

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

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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 PM_{2.5} 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 SO₂ is offset by wind from night hours, but the time-dependent effects for PM_{2.5} concentrations and ED admission rates is much weaker, potentially due to differences in exposure.

Keywords: Renewable Energy, Wind Energy, Morbidity, Emergency Department Visits

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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 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 a mechanism chain as follows. First, similar to other studies described below, we show that wind energy in Texas reduces generation 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 (PM_{2.5}). Finally, using zip-code level ED admission rates, we find that increased wind energy is associated with small, but statistically

¹These 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.

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 and for conditions likely more related to air quality.

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, Kaffine and Novan (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 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, Kaffine and Novan (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 SO₂ 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, Lavy and Roth (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. Thus, we provide an identification concept similar in spirit to that employed by Schlenker and Walker (2016).

Our paper is most similar in its research questions to that of Rivera, Ruiz-Tagle and Spiller (2021). In that study, Rivera, Ruiz-Tagle and Spiller (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.

²Prior work has shown a meaningful link between coal and infant mortality both in early industrial economies (e.g., Beach and Hanlon, 2017) and in modern times as alternative fuel sources displace coal (e.g., Cesur, Tekin and Ulker, 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.

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 Figure 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 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 Figure 2(a), 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 Figure 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 Figure 2(b)). As such, the geographic distribution of wind generation, load, and fossil-fuel power plants is 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.

3 Data

For our analysis, we collect data across three primary categories: electricity generation, meteorological and air quality, and emergency department admission records. 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 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. Thus, to better identify the effect of wind generation separate 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. 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 Figure 2). A map of the ZCTAs remaining after these restrictions are imposed is given in Figure 4.³

All primary variables used in this analysis are summarized in Table 1. 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

³Note we also consider specifications where we consider ZCTA’s with longitudes greater than -97, -96, and -95 degrees, with these subsamples of ZCTA’s having correlations between ZCTA-specific windspeeds and ERCOT wind generation of 0.36, 0.29, and 0.26, respectively. The response of ED admission rates and PM2.5 concentrations to wind generation for these subsamples are quantitatively similar to the results presented below.

over the years 2016 - 2019 based on ERCOT’s publicly available data on its historic generation fuel mix (<http://www.ercot.com/gridinfo/generation>).⁴ 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.⁵ 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 SO₂, NO_x, and CO₂.⁶ 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 a zip code tabulation area’s (ZCTAs) proximity to fossil fuel generation.

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° × 0.25° latitude/longitude grid (Christoph A. Keller (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 lati-

⁴The downloadable "Fuel Mix Report: 2007 - 2019" data is given as the 15-minute generation by source across the ERCOT grid. We aggregated this 15-minute data to the hourly level.

⁵ERCOT 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>.

⁶We 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.

tude/longitude of the gridded PM2.5 data.⁷

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 $30\text{km} \times 30\text{km}$) 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. Because our main specification includes lags, the sample includes data for 699 ZCTAs over 1,455 days for a sample size of 973,395.

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). 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, and, importantly, diagnosis code. To form an admissions rate, we sum the admissions by ZCTA and divide by the ZCTAs population.⁸

Table 1 presents Emergency Department admissions rates per 1 million persons aged

⁷We 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.

⁸The 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.

65 and older first as a total and then separating out by primary diagnosis.⁹ Air pollution has been associated with a wide variety of adverse health and cognitive outcomes.¹⁰ Following Jha and Muller (2018) and Schlenker and Walker (2016), we define conditions that are more or less likely to be related to pollution. Most broadly, we consider “Less Related” diagnosis codes to be those with the ICD-10-CM codes S, T, V, W, X, and Y, which includes admissions for reasons related to, among other causes, assaults, injuries to the head, burns, skips, and passenger vehicle accidents. Then, our “More Related” conditions are defined simply *not* having a primary diagnosis for an unrelated condition. We refine this category by including only those individuals with a primary diagnosis for respiratory or circulatory conditions, denoted by ICD-10-CM codes I and J, which are frequently associated with air quality.

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

$$y_t = \beta Wind_t + \mathbf{X}_t' \boldsymbol{\theta} + \gamma_t + \epsilon_t \quad (1)$$

where y_t is either the aggregate fossil-fuel generation from a type of generator class (e.g. coal,

⁹The data include an admitting and a principal diagnosis code, so we define diagnosis as having the value for either the admitting or principal diagnosis.

¹⁰For 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 activity.

natural gas simple cycle, 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).¹¹ We estimate model at the daily level and quadratic specifications of $Wind_t$ and interaction terms including measures of intra-day wind generation timing.

We 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:

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

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 county 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.

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.¹² We therefore also estimate (2) using the post double selection LASSO (PDS-LASSO) proposed by Belloni, Chernozhukov and Hansen (2014) and Belloni et al. (2016). The PDS-LASSO works essen-

¹¹For 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>).

¹²In 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 locationally specific wind direction effects by interacting ZCTA-specific north/south and east/west, respectively, wind speeds (contemporaneous and lagged) with three-digit ZCTA indicator variables. 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.

tially by selecting variables in \mathbf{X} via a LASSO estimator that predict the dependent variable of interest, y_{it} , 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.¹³

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 admission rates in total and for certain subsets of diagnosis codes.¹⁴ 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.

5 Results

The effect of wind on generation on fossil fuel generation types and emissions from the electricity sector, as estimated via equation (1), are given in Table 2. As can be seen by summing the coefficients on wind generation across the “Coal”, “NGCC”, and “NGGT” 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 .¹⁵

¹³In 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.

¹⁴Note 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 A.3). 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.

¹⁵We estimated a similar functional form to (1) using hourly data. The parameters on wind generation are numerically similar to those given in Table 2.

The next step is to verify if this wind-generation-induced reduction in fossil-fuel generation and associated emissions results in improved air quality in the eastern portion of Texas and subsequently reduced ED admission rates. Results of this analysis are presented in Table 3, Panel A. The first column of Table 3 presents wind generation effect where the dependent variable is the ZCTA-level PM2.5 measure. Here we find a statistically significant and negative effect of wind generation on the PM2.5 concentrations. 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 across the east Texas counties.

Having provided evidence that wind generation reduces fossil fuel generation, consistent with previous studies, and leads to statistically significant reductions in PM2.5 concentration levels, we next show the wind generation effects on ED admission rates. Table 3 presents the results for a variety of ED-admission-related dependent variables. All dependent variables specifications in Table 3 are based on admission rates for the age ≥ 65 subgroup, with other groupings explored in the subsequent section, and all results use the PDS-LASSO procedure to select the control variables other than lagged wind generation, its interaction with the near-coal dummy variable, and year-by-month and day-of-week fixed effects.

As noted above, we have information on the patients' diagnosis codes, which allows us to consider effects on more specific conditions. As described in Section 3, we consider broad groupings of diagnosis codes when forming the ED admission rates. The dependent variables for the columns of Table 3 are the ED admission rate with no diagnosis code restrictions ("Total" column), all admissions except those deemed possibly less related to air-quality ("More Related" column), admissions from diagnosis codes pertaining to respiratory and circulatory issues ("Resp. & Circ."), and admissions from diagnosis possibly less related to air-quality ("Less Related") for patients age ≥ 65 .¹⁶ For the total admissions rate, rates

¹⁶We consider the age ≥ 65 cohort 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 A.2.

based on excluding likely air-quality-unrelated admissions, and rates based on circulatory and respiratory issues we find that on average across ZCTAs in east Texas an increase in the lagged daily wind generation decrease ED admission rates. At the same time, the effect on admission rates for diagnosis codes less related to air quality is smaller in magnitude and statistically insignificant at standard significance levels. In addition, while the parameter estimate for lagged wind with “Total” as the dependent variable is about double in magnitude that for “Resp. & Circ.”, the parameter estimates imply that a standard deviation increase in lagged wind generation lowers “Total” and “More Related” rates by about 0.6% of its mean and “Resp. & Circ.” rates by about 0.7% of its mean.

As noted above, we also consider heterogeneous effects of wind generation for those ZCTA’s near coal-fired power plants, which have considerably higher emissions intensities and total production of most relevant pollutants compared to natural gas fired plants, by interacting lagged wind generation with a near coal-fired plants indicator variable. We consider two different specifications of this near-coal indicator variable. The first indicator variable, $1(\text{Coal Cap} \leq 30)$, equals one if a ZCTA’s centroid is within 30 miles of coal-fired generation capacity. In the second specification, $1(\text{Coal Gen}_{t-1} \leq 30)$, the indicator is equal to one if a ZCTA’s centroid is within 30 miles of a coal generator that had positive generation on day $t - 1$.¹⁷ Panel B of Table 3 indicates a larger effect of wind generation on ED rates for those patients within 30 miles of a coal-fired power plant, regardless of its operation status. Relative to the mean admission rates for those from ZCTAs within 30 miles of a coal plant, the parameters of Table 3 Panel B imply that a a standard deviation increase in lagged wind generation lowers “Total” rates by about 0.8% and for “More Related” and “Resp. & Circ.” rates by about 1% of their respective means. Note that the mean hospitalization rate for less-related diagnosis is much smaller than the total rate, 209 per 1 million vs. 1475. Thus, while the point estimate is smaller, this is a much larger relative effect (about a 1% reduction in the mean for less related diagnoses).

¹⁷Note we also consider indicator variables where we allowed the centroid of a ZCTA to be within 60 miles of coal-fired plant. These results are included in the appendix.

Panel C of Table 3 presents the results where we also include a “near coal” indicator variable that is equal to one if the ZCTA is within 30 miles of a coal plant that had positive generation on day $t - 1$.¹⁸ Results here indicate little impact of lagged wind generation for ED rates of residents in ZCTA’s not near coal plants or near coal plants that were not running at $t - 1$, but a relatively large negative effect of lagged wind generation on ED rates for ZCTA’s near generating coal plants. The parameter estimates imply that a standard deviation increase in wind generation lowers ED admission rates across all diagnosis code groupings considered by about 1.1% of their respective means. Alternatively, PM2.5 responses are only modestly larger (in magnitude) for those near coal plants with positive generation. Also note that, while the point estimates for the coefficient on the interaction term between wind generation and having a non-operating coal plant within 30 miles is statistically significant for both more and less related diagnoses, the sum with the non-interacted wind term is a precisely measured zero.

6 Lead/Lag Structure and Patient Coding

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 ($t - 1$ and $t - 2$) and leads ($t + 1$ and $t + 2$) wind generation controls.¹⁹ The first column of Table 4 refers to specifications with PM2.5

¹⁸A 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 days in which coal plants have zero generation occurs in the midst of at least a five-day window in which the plant 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 an 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.

¹⁹For ease of presentation, the results from the “Less Related” diagnosis codes grouping are suppressed for this specification, and the remainder of the results shown, given the general lack of statistical significance for the effect of wind generation.

as the dependent variables and the remaining three columns are from specifications with ED admission rates for the age ≥ 65 cohort across different diagnosis code groupings. Although not apparent from the parameter estimates presented, the joint effect of the contemporaneous wind generation plus one- and two-day leads is small in magnitude and statistically insignificant across the different dependent variable settings and across the not-near- and near-coal regions for all dependent variable specifications. For the case of PM2.5, the joint effect of the two lagged wind generation values is statistically significant and effectively equivalently-sized for regions not-near- and near-coal generators. Additionally, the combined effect size of the two-periods of lagged wind generation is close in magnitude to that shown in Table 3 for lagged wind generation alone. Similarly, for the specifications using ED admission rates as the dependent variable, we find that the joint effect of contemporaneous and two wind generation leads is small and statistically significant, whereas the joint effect of the two-periods of lagged wind generation is similar in magnitude to that of just the one-period lagged wind generation presented in Table 3. Given these results, we proceed with models focused on the effect of 1-period lagged wind generation alone.

Another dimension that may alter the effects is the consideration of ED admissions that are listed as in-patient versus those listed as out-patient. In-patient procedures, even those admitted through the ED, are frequently scheduled procedures and, thus, may be less likely to be affected by day-to-day variations in air quality derived from wind generation fluctuations. To explore this, we create dependent variables for in-patient (IP) and out-patient (OP) ED admissions separately using our “Total”, “Relevant”, and “Resp. & Circ.” diagnosis code groupings. These results are presented in Table 5, where “Total” groupings for in-patient and out-patient admissions are denoted by “Tot-IP” and “Tot-OP”, respectively. Similarly, “Rel-X” and “RC-X” represent either the in-patient ($X = IP$) or out-patient ($X = OP$) admission rates for the “More Related” and “Resp. & Circ.” diagnosis codes groupings, respectively. As expected, across these diagnosis code groupings, 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. For example, given that demand for electricity varies throughout the day and that generators have heterogeneous marginal costs across generation technologies, then the marginal generator will vary throughout the day. Similarly, the level of wind generation can alter which generator is marginal, as the level of wind generation determines how much the positive marginal cost portion of the supply curve is shifted in or out. Because emissions also vary by fossil-fuel generators, emissions offset by increased wind generation also varies throughout the day and as the level of wind generation varies (see Cullen (2013) and Novan (2015)). Similarly, Fell, Kaffine and Novan (2021) have shown that wind generation in ERCOT coming during periods of grid congestion reduces the emissions offset from generation sources in the more densely populated eastern portion of the state. Finally, 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.²⁰ For specifications using ZCTA-specific PM2.5 concentrations and ED admission rates, we also explore the varying marginal responses to wind generation separately for ZCTAs 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 SO₂ and NO_x. 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 SO₂ 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.²¹ 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 SO₂, 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 SO₂ 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, Kaffine

²⁰For 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 its 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.

²¹Off-peak hours are defined as hours beginning 0-7 and 20-23.

and Novan (2021) and define grid congestion as hours when the average pairwise difference in 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 SO₂ and NO_x. This is consistent with Fell, Kaffine and Novan (2021) result that congestion diminishes wind generation’s effect on environmental damages in ERCOT.²²

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 ZCTAs 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 (Figure 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)).

The results using ED admission for more-related diagnosis codes as the dependent

²²We also include similar marginal response plots for dependent variables based aggregate generation from coal, NGCC, and NGSC plants in east Texas. 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.

variable differ somewhat from those with PM2.5 concentrations. To begin, for patients residing near coal plants, we find no diminishing marginal effect of wind generation (Figure 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 patients, 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 patients when the majority of wind generation comes during periods when the grid 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 patients not near coal plants are smaller and statistically insignificant over the range of off-peak and uncongested wind generation shares.

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

8 Conclusion

Wind generated electricity has grown rapidly in the U.S. and elsewhere in the past two decades. However, given its nondispatchability and typical siting in less densely populated regions, it is not a given that this emissions-free generation delivers 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 PM_{2.5} concentrations across east Texas counties. Finally, we find that an increases in lagged wind generation reduces ED admission rates among individuals in age 65 or older cohort. 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 0.6% of the mean rate, the effect is relatively precisely measured and consistent across a variety of model specifications.

We consider several alternative specifications to find evidence of heterogeneous treatment effects along several dimensions that are relevant to energy policy considerations. First, we explore the effect of wind generation on ED admission rates for patients 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 those that live farther from these facilities.

Next, we explored how the wind generation effect varies by the distribution of wind generation throughout the day and across periods of grid congestion, both of which are important considerations for the value of energy storage and transmission network expansion. We find that the wind generation effect on reducing ED admission rates is slightly larger when more of the wind generation comes during off-peak hours and, more noticeably, when more wind generation comes during periods when the transmission network is more likely not congested. The results are relatively well-aligned with effects of wind generation on power

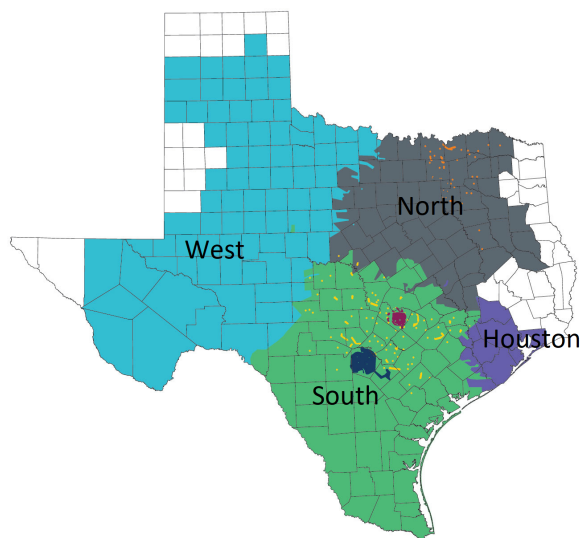
plant emissions.

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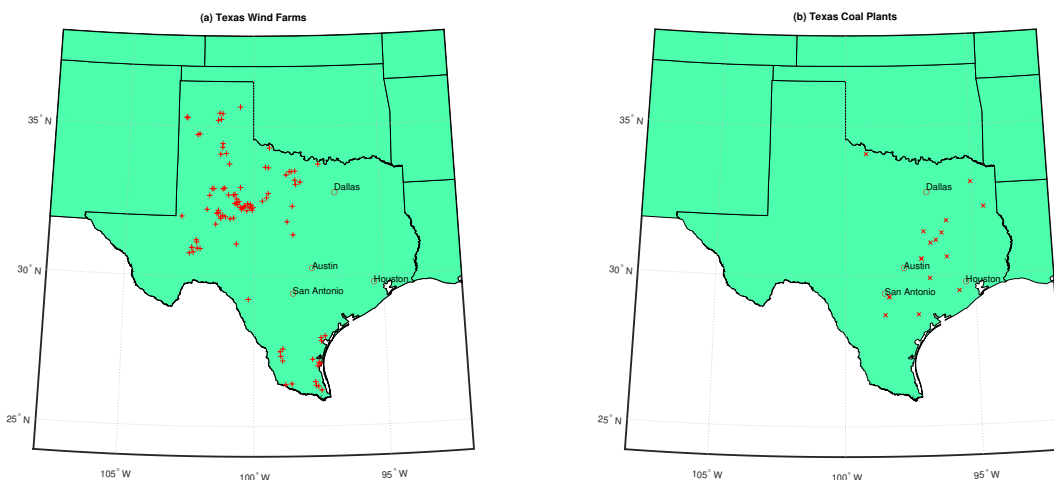
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Figure 1: ERCOT Geographic Footprint



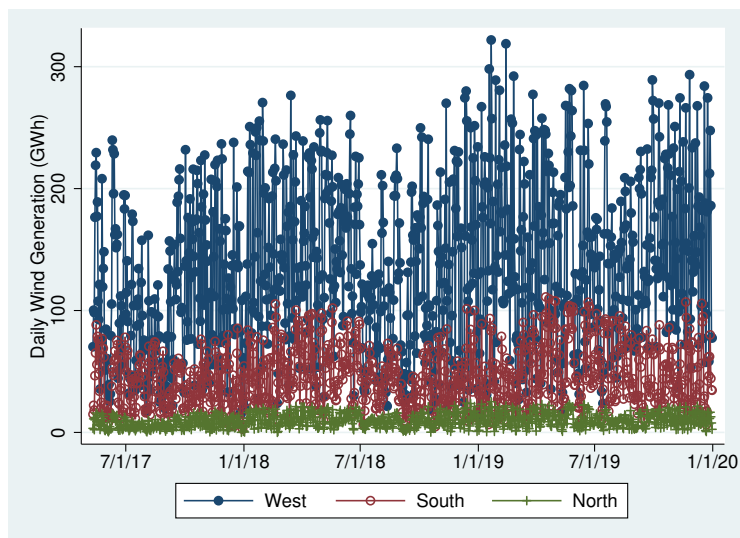
Notes: The labeled regions West, North, South, and Houston make up the ERCOT geographic footprint and designate the four primary load zones of ERCOT (source: ERCOT, <http://www.ercot.com/news/mediakit/maps>).

Figure 2: Texas Wind Farms and Coal Plants in 2016



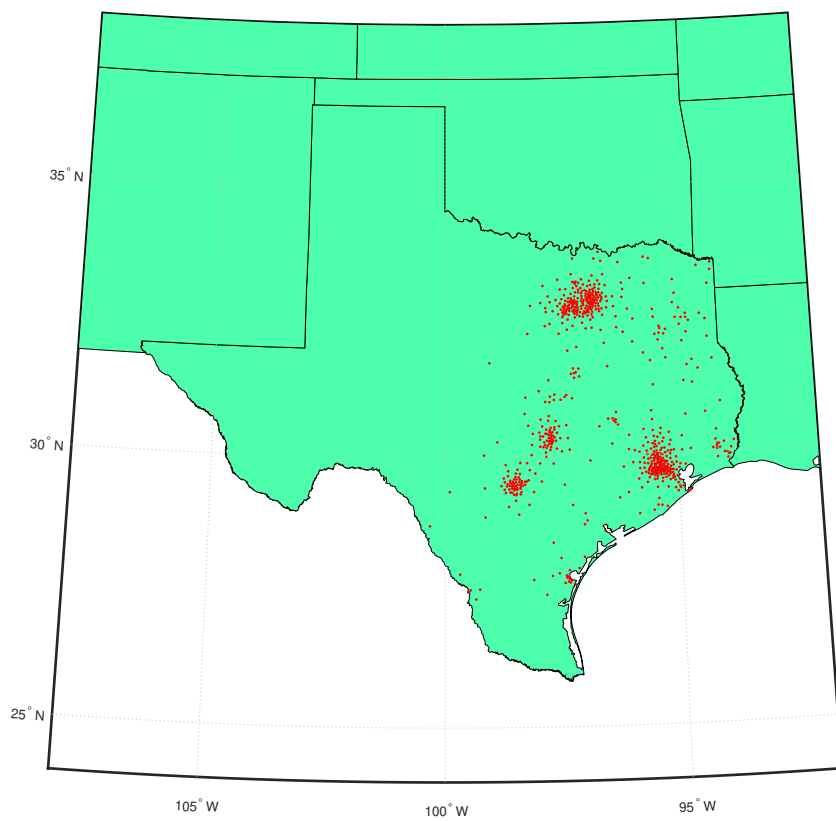
Notes: Panel (a) plots the location of the wind farms in Texas as of the end of 2016 and panel (b) plots the plant locations of facilities with coal-fired generation (source: Energy Information Agency Form 860).

Figure 3: ERCOT Zonal Wind Generation



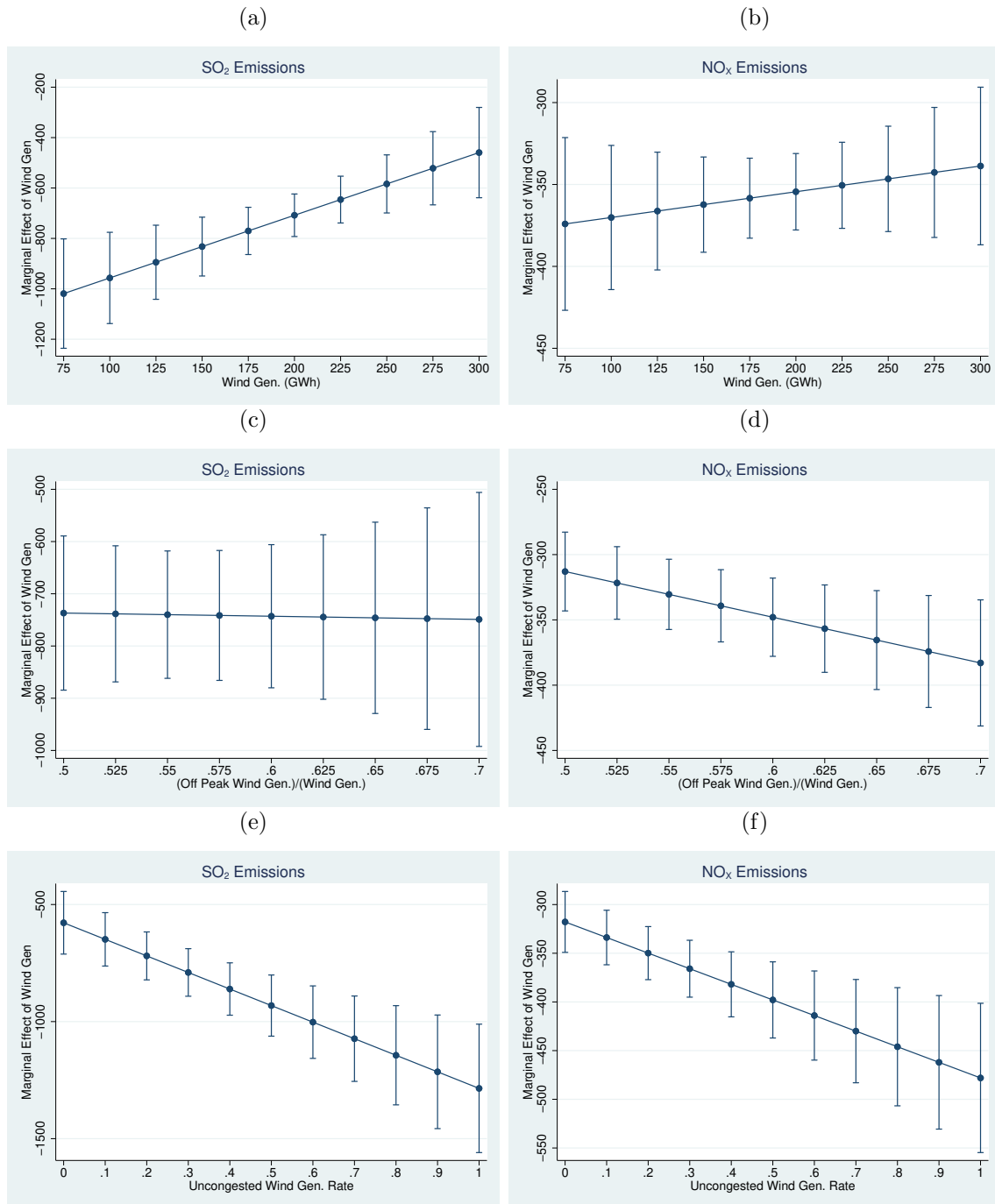
Notes: The plots are of daily sum of hourly wind generation by ERCOT Load Zones shown in Figure 1 as provided by ERCOT (<http://www.ercot.com/gridinfo/generation>).

Figure 4: Included ZCTAs



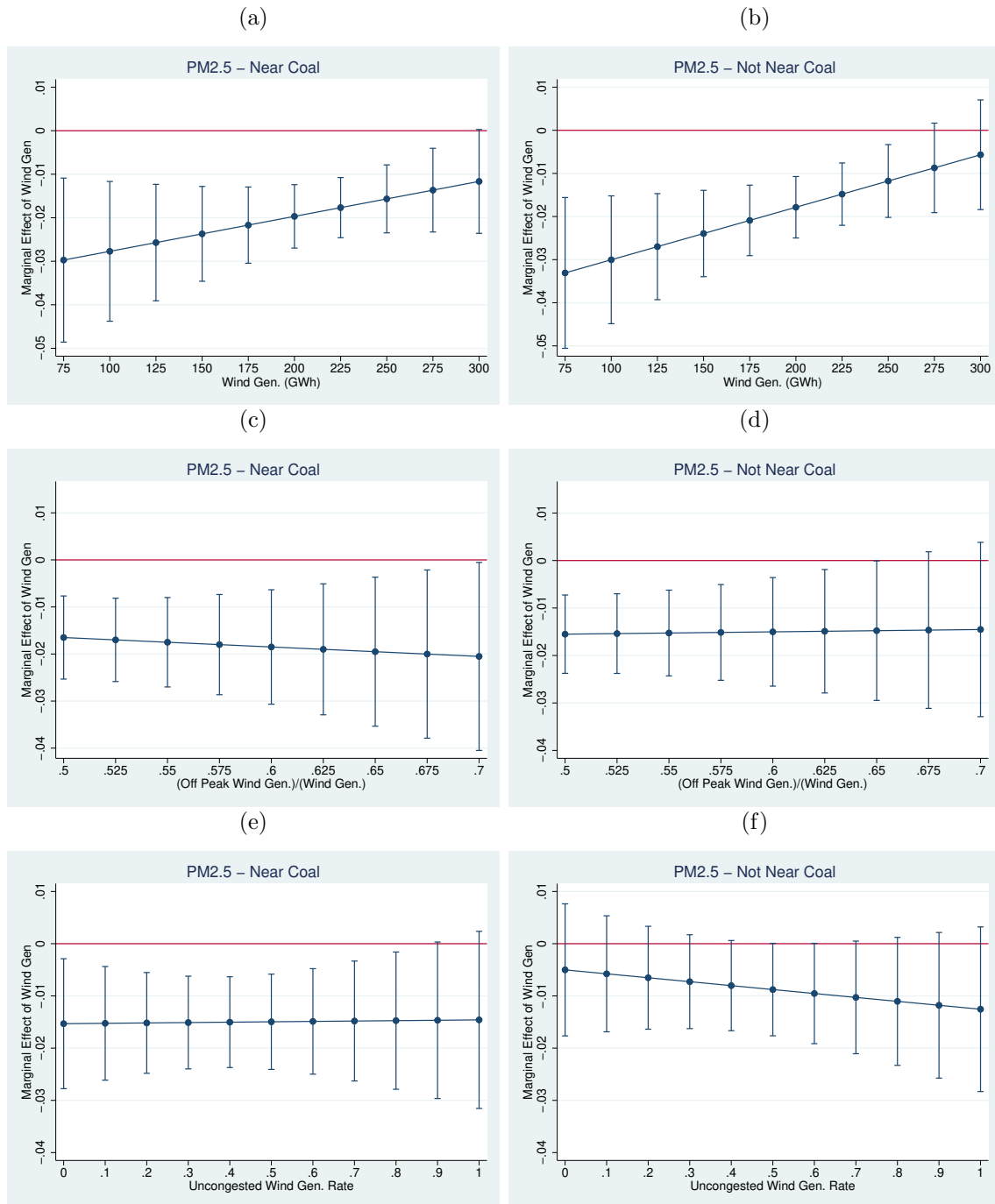
Notes: Each dot represents the centroid of a ZCTA included in the sample of the main specifications.

Figure 5: Emissions Marginal Responses



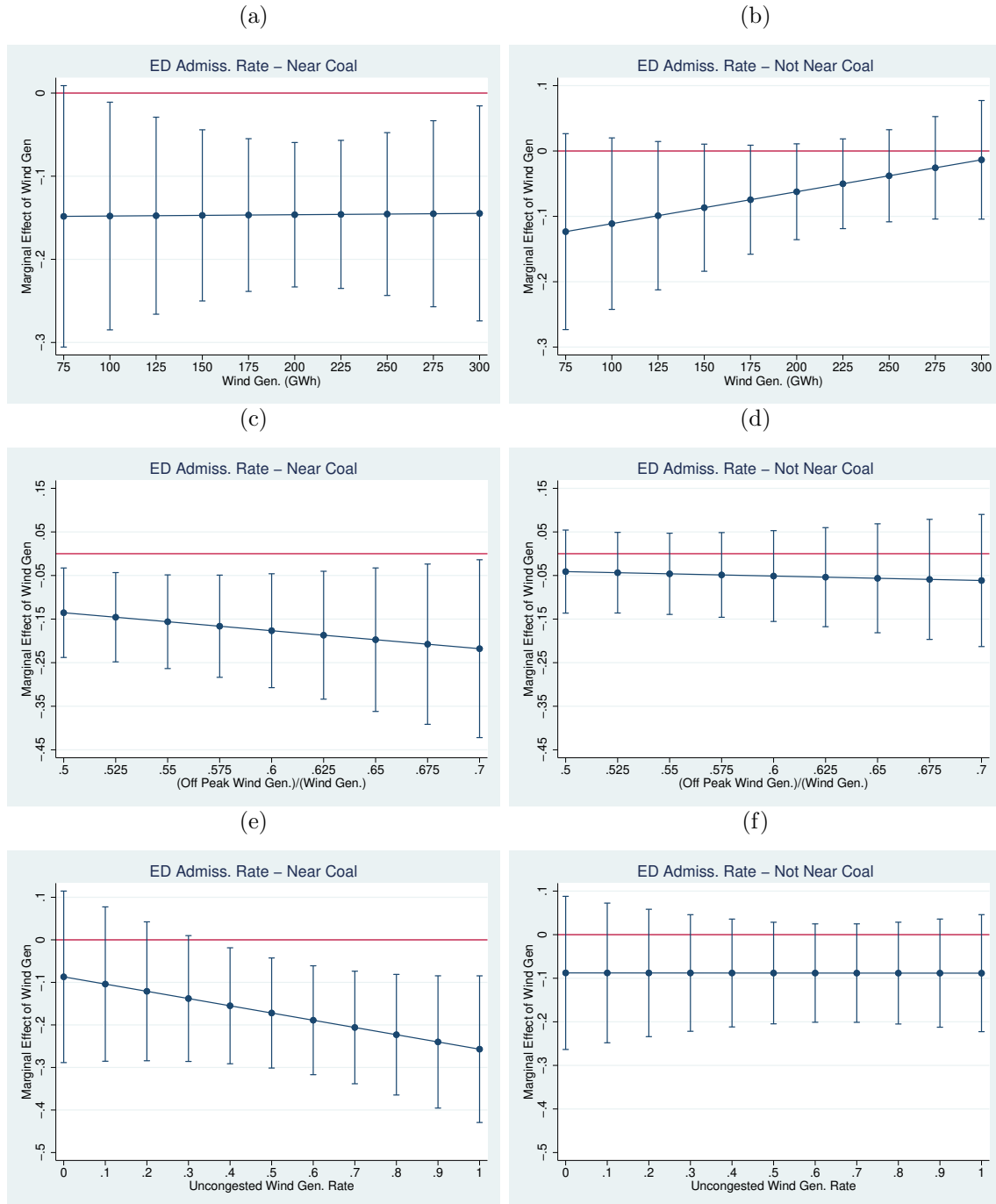
Notes: This figure plots the marginal response with respect to wind generation of emissions from power plants not in the West Load Zone of ERCOT for pollutants listed at the top of each sub-figure. Subplots correspond to parameter estimates from Table A.5. Point estimates are represented by the dots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

Figure 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 A.6 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.

Figure 7: ED Admission Rate Marginal Responses



Notes: This figure plots the marginal response with respect to wind generation of ED admission rates for the cohort with age ≥ 65 and based on “More Related” diagnosis codes. Subplots correspond to parameter estimates from Table A.7 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.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
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
Air Quality and Emissions Variables					
PM2.5	485025	16.24	10.10	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)	973395	0.987	2.772	-11.302	10.584
E/W Wind (m/s)	973395	-0.534	1.496	-9.714	11.061
Wind Speed (m/s)	973395	2.990	1.498	0.003	11.728
Precipitation (mm)	973395	0.088	0.299	0	11.239
Relative Humidity	973395	14.34	0.169	13.37	14.65
Boundary Layer (m)	973395	654	270	61	1674
Wet Bulb Temp	973395	352	12	305	371
ED Admission Rates (per 1m population)					
Total	973395	999	565	0	10275
Total Age \geq 65	973395	1475	931	0	16000
More Related Age \geq 65	973395	1266	853	0	16000
Resp. & Circ. Age \geq 65	973395	417	457	0	12000
Less Related Age \geq 65	973395	209	298	0	6000

Notes: Age-group specific ED admission rates are based on that age group's population. "Total", "More Related", and "Resp. & Circ." refer to hospitalization rates for the cohort aged 65 or older based on all admission codes, all admission codes less likely to be associated with air quality, and a admission codes related to respirator and circulatory diagnosis codes, 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. "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. 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.

Table 2: Generation and Emission Effects

	Coal	NGCC	NGGT	SO ₂	NO _x
Wind	-0.22*** (0.010)	-0.64*** (0.009)	-0.14*** (0.009)	-743.1 (47.0)	-458.5 (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

Notes: 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. “SO₂” 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.

Table 3: Air Quality and ED Admission Rate Effects

Panel A: Average Effect					
	PM2.5	Total	More Related	Resp. & Circ.	Less Rel.
Wind _{t-1}	-0.018*** (0.00345)	-0.100** (0.0409)	-0.0930** (0.0373)	-0.0376* (0.0200)	.0078 (0.0068)
Panel B: Allowing “Near Coal Capacity” Effect					
	PM2.5	Total	More Rel.	Resp. & Circ.	Less Rel.
Wind _{t-1}	-0.017*** (0.00355)	-0.063** (0.0380)	-0.0630* (0.0380)	-0.0313 (0.0205)	0.0014 (0.0075)
Wind _{t-1} * 1(Coal Cap ≤ 30)	-0.002 (0.00170)	-0.089*** (0.0333)	-0.089*** (0.0317)	-0.019 (0.0129)	-0.0278*** (0.0101)
Panel C: Allowing “Near Generating Coal” Effect					
	PM2.5	Total	More Rel.	Resp. & Circ.	Less Rel.
Wind _{t-1}	-0.0173*** (0.00356)	-0.0119 (0.0444)	-0.0165 (0.0399)	-0.0159 (0.0219)	.0032 (0.0078)
Wind _{t-1} * 1(Coal Cap ≤ 30)	-0.000106 (0.00258)	0.0372 (0.0416)	0.0652* (0.0350)	0.0194 (0.0158)	-0.0262** (0.0118)
Wind _{t-1} * 1(Coal Gen ≤ 30)	-0.00135 (0.00126)	-0.206*** (0.0226)	-0.205*** (0.0195)	-0.0503*** (0.0113)	-0.0013 (0.0074)
Obs	485,025	973,395	973,395	973,395	973,395

Notes: *, **, *** 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. “Total”, “More Rel.”, “Resp. Circ.”, and “Less Rel.” refer to the dependent variable used and are the daily ED admission counts by ZCTA for patients aged 65 or older based on all admission codes, all admission codes minus admissions codes deemed less affected by air quality, respiratory and circulatory codes, and those codes likely less related to air quality, respectively. 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 4: Lead and Lag Length Sensitivity

	PM2.5	Total	More Related	Resp. & Circ.
Wind _t	0.00371 (0.00327)	-0.0363 (0.0346)	-0.0384 (0.0307)	-0.00439 (0.0145)
Wind _{t-1}	-0.0167*** (0.00347)	-0.0470 (0.0330)	-0.0490* (0.0294)	-0.0190 (0.0156)
Wind _{t-2}	-0.00823** (0.00370)	0.0106 (0.0346)	0.0111 (0.0314)	0.0106 (0.0155)
Wind _{t+1}	0.000218 (0.00365)	0.0329 (0.0337)	0.0267 (0.0313)	0.00787 (0.0138)
Wind _{t+2}	0.00718** (0.00347)	0.0633** (0.0303)	0.0578** (0.0266)	0.0320** (0.0142)
Wind _t * 1(Coal≤30)	-0.000704 (0.00172)	-0.0287 (0.0300)	-0.0381 (0.0281)	-0.0321** (0.0155)
Wind _{t-1} * 1(Coal≤30)	-0.00313 (0.00210)	-0.0396 (0.0318)	-0.0206 (0.0281)	-0.00705 (0.0138)
Wind _{t-2} * 1(Coal≤30)	0.00217 (0.00224)	-0.0307 (0.0308)	-0.0308 (0.0259)	-0.00431 (0.0119)
Wind _{t+1} * 1(Coal≤30)	0.000334 (0.00170)	-0.00684 (0.0295)	-0.00636 (0.0273)	0.0165 (0.0151)
Wind _{t+2} * 1(Coal≤30)	-0.00361* (0.00204)	-0.0596* (0.0329)	-0.0595** (0.0270)	-0.0294** (0.0135)
Observations	483,687	972,057	972,057	972,057

Notes: "PM2.5" is a measure of daily average PM2.5 concentrations. "Total", "More Related", and "Resp. Circ." refer to the dependent variable used and are the daily ED admission counts by ZCTA for patients aged 65 or older based on all admission codes, all admission codes minus admissions codes deemed less affected by air quality, and respiratory and circulatory codes, respectively. *, **, *** 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 (or county), year-by-month, and day-of-week fixed effects controls, controls for N/S and E/W wind speeds and other meteorological controls, and weather-zone load at t , $t - 1$, and $t - 2$ levels.

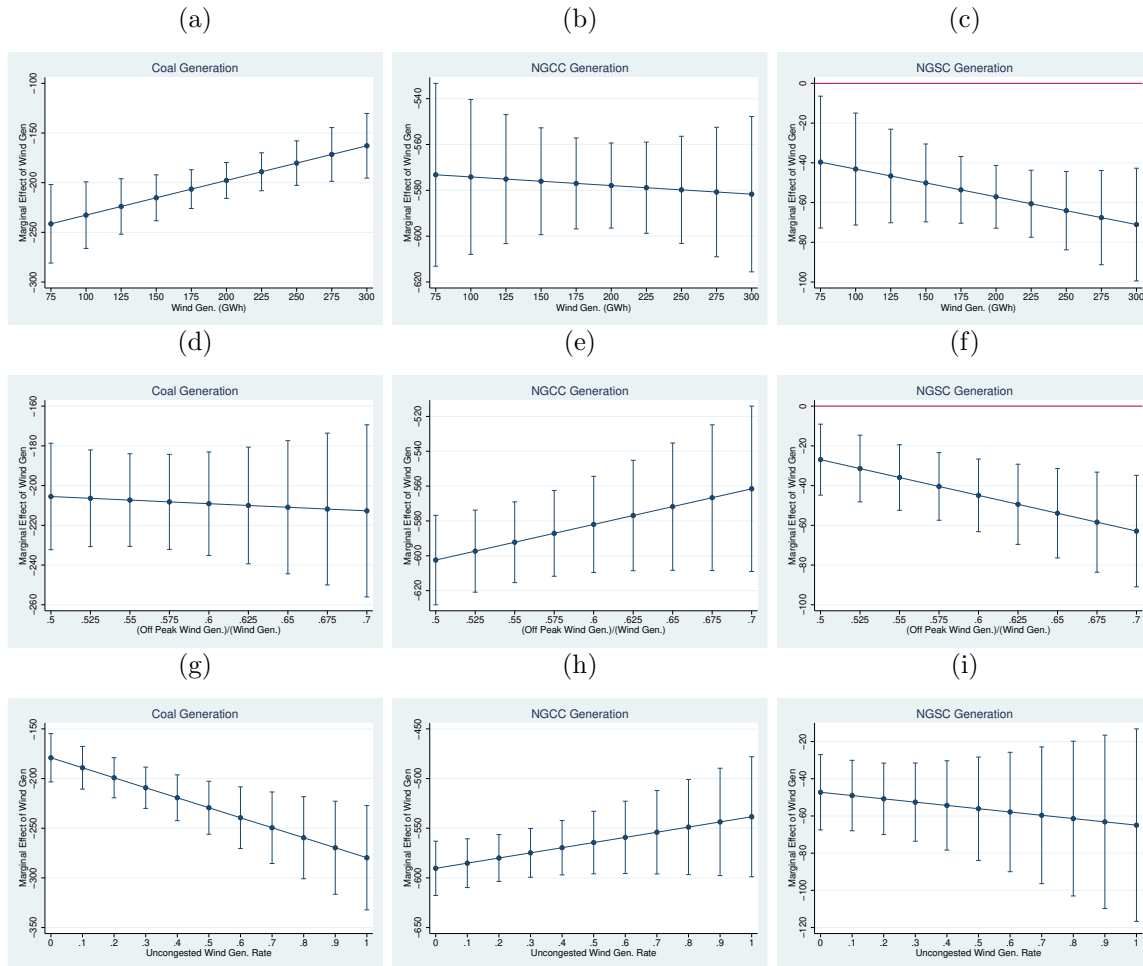
Table 5: In-Patient and Out-Patient Results

Panel A: Average Effect						
	Tot-OP	Tot-IP	Rel-OP	Rel-IP	RC-OP	RC-IP
Wind _t	-0.0674*** (0.0250)	-0.0329 (0.0251)	-0.0635*** (0.0220)	-0.0302 (0.0232)	-0.0192* (0.0113)	-0.0166 (0.0128)
Panel B: Allowing “Near Coal” Effect						
	Tot-OP	Tot-IP	Rel-OP	Rel-IP	RC-OP	RC-IP
Wind _t	-0.0317 (0.0250)	-0.0300 (0.0268)	-0.0374* (0.0215)	-0.0278 (0.0246)	-0.0154 (0.0111)	-0.0141 (0.0138)
Wind _{t-1} * 1(Coal ≤ 30)	-0.105*** (0.0321)	-0.00975 (0.0149)	-0.0763*** (0.0268)	-0.00847 (0.0141)	-0.0104 (0.0107)	-0.00672 (0.00842)
Obs	973,395	973,395	973,395	973,395	973,395	973,395

Notes: *, **, *** 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. “OP” and “IP” designations signify out-patient and in-patient admissions, respectively. “Tot”, “Rel”, and “RC” refer to ED rates for the cohort aged ≥ 65 based on all admission codes, all admission codes minus admissions codes deemed less affected by air quality, and respiratory and circulatory codes, respectively. 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.

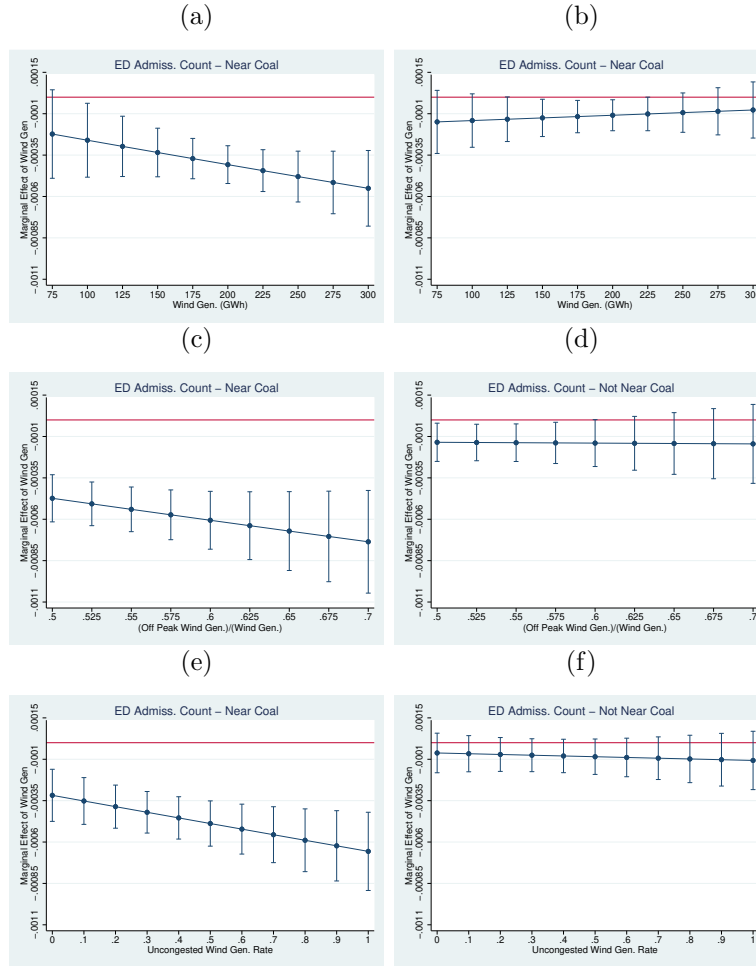
A Appendix Tables and Figures

Figure A.1: 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 A.4. Point estimates are represented by the dots with vertical lines representing the 95% confidence intervals.

Figure A.2: ED Admission Count Marginal Responses



Notes: This figure plots the marginal response of ZCTA-level, daily ED admission counts for "More Related" diagnosis codes as estimated via a Poisson pseudo-likelihood regression. Subplots (a) and (b), (c) and (d), and (e) and (f) are derived from parameter estimates in columns (1), (2), and (3), respectively, of Table ???. Point estimates are represented by the dots with vertical lines representing the 95% confidence intervals.

Table A.1: Fixed Regressors Results

	Total	More Rel.	Resp. & Circ.	PM2.5
Wind _{t-1}	-0.0554 (0.0416)	-0.0563 (0.0374)	-0.0180 (0.0201)	-0.0179*** (0.00356)
Wind _{t-1} *1(Coal ≤ 30)	-0.0780** (0.0370)	-0.0635** (0.0313)	-0.0231* (0.0122)	-0.00279 (0.00170)
Precip _t	-48,310*** (5,161)	-42,679*** (4,563)	-11,326*** (1,871)	-1,473** (737.2)
Wet Bulb Temp _t	1.812*** (0.436)	1.972*** (0.380)	0.530*** (0.184)	0.280*** (0.0633)
BLH _t	0.0208** (0.0106)	0.0138 (0.00935)	0.00263 (0.00416)	-0.00833*** (0.00154)
North _t	0.00253 (0.00316)	0.00330 (0.00299)	0.00355** (0.00158)	8.25e-05 (0.000392)
North Central _t	-7.28e-05 (0.000251)	-6.98e-05 (0.000242)	-0.000124 (0.000117)	-1.32e-05 (2.63e-05)
South _t	-0.00162*** (0.000576)	-0.00165*** (0.000618)	-0.000578 (0.000356)	-0.000116* (6.40e-05)
South Central _t	-0.000135 (0.000398)	2.06e-05 (0.000374)	-6.27e-05 (0.000205)	-5.64e-05 (4.22e-05)
East _t	0.000131 (0.00224)	-0.000110 (0.00211)	-0.000146 (0.000916)	0.000150 (0.000206)
Coast _t	0.000954*** (0.000185)	0.000851*** (0.000174)	0.000282*** (8.06e-05)	4.59e-05* (2.43e-05)
West _t	-0.00220 (0.00338)	-0.00229 (0.00300)	0.000378 (0.00163)	0.000377 (0.000305)
Far West _t	-0.00246 (0.00165)	-0.00241* (0.00143)	-0.00197*** (0.000736)	-0.000144 (0.000162)
Observations	974,064	974,064	974,064	485,025
R ²	0.265	0.254	0.171	0.438

Notes: *, **, *** 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”, “More Rel.”, and “Resp. Circ.” refer to the dependent variable used and are the daily ED admission counts by ZCTA for patients aged 65 or older based on all admission codes, all admission codes minus admissions codes deemed less affected by air quality, and respiratory and circulatory codes, respectively. In addition to the variables shown, all specifications also include month-by-year, day of week, and ZCTA (or county for the AQI-dependent-variable specification) fixed effects and lagged ($t - 1$) values of all variables show above.

Table A.2: Hospital Admission Rate Effects: All Ages and Age \leq 5

	All Ages			Age \leq 5		
	Total	More Rel.	Res. & Cir.	Total	More Rel.	Res. & Cir.
Wind $_{t-1}$	-0.0283 (0.0206)	-0.0335* (0.0189)	-0.0075 (0.0132)	0.0943 (0.0736)	0.0879 (0.0708)	-3.97e-05 (0.0438)
Wind $_{t-1}$ *1(Coal \leq 30)	-0.0261* (0.0154)	-0.0102 (0.0129)	0.00518 (0.00939)	-0.109** (0.0526)	-0.0781 (0.0487)	0.0204 (0.0260)
Observations	973,395	973,395	973,395	973,395	973,395	973,395

Notes: *, **, *** 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. “Total” refers to specifications with ED admission rate dependent variables using all ED admissions for either all ages (“All Ages”) or for those patients five and under (“Age \leq 5”). “More Rel.” refers to specifications with dependent variables of ED admission rates for individuals admitted either in-patient or out-patient excluding those admitted with diagnosis codes likely unrelated to air quality. “Res. & Cir.” refers to dependent variable specifications based on admissions with diagnosis code classified as respiratory or circulatory conditions. All specifications include ZCTA or county, year-by-month, and day-of-week fixed effects. Additional controls are selected using the post-double LASSO selection procedure.

Table A.3: Poisson Regression Results - Base Specification

	Total	More Related	Resp. & Circ.
Wind _{t-1}	-2.05e-05*	-2.61e-05**	-1.71e-05
	(1.06e-05)	(1.13e-05)	(1.94e-05)
Wind _{t-1} *1(Coal ≤ 30)	-7.11e-05***	-7.01e-05***	-8.00e-05***
	(1.39e-05)	(1.49e-05)	(2.59e-05)
Precip _t	-33.74***	-34.35***	-27.05***
	(2.225)	(2.380)	(3.922)
BLH _t	-7.74e-06**	-1.07e-05***	-1.14e-05*
	(3.72e-06)	(3.99e-06)	(6.87e-06)
Wet Bulb Temp _{t-1}	0.00408***	0.00450***	0.00367***
	(0.000214)	(0.000229)	(0.000391)
Observations	974,064	974,064	974,064

Notes: 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. Additional controls include contemporaneous and lagged ZCTA-level precipitation, boundary layer height, relative humidity, wet-bulb temperature, windspeed, weather-zone load, N/S wind speed by 3-digit zip codes, and month-by-year, day-of-week, and ZCTA fixed effects.

Table A.4: Heterogeneous Effects: Generation

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

Notes: The dependent variable for each specification 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 A.5: Heterogeneous Effects: Emissions

	SO ₂	SO ₂	SO ₂	NO _x	NO _x	NO _x
Wind _{t-1}	-1,205*** (167.5)	-1,165 (953.3)	-568.5 (466.4)	-385.9*** (40.86)	-705.4*** (254.6)	-163.0 (109.2)
Wind _{t-1} ²	1.243*** (0.404)	1.279 (2.634)	-1.998 (1.379)	0.0786 (0.101)	1.583** (0.678)	-0.879** (0.356)
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$		716.6 (446.9)			127.6 (239.0)	
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$		-2.976** (1.255)			-0.537 (0.651)	
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$			0.289 (0.564)			0.167 (0.130)
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$			-0.003* (0.0016)			-0.001** (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

Notes: 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 A.6: Heterogeneous Effects: PM2.5

	(1)	(2)	(3)
Wind _{t-1}	-0.0422*** (0.0130)	0.00743 (0.0774)	0.000567 (0.0235)
Wind _{t-1} ²	6.09e-05** (2.98e-05)	-6.34e-05 (0.000223)	-1.39e-05 (4.86e-05)
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$		-0.0928 (0.145)	
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$		0.000244 (0.000426)	
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$			-0.0770** (0.0327)
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$			0.000173** (8.16e-05)
Wind _{t-1} *1(Coal ≤ 30)	0.00646 (0.00846)	0.0147 (0.0484)	-0.0309** (0.0122)
Wind _{t-1} ² *1(Coal ≤ 30)	-2.07e-05 (1.90e-05)	-8.06e-06 (0.000117)	5.15e-05** (2.50e-05)
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$ *1(Coal ≤ 30)		-0.00578 (0.0845)	
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$ *1(Coal ≤ 30)		-4.80e-05 (0.000216)	
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$ *1(Coal ≤ 30)			0.0645*** (0.0211)
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$ *1(Coal ≤ 30)			-0.000140*** (4.81e-05)
Observations	485,025	485,025	485,025

Notes: 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 A.7: Heterogeneous Effects: ED Admissions Rate

	(1)	(2)	(3)
Wind _{t-1}	-0.160 (0.106)	-0.350 (0.536)	-0.411 (0.380)
Wind _{t-1} ²	0.000244 (0.000217)	0.00101 (0.00168)	0.000627 (0.000692)
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$		0.475 (1.020)	
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$		-0.00161 (0.00330)	
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$			0.446 (0.572)
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$			-0.00134 (0.00129)
Wind _{t-1} * 1(Coal ≤ 30)	0.0105 (0.102)	0.383 (0.659)	0.354 (0.349)
Wind _{t-1} ² * 1(Coal ≤ 30)	-0.000236 (0.000247)	-0.000901 (0.00199)	-0.000859 (0.000681)
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$ * 1(Coal ≤ 30)		-0.654 (1.174)	
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Off}}}{\text{Wind}_{t-1}}\right)$ * 1(Coal ≤ 30)		0.000959 (0.00375)	
Wind _{t-1} * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$ * 1(Coal ≤ 30)			-0.524 (0.494)
Wind _{t-1} ² * $\left(\frac{\text{Wind}_{t-1}^{\text{Uncong}}}{\text{Wind}_{t-1}}\right)$ * 1(Coal ≤ 30)			0.00106 (0.00114)
Observations	973,395	973,395	973,395

Notes: The dependent variable for all specifications is daily, ZCTA-level ED admission rates (per 1 million residents) for “Relevant” diagnosis codes. *, **, *** 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.

B Data Sample Description

In this section, we describe how our sample is formed and 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. Note while we have ED data for all of 2019, for the specifications using ED-related data, we exclude the last four days of the 2019 (resulting in 1457 days) to reduce the likelihood that we keep an ED visit that lasts longer than X days, which is likely a miscoded visit.

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. These cuts results in a sample of 669 ZCTA’s. Thus, the entire sample analyzed includes 974,733 observations (669×1457). However, this number is reduced as we allow for lagged controls.

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 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 973,395 (669×1455).

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 cohort 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 contemporaneous and lagged and in levels and squared, interacted with various 3-digit ZCTA identifiers. When also allow the treatment to vary for those ZCTAs 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, 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. After accounting for lagged controls and the exclusion of the days at the end of 2019, we have 725 sample days with PM2.5 readings over 669 ZCTAs for a total of 485,025 observations.