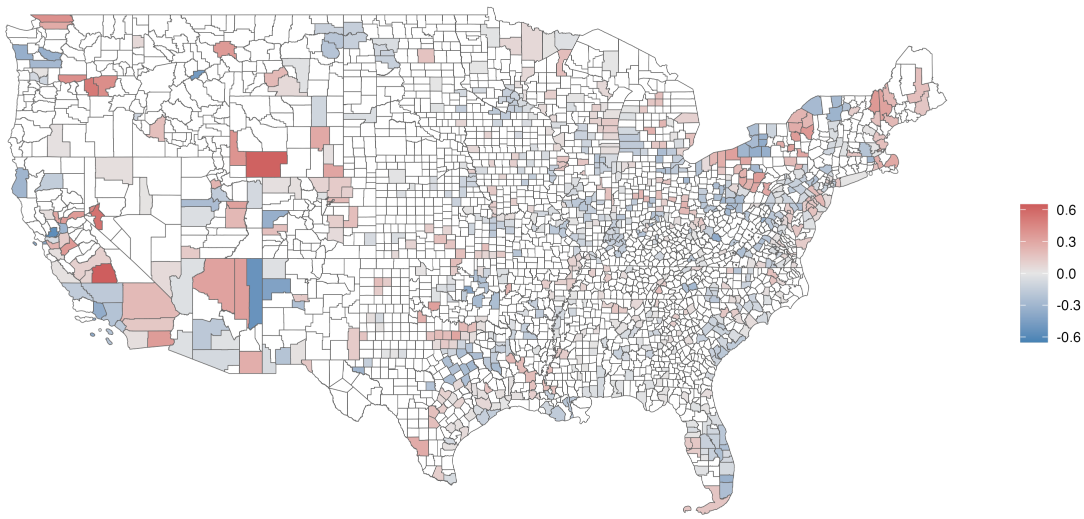
(b) Gas-fired Power Plants



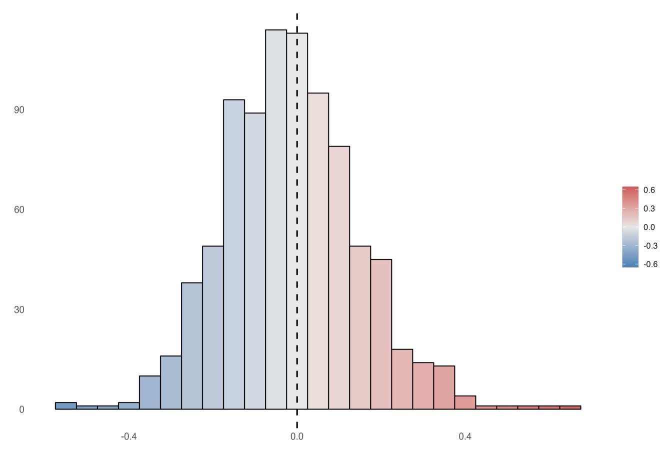
Notes: Panel (a) shows the spatial distribution of coal-fired power plants, while Panel (b) shows the spatial distribution of gas-fired power plants. The size of each point represents the capacity of the power plant, with larger points indicating higher capacities.

Appendix Figure A2. County Average Downwind Index

(a) *Map*



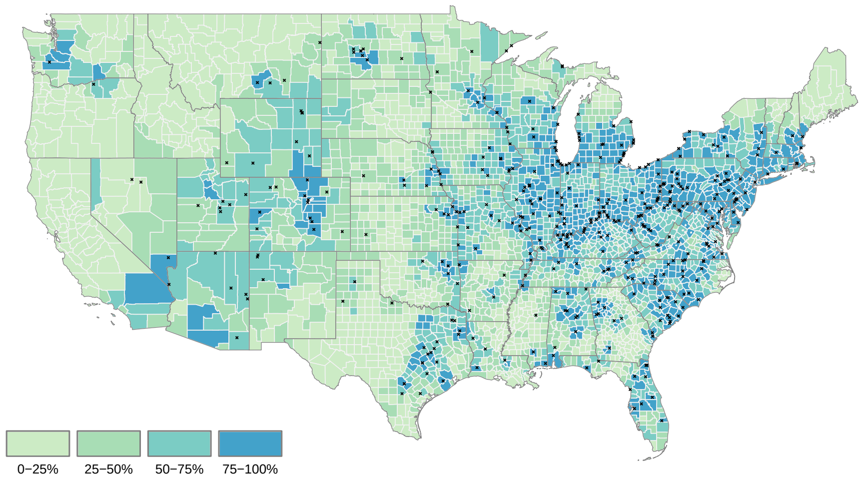
(b) *Histogram*



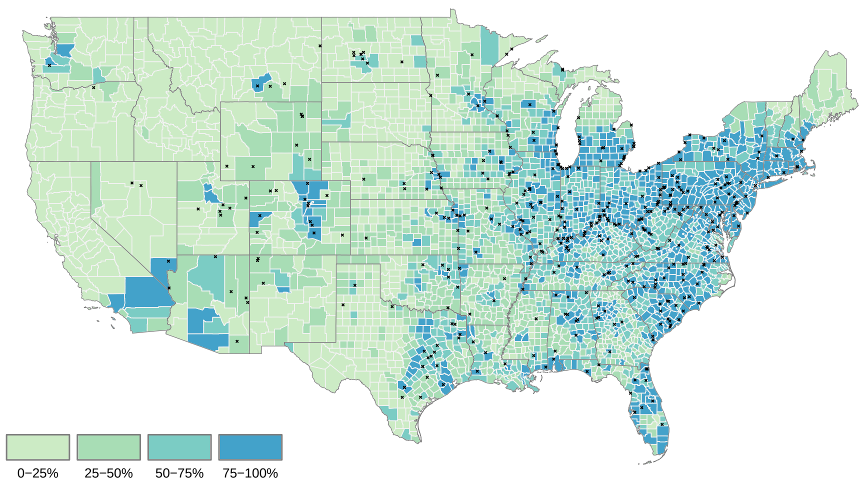
Notes: This figure presents two visualizations of the downwind index, as defined in equation (2). Panel (a) illustrates the spatial distribution of the county-level average downwind index, while Panel (b) displays a histogram of downwind index values. The majority of indices are centered around 0, indicating substantial variation in wind direction within each county. Conversely, if most indices were close to 1 or -1, it would imply that power plants are consistently downwind or upwind, suggesting highly stable and directional wind patterns, which would be problematic for my analysis.

Appendix Figure A3. Increases in Air Pollutants Induced by Strategic Emissions

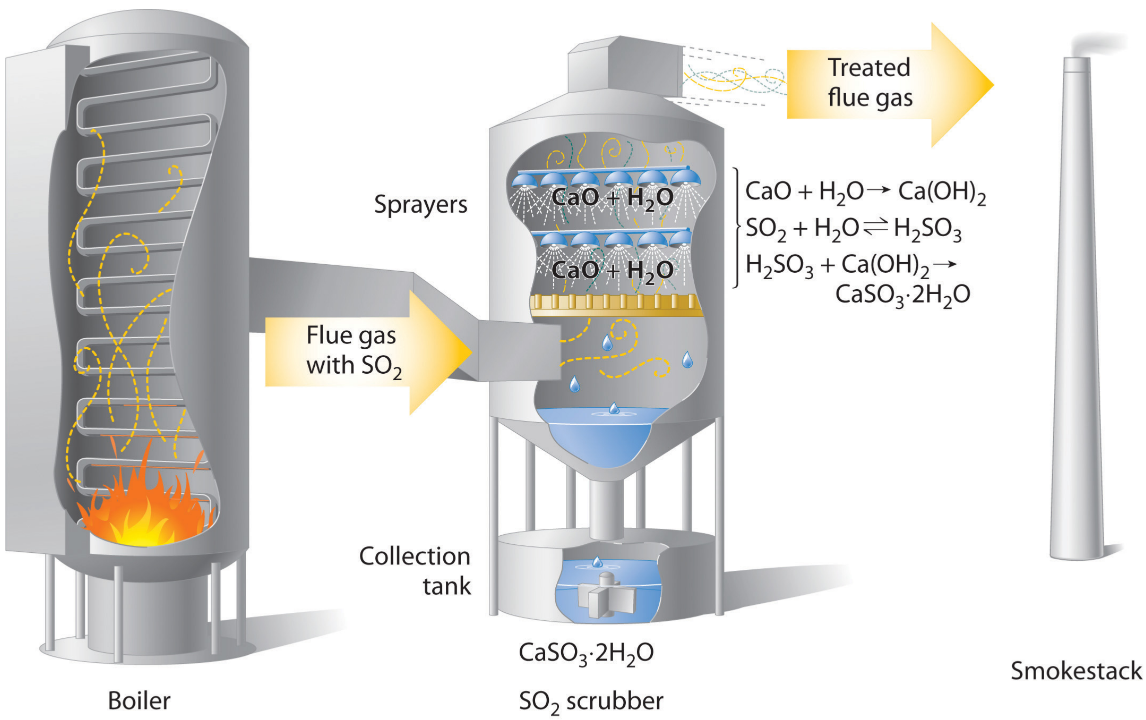
(a) SO_2



(b) NO_x



Notes: This map illustrates the distribution of SO_2 (panel A) and NO_x (panel B), simulated using the InMAP model. The black crosses represent the locations of coal-fired power plants. The colors indicate the concentration quantiles (0–25%, 25–50%, 50–75%, 75–100%), with darker colors indicating higher concentrations.



Appendix Figure A4. Scrubber Example

Source: https://users.highland.edu/ jsullivan/principles-of-general-chemistry-v1.0/s08-07-the-chemistry-of-acid-rain.html