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The Impact of Wind Energy on Air Pollution and Emergency Department Visits

Harrison Fell[1] · Melinda Sandler Morrill[2,3]

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Abstract

Using daily variation in wind power generation in the western portion of Texas, we show that the resulting lower fossil fuel generation in the eastern portion of the state leads to air-quality improvements and, subsequently, to fewer emergency department (ED) visits. Spatially, the impact on pollution is widespread, but wind energy reduces ED admission rates more in zip codes closer to coal plants. Using intra-day wind generation and electricity pricing data, we find that more wind generation coming from hours when congestion on the electricity grid is less leads to higher reductions in emissions from east Texas power plants and PM2.5 concentrations and ED admission rates in east Texas. Comparing wind generation effects across low-demand night hours to higher-demand day hours, more NO_X and SO_2 is offset by wind from night hours, but the time-dependent effects for PM2.5 concentrations and ED admission rates is much weaker, potentially due to differences in exposure.

Keywords Renewable energy · Wind energy · Air pollution · Morbidity · Emergency department visits

1 Introduction

Renewable energy sources are an appealing alternative to fossil fuel-based power generation in terms of preserving natural resources, alleviating pollution, and, increasingly, providing a lower-cost generation source. In the last decade, renewable energy investment has risen drastically, resulting in an expansion of both wind and solar power generation. Despite this growth, wind and solar power still provided only 8.4 and 2.3 percent of

✉ Harrison Fell
hfell@ncsu.edu

Melinda Sandler Morrill
melindamorrill@ncsu.edu

1 Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, NC, USA

2 Department of Economics, North Carolina State University, Raleigh, NC, USA

3 NBER, Cambridge, MA, USA

electricity generated, respectively, in the United States in 2020.[1] In addition, renewable energy sources are non-dispatchable, relying on having adequate meteorological conditions to generate, and, thus, not necessarily operating in periods that provide the most societal benefits. Finally, renewable energy generators, particularly wind generators, have often been sited in locations far from demand centers. With limited transmission capacity, these siting locations may limit the ability of renewable generators to offset generation from fossil fuel plants that have traditionally been sited closer to demand centers. These features, and potentially others, may limit the ability of renewable energy to deliver detectable short term human health benefits. In this paper, we use hospital emergency department (ED) admission data to examine short-term health effects of wind energy in the relatively wind-rich state of Texas. Despite some of the logistic and technological barriers, we find wind energy already has displaced fossil generators in a sufficient way to detect small, but precise and robust, public health benefits.

The analysis builds empirical support for a mechanism chain as follows - increased wind generation lowers electricity-sector emissions, which in turn improves local air quality, and finally leads to lower ED admission rates. To do this we first, similar to other studies described below, show that wind energy in Texas does indeed reduce generation and emissions from both coal- and natural gas-fired generators. Subsequently, using daily measures of particulate matter concentrations we find increased wind energy leads to reductions in concentration of particulate matter of diameter 2.5 micrometers and smaller (PM2.5). Finally, using zip code specific ED admission rates, we find that increased wind energy is associated with small, but statistically significant and robust, decreases in ED admission rates among older (age 65+) residents. Specifically, a standard deviation increase in lagged wind generation lowers total ED admissions by about 0.6%. Furthermore, the magnitude of the effect is greater in zip codes near coal-fired power plants.

One concern about wind energy is that it is most plentiful in the night hours, often referred to as "off-peak" hours, when the demand for electricity is lowest. Energy storage has been discussed as a way to increase the market value of wind energy as it allows generators to move wind-generated electricity from the wind-rich, demand-poor night hours to wind-poor, demand-heavy daytime hours. While the market motivation for this intertemporal substitution are clear, the environmental and health impacts are less understood. We, thus, consider how the share of wind generation coming from off-peak hours affects the benefits of wind energy. Similarly, wind generation during periods when there is transmission congestion can lower the value of the emissions avoided as it tends to lead to more emission reductions in the less-populated western portion of the state (Fell et al. 2021). We, therefore, also assess the effect of wind generation under grid congestion on air quality and ED admission rates.

We find that the effect of wind generation on PM2.5 concentrations appear largely unaffected by the share of wind generation coming from either off-peak generation or during hours when there is likely transmission grid congestion. However, the effect of wind generation on ED admission rates for zip codes near coal plants appears to increase in magnitude (become more negative) when more wind generation comes during grid-uncongested hours and, to a lesser extent, during off-peak wind periods. These results are consistent with power-sector emissions responses to wind generation among plants in the eastern

[1] These values are based on the Energy Information Administration's electric power monthly reports (https://www.eia.gov/energyexplained/electricity). For 2019, the final year of our sample, percentages are similar.

portion of Texas. Additionally, for zip codes not near coal plants we find the effect of wind is smaller in magnitude and unaffected by wind generation timing or grid congestion issues. The results suggest reducing grid congestion can deliver greater human health benefits, though perhaps to a lesser extent if the grid congestion is reduced via intra-day re-allocation of wind generation from off-peak to peak hours as we would expect with greater battery storage.

Our analysis contributes to the literature in several ways. First, there have been many studies looking at the environmental value of renewable generation, however much of this work has looked at emission reductions associated with increased renewable generation (e.g., Cullen 2013; Fell and Kaffine 2018; Holladay and LaRiviere 2017; Novan 2015).

Given the location of wind farms and the timing of wind generation, it is not a given that these wind-generation-attributed reductions in emissions lead to detectable air quality and health effects, particularly in the short-run. There have been some more recent analyses that not just assess the emissions avoided, but also incorporate site-specific damages associated with these avoided emissions (see Fell et al. 2021; Sexton et al. 2018). However, the damage estimates used in these studies are based on average conditions and assumed dispersion rates (e.g., given average meteorological and atmospheric conditions a ton of SO_2 emission from county X results in Y dollars of damages). Again, given the variation in timing of emissions avoided by non-dispatchable renewable generation, the benefits of the associated emission reductions may be considerably different than the the value of avoided damages associated with average damage estimates. Our analysis contributes to our understanding of the value of emission reductions both in terms of where and when those reductions occur.

There has also been considerable research on health and cognitive effects of air pollution, both in long-term exposure (Chay and Greenstone 2003; Anderson 2020) and on short-term variation (Deryugina et al. 2019; Di et al. 2017; Schlenker and Walker 2016; Ebenstein et al. 2016; Herrnstadt et al. 2021). While these estimates are useful, they often are focused on the effects of a single pollutant. Identifying the effect of a single pollutant is notoriously difficult given the co-emissions of many pollutants. We instead focus on the effect of wind generation and remain agnostic as to the direct pollutant. In this respect, our estimates are more germane to the discussion of the benefits of renewable generation directly. In addition, wind generation varies considerably day-to-day and, as discussed below, is relatively concentrated in the west portion of Texas. Thus, we have considerable temporal variation in our variable of interest.[2] The spatial concentration allows us to isolate the impacts of that wind generation on distant regions that may be affected by wind generation through a connected electricity market, but are spatially distant from the generation and therefore have lower correlations between relevant local meteorological conditions (e.g., wind speeds) and wind generation levels.[3] Thus, we provide an identification

[2] Prior work has shown a meaningful link between coal and infant mortality both in early industrial economies (e.g., Beach and Hanlon 2018) and in modern times as alternative fuel sources displace coal (e.g., Cesur et al. 2017). Similarly, Lavaine and Neidell (2017) demonstrate a strong link between newborn health and pollution using variation in oil refinery production induced by strikes in France, while Luechinger (2014) finds similar estimates when leverages variation in pollution levels following mandated pollution reduction (scrubbers) at power plants in Germany. Our study leverages daily variation in coal production so is not able to capture health impacts of longer run exposure that might lead to worse infant health outcomes or higher infant mortality rates.

[3] One might be concerned that the choice of siting wind turbines is endogenous. Siting of wind generation assets in the U.S. has been influenced, to a large extent, by the federal production tax credit. This sizeable credit rewarded developers for siting wind farms in high wind speed regions, such as west Texas. We are

concept similar in spirit to that employed by Schlenker and Walker (2016). In that paper, the authors show how changes in taxiing times at airports affects ED admission rates for those that live near the airport. To do this they exploit changes in taxiing times at California airports that is due to airport congestion at three other, distant major airports (Chicago O'Hare, Atlanta Hartsfield-Jackson, New York John F. Kennedy). That is, similar to what is done here, they exploit how an activity from a relatively distant location can affect the emissions of local sources and therefore effect air quality and health outcomes.

Our paper is most similar in its research questions to that of Rivera et al. (2021). In that study, Rivera et al. (2021) explore the effect of solar power generation on daily hospital admissions in Chile. As such, their study differs in two key ways. First, by exploring the effects of solar generation, which has less day-to-day variation, their identification relies more on the long-term expansion of solar generation capacity and can thus be viewed more as a longer-run effect of an increase in zero-emissions generation on morbidity. By using wind generation, which has considerable day-to-day and intra-day variation, our estimates can be interpreted as the near-immediate effect of increased zero-emissions generation on ED admissions and, as such, is also not compromised by potential coincidental long-run changes to health care provision. Second, their study uses data from a region, Chile, that has considerably worse air quality and lower per capita incomes, on average, than our study region of Texas. This difference in setting could create differences based both from dose-response and access to health care angles.

The paper is organized as follows. The following section discusses relevant background information for our particular empirical context. Section 3 discusses the data used in this application. Our empirical methodology is introduced in Sect. 4 and results are give in Sects. 5, 6 and 7. Concluding remarks are given in Sect. 8.

2 Background

The geographic setting for our analysis is the market area managed by the Electricity Reliability Corporation of Texas (ERCOT). The ERCOT footprint covers most of the geographic area of Texas (see Fig. 1) and about 90% of the electricity consumption in the state. ERCOT manages the wholesale market for electricity, where, from a simplified standpoint, electricity generating units bid electricity sales into the market and so-called load serving entities buy the electricity, which they in turn sell to final consumers.

From a generating standpoint, Texas is by far the nation's leading state in terms of wind energy generation, with ERCOT's daily wind generation averaging about 18% of daily electricity demanded, often referred to as load. But, this renewable generation is not evenly distributed geographically across the state. As can be seen in Fig. 2a, the majority of the wind farms are in the west part of the ERCOT footprint and, indeed, wind generation in the West Zone makes up about 70% of the region's total wind generation (see Fig. 3). On the other hand, the larger fossil fuel generating units, particularly the coal generating units, are located in the more densely populated eastern regions of the state (see Fig. 2b). As such, the geographic distribution of wind generation, load, and fossil-fuel power plants is

Footnote 3 (continued)

leveraging this incentive in our identification strategy to some degree because this incentive created a siting pattern that resulted in most of wind generation being in the west portion of the state, reasonably far, and therefore meteorologically differentiated, from the population centers in the eastern part of the state.

a microcosm of that for the entire U.S., where wind generation is concentrated in the less-densely populated mid-continent region. Furthermore, the emissions from these fossil-generated plants in Texas is significant. In 2019, Texas had the most electricity-sector based emissions of sulfur dioxide (SO_2) and nitrogen oxide (NO_X) among the U.S. states and was 19th among U.S. states in terms of SO_2 emissions per megawatt-hour (MWh) of generation (https://www.eia.gov/electricity/state/Texas/).

We exploit this geographic distribution of generation to aid in the identification of the wind generation effects on hospitalization rates. Specifically, given that the wind generation is focused in the west portion of the state and the fossil generators are concentrated in the east, we examine effects of wind generation on eastern portion of Texas. This provides two benefits. First, by focusing on the east portion of the state we are examining the area most likely to benefit from the wind generation's displacement of fossil generation. Second, by looking at the eastern portion of the state, we are more able to distinguish between the effects of local meteorological conditions and wind generation than would be possible if one were to examine the effects of renewable generation occurring in approximately same geographic area as the measured health outcomes.

Note also that our point estimates cannot be generalized and applied directly to other regions as the estimate of wind generation effects will depend on locally-varying determinants such as other types of generators on the system, pollutant dispersion patterns, and population concentrations. However, as discussed in Fell et al. (2021), the general pattern of wind generation being concentrated in remote, low-population-density regions that is relatively far from electricity demand centers and its accompanying fossil-fuel generators that we see in Texas is a common development pattern we see in other parts of the world. We focus on Texas for two main reasons. One, it has readily available electricity sector data, as well as relatively accessible Emergency Department data. Second, ERCOT is essentially isolated from the other electricity grids in the U.S., limiting the need to address effects from electricity imports and exports.

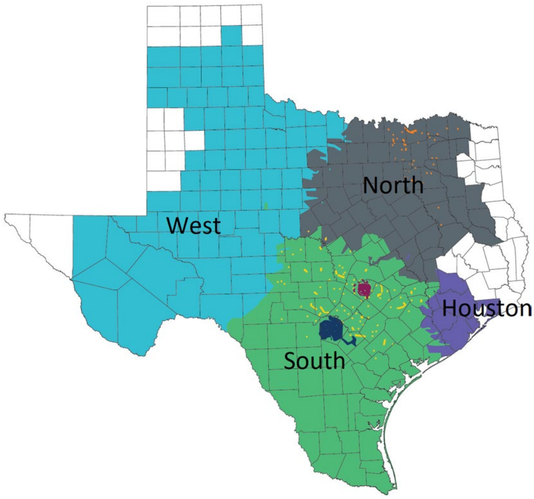
3 Data

For our analysis, we collect data across three primary categories: electricity generation, meteorological and air quality, and emergency department admission records. All primary variables used in this analysis are summarized in Table 1. The data are collapsed to ZIP Code Tabulation Areas (ZCTA's), which is the U.S. Census Bureau's approximation of zip codes.[4] The sample includes data for 669 ZCTAs over 1,459 days for a sample size of 976,071.

As noted above, much of the wind generation capacity and production is concentrated in the western regions of Texas. As such, one concern is that in these regions, there is a high degree of correlation between wind generation and wind speed (or other meteorological factor), and wind speed itself likely impacts pollution concentrations and ED admission

[4] The U.S. Census Bureau creates ZCTAs, but ZCTAs do not always perfectly correspond to zip codes, which is the given spatial identifier in the ED-RDF. We use the 2016 zip code-to-ZCTA crosswalk provided by UDS Mapper. For the populations of the ZCTAs, we use the Census Bureau's American Community Survey (ACS) Demographic and Housing Estimates five-year average from 2016. We restrict to zip codes that are within the State of Texas, have a population of at least 10,000, and have at least 20 people over the age of 65 in the ACS.

Fig. 1 ERCOT geographic footprint. Notes: The labeled regions West, North, South, and Houston make up the ERCOT geographic footprint and designate the four primary load zones of ERCOT (source: ERCOT, http://www.ercot.com/news/mediakit/maps)



rates directly. Indeed, ZCTA-specific wind speeds for ZCTAs in the"West" load zone have a correlation coefficient with ERCOT wind generation of 0.51, while for ZCTAs located in other zones correlation coefficient is only 0.38. If we consider further east zip codes, correlation between wind generation and ZCTA-specific wind speeds continues decline. For example, ZCTA's with longitudes greater than −97, −96, and −95 degrees have correlations between ZCTA-specific windspeeds and ERCOT wind generation of 0.36, 0.29, and 0.26, respectively. However, the response of ED admission rates and PM2.5 concentrations to wind generation for these subsamples are quantitatively similar to the results presented below. Furthermore, as can be seen in Appendix Fig. 8, there are other general meteorological differences across the state that we can exploit. Thus, to better identify the effect of wind generation separately from the effect of wind speeds or other meteorological variables, we consider only those ZCTAs in the non-West zones of ERCOT in our base specifications (see Fig. 1). We also drop those ZCTAs in the far south part of the state (below 27° latitude) as there is some wind generation capacity in that area (see Fig. 2). A map of the ZCTAs remaining after these restrictions are imposed is given in Fig. 4.[5]

The health outcome variable of interest is hospital emergency department (ED) admission rates. These rates are derived from hospital discharge data made available to us by the Texas Department of State Health Services through their Texas Hospital Emergency Department Research Data File (ED-RDF).[6] The ED-RDF contain data from the Inpatient and Outpatient RDF on inpatients admitted through the ED and outpatients receiving services in the ED. The ED-RDF provides individual ED admissions details, including date of admissions, zip code of the admitted patient, patient's age, inpatient or outpatient status,

[5] Additionally, we consider a specification where we remove extreme windspeed and precipitation days given there may be a concern that extreme weather events are correlated with health outcomes and more correlated with wind generation. These results are presented in Table 7 and yield responses similar to our primary results shown below.

[6] Details on the Texas Health Care Information Collection (THCIC) can be found at: https://www.dshs.texas.gov/thcic/.

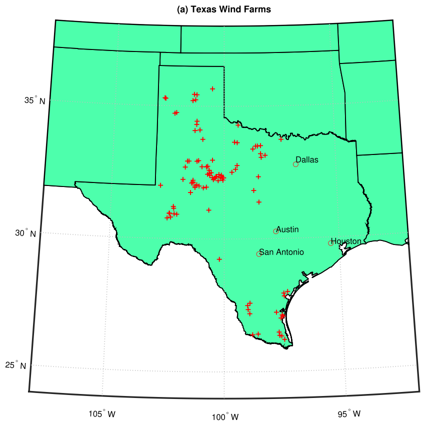


Fig. 2 Texas Wind Farms and Coal Plants in 2016. Notes: Panel **a** plots the location of the wind farms in Texas as of the end of 2016 and panel **b** plots the plant locations of facilities with coal-fired generation (source: Energy Information Agency Form 860)

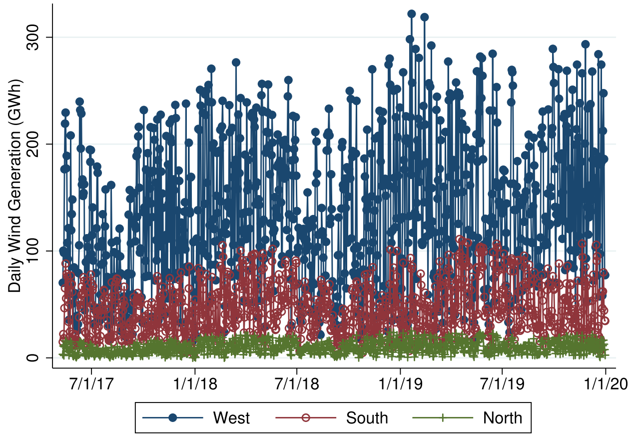


Fig. 3 ERCOT Zonal Wind Generation. Notes: The plots are of daily sum of hourly wind generation by ERCOT Load Zones shown in Fig. 1 as provided by ERCOT (http://www.ercot.com/gridinfo/generation)

and, importantly, primary diagnosis code.[7] To form an admissions rate, we sum the admissions by ZCTA and divide by the ZCTAs population.

Table 1 presents Emergency Department admissions rates per 1 million persons aged 65 and older, our main dependent variable of interest. Means are also presented without the age restriction and then by diagnosis type. Air pollution has been associated with a wide variety of adverse health and cognitive outcomes.[8] Following Jha and Muller (2018) and

[7] We restrict the sample to outpatient records with length of stays between 0 and 2 days, inclusive, and inpatient stays greater than 0 days and fewer than 14 days. We further restrict to admissions from the emergency department, urgent care, and trauma center.

[8] For example, using atmospheric temperature inversions as a source of exogenous variation in air pollution, Sager (2019) finds a small and statistically significant increase in vehicle accidents due to increased PM2.5 levels. Similarly, Herrnstadt et al. (2021) establishes a link between air pollution and criminal activ-

Table 1 Summary statistics

Variable	Obs	Mean	Std. Dev	Min	Max
	ED Admission rates (per 1 m population)				
ED Visits Age≥ 65	976071	1471	927	0	16000
ED Visits, All Ages	976071	994	560	0	9671
Resp & Circ. Age≥ 65	976071	407	437	0	8621
Injury Age≥ 65	976071	254	331	0	6000
Inf & Neo. Age≥ 65	976071	85	187	0	5236
	Air quality and emissions variables				
PM2.5	487701	16	10	1.09	248.1
NO_X (lbs)	1461	429507	119413	171390	757344
SO_2 (lbs)	1461	983318	352704	314294	1899947
	Meteorological variables				
N/S Wind (m/s)	976071	0.983	2.772	−11.302	10.584
E/W Wind (m/s)	976071	−0.531	1.499	−9.714	11.061
Wind Speed (m/s)	976071	2.990	1.497	0.003	11.728
Precipitation (m)	976071	0.0001	0.0004	0	0.01
Relative Humidity	976071	14.34	0.169	13.37	14.65
Boundary Layer (m)	976071	596	246	61	1674
Wet Bulb Temp (K)	976071	352	12	305	371
	Load and generation variables (in GWh)				
Coast Zone	1461	289	50	206	408
East Zone	1461	35	6	23	55
Far West Zone	1461	65	13	45	95
North Zone	1461	20	3	15	29
North Cent. Zone	1461	322	66	214	499
South Zone	1461	84	15	57	135
South Cent. Zone	1461	161	32	113	239
West Zone	1461	29	4	21	44
ERCOT-Wide	1461	1005	176	716	1449
Wind Gen	1461	179	83	26	430
Coal Gen	1461	265	74	71	420
Gas Turbine Gen	1461	61	43	8	226
Gas Comb. Cycle Gen	1461	378	117	95	650

Zonal load variables correspond to the ERCOT-defined weather zones and "ERCOT-Wide" is the total load across ERCOT. "Gas Turbine Gen" and "Gas Comb. Cycle Gen" refer to natural gas fired generation from single cycle and combined cycle generators, respectively. "N/S" and "E/W" refer to North/South and East/West, respectively, such that North and East winds are positive value and South and West winds are negative. "Precipitation" is given as day t's hourly average precipitation. "Boundary Layer" is the distance from the Earth's surface to the capping inversion. The "Wet Bulb Temp" is derived from the temperature and relative humidity variables sourced from ERA5 model. Age-group specific ED admission rates are based on that age group's population. Disease-specific groupings refer to primary diagnosis for respiratory and circulatory disease, injuries and poisonings, and infectious disease and neoplasms, respectively

Footnote 8 (continued)
ity. Bishop et al. (2022) use variation in PM2.5 exposure due to implementation of the Clean Air Act and find a significant impact of PM2.5 on dementia rates.

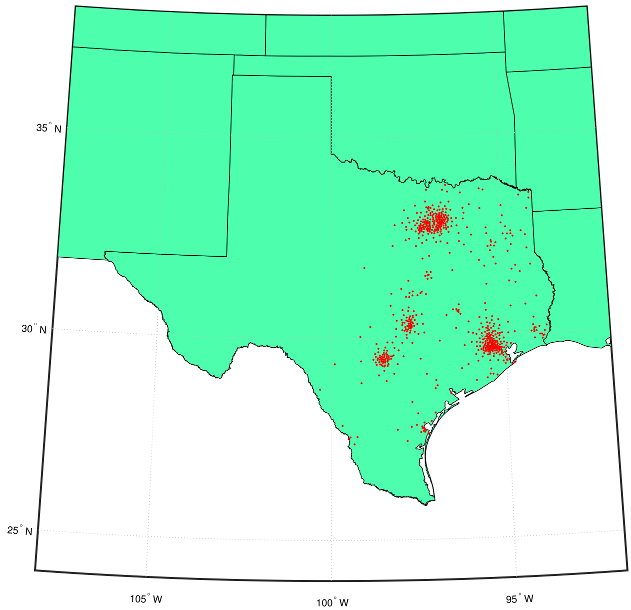


Fig. 4 Included ZCTA's. Notes: Each dot represents the centroid of a ZCTA included in the sample of the main specifications

Schlenker and Walker (2016), we define conditions that are more or less likely to be related to pollution. We use the HCUP Clinical Classifications Software to group ICD-10-CM primary diagnosis codes.[9] For the population under study, those ages 65 and older, relevant conditions include respiratory and circulatory diseases (i.e., CIR and RSP in the HCUP classification) and "injury, poisoning, and certain other consequences of external causes" (INJ). In contrast, we group together two sets of conditions that are much less likely to be related to air-quality: neoplasms (NEO) and infectious and parasitic diseases (INF).

For a measure of air quality, we use gridded PM2.5 predictions from NASA's Goddard Earth Observing System composition forecast (GEOS-CF) system. This system combines NASA satellite-based aerosol measurements with an atmospheric chemistry model (GEOS-Chem) to make hindcast predictions of PM2.5 concentrations on a $0.25° \times 0.25°$ latitude/longitude grid (Keller et al. 2021). The data is available from 2018 onward. From this data we derive ZCTA-specific, daily PM2.5 measures by using a bilinear interpolation referenced to the latitude and longitude of the ZCTAs centroid and the latitude/longitude of the gridded PM2.5 data. Note that PM2.5 is not a perfect, nor complete, measure of air quality, but rather we use it as measure indicative of improvements of air quality.[10]

[9] Clinical Classifications Software Refined (CCSR)for ICD-10-CM Diagnoses. Healthcare Cost and Utilization Project (HCUP). February 2022. Agency for Healthcare Research and Quality, Rockville, MD. www.hcup-us.ahrq.gov/toolssoftware/ccsr/dxccsr.jsp, [accessed November 2022].

[10] We also explored the use of EPA's Air Quality Index (AQI) data, which is based on monitor readings and provides an index value for the general air quality, based on reading over several pollutants including PM2.5, ozone, NOX, and SO2. However, this data is not as spatially resolute, providing data at only the county or major metropolitan area level, and has some missing data as monitors fail to report some days. That written, the AQI based results are generally directionally consistent with the results presented below for the satellite-derived PM2.5 data.

The meteorological data comes from the European Centre for Medium-Range Weather Forecasts' ERA5 climate reanalysis model. The ERA5 climate reanalysis provides data on various meteorological variables by combining forecast models with weather station observations. The data is produced at a $0.25^\circ \times 0.25^\circ$ (roughly 30 km × 30 km) spatial resolution at the sub-daily temporal level over our analysis period of 2016-2019. Using this data, we form daily averages and assign values to each ZCTA using a bilinear interpolation referenced to the latitude and longitude of the ZCTAs centroid. The meteorological variables collected include precipitation, boundary layer height, temperature, relative humidity, dew temperature, and u (east/west) and v (north/south) wind speeds. From these variables, we also form wet bulb temperature and wind speed values.

With respect to electricity generation data, we collect hourly wind generation, along with hourly generation from coal-fired, natural gas combined cycle, and natural gas simple cycle sources, for ERCOT over the years 2016–2019 based on ERCOT's publicly available data on its historic generation fuel mix.[11] We then aggregated this data to get daily measures of generation by sources, as well as measures of wind generation over peak-demand hours (hours beginning 8–19) and offpeak-demand hours (hours beginning 0–7 and 20–23). ERCOT also publishes hourly data on total load and load by weather zone which we use as additional controls.[12] We have data for the 1,461 days from January 2016–December 2019 at the ERCOT-wide level.

We also collect data on generation and emissions from individual fossil-fueled generating units in ERCOT through the Environmental Protection Agency's Air Markets Program Database (EPA-AMPD). The EPA-AMPD data gives hourly generation from all fossil-fuel plants with capacity's of at least 25 MW. The data also contains hourly emissions from these sources for SO_2 and NO_X, both of which are precursors to PM2.5 and other pollutants harmful to human health, as well as CO_2.[13] With this facility-level data we are able to calculate the vast majority of the hourly and daily emissions from electricity generators in the ERCOT area. The facility level data also allows us to estimate heterogeneous treatment effects of wind generation based on the ZCTA's proximity to fossil fuel generation.

4 Methodology

The aim of this research is to estimate the effect of wind generation on ED admission rates and to build a mechanism chain for this result through the effects of wind generation on fossil-fuel generation and on measures of PM2.5 concentrations. We begin with these latter two estimations.

As noted above, several studies have demonstrated the effect of wind generation on fossil-fuel generators and emissions from these generators. We estimate similar models to ensure that these previously-estimated relationships between fossil-fuel generation/

[11] The downloadable "Fuel Mix Report: 2007–2019" data is given as the 15-min generation by source across the ERCOT grid. We aggregated this 15-min data to the hourly level. (See http://www.ercot.com/gridinfo/generation).

[12] ERCOT is divided into eight weather zones: North, North Central, Far West, West, South Central, South, East, and Coast. A map of the zones can be found at http://www.ercot.com/news/mediakit/maps.

[13] We pair the EPA-AMPD data with the Energy Information Agency's Form 860 (EIA-860) data (https://www.eia.gov/electricity/data/eia860/) to determine which generating units participate in the ERCOT market, as designated by the assigned "Balancing Authority Area" listed in the EIA-860 data.

emissions and wind generation continue to hold over our sample period. Specifically, we estimate the following:

$$y_t = \beta Wind_t + \mathbf{X}_t^{'}\boldsymbol{\theta} + \boldsymbol{\gamma}_t + \epsilon_t \tag{1}$$

where y_t is either the aggregate fossil-fuel generation from a type of generator class (e.g., coal, natural-gas single gas turbine, natural-gas combined cycle) or aggregate emissions (SO_2 or NO_X) for ERCOT in time period t, $Wind_t$ is ERCOT wind generation, $\mathbf{X}_t$ is a vector of control variables including measures of load and natural gas prices, $\boldsymbol{\gamma}_t$ is a vector of time fixed effects (month-by-year and day-of-week fixed effects).[14] We estimate model at the daily level and quadratic specifications of $Wind_t$ and interaction terms including measures of intra-day wind generation timing.

Changes in emissions from fossil-fuel generators due to wind generation may or may not lead to detectable changes in ambient air quality due to dispersion patterns. We, therefore, next consider the effect of wind generation on ambient air quality, as represented by the above-described PM2.5 measure. We estimate variants of the following:

$$y_{it} = \beta Wind_{t-1} + \mathbf{X}_{it}^{'}\boldsymbol{\theta} + \boldsymbol{\gamma}_{it} + \alpha_i + \epsilon_{it} \tag{2}$$

where y_{it} is a measure of PM2.5 concentration in ZCTA i on day t. Because pollutants may take several days before deposition, we include lagged wind generation ($Wind_{t-1}$) as a control, though we explore other wind-generation specifications. $\mathbf{X}_{it}$ is a set of controls, inclusive of contemporaneous and lagged local meteorological variables and weather-zone measures of load, and α_i is a zip code fixed effect. The remaining terms in (2) are the same as in (1). We similarly explore interaction terms with $Wind_{t-1}$ as with (1) and additionally include interaction terms with coal-fired-generation-proximity indicator variables.[15]

Note that the likelihood of nonlinear effects of many of the meteorological effects, along with locationally-specific effects of wind direction and wind speed variables, means there is a possibility of many control variables and a concern of over-fitting.[16] We therefore also estimate (2) using the post double selection LASSO (PDS-LASSO) proposed by Belloni et al. (2014) and Belloni et al. (2016). The PDS-LASSO works essentially by selecting variables in $\mathbf{X}$ via a LASSO estimator that predict the dependent variable of interest, y_{it},

[14] For natural gas prices, we use daily Henry Hub prices as reported by the Energy Information Agency (https://www.eia.gov/dnav/ng/hist/rngwhhdD.htm).

[15] One may also consider specifications where the effect of wind generation depends not only on being near a coal plant, but also downwind from the plant as was done in Rivera et al. (2021). However, the particular geography and climate of Texas, coupled with the dispersion of power plants and population centers in East Texas, makes differentiated downwind effects less pronounced in this setting. Indeed, Luo et al. (2021) model pollution dispersion from fossil-fuel power plants in Texas over several historical dates and do not observe obvious patterns of PM2.5 concentration increases indicative of clearly visible downwind effect. Similarly, in our estimation of the effect of wind generation on PM2.5 concentrations or ED admission rates, we find no evidence of a differentiated effect being in a ZCTA that is both near a coal plant and downwind from the coal plant on a given day compared to simply being near a coal plant.

[16] In our complete universe of controls, we consider controls that include contemporaneous and lagged ZCTA-level precipitation, boundary layer height, relative humidity, wet-bulb temperature, windspeed, and weather-zone-specific load. These variables are considered in levels, squared and cubed. We also allow for location-specific wind direction effects by interacting 3-digit-ZCTA-identifiers with north/south and east/west wind speeds (contemporaneous and lagged). That is, we allow the effect of north/south and east/west wind speed measures to vary by ZCTA's that share common first three digits and are, therefore, geographically close to one another.

and then running a second LASSO estimator to select the variables in $\mathbf{X}$ that predict the exogenous variable of interest, $Wind_{t-1}$. The final estimation uses the variables in $\mathbf{X}$ that are selected in either of the first two LASSO estimator steps by a more standard fixed-effects estimation.[17]

The final estimation procedure of considering the effect of wind generation on ED admission rates is carried out in much the same way as the air quality estimation steps. Here, we replace y_{it} in (2) with ED visits.[18] The controls in $\mathbf{X}_{it}$ are the same as those used in the air quality estimation. Again, we employ the PDS-LASSO estimation procedure, but also consider a standard fixed-effects estimation with a paired down choice of control variables (see Table 6).

Finally, though wind generation has been used as an exogenous variable in several studies as it is largely driven by wind speeds, one may be concerned about some choice aspects of wind generation that may lead to an endogeneity issue.[19] To account for this, we instrument for wind generation with a capacity-weighted average of wind speeds at wind generating facilities in the West zone of ERCOT. The results of this estimation are given in Table 8 and are qualitatively and quantitatively similar to the non-IV approaches. Note that, because of power limitations, we cannot estimate the IV model with standard errors clustered by week (as is done in the main estimation). Therefore, we proceed with the non-IV approaches for our primary analysis.

5 Results

The effect of wind on fossil fuel generation by type and emissions from the electricity sector, as estimated via Eq. (1), are given in Table 2. As can be seen by summing the coefficients on wind generation across the “Coal”, “NGCC” (natural-gas combined cycle), and “NGGT” (natural-gas single gas turbine) dependent variable specifications, an extra GWh of wind offsets almost exclusively one of these three fossil-fuel generation types. Additionally, while wind generation primarily offsets relatively low-emitting NGCC, wind generation still reduces significant amounts of SO_2 and NO_X.[20]

The next step is to verify if this wind-generation-induced reduction in fossil-fuel generation and associated emissions results in improved air quality, as measured by PM2.5

[17] In our estimation, we leave the time and cross-sectional fixed effects unpenalized by the LASSO estimators such that they are always included in the final estimation step. Note also that this method leads to computable standard errors for the exogenous variable of interest, $Wind_{t-1}$ and $Wind_{t-1}$ interaction terms in our case. Additionally, we considered specifications with a fixed set of independent variables. Results from these regressions are given Table 6 in the Appendix and produce effects from wind generation similar to those from the LASSO procedure.

[18] Note that in using daily ED admission rates, even after trimming the sample to exclude small towns, there are still a high number of “0” observations depending on which ED admission rate variation is used. Given this, we employ Poisson estimators, with ED admission count data as dependent variables, for the various different specifications we explore in this analysis (see Appendix Table 10). The Poisson estimators generally yield parameter estimates in the same direction as the PDS-LASSO estimates with ED admission rates and the implied scale of the marginal effects relative to the mean ED admission counts is near that for the results based on ED admission rates.

[19] Curtailment of wind generation is one aspect where the wind generation is actively controlled by the generator or system operators. However, in our sample period, curtailed wind production is quite low, averaging around two percent of total wind generation (U.S. Energy Information Agency (2023)).

[20] We estimated a similar functional form to (1) using hourly data. The parameters on wind generation are numerically similar to those given in Table 2.

concentrations, and lowered ED Admission rates in the eastern portion of Texas. Results of this analysis are presented in Panel A for PM2.5 concentrations and Panel B for all-causes ED admission rates for the age ≥ 65 group of Table 3.[21] For each panel, we consider three basic specifications. Column (1) results consider a specification with lagged wind generation (Wind_{t-1} alone as the covariate of interest). Column (2) results allow for the effect to be different for those near major-emitting coal-fired generation sources by interacting lagged wind generation with an indicator variable equal to one if the given ZCTA's centroid is within 30 miles of a coal-fired generator ($\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$). For column (3) results, we further refine this possibility for a heterogeneous effect by including an interaction between lagged wind generation and an indicator equal to one if the given ZCTA's centroid is within 30 miles of a coal-fired generator that has positive generation on day $t-1$, thereby allowing generators a margin to respond to the wind generation.[22] All results use the PDS-LASSO procedure to select the control variables other than lagged wind generation, its interaction with the near-coal capacity and near-coal generation dummy variables, and year-by-month and day-of-week fixed effects.

Considering the results from Column (1) of Panels A and B in Table 3, we find lagged wind generation in ERCOT has a negative and statistically significant effect on both PM2.5 concentrations and ED admission rates among the age ≥ 65 group for East-Texas ZCTA's. These parameters are such that a one standard deviation increase in the lagged daily wind generation reduces day t PM2.5 concentrations by an average of about 10% of the mean and ED admission rates by about 0.5% across the East-Texas.

The column (2) results from Table 3 indicate that ZCTA's near coal plants PM2.5 concentrations reduce slightly more than those not near coal plants in response to lagged wind generation, but the differential is small and statistically insignificant. On the other hand, the column (2) results indicate that ED admission rates response to wind generation is considerably larger in magnitude for ZCTA's near coal-generating capacity.[23] The parameters from column 2 of Panel B imply that a one standard deviation increase in wind generation reduces ED admission rates for the age ≥ 65 group within 30 miles of a coal-fired generator by about 0.9% of the daily mean of those ZCTA's. Similarly, for the column (3) results of Table 3, we find slightly larger magnitudes of response for PM2.5 concentrations to lagged wind generation among ZCTA's near coal-fired plants that are generating, but the

[21] We consider the age ≥ 65 group for our base specification as this population has been shown to be relatively more affected by air quality issue (Deryugina et al. (2019)). We also consider dependent variable specifications based ED admission rates with no age restrictions and for patients with age ≤ 5. Results from these groupings are given in Table 9.

[22] A concern with using this specification is that a coal plant may turn production to zero in response to higher wind generation and thus we would be understating the effect of wind generation. However, in our data, over 95% of the days in which coal generators have zero generation occurs in the midst of at least a five-day window in which the generation has no daily generation. This is likely due to the long start-up times and relatively high start-up costs for coal plants. Given the propensity to shut down for extended periods, considering a near-coal indicator that is one only on days when the nearby coal plant has positive generation may better highlight the role of wind generation at limiting coal-fired emissions.

[23] We also consider specifications where we interact lagged wind generation with a continuous measure of a ZCTA's distance to the nearest coal plant and that distance squared. These results indicate, for ED admission rates, a nonlinear coal-plant-distance interaction effect where the magnitude of the effect of lagged wind on ED admissions is increasing up to about 30 miles from the nearest coal plant and then begins to attenuate. Effect sizes wind generation for within 30 miles of a coal plant are in line with the column (2) and (3) results of Panel B in Table 3. For PM2.5 concentrations, this continuous-distance-interaction model showed little change in the effect of wind on concentrations at various distance-to-coal-plant values. For these reasons, we elected to present the easier-to-interpret binary "near coal" specifications.

differential is again small and not statistically significant, whereas the the effect of lagged generation on ED admission rates appears to be concentrated in ZCTA's near currently-generating coal-fired plants. This finding is as expected given the majority of observations from ZCTA's near coal generators are near facilities that have positive generation (276,450 observations are from ZCTA's within 30 miles of a coal-fired generator and, of those, 257,090 are near coal generators with positive generation on day $t-1$).

The disparity between the near-coal effects of lagged wind generation on PM2.5 concentrations and ED admission rates could be reconciled for several possible reasons. First, PM2.5 concentrations are based on modeled predictions based off of satellite-derived aerosol readings and then further bilinearly interpolated to get a ZCTA-specific measure. This process obviously creates various levels of imprecision that may limit our ability to find highly region-specific effects. Second, there are other pollutants emitted from coal-fired power plants that may also affect health outcomes, but disperse less uniformly than PM2.5 may. Additionally, long-run exposure to pollutants of individuals near coal plants may be different than those further away which may drive different health outcome responses to changes in pollution concentrations.

6 Lead/Lag Structure and Diagnosis Codes

Next, we consider additional specifications to explore the robustness of the results and relevant policy angles for renewable energy. To begin, our primary results presented above are based on lagged daily wind generation and other contemporaneous and lagged controls to account for the multi-day pollutant deposition process. In Table 4, we explore the sensitivity of lag length by including current and 2-day lags (t and $t-2$) and leads ($t+1$ and $t+2$) wind generation controls.[24]

The first column of Table 4 shows estimates from a regression PM2.5, while in the second column the dependent variable is ED admissions rates for the age ≥ 65 group. The summations of the lead and lag coefficients are presented at the bottom of the table. The row labeled "Sum of Near Coal Lags $\{t, t-1, t-2\}$" shows the joint estimate for the six lagged coefficients. These sums are negative and statistically significant, although the largest point estimate is for the one-day lag. Below that, the row labeled "Sum of Near Coal Leads $\{t+1, t+2\}$" presents the joint effect of the four lead coefficients. Although the individual point estimate on the day $t+2$ lead interacted with near coal is negative and statistically significant, the estimated coefficient on the not-near coal $t+2$ lead is positive and statistically significant. Thus, the joint effect of the four lead coefficients is small and not statistically significant. The estimated effect of the two-day lagged wind generation is larger in magnitude and numerically similar to that of just the one-day lagged wind generation presented in Table 3. These results support the use of a one-day lagged wind generation as the key explanatory variable of interest. Given this, we proceed with models focused on the effect of 1-period lagged wind generation alone.[25]

[24] Using variation in pollution levels in China, Xia et al. (2022) show that exposure to pollution over consecutive days can lead to even higher morbidity impacts.

[25] We also considered specifications with up to seven leads and lags of wind generation. With these specifications we continue to find that only the joint effect on lagged wind generation has statistically and economically significant impacts day t PM2.5 concentrations and ED admission rates. Furthermore, with the seven day lead and lag specification, none of the individual parameters on the forward looking wind generation ($t+1, t+2, \ldots$) variables are statistically significant for both the PM2.5 and ED admission rate regressions.

As noted above, we have information on the patients' diagnosis codes, which allows us to consider effects on specific conditions that may be more or less related to contemporaneous air-quality. As described in Sect. 3, we consider broad groupings of diagnosis codes when forming the ED admission rates. The dependent variables for the columns of Table 5 are the ED admission rates for (1) respiratory and circulatory diseases, (2) injuries and poisonings, and (3) neoplasms (cancer) and infectious and parasitic diseases. These results are all based on specifications that interact the lagged wind generation with the indicator for the given ZCTA being near (within 30 miles) of a coal generator. The row labeled "Near Coal Eff." gives the summed coefficients of the lagged wind and lagged wind interacted with the near-coal indicator, with standard errors below. As described in Sect. 3, we anticipate the largest impact on respiratory and circulatory conditions, but prior work has found a causal link from air pollution to a broader range of health outcomes including cognitive performance and accidents. Thus, neoplasms and infectious and parasitic diseases provide the most defensible falsification test.

In Table 5, we find negative and statistically significant effect of lagged wind generation on admissions related to respiratory and circulatory diagnosis codes, as well as for those indicating some bodily injury, for ZCTA's near coal plants. These parameters imply that a standard deviation increase in wind generation lowers both respiratory and circulatory admission rates and bodily-injury admission rates for the age ≥ 65 group from ZCTA's near coal plants by about 1.1% of their respective means. On the other hand, admissions given diagnosis codes related to infections and neoplasms (cancer), have small, both in absolute magnitude and relative to its mean, and statistically insignificant responses to wind generation. This is as expected given ailments associated with these diagnosis codes are likely unaffected by air quality conditions.

We also consider the wind-generation effects on ED admissions classified as out-patient and in-patient admissions, where admissions classified as "out-patient" are those where the patient is released without an overnight stay and in-patient admissions require longer hospital stays and, thus, may be more likely related to some chronic condition. In Table 5, we find lagged wind generation has a larger (in magnitude) and more statistically significant effect on out-patient admissions than in-patient admissions. However, the proportional effects relative to the mean of the IP or OP admission rate are similar across admission types, thus for subsequent analyses we continue to consider admission rates based on the pooled IP and OP admissions.

7 Wind Generation Timing

The intermittent nature of wind generation means system operators do not choose, for the most part, when to dispatch generation from wind farms. This non-dispatchability has several consequences related to the potential hospital visits avoided by more wind generation. First, given that demand for electricity varies throughout the day and that generators have heterogeneous marginal costs across generation technologies, which generators are marginal potentially varies throughout the day. Similarly, the level of wind generation can alter which generators are marginal, as the level of wind generation determines how much the positive marginal cost portion of the supply curve is shifted in or out. Also, because emissions vary by fossil-fuel generator types, there is variation in the amount and type of emissions offset by increased wind generation throughout the day and at different levels of wind generation (see Cullen 2013; Novan 2015). At the same time, Fell et al. (2021) have

Table 2 Generation and emission effects

	Coal	NGCC	NGGT	SO_2	NO_x
Wind	−0.22***	−0.64***	−0.14***	−743.1***	−458.5***
	(0.010)	(0.009)	(0.009)	(47.0)	(13.5)
Obs	1,461	1,461	1,461	1,461	1,461
R^2	0.94	0.98	0.89	0.92	0.95

The data are given at the daily level from 2016-2019. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. "Coal", "NGCC", and "NGGT" refer to dependent variables of ERCOT-wide generation (in GWh's) from coal units, natural gas combined cycle units, and natural gas single-cycle turbines, respectively. "SO_2" and "NO_x" refer to ERCOT-wide electricity-sector emissions of sulfur dioxide (in lbs) and nitrogen oxides (in lbs), respectively. "Wind" refers to ERCOT-wide wind generation in GWh's. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. All specifications include year-by-month and day-of-week fixed effects, load by weather zone, and Henry Hub natural gas prices as additional controls

shown that wind generation in ERCOT coming during periods of grid congestion reduces the amount of emissions offset from generation sources in the more densely populated eastern portion of the state. Thus, the extent to which wind generation is anticipated to reduce ED hospital visits might vary by time of day, level of production, and amount of grid congestion.

Exploring wind generation timing effects is of interest because with growing energy storage capabilities, market arbitragers will be able to effectively temporally move wind generation from low-demand/low-price periods to high-demand/high-price periods. The effect of such a move on health outcomes remains an open question.

To explore these issues, we estimate various specifications of wind generation timing and level effects on emissions from east Texas generating facilities, PM2.5 concentrations, and ED admission rates. More specifically, we look consider variations of (1) and (2) to allow for quadratic wind generation controls. We also explore specifications interacting linear and quadratic wind generation controls with the share of daily wind generation coming during low-demand (off-peak) hours and the share of daily wind generation coming during hours when the transmission grid appears uncongested.[26] For specifications using ZCTA-specific PM2.5 concentrations and ED admission rates, we also explore the varying marginal responses to wind generation separately for ZCTA's near coal-fired plants (e.g., within 30 miles) and those not near coal plants.

Figure 5 plots the marginal responses of emissions from ERCOT electricity generation facilities in east Texas (i.e. those not in the West Load Zone) for pollutants SO_2 and NO_x.

[26] For off-peak share calculations we sum wind generation from day $t-1$ coming in hours beginning 0–7 and 20–23 and divide that off peak wind generation by day $t-1$'s total wind generation. One concern with this approach may be that wind generation from $t-1$'s hours 20–23 have a different effect on day t's PM2.5 and ED rates due to it temporal proximity than $t-1$'s generation from hours 0–7. Accordingly, we also consider a lagged wind and lagged off-peak wind share that runs from hour 20 of day $t-2$ through hour 19 of day $t-1$. In this setting, off-peak lagged wind generation is the continuous set of hours from hour 20 of $t-2$ to hour 7 of $t-1$. Results from this specification are not materially different from those presented below.

Table 3 Air quality and ED admission rate effects

	Panel A: PM 2.5		
	(1)	(2)	(3)
Wind_{t-1}	−0.0181***	−0.0175***	−0.0177***
	(0.00340)	(0.00345)	(0.00348)
$\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$		−0.00148	−0.00182
		(0.00163)	(0.00226)
$\text{Wind}_{t-1} * 1(\text{Coal Gen} \leq 30)$			0.000613
			(0.00205)
Observations	487,701	487,701	487,701
	Panel B: ED Admiss. Rate		
	(1)	(2)	(3)
Wind_{t-1}	−0.0929**	−0.0536	−0.0541
	(0.0404)	(0.0416)	(0.0415)
$\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$		−0.111***	0.0231
		(0.0367)	(0.0528)
$\text{Wind}_{t-1} * 1(\text{Coal Gen} \leq 30)$			−0.147***
			(0.0426)
Observations	976,071	976,071	976,071

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. All specifications include ZCTA, year-by-month, and day-of-week fixed effects. “PM2.5” is a measure of daily average PM2.5 concentrations. “ED Admiss. Rate” are the daily ED admission rates per million residents by ZCTA for patients aged 65 or older. Other controls, selected by the post-double selection LASSO method, are excluded as the standard errors cannot be calculated directly. The possible other controls include contemporaneous and $t-1$ and $t-2$ lagged zcta-specific meteorological variable, zonal load, natural gas prices, North/south and east/west wind speeds by 3-digit ZCTA values. All possible controls enter in levels up to a third-order polynomial

Subplots (a) and (b) plot the marginal responses of emissions of the two pollutants to wind generation from an augmentation of (1) that includes linear and quadratic controls of wind generation. With this quadratic specification, we find a clear diminishing marginal effect of wind generation for SO_2 and, to a lesser extent, for NO_x. Subplots (c) and (d) plot the marginal response to wind generation for the specification that interacts wind generation terms with the share of daily wind generation that comes during off-peak hours.[27] The marginal effects are evaluated at varying levels of off-peak wind shares with wind generation held at its mean value. Here we find effectively no impact of off-peak wind share on the marginal effect of wind with respect to SO_2, but the magnitude of the wind effect increases with more off-peak wind generation for NO_x.

Finally, subplots (e) and (f) plot the marginal responses of SO_2 and NO_x emissions from east Texas power plants with respect to wind generation for specifications that interact linear and quadratic wind generation terms with the share of daily wind generation coming during hours when the grid is uncongested. To determine this share, we first follow Fell et al. (2021) and define grid congestion as hours when the average pairwise difference in

[27] Off-peak hours are defined as hours beginning 0-7 and 20-23.

load-zone wholesale prices is greater than \$1/MWh. We then sum the wind generation for ERCOT across hours in a given day when the grid is *not* congested and divide that by the total daily wind generation. Plotting the marginal effects across a range of uncongested wind shares, while holding wind generation at its mean value, we find a clear increase in the magnitude of the wind generation effect on offsetting SO_2 and NO_x. This is consistent with Fell et al. (2021) result that congestion diminishes wind generation's effect on environmental damages in ERCOT.[28]

These more nuanced relationships between wind energy and power plant emissions motivate further exploration of the effects of wind generation on air quality and ED admission rates. Figures 6 and 7 present marginal response results from the specifications including linear and quadratic lagged wind generation terms, those wind generation terms interacted with the share of lagged wind generation coming from off-peak hours, and the those wind generation terms interacted with the share of lagged wind generation coming from uncongested hours. We further interact all these additional terms with a "near coal" indicator variable to explore differential effects for those ZCTA's near coal generation plants.

For the results with daily, ZCTA-level PM2.5 concentrations as the dependent variable, we find similar to the results for power-plant emissions, a strong diminishing (in magnitude) marginal effect of wind generation for regions both near and not near coal plants (Fig. 6, subplots (a) and (b)). However, unlike the effects of wind generation on emissions, the marginal effects of PM2.5 concentrations with respect to wind generation appear relatively unaffected by the share of wind generation coming during off-peak hours (subplots (c) and (d)) or the share of wind generation coming from periods when the grid is likely uncongested (subplots (e) and (f)).[29]

The results using ED admission rates across all diagnosis codes for the age ≥ 65 group as the dependent variable differ somewhat from those with PM2.5 concentrations. To begin, for ZCTA's near coal plants, we find no diminishing marginal effect of wind generation (Fig. 7, subplot (a)). For those not near coal, the marginal effect of wind does diminish somewhat, though 95% confidence intervals of point estimates are inclusive of zero for all wind generation levels considered. For near-coal ZCTA's, we find some degree of an increasing (in magnitude) marginal effect of wind generation as more wind generation comes during off-peak hours (subplot (c)). When considering the effects of grid congestion, we find a much larger magnitude of the marginal effect of wind generation on ED admission rates for near-coal ZCTA's when the majority of wind generation comes during periods when the grid is likely not congested relative to when wind generation is coming during grid-congested hours (subplot (e)). Similar to the base specifications results in Table 3, the ED admission rates for ZCTA's not near coal plants are smaller and statistically insignificant over the range of off-peak and uncongested wind generation shares.[30]

These results have particular policy relevancy as it relates to energy storage and transmission network expansion. With respect to wind generation, storage provides the

28 Parameter estimates from which the Fig. 5 are derived are given in Table 12 in the Appendix. We also include similar marginal response plots for dependent variables based aggregate generation from coal, NGCC, and NGSC plants in east Texas (see Fig. 9 and associated Table 11). As expected, the marginal response plots from specifications using emissions as the dependent variable follow a similar pattern to those with coal generation as the dependent variable.

29 Fig. 6 is derived from the parameter estimates reported in Table 13.

30 Fig. 7 is derived from the parameter estimates reported in Table 14.

Table 4 Lead and lag length sensitivity

	PM 2.5	ED Admiss. Rate
	(1)	(2)
Wind_t	0.00347	−0.0369
	(0.00330)	(0.0345)
Wind_{t-1}	−0.0173***	−0.0465
	(0.00349)	(0.0319)
Wind_{t-2}	−0.00785**	0.0129
	(0.00368)	(0.0341)
Wind_{t+1}	0.000435	0.0285
	(0.00353)	(0.0331)
Wind_{t+2}	0.00709**	0.0558*
	(0.00346)	(0.0297)
$\text{Wind}_t * 1(\text{Coal} \leq 30)$	−0.000826	−0.0291
	(0.00170)	(0.0297)
$\text{Wind}_{t-1} * 1(\text{Coal} \leq 30)$	−0.00299	−0.0387
	(0.00206)	(0.0316)
$\text{Wind}_{t-2} * 1(\text{Coal} \leq 30)$	0.00186	−0.0257
	(0.00215)	(0.0302)
$\text{Wind}_{t+1} * 1(\text{Coal} \leq 30)$	0.000303	−0.00540
	(0.00170)	(0.0295)
$\text{Wind}_{t+2} * 1(\text{Coal} \leq 30)$	−0.00378*	−0.0552*
	(0.00202)	(0.0326)
Sum of Near Coal Lags $\{t, t-1, t-2\}$	−0.0236***	−0.164***
	(0.0064)	(0.0655)
Sum of Near Coal Leads $\{t+1, t+2\}$	0.00405	0.0238
	(0.0044)	(0.0479)
Observations	483,687	972,057

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Dependent variables are given in the column headers, with "PM2.5" denoting the ZCTA-specific PM2.5 concentration measure and "ED Admiss. Rate" denoting the daily, ZCTA-specific ED admissions per 1 million residents for the age ≥ 65 group. See Table 3 for a description of the sample and control variables

opportunity to move electricity temporally, from low-value off-peak hours to high-value peak-demand hours. Our results indicate that such a temporal redistribution of wind generation may attenuate its impact on emissions of NO_X. However, the temporal redistribution does not appear to have any significant impact on wind generation's effect on PM2.5 concentrations and relatively minor effects of ED admission rates. To the extent that energy storage or other transmission expansions alleviate grid congestion, our results indicate that such investments will increase the effect of wind generation in offsetting emissions of local pollutants from power plants located farther from wind farms and in reducing ED admission rates for those living near emissions-intensive generators. This, again, highlights the non-market benefits of grid infrastructure investments.

Table 5 Heterogeneity by diagnosis and in-patient vs. out-patient

	Resp & Circ (1)	Injury (2)	Inf & Neo (3)	Out-Patient (4)	In-Patient (5)
$Wind_{t-1}$	−0.0299	−0.00353	−0.00821	−0.0262	−0.0332
	(0.0194)	(0.00805)	(0.00523)	(0.0234)	(0.0288)
$Wind_{t-1} * 1(\text{Coal Cap} \leq 30)$	−0.0248**	−0.0311***	0.0127**	−0.0973***	−0.00902
	(0.0122)	(0.0111)	(0.00521)	(0.0316)	(0.0142)
Near Coal Eff	−0.0548***	−0.0346***	0.00445	−0.123***	−0.0422
	(0.0201)	(0.0113)	(0.00572)	(0.0349)	(0.0269)
Dep. Var. Mean	406.9	254.5	84.85	958.7	512.3
Observations	976,071	976,071	976,071	976,071	976,071

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Sample and specification parallels Table 3, Column (2). The dependent variable is indicated by the column heading. "Near Coal Eff." gives the summed effect of the parameters on $Wind_{t-1}$ and $Wind_{t-1} * 1(\text{Coal Cap} \leq 30)$, with standard errors below in parentheses. "Dep. Var. Mean" gives the mean of the dependent variable labeled in the column headers. "Resp. & Circ", "Injury", and "Inf. & Neo." refer to admissions with diagnosis codes that correspond to HCUP Clinical Classification System diagnosis groupings of respiratory and circulatory, injuries, and infections and neoplasms (cancer), respectively. "Out-Patient" refers to ED visits that do not lead to an overnight admission and "In-Patient" visits are those that are initiated in the ED and lead to an overnight hospital stay. Other controls, selected by the post-double selection LASSO method, are excluded as the standard errors cannot be calculated directly. The possible other controls include contemporaneous and $t-1$ and $t-2$ lagged zcta-specific meteorological variable, zonal load, natural gas prices, north/south and east/west wind speeds by 3-digit ZCTA values. All possible controls enter in levels up to a third-order polynomial

8 Conclusion

Wind generated electricity has grown rapidly in the U.S. and elsewhere in the past two decades. However, given its non-dispatchability and typical siting in less densely populated regions, this emissions-free generation may not necessarily deliver significant short-term health benefits. We examine this issue by exploring the effect of short-term variation in wind generation levels in the ERCOT market on ED admission rates across the more heavily-populated east Texas region.

We build a causal chain, showing first, consistent with others, that wind generation reduces fossil generation and associated emissions in the ERCOT market. We then show that increases in lagged daily wind generation lowers PM2.5 concentrations across east Texas counties. Finally, we find that an increases in lagged wind generation reduces ED admission rates among individuals ages 65 or older. Additionally, while the effect size is small, with a standard deviation increase in near-term daily average wind generation levels reducing ED admission rates by about 0.5% of the mean rate, the effect is precisely measured and consistent across a variety of model specifications.

We consider several alternative specifications to find evidence of heterogeneous treatment effects along dimensions relevant to energy policy considerations. First, we explore the effect of wind generation on ED admission rates for ZCTA's near coal-fired plants and find the effect of wind generation on ED admission rates nearly doubles for those within 30 miles of coal plants relative to the mean effect across all East-Texas ZCTA's.

In addition to reducing the total amount of energy generation from fossil fuels, energy storage has the potential to both alter the timing of fossil fuel generation and to reduce the

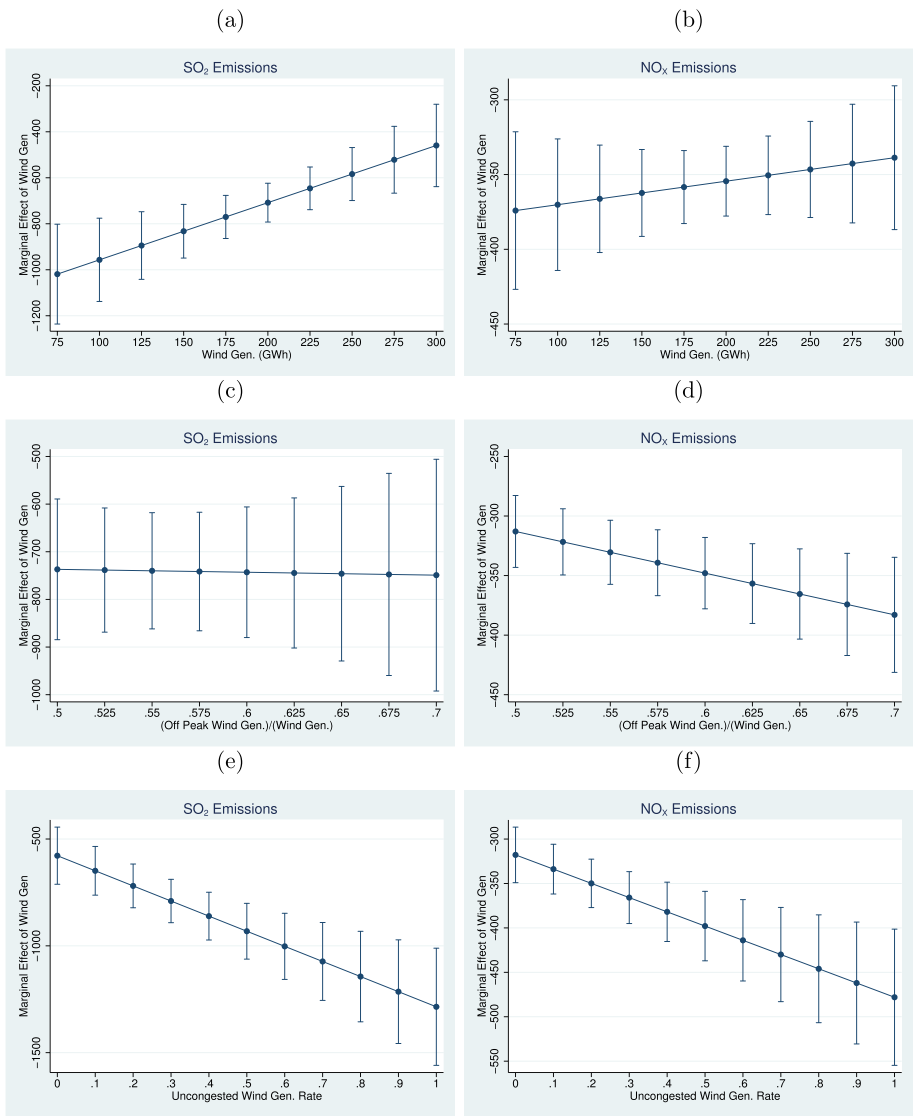


Fig. 5 Emissions Marginal Responses. Notes: This figure plots the marginal response with respect to wind generation of emissions from power plants not in the West Load Zone of ERCOT for pollutants listed at the top of each sub-figure. Subplots correspond to parameter estimates from Table 12. Point estimates are represented by the dots with vertical lines representing the 95% confidence intervals

amount of grid congestion. To model how this might impact the health benefits of wind generation, we explore how the marginal impacts of wind on ED visits varies by time of day and by grid congestion. First, we find that the effect of wind generation on ED visits is slightly larger when more of the wind generation comes during off-peak hours, but this relationship is attenuated relative to the amount of fossil fuel generation that is displaced. This suggests that policies affecting the *timing* of fossil fuel generation may have only a

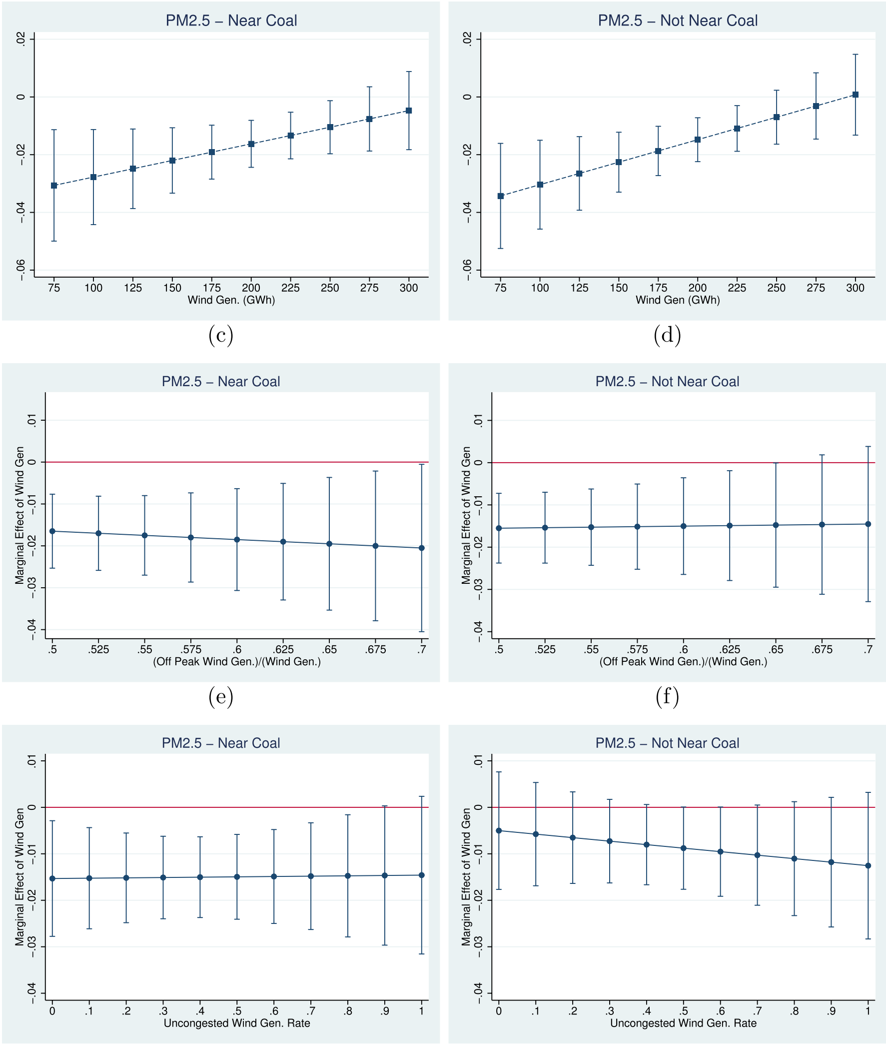


Fig. 6 PM2.5 Marginal Responses. Notes: This figure plots the marginal response with respect to wind generation of ZCTA-level, daily PM2.5 concentrations. Subplots correspond to parameter estimates from Table 13 from column (1) for plots (a) and (b), column (2) for plots (c) and (d), and column (3) for plots (e) and (f). Point estimates are represented by the dots with vertical lines representing the 95% confidence intervals

limited impact in isolation. However, when more wind generation comes during periods when the transmission network is not congested, the impact on health is more substantial. These latter results suggest that alleviation of congestion, either via more transmission lines or through effectively altering the timing of wind generation through energy storage to reduce congestion, could significantly increase the health benefits associated with wind generation.

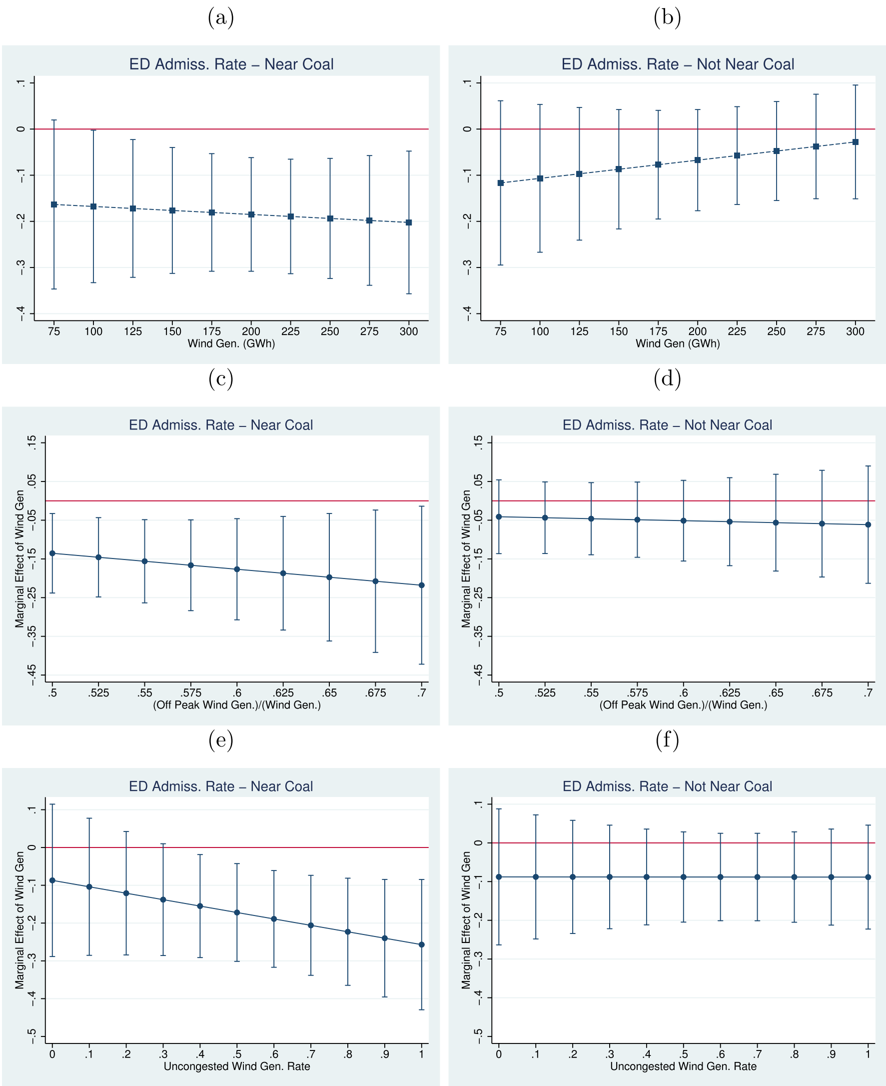


Fig. 7 ED Admission Rate Marginal Responses. Notes: This figure plots the marginal response with respect to wind generation of ED admission rates for individuals age ≥ 65 and based on "More Related" diagnosis codes. Subplots correspond to parameter estimates from Table 14 with column (1) for plots (a) and (b), column (2) for plots (c) and (d), respectively, and column (3) for plots (e) and (f). Point estimates are represented by the dots with vertical lines representing the 95% confidence intervals

Appendix

See Figs. 8 and 9 and Tables 6, 7, 8, 9, 10, 11, 12, 13 and 14.

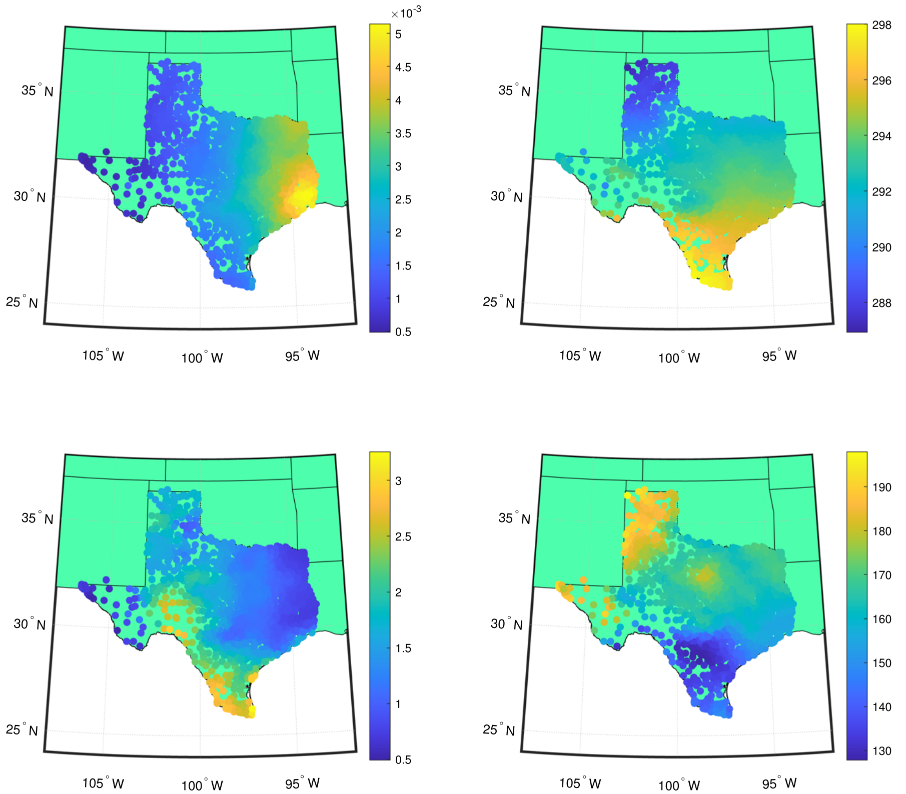


Fig. 8 Meteorological Conditions. Notes: Moving clockwise from the upper left plot, these maps plot the daily average of hourly precipitation (m), temperature (K), wind speed (m/s), and wind direction (degrees relative to due North) by zip code in Texas over the 2016-2019 sample period. Units of the data are the same for these variables as given in Table 1

Data Sample Description

In this section, we describe the universe of possible control variables from which the PDS-LASSO procedure selects a subset. To begin, our complete data sample runs, daily, from 01/01/2016 - 12/31/2019, for a total of 1461 days. There is a total of 786 ZCTA's in our data. To reduce the correlation between local meteorological conditions and wind generation, we exclude ZCTA's in the wind-generation-heavy West load zone of ERCOT and those south of 27 degrees latitude as there is another cluster of wind generators in the southern portion of Texas. We also exclude ZCTA's with populations of age ≥ 65 residents less than 10,000. These cuts results in a sample of 669 ZCTA's.

For the PDS-LASSO procedure, we allow for a large set of controls. The summary statistics table (Table 1) lists the root control variable (Meteorological Variables and zonal and ERCOT-wind Load Variables), from which we form additional control variables through lags, higher order polynomials, and interactions with three-digit ZCTA-identifiers to allow for region-specific effects. For each of these variables, except the N/S and E/W wind speed variables, we include as a possible control the given variable in levels, squared, and cubed for the contemporaneous, 1-day lagged, and 2-day lagged versions of

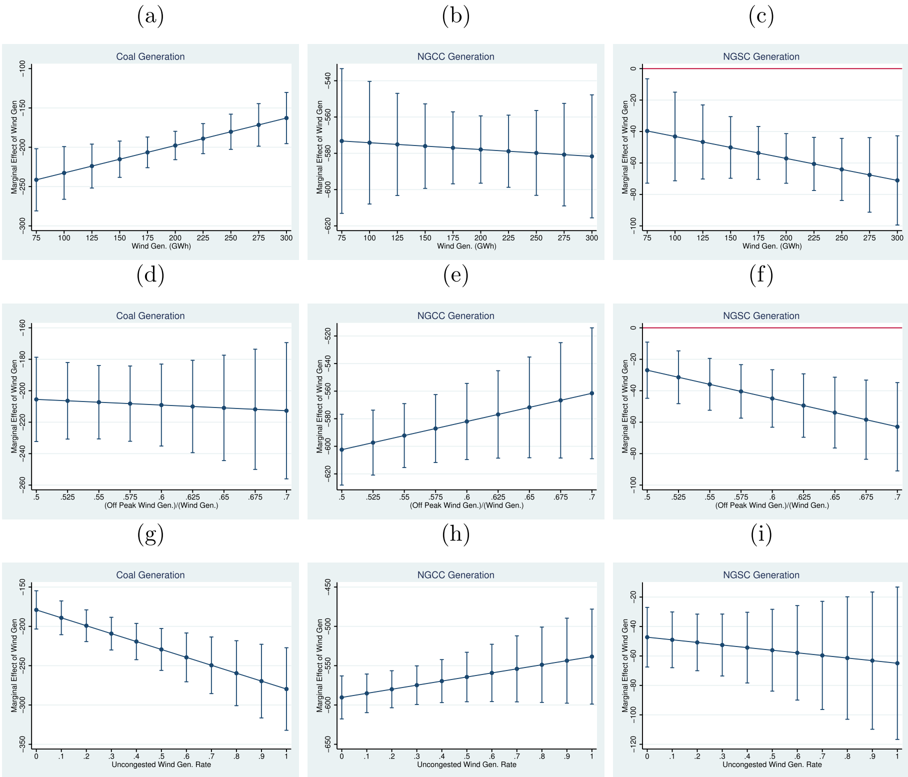


Fig. 9 Generation Marginal Responses. Notes: This figure plots the marginal response of aggregate daily generation of different technology types for plants not in the ERCOT West Load Zone with respect to wind generation. Subplots correspond to parameter estimates from Table 11. Point estimates are represented by the dots with vertical lines representing the 95% confidence intervals

the variable, for a total of 135 possible controls. For the N/S and E/W wind speed based variables, we interact the contemporaneous and 1-day lag variables, in levels and squared, with 3-digit ZCTA identifiers to allow for the directional wind speed effects to vary by region. There are 34 3-digit ZCTA's for our sample that excludes the West load zone and ZCTA's south of 27° latitude, so the total number of possible N/S- and E/W-based wind speed controls is 408. Given this set up, the PDS-LASSO procedure selects variables from a possible 543 controls. In addition to these possible controls, we also control month-by-year and day-of-week fixed effects which are excluded from the LASSO selection procedure. Note also, because we allow for control variables lagged 2-days, our total possible number of observations falls to 976,071 (669*1459).

The number of selected variables via the PDS-LASSO procedure varies by dependent variable and "treatment" variable(s) (e.g., lagged wind, lagged wind interacted with the off-peak-to-peak wind ratio) used. For example, in our base specification using the "Total" ED admission rates for the 65+ age group and lagged wind generation as the treatment variable of interest, the PDS-LASSO procedure selects 103 of the possible 543 possible controls. The set of controls includes wind speed, precipitation, boundary-layer height, and wet-bulb temperature, as well as many N/S and E/W wind speed measures, both

Table 6 Fixed regressors results

	PM 2.5	Total	Resp & Circ	Injury	Inf & Neo
$Wind_{t-1}$	−0.0193***	−0.0573	−0.0113	−0.00384	−0.00660
	(0.00368)	(0.0407)	(0.0189)	(0.00863)	(0.00546)
$Wind_{t-1} * 1(\text{Coal Cap} \leq 30)$	−0.00215	−0.0755**	−0.0328***	−0.0171	0.00991*
	(0.00169)	(0.0365)	(0.0113)	(0.0108)	(0.00505)
$Precip_t$	−466.7	-48,102***	−11,720***	−9,801***	-1,967***
	(596.9)	(5,104)	(1,678)	(1,224)	(639.4)
Wet $Bulb_t$	0.309***	2.182***	0.590***	−0.0413	0.234***
	(0.0658)	(0.469)	(0.191)	(0.108)	(0.0717)
BLH_t	−0.00443***	0.0262**	−0.000959	0.0110***	0.00334**
	(0.00149)	(0.0110)	(0.00476)	(0.00272)	(0.00155)
$North_t$	0.000104	0.00282	0.00295*	−0.000821	0.00108*
	(0.000399)	(0.00308)	(0.00155)	(0.000742)	(0.000548)
North $Central_t$	−2.16e−05	-9.75e−05	−9.10e−05	-7.49e−06	−6.58e−05**
	(2.68e−05)	(0.000244)	(0.000114)	(4.55e−05)	(3.00e−05)
$South_t$	−0.000109*	−0.00122*	−0.000547	5.34e−05	-6.80e−05
	(6.26e−05)	(0.000642)	(0.000381)	(0.000141)	(7.93e−05)
South $Central_t$	−7.01e−05	−0.000293	-9.59e−05	−0.000156	-1.50e−05
	(4.26e−05)	(0.000400)	(0.000187)	(0.000116)	(7.02e−05)
$East_t$	0.000304	0.000919	−1.30e−05	0.000337	0.000438
	(0.000218)	(0.00229)	(0.000893)	(0.000428)	(0.000310)
$Coast_t$	3.65e−05	0.000821***	0.000289***	9.52e−05**	6.32e−05***
	(2.56e−05)	(0.000189)	(7.73e−05)	(3.83e−05)	(2.37e−05)
$West_t$	0.000295	−0.00350	−0.000639	−0.000160	−0.000398
	(0.000310)	(0.00381)	(0.00156)	(0.000741)	(0.000586)
Far $West_t$	−7.35e−05	−0.00120	−0.000980	0.000137	−5.89e−06
	(0.000167)	(0.00201)	(0.000774)	(0.000433)	(0.000312)
Observations	487,701	976,740	976,740	976,740	976,740

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. Presented results are estimated from specifications with a fixed set of regressors. The dependent variable is given in the column header. "PM2.5" refers to average daily PM2.5 measures at the ZCTA level for years 2018-2019 as derived from the NASA MODIS model. "Total" refers to the total ED admission rate for age ≥ 65 patients. "Resp. & Circ", "Injury", and "Inf. & Neo." refer to admissions with diagnosis codes that correspond to HCUP Clinical Classification System diagnosis groupings of respiratory and circulatory, injuries, and infections and neoplasms (cancer), respectively. All diagnosis code admissions are for the age ≥ 65 group. In addition to the variables shown, all specifications also include month-by-year, day of week, and ZCTA fixed effects and lagged ($t-1$) values of all variables show above

contemporaneous and lagged and in levels and squared, interacted with various 3-digit ZCTA identifiers. When also allow the treatment to vary for those ZCTA's with 30 miles of a coal plant (lagged wind interacted with a within-30-miles-of-coal indicator), the PDS-LASSO procedure selects even more controls, 132, out of the possible 543. The primary difference between the selected variables of these two specification, and more generally,

Table 7 Removal of extreme wind/precipitation days

	PM2.5		ED Admiss. Rate	
	(1)	(2)	(3)	(4)
Wind_{t-1}	−0.0177***	−0.0187***	−0.0612	−0.0528
	(0.00375)	(0.00384)	(0.0492)	(0.0516)
$\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$	−0.00182	−0.00238	−0.0860**	−0.0748*
	(0.00173)	(0.00187)	(0.0390)	(0.0410)
Observations	423,271	386,859	850,684	778,994

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. ZCTA-level PM2.5 measures is the dependent variable for results in columns (1) and (2) and ZCTA-level total ED admission rates for those 65 and older is the dependent variable for columns (3) and (4). Results in columns (1) and (3) remove observation days $t, t-1, \text{and} t+1$ if the ZCTA's windspeed or precipitation on day t is greater than the 97.5 percentile of the ZCTA's windspeed or precipitation measure. Column (2) and (4) results are based on samples similarly defined, but remove days $t, t-1, t-2, t+1, \text{and} t+2$ if windspeed or precipitation measures are above the 97.5 percentile values. Other controls, selected by the post-double selection LASSO method, are excluded as the standard errors cannot be calculated directly. The possible other controls include contemporaneous and $t-1$ and $t-2$ lagged zcta-specific meteorological variable, zonal load, natural gas prices, north/south and east/west wind speeds by 3-digit ZCTA values. All possible controls enter in levels up to a third-order polynomial

Table 8 Instrumental variables approach

	PM2.5		ED Admiss. Rate	
	(1)	(2)	(3)	(4)
Wind_{t-1}	−0.0268***	−0.0270***	−0.0479**	−0.0156
	(0.0003)	(0.0003)	(0.0197)	(0.0217)
$\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$		0.000748*		−0.0966***
		(0.0004)		(0.0252)
Observations	487,701	487,701	976,740	976,740

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. ZCTA-level PM2.5 measures is the dependent variable for results in columns (1) and (2) and ZCTA-level total ED admission rates for those 65 and older is the dependent variable for columns (3) and (4). In all specifications, Wind_{t-1} and $\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$ are instrumented for using a capacity-weighted average wind speed at wind farms in the West load zone of state and that interacted with $1(\text{Coal Cap} \leq 30)$, respectively. Other controls include contemporaneous and $t-1$ lagged zcta-specific meteorological variable, zonal load, natural gas prices, north/south and east/west wind speeds by 3-digit ZCTA values

is the number of N/S and E/W windspeed interacted with 3-digit ZCTA identifiers that are included.

For the specifications using ZCTA-level PM2.5 concentration measure, the sample count is reduced because the data is only available for years 2018 and 2019. We have 729 sample days with PM2.5 readings, with reading unavailable in our data for May 19, 2019, over 669 ZCTAs for a total of 487,701 observations. Note also, the results of the various specifications using ED Admission as the dependent variable, but restricted to the

Table 9 Hospital admission rate effects: all ages and age≤5

	All ages			Age ≤ 5		
	Total	R & C	Inj	Total	R & C	Inj
Wind_{t-1}	−0.0269	−0.00523	0.00683*	0.0630	0.0371	0.00490
	(0.0198)	(0.00907)	(0.00383)	(0.0653)	(0.0411)	(0.0111)
$\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$	−0.0240	0.0105*	−0.0219***	−0.110**	0.0230	−0.0377***
	(0.0150)	(0.00567)	(0.00427)	(0.0458)	(0.0230)	(0.0133)
Observations	976,071	976,071	976,071	976,071	976,071	976,071

*, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. The first two columns refer to the grouping of ED patients from all ages and the second two columns are based on ED admission rates for the age group less than or equal to 5. "Total" refers ED admission rate dependent variables using all ED admissions "R. & C." refers to dependent variable specifications based on admissions with diagnosis code classified as respiratory or circulatory conditions under the HCUP classification system. All specifications include ZCTA, year-by-month, and day-of-week fixed effects. Additional controls are selected using the post-double LASSO selection procedure

Table 10 Poisson regression results - base specification

	Total	Resp & Circ	Injury	Inf & Neo
Wind_{t-1}	−1.74e−05	−4.00e−06	1.48e−06	−4.48e−05
	(1.06e−05)	(1.95e−05)	(2.46e−05)	(4.20e−05)
$\text{Wind}_{t-1} * 1(\text{Coal Cap} \leq 30)$	−6.83e−05***	−7.27e−05***	−8.07e−05**	8.04e−05
	(1.38e−05)	(2.61e−05)	(3.23e−05)	(5.53e−05)
Windspeed_t	−0.00113**	−0.000467	−0.00176	0.00105
	(0.000547)	(0.00100)	(0.00127)	(0.00216)
Precipitation_t	−31.24***	−28.80***	−40.18***	−23.97***
	(1.748)	(3.114)	(3.923)	(6.503)
BLH_t	−8.12e−06**	−2.25e−05***	1.49e−05	2.39e−06
	(4.11e−06)	(7.57e−06)	(9.52e−06)	(1.64e−05)
Wet Bulb_t	0.00412***	0.00366***	0.00172***	0.00459***
	(0.000217)	(0.000396)	(0.000502)	(0.000856)
Observations	976,740	976,740	976,740	976,740

Parameter estimates are estimated via a Poisson pseudo-likelihood regression. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Robust standard errors are included in parentheses below the parameter estimates. Dependent variables are age 65+ ED admission rates for the diagnosis code groupings given in the column headers. Parameters beyond the wind generation and wind generation interaction terms are for ZCTA-specific daily mean values of windspeed (Windspeed_t), precipitation (Precipitation_t), boundary layer height (BLH_t), and wet-bulb temperature (Wet Bulb_t). Additional controls include contemporaneous and lagged ZCTA-level windspeed, precipitation, boundary layer height, relative humidity, wet-bulb temperature, weather-zone load, N/S wind speed by 3-digit ZCTAs, and month-by-year, day-of-week, and ZCTA fixed effects

2018-2019 period as the PM2.5 data is, leads to qualitatively similar results as those shown in this study.

Table 11 Heterogeneous effects: generation

	Coal	Coal	Coal	NGCC	NGCC	NGCC	NGSC	NGSC	NGSC
$Wind_{t-1}$	−267.6***	−151.1	−230.5***	−570.4***	−525.2***	−555.7***	−29.17	−208.6	−24.54
	(29.81)	(165.0)	(37.97)	(30.18)	(183.8)	(43.53)	(25.04)	(127.4)	(32.97)
$Wind^2_{t-1}$	0.175**	−0.102	0.144*	−0.0188	−0.501	−0.0968	−0.0698	0.758**	−0.0634
	(0.0702)	(0.443)	(0.0849)	(0.0718)	(0.534)	(0.0966)	(0.0595)	(0.374)	(0.0749)
$Wind_{t-1} * \left(\frac{Wind^{Off}_{t-1}}{Wind_{t-1}}\right)$		−205.1			−160.6			402.3*	
		(282.3)			(318.0)			(228.0)	
$Wind^2_{t-1} * \left(\frac{Wind^{Off}_{t-1}}{Wind_{t-1}}\right)$		0.472			1.019			−1.624**	
		(0.823)			(0.989)			(0.704)	
$Wind_{t-1} * \left(\frac{Wind^{Uncong}_{t-1}}{Wind_{t-1}}\right)$			104.2			−214.1**			42.23
			(98.44)			(97.86)			(81.01)
$Wind^2_{t-1} * \left(\frac{Wind^{Uncong}_{t-1}}{Wind_{t-1}}\right)$			−0.572**			0.742**			−0.167
			(0.268)			(0.301)			(0.241)
Observations	1,461	1,461	1,461	1,461	1,461	1,461	1,461	1,461	1,461
R^2	0.941	0.941	0.942	0.970	0.970	0.970	0.813	0.825	0.814

The dependent variable for each specifications is daily summed generation from fossil-fuel plants in ERCOT excluding those from the West Load Zone for the fuel type-technology given in the column header. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. Additional controls ERCOT aggregate load, Henry-hub natural gas prices, and month-by-year and day-of-week fixed effects

Table 12 Heterogeneous effects: emissions

	SO_2	SO_2	SO_2	NO_X	NO_X	NO_X
$Wind_{t-1}$	−1,205***	−1,165	−568.5	−385.9***	−705.4***	−163.0
	(167.5)	(953.3)	(466.4)	(40.86)	(254.6)	(109.2)
$Wind^2_{t-1}$	1.243***	1.279	−1.998	0.0786	1.583**	−0.879**
	(0.404)	(2.634)	(1.379)	(0.101)	(0.678)	(0.356)
$Wind_{t-1}*\left(\frac{Wind^{Off}_{t-1}}{Wind_{t-1}}\right)$		716.6			127.6	
		(446.9)			(239.0)	
$Wind^2_{t-1}*\left(\frac{Wind^{Off}_{t-1}}{Wind_{t-1}}\right)$		−2.976**			−0.537	
		(1.255)			(0.651)	
$Wind_{t-1}*\left(\frac{Wind^{Uncong}_{t-1}}{Wind_{t-1}}\right)$			0.289			0.167
			(0.564)			(0.130)
$Wind^2_{t-1}*\left(\frac{Wind^{Uncong}_{t-1}}{Wind_{t-1}}\right)$			−0.003*			−0.001**
			(0.0016)			(0.0004)
Observations	1,461	1,461	1,461	1,461	1,461	1,461
R^2	0.918	0.918	0.919	0.956	0.958	0.957

The dependent variable for each specifications is daily summed emissions from fossil-fuel plants in ERCOT excluding those from the West Load Zone for the pollutant given in the column header. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. Additional controls ERCOT aggregate load, Henry-hub natural gas prices, and month-by-year and day-of-week fixed effects

Table 13 Heterogeneous effects: PM2.5

	PM 2.5		
	(1)	(2)	(3)
Wind_{t-1}	−0.0460***	0.0775	−0.00329
	(0.0138)	(0.0874)	(0.0241)
Wind^2_{t-1}	7.79e−05**	−0.000264	−2.38e−06
	(3.21e−05)	(0.000249)	(5.06e−05)
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right)$		−0.230	
		(0.164)	
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right)$		0.000641	
		(0.000477)	
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right)$			−0.0634*
			(0.0345)
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right)$			0.000119
			(8.50e−05)
$\text{Wind}_{t-1} * 1(\text{Coal} \leq 30)$	0.00669	−0.00979	−0.0324**
	(0.00852)	(0.0565)	(0.0131)
$\text{Wind}^2_{t-1} * 1(\text{Coal} \leq 30)$	−2.03e−05	5.59e−05	5.31e−05*
	(1.94e−05)	(0.000138)	(2.74e−05)
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$		0.0365	
		(0.101)	
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$		−0.000162	
		(0.000254)	
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$			0.0689***
			(0.0216)
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$			−0.000145***
			(4.85e−05)
Observations			

The dependent variable for all specifications is daily, ZCTA-level PM2.5 measures. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. Additional controls are selected using the post-double LASSO selection procedure using lagged wind and lagged wind squared (column (1)) or lagged wind interacted with the off-peak ratio (column (2)) or lagged wind interacted with the uncongested rate (column (3)) as the treatment variables. All specification include month-by-year and day-of-week fixed effects

Table 14 Heterogeneous effects: ED admissions rate

	ED Admiss. Rate		
	(1)	(2)	(3)
Wind_{t-1}	−0.146	−0.605	−0.320
	(0.121)	(0.590)	(0.242)
Wind^2_{t-1}	0.000197	0.00157	0.000606
	(0.000234)	(0.00182)	(0.000430)
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right)$		0.918	
		(1.102)	
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right)$		−0.00249	
		(0.00350)	
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right)$			0.400
			(0.319)
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right)$			−0.00104
			(0.000754)
$\text{Wind}_{t-1} * 1(\text{Coal} \leq 30)$	−0.00415	0.778	0.432**
	(0.110)	(0.737)	(0.217)
$\text{Wind}^2_{t-1} * 1(\text{Coal} \leq 30)$	−0.000284	−0.00173	−0.00125***
	(0.000273)	(0.00222)	(0.000445)
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$		−1.327	
		(1.328)	
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Off}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$		0.00223	
		(0.00420)	
$\text{Wind}_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$			−0.726**
			(0.323)
$\text{Wind}^2_{t-1} * \left(\frac{\text{Wind}^{\text{Uncong}}_{t-1}}{\text{Wind}_{t-1}}\right) * 1(\text{Coal} \leq 30)$			0.00150*
			(0.000801)
Observations	976,071	976,071	976,071

The dependent variable for all specifications is daily, ZCTA-level ED admission rates (per 1 million residents) for the age ≥ 65 group. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors, clustered at week of sample, are included in parentheses below the parameter estimates. Additional controls are selected using the post-double LASSO selection procedure using lagged wind and lagged wind squared (column (1)) or lagged wind interacted with the off-peak ratio (column (2)) or lagged wind interacted with the uncongested rate (column (3)) as the treatment variables. All specification include month-by-year and day-of-week fixed effects

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Data Availibility The data in this paper were purchased from the Texas Health Care Information Collection (THCIC), Emergency Department Visits restricted data (see: https://www.dshs.texas.gov/thcic/). We will provide all programs required to replicate the analysis. We can also share the publicly available data on electricity generation and air quality. This study has received IRB approval.

Declarations

Conflict of interest Harrison Fell declares that he has no relevant or material financial interests that relate to the research described in this paper. Melinda Morrill declares that she has no relevant or material financial interests that relate to the research described in this paper.

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