Wind Turbines and Ambient Air Pollution

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Abstract

Wind energy has experienced rapid growth over the past few decades. However, the relationship between wind turbines and ambient air pollution remains unclear. Using high-resolution grid-level pollution data between 2007 and 2016 and employing a two-way fixed effects model, I empirically assess the impact of wind turbine operations on local air pollution levels. The results suggest that the transition from polluting power plants to wind turbines generally improves air quality, despite a slight localized increase in ozone levels associated with turbine operation. These findings contribute to a better understanding of the interaction between wind energy and air pollution, providing policy-relevant evidence for balancing renewable energy expansion with air quality goals..

1 Introduction

Air pollution is a major global issue. According to the United Nations International Children's Emergency Fund (UNICEF), air pollution was responsible for 8.1 million deaths globally in 2021, making it the second leading risk factor for death [1]. Wind power is a renewable energy source whose cost has decreased dramatically and undergone rapid development. Like all other renewable energy sources, wind power is seen as an alternative to fossil fuels, which would ease the pressure on fossil resources, help mitigate global climate change, and reduce the pollution produced in the traditional electricity generation process. As wind turbines convert kinetic energy into electricity, they alter the air flow around them, which may, in turn, affect local pollution levels. However, the relationship between wind energy and air pollution is not widely discussed.

[1] United Nations International Children's Emergency Fund (UNICEF), *State of Global Air Report 2024*, https://www.stateofglobalair.org/resources/report/state-global-air-report-2024

Given that wind power generation may influence both the formation of air pollutants—by displacing emissions from conventional power plants—and the dispersion of air pollutants—by altering local wind patterns and microclimates around turbines—this paper aims to answer the following questions: From a highly localized perspective, will the operation of wind turbines affect ambient air pollution levels? If so, what is the direction and magnitude of the effect? Furthermore, are these effects primarily driven by substitution effercts (i.e., reduced fossil fuel emissions) or by dispersion effects (e.g., altering pollutant transport and mixing)?

In this paper, I study the relationship between wind energy development and ambient air pollution, focusing on Texas. The electricity supply in Texas is managed by the Electric Reliability Council of Texas (ERCOT), which operates a relatively independent power system. Additionally, wind energy development in Texas has been relatively steady over time, making it a suitable setting for study. By utilizing variations in wind energy development and detailed grid-level pollution data, I analyze the local effects of wind turbine operation on air pollution levels. Using a two-way fixed effects model and accounting for spillover effects, I assess how wind turbines affect ambient air pollution levels and distinguish between substitution and dispersion effects. The estimation is based on a ZIP Code Tabulation Area (ZCTA)-level[2] panel dataset from 2007 to 2016, covering a total of 1,700 ZCTAs.

The operation of wind turbines primarily affects ambient air pollution levels through two channels: substitution effects and dispersion effects. Substitution effects describe the scenario in which the installation and operation of wind turbines displace polluting power plants within the electricity grid. This displacement reduces emissions from those plants, thereby lowering the amount of pollution that would have otherwise impacted the areas surrounding the turbines. Dispersion effects refer to the case where wind turbine operation alters wind speeds, creates turbulence, and changes air flow around the turbines, which affects the dispersion of ambient pollutants. To separate these two effects, I build on prior work on spillover in the innovation literature, as outlined by Aghion et al., 2016. This approach enables me to effectively distinguish between the substitution and dispersion effects of wind turbine operation.

This paper first contributes to the literature on wind turbines' externalities. Researchers have focused on understanding the impact of wind turbines on both the natural environment and human communities during their construction and operational phases. Evidence shows that the construction of wind turbines increases county-level personal income and employment, but also negatively affects residents' self-reported well-being (Brown et al., 2012; Krekel and Zerrahn, 2017).

[2]ZCTA refers to the ZIP code tabulation area, which is a geographic area defined by the U.S. Census Bureau for statistical purpose

During the operational phase, research by Kaffine (2019) highlights a positive association between wind turbines and crop yields. However, much of the literature emphasizes the negative externalities wind turbines impose on ecosystems and economic well-being. These include noise that disrupts bat activity, as well as the risks posed to both bat and bird populations by their rotating blades (Barrios and Rodriguez, 2004; Ellerbrok et al., 2024; Pearce-Higgins et al., 2012; Sotillo et al., 2024). Wind turbines also reduce the aesthetic value of landscapes (Betakova et al., 2015; Krekel and Zerrahn, 2017; Molnarova et al., 2012), and several studies show that their presence negatively impacts nearby housing prices (Dröes and Koster, 2016; Gibbons, 2015; Heintzelman and Tuttle, 2012).

By examining the potential impact of wind turbines on air pollution, this paper is, to my knowledge, the first to use econometric methods to assess the ambient pollution externalities associated with their operation.

This paper also contributes to the literature on the environmental impacts of renewable energy. Previous studies have demonstrated that wind energy plays a crucial role in reducing carbon emissions as well as other air pollutants from electricity generation (Barthelmie and Pryor, 2014; Cullen, 2013; Fell and Kaffine, 2018; Kaffine et al., 2013; Katzenstein and Apt, 2009; Long et al., 2023; Lu et al., 2020; Novan, 2015). However, few studies have directly linked the substitution of polluting power plants by wind energy to measurable changes in local air quality. Instead, much of the existing literature connects emission reductions to health benefits using models such as EASIUR, APEEP, EPA-RIA, and COBRA (Millstein et al., 2017; Sergi et al., 2020; Siler-Evans et al., 2013; Wiser et al., 2016; Wiser et al., 2017). These models estimate the monetary benefits associated with a one-unit reduction in air pollutant emissions, inherently accounting for changes in local air pollution levels. Some studies also use reduced-form econometric analyses to estimate health outcomes (Fell and Morrill, 2024).

One notable exception is the study by M. Qiu et al. (2022), which uses GEOS-Chem to simulate changes in ozone and PM2.5 concentrations following wind power deployment and subsequently links those changes to health benefits. However, that study does not directly show changes in ambient air quality levels. Instead, it relies on archived model outputs from Dedoussi et al. (2020).

Building upon this body of work, this paper distinguishes between dispersion effects and substitution effects and directly quantifies the changes in local air pollution levels resulting from the deployment of wind power.

Furthermore, this paper contributes to the broader body of literature on the unintended con-

sequences of environmental practices. While wind power is deployed to replace coal plants and mitigate global warming, the operation of wind turbines to harness wind power can lead to unforeseen real-world outcomes. This type of phenomenon is not unique and has been widely observed in previous studies. The Clean Air Act, intended to improve air quality, inadvertently increased market power among gasoline firms (Chakravorty et al., 2008). Similarly, the Forest Stewardship Council, which strives to balance commercial timber extraction with the rights of local Aka people, has led to increased food insecurity and higher illness rates among Aka households (Doremus, 2019). Restoring wolf populations has been shown to decrease deer–vehicle collisions, reducing the associated economic losses by $10.9 million each year (Raynor et al., 2021).

The paper proceeds as follows. Section 2 provides background on wind energy development and offers scientific intuition on dispersion effects. Section 3 describes the data used in the analysis. Section 4 presents the empirical model. Section 5 presents the conclusion.

2 Connecting Wind Energy and Air Pollution: Rationale and Evidence

Air pollution remains a pressing concern. While the Clean Air Act, enacted in 1963, has greatly reduced air pollution in the U.S., approximately 66 million tons of pollution continued to be released into the atmosphere in 2023[3], and many areas exceeded national air quality standards for at least one of the six major pollutants[4].

A substantial body of research has documented the adverse effects of air pollution on both physical and mental health, particularly in relation to the respiratory and cardiovascular systems (Chu et al., 2023; Ferro et al., 2024; Imelda, 2020; Y. Qiu et al., 2024; Salvo et al., 2024; Samakovlis et al., 2005; Tanaka, 2024). Increased pollution levels are also associated with higher healthcare costs, reduced labor productivity, and changes in mobility patterns (Chen et al., 2022; Dai et al., 2024; Gilraine and Zheng, 2024; Mo et al., 2023; Xia et al., 2022).

Fossil fuel combustion is widely recognized as a major contributor to air pollution (Perera, 2018). During combustion, incomplete burning and impurities in raw materials produce solid and liquid particles that form PM_{10} and $PM_{2.5}$. Sulfur content in coal and oil reacts with oxygen to form SO_2, while nitrogen and oxygen in the air form NO_X at high temperatures. NO_X and volatile

[3] https://www.epa.gov/air-trends/air-quality-national-summary
[4] https://www.epa.gov/clean-air-act-overview/air-pollution-current-and-future-challenges

organic compounds (VOCs), another type of pollutant released during combustion, then participate in photochemical reactions under sunlight, producing ground-level ozone.

In response to the severe environmental and health consequences of fossil fuel combustion, there has been a global push toward renewable energy. Among these, wind power has emerged as one of the most promising alternatives due to its scalability, cost-efficiency, and minimal pollutant emissions during operation.

Wind power has been harnessed by humans for centuries. Initially, it was used for sailing boats on rivers and lakes, later expanding to sea vessels. On land, wind energy was employed for various purposes, including grinding grain, sawing wood, shredding tobacco, pressing oil, and pumping water (Möllerström and Gipe, 2024; Ragheb, 2017). The first wind turbine in the United States was installed by industrialist Charles Brush in 1888 in Cleveland, Ohio[5].

The major expansion of wind turbines in the U.S. began in California during the 'California Wind Rush', spurred by the introduction of fixed feed-in tariffs for renewable energy and tax credits that covered up to 50% of wind energy investments. By the end of 1985, California had over 12,000 wind turbines installed, with a combined capacity exceeding 1,000 MW (Möllerström and Gipe, 2024).

After the California Wind Rush, the federal Production Tax Credit and Renewable Portfolio Standards became key drivers of wind turbine installations across the country (Ackermann and Söder, 2000). Today, leveraging these credits, standards, and grant programs, various states have developed more tailored and flexible policies for wind energy. As of November 20, 2024, the U.S. has 74,695 turbines spread across 45 states, with a total rated capacity exceeding 150,000 MW (U.S. Wind Turbine Database).

Currently, wind power is widely regarded as a more sustainable alternative to fossil fuels, as it generates almost no pollutant releases during electricity production. It has also undergone rapid development, leading to significant cost reductions. According to EMBER[6], global wind generation has nearly tripled since 2015, contributing 7.8% (2,304 TWh) of global electricity in 2023[7]. In the United States alone, the U.S. Energy Information Administration (EIA) reports that wind power produced 425 terawatt-hours (TWh) of electricity production in 2023, accounting for approximately 10.2% of the country's total electricity generation. The cost of onshore wind turbines has also dropped significantly, with the global weighted average levelized cost of electricity

[5] https://wind-works.org/austrian-was-first-with-wind-electric-turbine-not-byth-or-de-goyon/

[6] Ember began in 2008 as Sandbag, focusing on reforming the EU carbon market. In 2020, the organization rebranded to Ember.

[7] EMBER. (2024). *Global Electricity Review 2024*.

(LCOE) falling to USD 0.033/kWh in 2023, marking a 70% decrease from the 2010 cost[8].

Despite these benefits, the large-scale expansion of wind power raises concerns about potential environmental externalities associated with the operational characteristics of wind turbines. These concerns are often reflected in the resistance to wind energy projects. Meteorological research has focused on how turbine operations affect the local microclimate. Studies indicate that wind turbine operations induce seasonal and diurnal changes in the characteristics of the local atmospheric boundary layer (Wang et al., 2019). Wind farms significantly affect near-surface air temperatures and alter local atmospheric conditions through wake effects, which are characterized by reduced wind speeds and increased turbulence (Armstrong et al., 2014; Baidya Roy et al., 2004; Baidya Roy and Traiteur, 2010; Bodini et al., 2021; Fitch et al., 2013; Fitch et al., 2012; Lundquist et al., 2019; Miller and Kleidon, 2016; Smith et al., 2013). Furthermore, wind turbines have been shown to increase the movement of CO_2 in the surrounding environment and slightly raise ozone levels in nearby areas (Rajewski et al., 2014; Golbazi and Archer, 2024).

Thus, while replacing coal-fired electricity with wind power offers substantial environmental benefits, it is essential to consider the ecological and atmospheric interactions caused by the operation of wind turbines and how these might alter the surrounding environment.

3 Data

3.1 Wind data

3.1.1 Wind turbine data

I obtain wind turbine data from the United States Wind Turbine Database (USWTDB), a collaborative project supported by the U.S. Department of Energy (DOE), the U.S. Geological Survey (USGS) Energy Resources Program, and the American Clean Power Association (ACP) (Hoen et al., 2018). The USWTDB provides precise geographic coordinates (latitude and longitude) for both onshore and offshore wind turbines in the United States, along with detailed turbine specifications and project-level information, including hub height, rotor diameter, rated capacity, and operational start year. Using these geographic coordinates, I map each turbine to its corresponding

[8]International Renewable Energy Agency (IRENA), *Renewable Power Generation Costs in 2023*, https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Sep/IRENA_Renewable_power_generation_costs_in_2023.pdf.

ZIP Code Tabulation Area (ZCTA). ZCTAs are polygonal approximations of ZIP codes created by the U.S. Census Bureau to enable consistent spatial analysis; unlike traditional ZIP codes designed for mail delivery, ZCTAs represent stable geographic areas and provide a more suitable unit for environmental data aggregation. To further enrich the temporal resolution of operational status, I merge this dataset with the Energy Information Administration's Form 860 (EIA-860)[9], which reports the operational start month for each turbine. Since only the month of operation is available, I assume turbines became operational on the first day of the respective month.

To evaluate potential dispersion effects, I investigate how pollution concentration levels vary across ZCTAs with differing levels of wind energy deployment. The rated capacity of turbines, provided by the USWTDB, serves as a static measure of their potential output under optimal conditions and allows for capturing spatial variation in wind infrastructure. By aggregating the rated capacities of all turbines operational in a given ZCTA by a specific date, I construct a measure for ZCTA wind capacity. Summing ZCTA-level wind capacities across the ERCOT region yields ERCOT wind capacity.

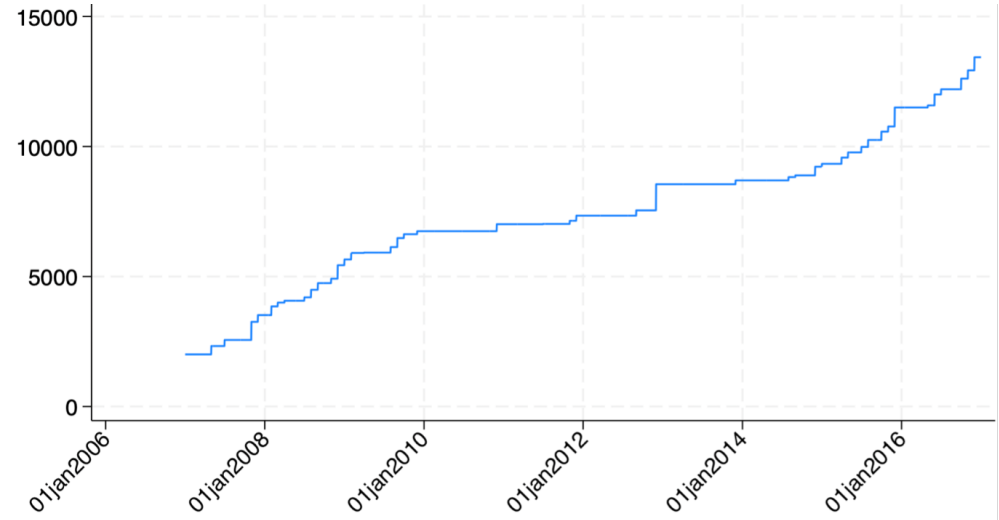


Figure 1: ERCOT Wind Capacity Trend

Figure 1 illustrates the growth trend of wind capacity in the ERCOT region from 2007 to 2016. Overall, wind capacity increased steadily over this period, from 2005.8 MW in 2007 to 13431.95 MW in 2016. The growth pattern resembles a step function, reflecting incremental capacity additions that occurred at irregular intervals. In terms of pace, wind capacity expanded rapidly before 2010, followed by a more moderate growth phase between 2010 and 2015. After 2015, the growth rate accelerated again.

[9] https://www.eia.gov/electricity/data/eia860/

3.1.2 Wind Electricity Generation Data

I obtain ERCOT wind electricity generation data from ERCOT's public data portal. The website provides electricity generation data at both 15-minute intervals and daily frequency, disaggregated by fuel type (e.g., coal, natural gas, wind, hydro). I extract daily wind generation data from this dataset, resulting in a time series covering daily wind electricity production from 2007 to 2016.

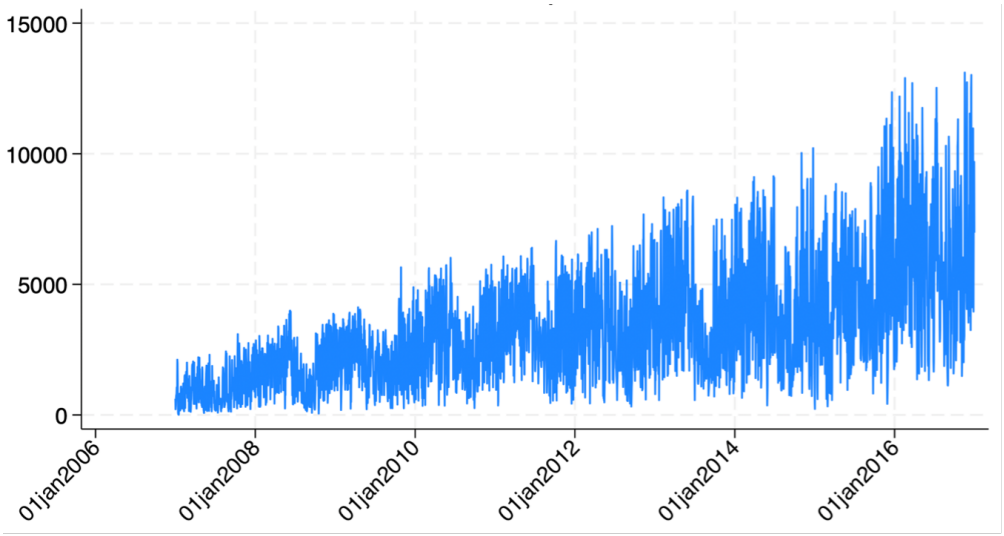


Figure 2: ERCOT Wind Generation Trend

Figure 2 presents the trend in wind electricity generation in ERCOT between 2007 and 2016. Overall, wind generation exhibited a steady upward trend, consistent with the increase in installed wind turbines and improved integration into the grid.

3.1.3 Independent variable construction

One methodological challenge arises from the temporal mismatch between wind capacity (which changes monthly) and other variables in my dataset (which are observed daily). While wind capacity is a fixed characteristic once a turbine is built, actual wind power generation varies from day to day due to changes in meteorological conditions. Unfortunately, ZCTA-level daily generation data is not available. To approximate daily variation at the ZCTA level, I construct a proxy variable for daily ZCTA wind generation using the following formula:

$$\text{WindGen}_{zt}^{\text{ZCTA}} = \left(\frac{\text{WindCap}_{zt}^{\text{ZCTA}}}{\sum_{j \in \text{ERCOT}} \text{WindCap}_{jt}^{\text{ZCTA}}} \right) \times \text{WindGen}_{t}^{\text{ERCOT}} \quad (1)$$

In this expression, $\text{WindCap}_{zt}^{\text{ZCTA}}$ denotes the total wind capacity installed in ZCTA z prior to month t, while the denominator $\sum_{j \in \text{ERCOT}} \text{WindCap}_{jt}^{\text{ZCTA}}$ represents the aggregate wind capacity across all ZCTAs within the ERCOT region for the same month. The resulting ratio reflects the share of ERCOT's total wind infrastructure situated in ZCTA z at time t. By multiplying this share with ERCOT's total daily wind generation, I approximate the daily wind output for each ZCTA under the assumption that generation is proportional to installed capacity.

This is admittedly a strong assumption, as real-world generation depends heavily on local wind conditions and turbine performance. To address potential bias, I plan to control for wind speed in subsequent specifications. Nonetheless, I am also exploring alternative methods to construct a more accurate and scientifically grounded measure of daily wind generation at the ZCTA level.

3.2 Ambient pollution

To evaluate changes in local air pollution, I use high-resolution (1 km) grid-level pollution data from NASA's Socioeconomic Data and Applications Center (SEDAC) (Requia et al., 2024; Requia et al., 2020), which provides daily 8-hour maximum concentrations of NO_2, $PM_{2.5}$, and ozone at a 1 km $\times$ 1 km apecial grid resolution. These pollutant concentrations are predictions derived from a combination of air monitoring data, satellite aerosol optical depth measurements, meteorological data, chemical transport model simulations, and land-use variables using machine learning models. The predicted values demonstrate an average cross-validated R^2 of 0.90 against observations, highlighting their reliability.

Since wind turbines and air quality monitoring stations are often located in different areas, relying solely on monitoring data would result in significant data loss and restrict the sample of turbines. In contrast, this gridded dataset allows for comprehensive spatial coverage. I aggregate pollution values to the ZCTA level using the same geographic boundaries employed for the turbine mapping. This approach ensures consistency in spatial units and allows for a more complete and accurate assessment of the air quality impacts associated with wind turbine operations.

To perform this aggregation, I first compute the mean pollutant level using all grids within each ZCTA. Since some grids only partially overlap with a given ZCTA, I plan to apply a weighted

average approach later, where the weight is determined by the proportion of the grid that falls within the ZCTA boundaries. This step ensures that pollution estimates accurately reflect the spatial distribution of air quality data.

Aggregating to the ZCTA level is crucial because prior meteorological research indicates that wind turbine impacts extend over distances of 2–10 km, which may not be fully captured at the finer 1 km grid scale. By using ZCTAs, I account for these broader effects, resulting in a more comprehensive dataset of daily ZCTA-level pollutant concentrations from 2007 to 2016.

3.3 Control variables

3.3.1 Load data

Electricity demand, referred to as load, plays a key role in determining both the volume of electricity generated and the associated pollutant emissions. I collect load data from ERCOT's publicly available data portal, which provides system-wide electricity demand at 15-minute intervals. To align with the temporal resolution of other datasets, I aggregate these 15-minute observations into daily values. This yields a continuous time series of daily electricity load spanning from 2007 to 2016.

3.3.2 Natural gas price

The interrelationship between natural gas and coal plays a significant role in the formation of air pollutants. Typically, natural gas is regarded as cleaner than coal due to its lower pollutant emissions during combustion. Therefore, it is crucial to include the natural gas price in the regression. I obtain the Henry Hub natural gas spot price from the EIA, which provides weekday prices and serves as a reliable index for natural gas pricing. To estimate weekend prices, I use spline interpolation to derive the missing data.

3.3.3 Weather data

I collect weather data from the ERA5 reanalysis dataset, a Copernicus product provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Copernicus Climate Change Service (C3S), 2024; Hersbach et al., 2023). This reanalysis dataset offers a more continuous and

consistent estimation of weather conditions across the contiguous U.S. Additionally, it provides a comprehensive range of weather variables, including wind direction, wind speed, boundary layer height, and solar radiation —an essential factor in ozone formation—all within a single dataset at a relatively fine spatial resolution.

For my analysis, I use ERA5 daily data at single levels, which is available on a $0.25° \times 0.25°$ latitude/longitude grid (approximately 30 km × 30 km). I further aggregate this grid-level data to ZCTA level for use in my study. The weather controls include wind direction, wind speed, boundary layer height, solar radiation, temperature, precipitation, and humidity.

3.4 Summary statistics

Table 1 presents the summary statistics. Ozone concentration refers to the average daily 8-hour maximum ozone concentration within each ZCTA. $WindGen^{\text{ZCTA}}$ denotes daily wind generation within each ZCTA, capturing dispersion effects, while $WindGen^{\text{ERCOT}}$ measures the total amount of wind energy produced per day across ERCOT, capturing substitution effects. Including both variables allows me to distinguish between dispersion and substitution effects. Load represents the daily electricity demand within ERCOT.

The dataset consists of daily observations from 1,700 ZCTAs in Texas, spanning the years 2007 to 2016, with a total of 6,196,240 observations. Among these, approximately 5.4% of ZCTAs (95 in total) had at least one wind turbine installed during this period.

Table 1: Summary Statistics

	Observations	Mean	Standard deviation	Min	Max
Ozone concentration (ppb)		38.7605	11.5618	6.4944	71.1381
NO2 concentration (ppb)		11.6696	8.1714	0.0000	126.5521
PM2.5 concentration (ppb)		9.3876	4.2473	0.0002	59.9087
$\text{WindGen}^{\text{ZCTA}}$ (GWh)		0.0465	0.4627	0.0000	24.7785
$\text{WindGen}^{\text{ERCOT}}$ (GWh)		79.2087	53.5078	0.1427	314.6381
Load (GWh)		894.8876	164.1809	609.9083	1375.8760
Natural gas price (Dollars per Million Btu)		4.4027	2.1063	1.4563	13.3100

Note: The dataset consists of daily observations from 1,709 ZCTAs in Texas from 2007 to 2016, totaling 6,196,240 observations. Approximately 5.4% of ZCTAs (95 in total) had at least one wind turbine installed during this period. A total of 46,426 ozone-related outlier observations were dropped.

4 Empirical model

I utilize both spatial and temporal variation in wind energy development to investigate the effects of wind power on ambient air pollution levels. The central objective is to assess how the operation of wind turbines influences local air quality, both through dispersion effects and substitution effects. To capture potential dispersion effects, I compare pollution levels across regions with differing intensities of local wind development. To assess broader substitution effects, and following the discussion from the innovation spillover literature (Aghion et al., 2016), I incorporate the total scale of wind energy generation into the analysis. My empirical model is as following:

$$log(p_{zt}) = \beta_0 + \left\{ \underbrace{\beta_1 \text{WindGen}_{zt}^{\text{ZCTA}}}_{\text{Dispersion Effects}} \right\} + \left\{ \underbrace{\beta_2 \text{WindGen}_{t}^{\text{ERCOT}} + \beta_3 (\text{WindGen}_{t}^{\text{ERCOT}})^2}_{\text{Substitution Effects}} \right\} \tag{2}$$
$$+ f_1(\text{load}_t) + f_2(\text{NGprice}_t) + \theta X_{zt} + \eta_z + \gamma_{\text{dow}} + \delta_{m \times y} + \epsilon_{zt}$$

The variable q_{zt} represents the (log-transformed) pollution level in ZCTA z on day t, including NO_2, $PM_{2.5}$, and ozone. $\text{WindGen}_{zt}^{\text{ZCTA}}$ refers to the wind generation in ZCTA z on day t, while $\text{WindGen}_{t}^{\text{ERCOT}}$ indicates the wind generation in ERCOT on day t, including a quadratic term. load_t represents the electricity demand in ERCOT on day t, and enters the regression as a flexible control function $f_1(\text{load}_t)$, including both linear and quadratic terms. Similarly, NG_t denotes the natural gas price and is controlled for using a flexible function $f_2(\text{NG}_t)$, which includes the linear, quadratic, and cubic terms. X_{zt} is a set of weather controls, including temperature, precipitation, wind speed, boundary layer height, relative humidity, and UV radiation. η_z represents ZCTA fixed effects, which account for unobserved factors that vary between ZCTAs but remain constant over time. γ_{dow} accounts for day-of-week fixed effects, capturing unobserved factors that vary by day of the week. $\delta_{m \times y}$ controls for month-by-year fixed effects, accounting for unobserved factors that vary over time but are constant across ZCTAs. ϵ_{zt} is the error term.

The parameters of interest in Equation 2 are β_1, β_2, and β_3. β_1 focuses on the dispersion effects: it examines how differences in wind generation levels across ZCTAs affect pollutant concentrations while keeping the total wind generation in ERCOT constant. In other words, β_1 tells us the marginal effect of a 1-unit change in local wind electricity generation on local air pollution, assuming all other factors remain unchanged. β_2 and β_3 address the substitution effects: they describe how changes in wind development in ERCOT (which may replace polluting power plants) influence local air pollution levels, while keeping local wind development constant. The marginal

effect of the substitution effect is given by

$$\beta_2 + 2 \times \beta_3 \times \text{MeanWindGen}_t^{\text{ERCOT}},$$

which quantifies the effect of a 1-unit change in ERCOT's wind generation on local air pollution concentration at the mean level of wind generation.

Another potential threat to identification is reverse causality. Areas with higher pollution levels may prioritize the development of clean energy and set higher capacity targets. However, this concern is somewhat mitigated because the siting of wind turbines is not arbitrary; turbines must be located in areas with high wind speeds. Furthermore, after accounting for ZCTA and time fixed effects, the placement of wind turbines is essentially random. Nevertheless, I could address this issue by restricting the sample to areas where pollution levels were relatively low prior to the installation of wind turbines. Alternatively, I might consider using an instrumental variable for the operation of wind turbines, such as the proximity to transmission lines.

There are also concerns that wind energy development in other grids could influence pollution levels around wind turbines in a different grid. As a result, controlling only for wind energy development within the same grid may not fully satisfy the SUTVA condition, primarily due to potential spillover across the electricity system. While some studies suggest that spillover are not a major concern, the development of other renewable energy sources may also pose a threat to the identification strategy. Although some studies suggest that such spillovers may be limited, the expansion of other renewable energy sources could also undermine the identification strategy. To mitigate this concern, I consider including controls for the development of other renewable energy sources within the same grid.

5 Results

I investigate the impact of wind turbine operations on ambient ozone concentrations, accounting for both dispersion and substitution effects. To distinguish between these, I use wind generation at the ZCTA level as a proxy for dispersion effects and wind generation at ERCOT level to capture substitution effects. This section presents the baseline results and offers insight into how these mechanisms influence ozone levels.

Table 2 summarizes the baseline results. Columns (1)–(3) report the estimates for ozone, NO_2, and $PM_{2.5}$, respectively. All specifications control for the full set of covariates and include

ZCTA fixed effects to account for time-invariant geographic characteristics, as well as day-of-week and month-by-year fixed effects to address unobserved temporal heterogeneity. Taking into account both dispersion and substitution effects, the estimates suggest negative effects on ozone and NO_2 concentrations, whereas the effect on $PM_{2.5}$ is positive.

Therefore, while the installation of wind turbines in a single ZCTA may lead to a slight local increase in ozone levels due to dispersion effects, the overall deployment of wind energy across the ERCOT region—with its significantly larger scale—results in a net reduction in ozone pollution. This highlights the importance of evaluating both local and regional effects when assessing the environmental impact of wind power.

Table 2: Baseline results

	(1) log(Ozone)	(2) $\log(\mathrm{NO}_2)$	(3) $\log(\mathrm{PM}_{2.5})$
$\text{WindGen}^{\text{ZCTA}}$	-0.001**	0.024***	0.019***
	(0.001)	(0.005)	(0.003)
$\text{WindGen}^{\text{ERCOT}}$	-0.000***	-0.002***	0.000***
	(0.000)	(0.000)	(0.000)
$(\text{WindGen}^{\text{ERCOT}})^2$	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Constant	2.576***	1.675***	-0.110***
	(0.018)	(0.030)	(0.024)
Mean $\text{WindGen}^{\text{ERCOT}}$	79.2087	79.2087	79.2087
Mean load	894.8876	894.8876	894.8876
Controls	Y	Y	Y
ZCTA FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Month-by-year FE	Y	Y	Y
Observations	6,208,400	6,208,400	6,208,400
R-squared	0.509	0.327	0.355
Number of ZCTA	1,700	1,700	1,700

Standard errors clustered at the ZCTA level are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Robustness Check

Because NO_2 and $PM_{2.5}$ concentrations are right-skewed, I apply the inverse hyperbolic sine (IHS) transformation to the dependent variables. The IHS transformation is defined as

$$\text{IHS}(x) = \ln\left(x + \sqrt{x^2 + 1}\right). \tag{3}$$

The IHS transformation has properties similar to the logarithmic transformation while remaining well-defined at zero. For sufficiently large values of x, it approximates a log transformation. Accordingly, the estimated coefficient of interest can be interpreted approximately as the percentage change in air pollution associated with a one GWh increase in wind generation.

Table 3 reports the regression results using the IHS-transformed pollution measures as dependent variables. Results ar epretty similar to baseline results.

7 Extension

Wind is the fundamental driver of wind turbine operation, as it enables turbines to spin and generate electricity. At the same time, wind also affects ambient air pollution through both dispersion and substitution mechanisms. When wind passes through a wind farm, turbulence and wake effects are generated, which may alter the local transmission of pollutants. Even in the absence of turbines, wind plays an important role in pollutant transport. Therefore, to properly evaluate the relationship between wind turbines and ambient air pollution, controlling only for wind speed is insufficient. It is also necessary to account for wind exposure at the ZCTA level. For example, even if a ZCTA hosts wind turbines, it may not be directly affected by turbine-induced pollutant dispersion if it is located upwind relative to the dominant wind direction. Conversely, downwind areas may experience stronger effects, including spillovers from turbines located in neighboring ZCTAs. To construct a measure of wind exposure, I first calculate the geographic centroid of each wind farm. Because turbines within the same wind farm are geographically clustered, I approximate each wind farm as a single generating unit. Next, by connecting the wind farm centroid and the ZCTA population centroid, I obtain the directional vector between them. Using daily wind direction data, I then determine the extent to which each ZCTA lies downwind of each wind farm. This allows me to assign a directional weight to each wind farm–ZCTA pair. Finally, I multiply wind generation at the wind farm level by these directional weights to construct a ZCTA-specific wind exposure

Table 3: Robustness check

	(1) ihs(Ozone)	(2) $ihs(\mathrm{NO}_2)$	(3) $ihs(\mathrm{PM}_{2.5})$
$\text{WindGen}^{\text{ZCTA}}$	-0.001*	0.023***	0.018***
	(0.001)	(0.004)	(0.003)
$\text{WindGen}^{\text{ERCOT}}$	-0.000***	-0.002***	0.000***
	(0.000)	(0.000)	(0.000)
$(\text{WindGen}^{\text{ERCOT}})^2$	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Constant	2.829***	2.359***	0.631***
	(0.016)	(0.029)	(0.024)
Mean $\text{WindGen}^{\text{ERCOT}}$	79.2087	79.2087	79.2087
Mean load	894.8876	894.8876	894.8876
Controls	Y	Y	Y
ZCTA FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Month-by-year FE	Y	Y	Y
Observations	6,208,400	6,208,400	6,208,400
R-squared	0.512	0.328	0.357
Number of ZCTA	1,700	1,700	1,700

Standard errors clustered at the ZCTA level are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

measure. This exposure variable captures both direct effects and potential spillover effects across ZCTAs. I am currently in the process of implementing this measure.

8 Conclusion

Renewable energy resources are increasingly recognized as a key solution to combat climate change and deteriorating air quality. This paper examines one of the fastest growing renewable sources, wind energy, and evaluates its impact on ambient air pollution, specifically ozone concentration. Wind turbine operations can influence air pollution through two distinct mechanisms: the dispersion effect and the substitution effect. The dispersion effect arises when wind turbines alter the local microclimate, thereby affecting the dispersion of pollutants in the surrounding area. In contrast, the substitution effect occurs as wind energy replaces fossil fuel-based power generation, leading to reduced emissions and less formation of air pollutants.

Using detailed wind turbine data combined with high-resolution grid-level pollution measurements, this study focuses on Texas and employs a two-way fixed effects model to separately identify the dispersion and substitution effects of wind energy. In this paper, I find evidence for both dispersion and substitution effects of wind power generation on ozone levels. On the one hand, local wind generation increases ozone concentrations due to weakened dispersion, with a marginal effect of 0.0661 ppb (or 0.1705% relative to the mean ozone level). On the other hand, regional wind generation reduces emissions by replacing polluting power plants, leading to a significant decrease in ozone levels, with a marginal effect of –0.0112 ppb per GWh (or a 0.0290% reduction).

While the marginal net effect implies a 0.1593% increase in ozone, the average effect—evaluated at mean generation levels—suggests a net reduction of approximately 0.884 ppb (or 2.28%). Therefore, although local wind installations may slightly raise ozone levels in surrounding areas, the overall expansion of wind power contributes to improved regional air quality.

These results provide a more nuanced understanding of the environmental consequences of wind energy development and offer valuable insights for policymakers and stakeholders interested in the air quality benefits of renewable energy expansion.

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