Wiring America: The Short- and Long-Run Effects of Electricity Grid Expansion*

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Abstract

According to the Net-Zero America study, the US needs to triple its electricity grid to decarbonize by 2050 (Larson et al. 2021). This paper examines the impact of large-scale grid expansion on price-cost markups and emissions from fossil fuel generators in the short-run and wind investment in the long-run. I focus on the rollout of a grid expansion project that linked windy areas in west Texas to population centers in the east. I find moderate declines in markups and emissions with total annual benefits of roughly $100 million. Counties that received investment in transmission infrastructure saw significantly higher wind capacity (+202%) in the long-run, preventing $271 million worth of carbon emissions in 2019. However, since the grid expansion in 2014, growing wind investment and fixed transmission capacity has led to higher wind curtailments near these counties. This could reduce the potential gains from transmission expansion.

JEL Classifications: L11, Q40, Q41, Q53.
Keywords: Electricity Markets, Emissions, Market Power, Transmission Expansion, Wind Energy

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1 Introduction

The US is headed towards rapid electrification and decarbonization in the coming decades in order to combat climate change. A key step in ensuring the success of these endeavors is massive investment in power grid expansion. This is because most wind and solar farms in the US are located far from where electricity is consumed. High capacity transmission lines enable moving this electricity over long distances to the demand centers. Investment in transmission lines is therefore crucial to support the growing renewable capacity and achieve ambitious energy policy targets. [1]

Inadequate transmission capacity not only impedes integration of electricity from renewable sources but also enhances the market power exerted by fossil fuel generators (Borenstein et al. 2000; Joskow and Tirole 2005). The resulting welfare loss due to market power and the forgone benefits from lower emissions can be in the order of hundreds of millions of dollars annually (Woerman 2019; Fell et al. 2021). I add to the empirical evidence on this issue by analyzing the short-run impact of grid expansion on price-cost markups, local and global emissions from fossil fuel generators. The main innovation of my approach is to study the market and non-market impacts under a common empirical framework which allows me to compare the potential benefits from these two channels.

Another implication of grid expansion is the higher investment in renewable resources in the long-run. However, any analysis to quantify this is plagued by endogeneity due to non-random siting of electricity transmission. Exploiting the rich spatial and temporal data from the rollout of a large scale transmission expansion project called Competitive Renewable Energy Zones (CREZ) in Texas, I provide first causal estimates in the economics literature on the magnitude of long term investment in wind energy in response to transmission expansion.

For the short-run analysis, I build a model of optimal bidding to understand how transmission line expansion affects the incentives of a marginal fossil fuel generator to set markups. This model is most closely related to Ryan (2021) who derives the optimal bidding condition for a fossil fuel generator and applies it in the context of the Indian

1. This issue has been covered widely in both energy and popular news outlets, pointing out the imminent necessity to build transmission lines in order to dramatically cut carbon emissions and achieve ambitions energy goals (New York Times 2016; Temple 2017; Meyer 2021). Figure E1 shows the locations of all solar and wind projects ($\geq$10 MW) and the county level population density.

electricity market. I extend this model by including a renewable sector which is connected by the demand centers through electricity transmission lines. I write this model in the context of a uniform auction wherein the generator participates by bidding the price and quantity of electricity. I specifically focus on the case of the marginal generator since its optimal bid determines the wholesale price. While the theoretical model is tailored to the empirical context in Texas, the findings are applicable to other regions in the US where transmission expansion would integrate renewable resources to the grid.

The model yields several predictions on how large scale transmission expansion affects the marginal generator's markups. In the short-run, transmission expansion integrates additional wind to the grid which in turn affects markups in two ways. First, the extent to which wind generation displaces production from fossil fuel generators at the margin. Second, the degree to which integration of wind affects the slope of the electricity dispatch curve at the margin. The relative magnitudes and directions of these two effects determine whether the marginal generator sets higher or lower markups.

From the theoretical model, I derive a two-step relationship between transmission expansion and markups set by a marginal generator. I use a fixed effects model which flexibly controls for electricity demand and seasonality to estimate the empirical analogues of this estimator. In the first step, I estimate the effect of transmission expansion on hourly wind generation, followed by estimating the effect of wind generation on hourly markups. I find that CREZ expansion led to a moderate decline in markups, with the magnitude of reduction greatest at periods of high wind generation. Counterfactual analysis suggests that CREZ led to a $44 million annual reduction in rents collected by marginal generators from consumers of electricity in the short-run.

I use the empirical framework above to study the impact of CREZ expansion on hourly emissions across different regions of Texas. I find a decline in emissions in the order of $54 million annually with about 60 percent of the decline due to local pollutants (SO_2 and NOx) and the remaining share from lower carbon emissions. While the value of damages prevented from carbon emissions is similar across different regions in Texas, the decline in local pollutants comes mainly from the west. Further, the results show an increase in emissions due to ramping up of coal generators at the margin as a result of wind intermittency during the early hours of the day.

Next, I estimate the extent to which investment in transmission spurs investment in wind generation in the long-run. The identification challenge is that locations with superior wind quality were selected to site CREZ lines. I implement Coarsened Exact Matching to address the selection issue. I match the counties on a wide range of pre-treatment observable dimensions that affected both selection into CREZ and investment in wind. These observables include geographic suitability, county demographics, factors affecting project costs, county specific wind regulation, and pre-grid expansion wind capacity. Therefore, conditional on matching counties on these characteristics, selection into CREZ is 'as good as' random.

Regressions using the matched sample suggest that counties that received transmission infrastructure saw 73 MW (+202%) higher wind capacity, 40 more turbines (+245%), and about 33 MW (+121%) bigger wind projects over 2012 to 2019. Back of the envelope calculation shows that this wind capacity prevented approximately $271 million in damages from carbon emissions in Texas in 2019. This highlights the long-run value of investment in transmission expansion, an understudied topic in economics.

These short-run and long-run effects have important implications for wind curtailments in Texas.[2] I provide descriptive evidence that CREZ led to significant reduction in wind curtailment by integrating wind in the short-run. However, wind farms near CREZ counties saw higher curtailments in the long-run compared to wind farms in other regions as a result of localized investment in wind energy. This could lead to low market prices and decrease the value of renewable investment in these regions. Therefore, policy makers should consider these long term responses while planning for transmission expansion in order to avoid grid congestion and prevent the erosion of short-run gains from transmission expansion.

The findings on markups and emissions highlight the role of utility scale energy storage and careful siting decisions. These could mitigate the rise in emissions due to wind intermittency during early hours of the day. This would be beneficial in preventing damages from emissions especially in more populated regions. Energy storage can be

2. Wind curtailment is defined as the reduction in electricity generated from a wind generator below the level that it could have produced given available resources (Bird et al. 2014).

instrumental in reducing wind curtailment during periods of high wind and fossil fuel markups at peak hours when wind generation is low.

Related Literature. This study builds on the insights from several sets of papers. First, it adds to the extensive literature on the incidence and consequences of market power in wholesale electricity markets. Studies focused on electricity markets post deregulation have found market power contributing to high wholesale prices (Borenstein et al. 2002) and misallocation due to sub-optimal bidding behavior (Hortacsu and Puller 2008; Hernández 2018). Existence of market power in sequential electricity markets is found to result in price premium across markets by causing lack of arbitrage (Saravia 2003; Borenstein et al. 2008; Ito and Reguant 2016). Several studies have highlighted the role of financial arbitrage (Borenstein et al. 2008; Birge et al. 2018; Mercadal 2018), vertical structures, and forward contracting in mitigating market power (Bushnell et al. 2008).

Second, I contribute to the growing literature focusing on the value of transmission infrastructure in mitigating market power in electricity markets. Theoretical studies in this area employ Cournot models and simulations to show how expansion in transmission capacity leads to higher competition and mitigates the effects of market power (Borenstein et al. 2000; Joskow and Tirole 2000, 2005). Recent empirical literature has looked at the welfare effects of geographical integration in electricity markets (Davis and Hausman 2016) and the effects of transmission constraints in exacerbating the market power exercised by generating firms (Woerman 2019; Ryan 2021). I make theoretical and empirical contributions to this literature by writing an auction based model of a price setting fossil fuel unit, and estimating the empirical analogues of the relationship between grid transmission and markups as derived from the model.

Third, this paper adds to the nascent literature looking at the link between transmission expansion, wind energy, and the wholesale electricity prices. This builds upon the empirical literature in economics exploring the impact of renewable generation in lowering emissions in the power sector (Cullen 2013; Kaffine et al. 2013; Novan 2015; Fell and Kaffine 2018; Fell and Johnson 2021). Recent papers find that CREZ led to significant reduction in wholesale market prices (LaRiviere and Lu 2020), congestion risk and the cost of hedging (Doshi and Du 2021). Fell et al. (2021) study how CREZ expansion enhanced the environmental value of wind measured by emissions avoided. Finally, along with Gonzales et al. (2022), this paper is amongst the first in economics to quantify the investment in renewable energy in response to transmission expansion.

Outline. The remainder of this paper is organized as follows. Section 2 describes the institutional context along with the CREZ expansion project. I provide a description of the data and some descriptive statistics in Section 3. The theoretical model for the short-run, empirical strategy, and the results are presented in Section 4. The long-run analysis is presented in Section 6. Section 7 discusses the implications of short- and long-run responses on wind curtailment. Section 8 provides a concluding discussion and policy implications of the results.

2 Institutional Details

2.1 The Texas electricity market

The Texas electricity market is one of the major deregulated electricity markets in the US. Electric Reliability Council of Texas (ERCOT) is mandated to maintain system reliability and manage the wholesale and retail electricity markets in Texas. One of the tasks of ERCOT is scheduling supply from generators in order to meet demand for electricity at all times. It does so by organizing a series of sequential auctions and real-time market operations. In this paper, I focus solely on the real time-market decisions by fossil fuel generators.

Even though the ERCOT interconnection spans a single state geographically, it overlooks over 46,500 miles of electricity transmission and 700 generators serving electricity demand from over 26 million consumers.[3] As of 2020, Natural Gas represented about 51 percent of electricity generating capacity followed by 25 percent by wind and 13.4 percent by Coal (ERCOT 2021). In terms of emissions, in 2019 power sector contributed to about 212.4 million metric tonnes of CO_2 emissions in 2017, about 12.3 percent of the total CO_2 emissions from the power sector in the US (EIA 2019). Clearly, Texas is an important context to study the behavior of fossil fuel generators and their environmental impact.

3. The ERCOT interconnection is comprised of six zones within Texas - Panhandle, West, North, South, Houston, and Coastal. Figure E2a provides a sense of geographic distribution of counties in these zones.

Figure 1 shows the distribution of all the utility scale wind projects and fossil fuel generators ($\geq$ 10 MW) in Texas along with the five major demand centers - Houston, Austin, Dallas, Forth Worth, and San Antonio. Most of the wind farms in Texas are located in the wind rich Panhandle and West. Most of the fossil fuel capacity and major demand centers are located in the East and South of Texas. The Texas electricity market is connected by a network of over 46,500 miles of transmission lines that carried about 74,820 MW of electricity at a record peak demand on August 12, 2019 (ERCOT 2021).[4]

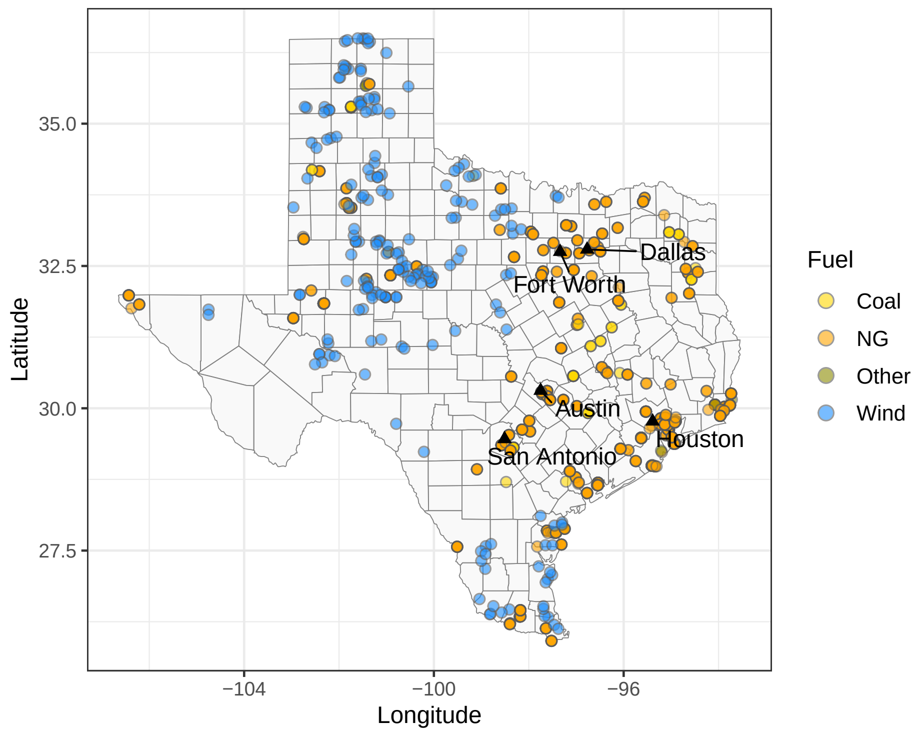


Figure 1: Utility scale wind farms and fossil fuel generators ($\geq$ 10 MW) in Texas

Note: 'NG' refers to Natural Gas generators. 'Other' fuel type includes petroleum, blast furnace gas, and other gas based generators. These generators are only 2 percent of total generators in Texas. Black triangles mark the locations of the five biggest population centers in Texas.

4. To put this in perspective, this amount of electricity is equivalent to powering about 15 million Texas homes during periods of peak demand (ERCOT 2021).

2.2 Competitive Renewable Energy Zones

In an electricity market, generating units are scheduled to dispatch in an increasing order of electricity generating costs. Thus, conditional on wind flow, wind based generators are always scheduled to dispatch first, followed by fossil fuel units. Natural gas generators are typically dispatched to meet any sudden surge in demand at Peak hours.[5] Inadequate transmission capacity between the west and other parts of Texas could lead to transmission congestion thereby preventing the trade of electricity from wind rich west to demand centers in the east and the south. Presence of transmission constraints would cause ERCOT to schedule electricity from local generating units that are typically fossil fuel fired fired generators. This not only leads to emissions that could have been offset by clean wind based electricity but also incentivize local fossil fuel generators to charge a markup over their marginal cost of production. [6]

I examine this phenomenon under the backdrop of a recent transmission expansion project, Competitive Renewable Energy Zones (CREZ) in Texas. CREZ was a large scale transmission expansion project aimed at integrating electricity generation from wind farms located in West to the major demand centers in North, South, and Houston Zones. The project, commissioned in 2008 by the Public Utilities Commission of Texas

5. ERCOT defines Peak hours as hours ending in 07:00 to 22:00 from Monday through Friday. The remaining hours are classified as Off-Peak hours. Wind based generators and low marginal cost fossil fuel generators are usually the base-load units whereas Natural Gas units are typically used to meet peak demand because of their ability to ramp-up at low cost at short notice.

6. Following example illustrates how inadequate transmission can prevent ERCOT from dispatching the cost effective generating units and incentivize them to exercise market power. Consider two regions- A and B. Region A consists of low cost generators that can provide up to 100 MW of electricity and region B consists of high cost generators that can also provide 100 MW of electricity. However, Region A and B are connected by a transmission line that can carry only 50 MW of electricity. Suppose at some time t there is a demand for 80 MW of electricity in region B by households. ERCOT as the planner, would like to dispatch all of the 80 MW from low cost generators in Region A. However, due to the transmission limit it can only dispatch 50 MW. At this point, the transmission constraint between A and B is said to be binding or there is transmission congestion between A and B. To meet the remaining demand, ERCOT has to dispatch 30 MW of electricity from high cost generators located in region B. Thus, presence of transmission constraints leads to dispatch of higher cost generators when the demand could have been met by low cost generators. Since electricity demand is fairly inelastic in the short-run, high cost generators could exercise market power by charging a price for electricity that is well above their marginal cost of generation. Note that the dispatch of electricity in reality is more complicated since the flow of current follows Kirchhoff's Laws. This example abstracts from such real life aspects in order to illustrate the impact of transmission constrains on generator dispatch.

was aimed to accommodate over 18.5 GW of electric power by building about 3,600 circuit miles of 345 kV electricity transmission lines. However, the transmission lines are open access meaning that the use is not limited to only wind generators (Billo 2017). Transmission lines were built over a period of 2011 through 2013 with a total cost of approximately $6.8 billion. All of the CREZ based transmission lines were brought in service by December 2013 (Lasher 2014).[7]

3 Data and Descriptive Statistics

I assemble multiple datasets with varying temporal resolution. For the short-run analysis of generator markups, I assemble a hourly generator level dataset from 2011 through 2014. For the long-run analysis on wind investment, I construct an annual dataset of wind projects from 2001 through 2019. Most of my data comes from publicly available sources like ERCOT, the Energy Information Administration (EIA), and the Environmental Protection Agency (EPA).

3.1 Markups

One of the main outcomes of interest for the short-run analysis is the generator markups. Markups are defined as $p - c$ where p is the Locational Marginal Price (LMP) and c is the marginal cost. LMP is defined as the price of supplying 1 MWh of electricity at a particular location. I use publicly data available from ERCOT to identify the price setting (marginal) generators and the corresponding LMP at each hour of the sample. The other component of markup is the marginal cost of generation. The generating technology assumes constant marginal cost of generation since fuel costs remains constant. The assumption of constant marginal costs is also common in the literature. The two major components of marginal cost are fuel costs and emissions permit costs based on emissions regulations for SO_2 and NOx. I calculate the marginal cost of each generator as the sum of these two components.

To compute fuel costs, I use weekly price data for coal and natural gas. For coal, I use Powder River Basin spot prices from EIA. For natural gas, I use Henry Hub Natural Gas prices from Quandl. I calculate fuel costs by multiplying fuel price and the heat rate

7. Figure E2b in Appendix shows the location of CREZ transmission lines along with the county level population.

(HR_i) of the generator.[8] I use hourly electricity generation data at the generator level from ERCOT and heat input data from EPA's Continuous Emissions Monitoring system (CEMS).

To compute the emissions permit costs, I use daily data on NOx and SO_2 allowances from S&P Global Market Intelligence. Using hourly emissions data from CEMS, I calculate the emissions rate (ER_i) for SO_2 and NOx by taking the ratio of emissions to net generation.[9] The generator's emission permit cost is thus the product of the permit price and emissions rate for each emission type. Thus, the marginal cost c_{it} of generator i in period t is:

$$c_{it} = \mathrm{HR}_{it} \cdot p_t^{\mathrm{fuel}} + \mathrm{ER}_{it}^{\mathrm{SO}_2} \cdot p_t^{\mathrm{SO}_2} + \mathrm{ER}_{it}^{\mathrm{NO}x} \cdot p_t^{\mathrm{NO}x} \tag{1}$$

Figure 2 shows the distribution of marginal costs ($/MWh) of coal and natural gas generators in the sample. The distribution of marginal cost for both the fuels is right skewed with the averages below $25/MWh for both the fuel types. The average marginal cost for coal generators is slightly higher than that of natural gas generators.

Table 1 reports descriptive statistics of key variables by fuel type. Each observation in the sample is a generator-hour combination. About 70 percent of the observations in the sample are natural gas generators and the coal generators are the remaining 30 percent. Even though the marginal cost of coal generators is on average $6.3/MWh higher than the marginal cost of natural gas generators, the average markups set by marginal natural gas generators is about four times that of the coal generators. This is reflective of the pattern of generator dispatch in the Texas electricity market wherein coal generators tend to be at the margin during the night and early hours of the day whereas natural gas generators operate at the margin during the peak demand hours. Thus, marginal natural gas generators have greater incentives to set high markups during peak demand hours.

8. EIA defines heat rate as the amount of energy used by a power plant to produce 1 KiloWatthour (kWh) of electricity. It is calculated as a ratio of fuel input to net electricity generated and is expressed in British thermal units (Btu) per net kWh.

9. Due to Clean Air Act (CAA) electricity generators are subjected to emissions regulations for SO_2, NOx or both. Generators are required to purchase emission permits for each ton of emissions (SO_2 and NOx) they emit.

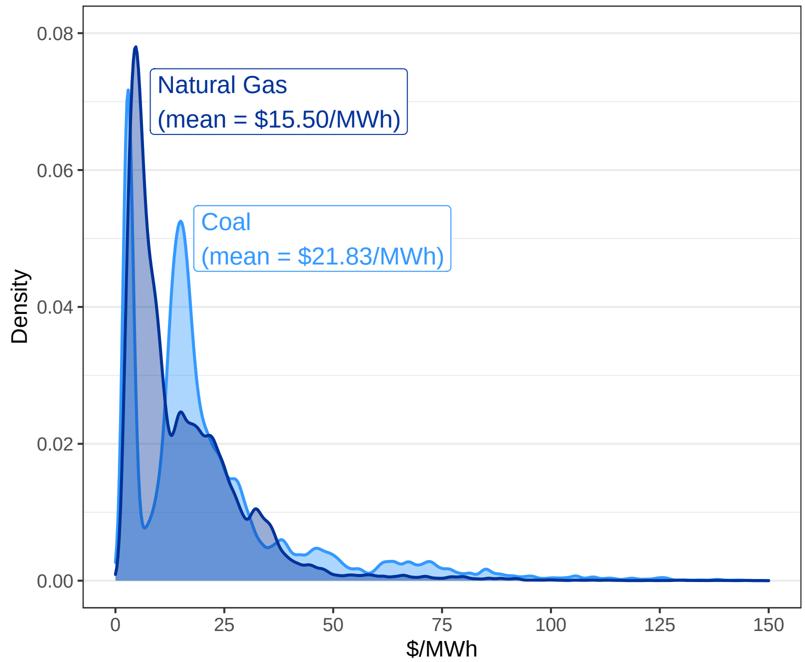


Figure 2: Distribution of marginal costs ($/MWh) of coal and natural gas generators

Generator markups exhibit quite a lot of hourly variation which is not apparent from Table 1. Figure 3b shows the average hourly markups of marginal generators from 2011 to 2014. From Figure 3b, we see that on an average markups were about $50/MWh during the peak hour of 16:00 in 2013 and over $30/MWh in 2011 and 2012. However, markups saw a dramatic drop in 2014 post CREZ expansion across peak hours of 14:00 to 17:00, perhaps most significant at 16:00. However, average markups show substantial hourly variation suggesting evidence of seasonality and generator idiosyncrasies.

Another key observation from Table 1 is that coal generators are much larger in capacity than natural gas generators. The average capacity of a coal generator in the sample is 602 MW wheres the average capacity of a natural gas generator is 190 MW. Further, coal generators are much more polluting than natural gas. For the ease of comparison, I present damage estimates (2020$) for CO_2 emissions, and SO_2 and NOx emissions per MWh of power generated. Damages from carbon emissions from coal generators for each MWh of electricity generated is about $79 compared to $25 from natural gas generators. Even more striking is the difference in damages from local pollutants. For each MWh of power generated, damages from NOx and SO_2 from coal generators is on average $101 higher than natural gas generators.

Table 1: Descriptive statistics of key variables by generator fuel type

Variable	Fuel	Mean	Std. Dev.	Min	Max
Marginal Cost ($/MWh)	Coal	21.83	21.04	0.82	143.78
	Natural Gas	15.50	14.22	0.00	149.85
Realized Markups ($/MWh)	Coal	4.18	31.97	−122.42	4597.90
	Natural Gas	16.58	60.40	−138.57	4899.21
Nameplate Capacity (MW)	Coal	602.37	200.99	174.60	1008.00
	Natural Gas	189.93	86.53	25.00	765.00
CO_2 damages/MWh	Coal	79.02	79.71	0.00	1375.50
	Natural Gas	24.77	27.90	0.00	4233.44
SO_2 & NOx damages/MWh	Coal	102.40	138.37	0.00	4659.02
	Natural Gas	0.76	2.87	0.00	725.97

Notes: This table presents descriptive statistics of key variables by generator fuel type. Sample is marginal generator-hour observations from August 2011 - December 2014. Total # generator-hour observations (N) is 619,864. Frequency of coal generators is 33.12% and Natural Gas generators are 66.88%. Damages (in 2020 $) computed using SCC of $44/ton for CO_2 emissions and county specific estimates from Holland et al. (2016) for SO_2 and NOx emissions.

3.2 Global and local emissions

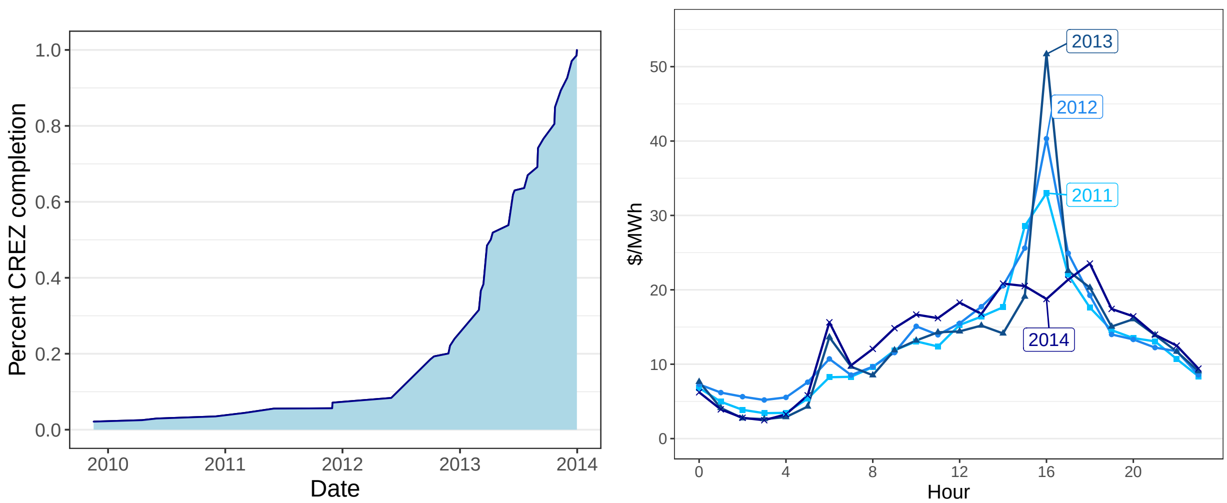
Another outcome of interest for the short-run analysis is the global (CO_2) and local (SO_2 and NOx) emissions. I use data on hourly CO_2, SO_2, and NOx emissions from fossil fuel generators from EPA's CEMS from 2011 to 2014. Since the impact of local pollutants vary across space due to differences in population densities, I use estimates of county-specific marginal damages due to additional ton of SO_2 and NOx from Holland et al. (2016).[10] I combine these county-specific damage estimates to SO_2 and NOx emissions from each generator to compute the $ value of the damages from these emissions.

3.3 CREZ Transmission Expansion

A key explanatory variable is the progress of CREZ transmission expansion. I use the publicly available Transmission Project and Information Tracking reports from ERCOT's website to construct a variable that tracks total miles of transmission lines built in a day

10. The county specific damage estimates reported in Holland et al. (2016) uses the AP2 air pollution model to capture the geographic variation in the environmental costs imposed by local pollutants.

under the CREZ expansion project. I express the CREZ progress variable as a cumulative ratio of total progress for the ease of interpretation. As shown in Figure 3a even though the CREZ started in 2010, over 80 percent of the project was completed in 2013.



(a) Daily progress of CREZ expansion.

(b) Average hourly generator markups ($/MWh) from 2011 - 2014.

Figure 3: Daily CREZ progress and generator markups over the years

Note: Figure 3a shows the cumulative share of CREZ lines (miles) completed each day from 2010 to 2014. Figure 3b shows the average hourly price-cost markups for the sample (N = 619,864).

4 Short-run: Impact of CREZ expansion on markups

4.1 Transmission Constraints and Market Power

For this analysis, I focus on the real-time electricity market which sets the expectation for prices in the day-ahead and forward markets (Potomac Economics 2019). The main purpose of a real-time market is to match supply with demand while operating the transmission system within established limits. Real-time operations involve participation from various market participants like generators, retailers, transmission service providers, and distributors. The Electric Reliability Council of Texas (ERCOT) serves as the regulatory body that manages the efficient operation of the real-time market including scheduling the dispatch of generators to meet the demand at all times.

Transmission constraints play a central role in determining the cost effective dispatch of generating resources. To understand how, it is important to recognize the role played by transmission infrastructure in electricity markets. Presence of transmission essentially enables flow of electricity between two points. Typically, generating units are located at regions far away from the demand centers. Therefore, a transmission network that is able to carry electricity from supply to demand at all times is of prime importance.

One of the main features of transmission lines is that they operate under certain capacity limits that need to be maintained. Transmission constraints between two points A and B are said to be binding when transmission lines between them operate at their maximum capacity. This is another way of saying that the transmission lines are congested. There could be various reasons for transmission congestion or binding transmission constraints, like increase in demand due to weather conditions, outages, insufficient transmission infrastructure to name a few.

How does presence of transmission constraints translate to generating firms exercising market power? Generators submit monotonically increasing offer curves which is a function of price and quantity of electricity they are willing to supply. Generators anticipate demand and transmission constraints and hence submit a bid that is composed of the marginal cost of supplying electricity and a markup term.[11] As I show in the theoretical model below, this markup term is dependent on the shape of the residual demand curve that the generator faces in the market which in turn is a function of the transmission capacity.

4.2 A Model of Optimal Fossil Fuel Markups

The theoretical model in this section aims to understand the effect of transmission expansion on the pricing decision of a profit-maximizing fossil fuel generator. I borrow elements of the merchant transmission investment model by Joskow and Tirole (2005), but extend it by including electricity generation from renewable sources. My model is based on Ryan (2021), however, I differ from it in two key ways. First, I introduce a wind generating sector which is isolated from the demand centers. Second, in my

11. In ERCOT, generators have access to demand forecasts and the information on transmission infrastructure. They use this publicly available information and any private information about the market to determine their offer curves.

model transmission expansion affects fossil fuel generators mainly by integrating electricity from the wind generating sector. This mimics my empirical setting wherein CREZ expansion impacted fossil fuel generators by integrating electricity generated by wind farms from the West. In what follows, I present the optimal markup rule for a fossil fuel generator and provide intuition on how it is affected by the transmission expansion.

4.2.1 Model Setup

Consider two geographically distinct regions $\mathcal{W}$ and $\mathcal{S}$. Region $\mathcal{W}$ is a wind rich region comprising of wind farms and region $\mathcal{S}$ is comprised of several fossil fuel generators that serve a large demand center. The presence of electricity transmission capacity (K) enables trade of electricity generated from wind in region $\mathcal{W}$ to demand centers in region $\mathcal{S}$. [12]

In this model, I focus on the pricing decision of a profit maximizing fossil fuel generator i located in region $\mathcal{S}$. Generator i submits an offer curve that is a vector of supply quantities Q_i at bid prices b_i while incurring cost $C_i(Q_i)$. The optimization problem of i entails finding the offer curve that maximizes its profit function $\pi_i(p) = p \cdot Q_i(p) - C_i(Q_i(p))$, where p is the market clearing price that resolves in $\mathcal{S}$.

However, the generator faces uncertainty over the offer schedules $\mathcal{S}_{-i} = (b_{-i}, Q_{-i})$ from other fossil fuel generators $(-i)$ in $\mathcal{S}$. Further, the generator has to consider any forward positions it has. I denote the forward price and quantity of generator as p^F and Q_i^F respectively. Therefore, the optimization problem is,

$$\max_{b_i, Q_i} \mathbb{E}_{\mathcal{S}_{-i}} \left[p \cdot Q_i(p) - C_i(Q_i(p)) + (p^F - p)Q_i^F \right] \tag{2}$$

The last term in Equation 2 is the payoff from the forward position that is resolved in the real time market. Market demand in $\mathcal{S}$ is denoted by D^S and is assumed to be perfectly inelastic.

Generator i faces a downward sloping residual demand curve $D_i^r(p, q_w; \mathrm{K})$ which is comprised of three elements: Market demand D^S; electricity generated from wind imported from $\mathcal{W}$, q_w; and the total electricity generated from competitor fossil fuel generators, $Q_f(q_w, p) = \sum_{j \neq i, j \in \mathcal{S}} Q_j(q_w, p)$. I express Q_f as a function of q_w because the

12. Figure E3 in Appendix illustrates this setup graphically.

dispatch of a fossil fuel generator depends on the amount of electricity generated by wind.[13] Recall that wind-based electricity generation incurs zero marginal cost and is always scheduled to dispatch first. $Q_f(q_w, p)$ is strictly increasing in p and strictly decreasing in q_w.[14] Mathematically, D_i^r can be written as,

$$D_i^r(p, q_w; \mathrm{K}) = D^S - q_w - Q_f(q_w, p) \tag{3}$$

The market clears when electricity generated by i equals residual demand, i.e. $Q_i(p) = D_i^r(p, q_w; \mathrm{K})$. The market clearing price p and the supply $Q_i(p, q_w)$ depend on the optimal bid price b_i that solves the generator i's problem,

$$\max_{b_i} \mathbb{E}_{\mathcal{S}_{-i}} \left[p(Q_i(p) - Q_i^F) + p^F Q_i^F - C_i(D_i^r(p, K)) \right]$$

Denote $Q_i(p, q_w) - Q_i^F$ as $Q_i^{net}(p, q_w)$. Taking first order condition with respect to b_i and rearranging,

$$\implies \mathbb{E}_{\mathcal{S}_{-i}} \left[\frac{\partial p}{\partial b_i} \left(Q_i^{net}(p, q_w) + \frac{\partial D_i^r(p, q_w)}{\partial p} \left[p - C_i'(D_i^r(p, q_w)) \right] \right) \right] \Bigg|_{p = b_i} = 0 \tag{4}$$

Equation (4) is the optimal pricing rule for generator i wherein it sets price equal to marginal cost plus a markup term. $\frac{\partial p}{\partial b_i}$ is the slope of market clearing price in the bid price and is equal to one if the bid is marginal and zero otherwise. In this paper, I focus on the case when b_i is the marginal bid and therefore determines the market clearing price. Thus, I refer to i as the marginal generator as its optimal bid sets the price. For simplicity, I assume constant marginal cost i.e. $C_i'(D_i^r(p, K)) = c_i$ and full information on other generators' strategy. Equation (4) reduces to,

$$p - c_i = -\frac{Q_i^{net}(p, q_w)}{\partial D_i^r(p, q_w) / \partial p} \tag{5}$$

Equation 5 shows that the markups are dependent on the net-production of electricity and the slope of its residual demand curve which is a negative quantity. The numerator measures the extent to which generator's production decision affects the markups.

13. I assume $D^S > q_w$, otherwise there wouldn't be any need to schedule electricity from fossil fuel generators as all of the market demand could be met by wind.

14. The interpretation of these assumptions is as follows:

1. $\frac{\partial Q_f}{\partial p} = \sum_{j \neq i, j \in \mathcal{S}} \frac{\partial Q_j}{\partial p} > 0$: generators have greater incentives to supply electricity at higher prices.
2. $\frac{\partial Q_f}{\partial q_w} = \sum_{j \neq i, j \in \mathcal{S}} \frac{\partial Q_j}{\partial q_w} < 0$: electricity generated from wind displaces a non-zero amount of electricity from fossil fuel generators.

With $Q_i^{net} > 0$, the generator is a net seller implying that it withholds output in the forward market to raise the market clearing price in the real-time market such that $p - c_i > 0$. Similarly, with $Q_i^{net} < 0$, the generator is a net buyer and pays price less than the marginal cost for the electricity generated.

The denominator which is the slope of residual demand curve determines the ability of the generator to set markups. A flatter residual demand curve implies that the generator has a lower potential to set markups whereas a steeper residual demand curve implies greater potential to set markups.

4.2.2 Predictions from the model

In order to characterize the effect of transmission line expansion (K) on markups, I perform comparative statics exercise by partially differentiating Equation (5) with respect to K,

$$\frac{\partial(p - c_i)}{\partial \mathrm{K}} = \frac{\left[-\frac{\partial Q_i^{net}(p,q_w)}{\partial \mathrm{K}} \cdot \frac{\partial D_i^r(p,q_w)}{\partial p}\right] + \left[Q_i^{net}(p, q_w) \cdot \frac{\partial^2 D_i^r(p,q_w)}{\partial p \partial \mathrm{K}}\right]}{\left[\frac{\partial D_i^r(p,q_w)}{\partial p}\right]^2} \tag{6}$$

I express Equation (6) as a percentage change in markups by multiplying both sides by the inverse of Equation (5). Algebraic simplification allows me to split the resulting expression into two terms that measure the effect of transmission line expansion on markups. I call these terms Δ*Displacement* and Δ*Slope* based on how they affect net production and slope of the residual demand curve.

$$\frac{1}{p - c_i} \cdot \frac{\partial(p - c_i)}{\partial \mathrm{K}} = \underbrace{\left[\frac{1}{Q_i^{net}(p, q_w)} \cdot \frac{\partial Q_i^{net}(p, q_w)}{\partial \mathrm{K}}\right]}_{\Delta\text{Displacement}} - \underbrace{\left[\frac{1}{\partial D_i^r / \partial p} \cdot \frac{\partial^2 D_i^r(p, q_w)}{\partial p \partial \mathrm{K}}\right]}_{\Delta\text{Slope}} \tag{7}$$

ΔDisplacement. Changes in transmission capacity K can affect the net-production by generator i causing a displacement of its residual demand curve.

$$\frac{\partial Q^{net}(p, q_w)}{\partial \mathrm{K}} = \frac{\partial Q^{net}(p, q_w)}{\partial q_w} \cdot \frac{\partial q_w}{\partial \mathrm{K}} \tag{8}$$

I summarize the intuition behind the directions of the two terms on the right hand side of Equation 8 in Propositions 1 and 2.

Proposition 1 *Transmission expansion leads to integration of electricity from wind into the grid.*

The second term in Equation (8) measures the magnitude of wind power that would be integrated to the grid in the short-run as a result of transmission expansion. Since the generating capacity of wind would remain fixed in the short-run, transmission expansion would enable higher imports of wind generation to demand centers, implying $\frac{\partial q_w}{\partial K} \geq 0$.

Proposition 2 *Integration of wind due to transmission expansion leads to a displacement of marginal generator's residual demand curve.*

The first term in Equation (8) measures the extent to which production decision of generator i is affected by addition of wind energy. Consider a hypothetical electricity dispatch curve shown in Figure 4a. The supply side assumes four fossil fuel generators indexed by their offer/bid price $c_j (j = 4)$ of supplying electricity. The dispatch curve is a step function comprised of generators arranged in an increasing order of the offer price. The dotted vertical line (D) is the demand of electricity and is assumed to be fixed. Generators are dispatched in the increasing order of the offer price until the demand is met. The generator(s) with the highest offer price that is dispatched is the marginal generator and it determines the wholesale price of electricity.[15] In the scenario below, generator i submits the highest offer price c_4 and is thus the marginal generator.

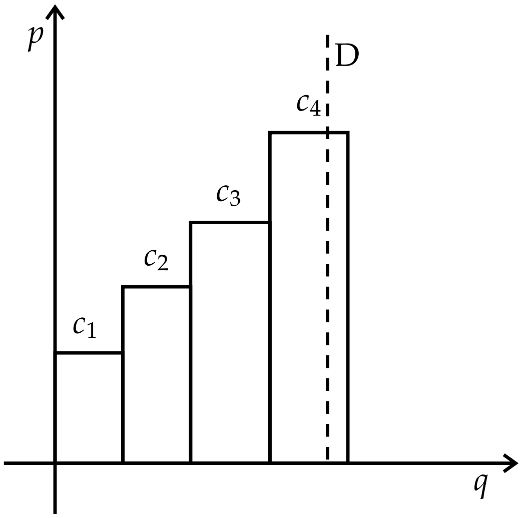
Consider the scenario in Figure 4b wherein additional wind (W) displaces electricity generated from i shown as the hashed area. Mathematically, this can be written as:

$$\frac{\partial Q^{net}}{\partial q_w} < 0 \tag{9}$$

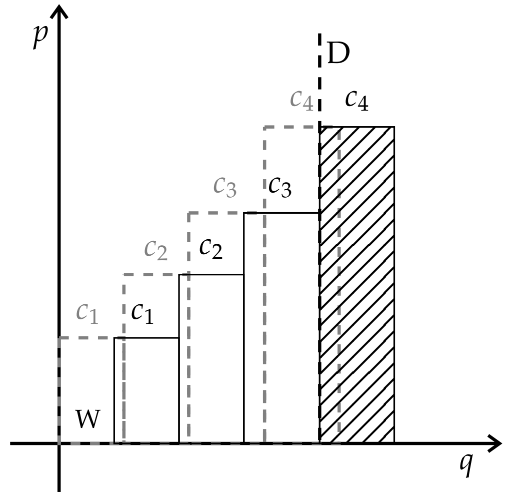
Thus, electricity from wind shifts the dispatch curve to the right, displacing power generated by the marginal generator i. This is reflected as an inward shift of i's residual demand curve which in turn reduces i's potential to set higher markups. This is shown in Figure 4c with the generator moving from point A to point B of its offer curve post wind integration. Compared to point A, point B is associated with a flatter region of the offer curve thereby reducing i's ability to set higher markups.

ΔSlope. This term measures the impact of transmission capacity (K) on the slope of marginal generator i's residual demand curve. To understand the direction of this term, I take the derivative of the slope of i's residual demand curve with respect to K. Since

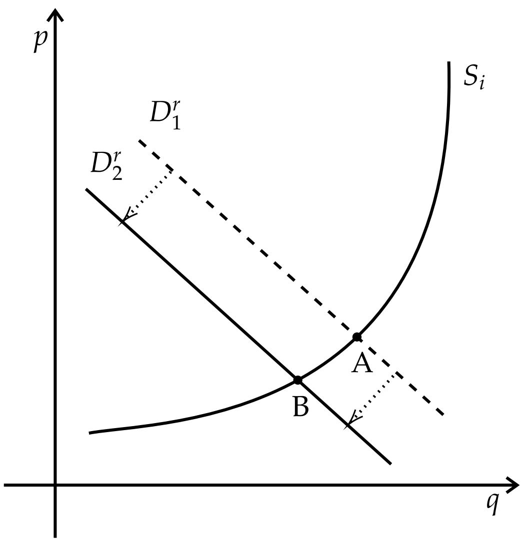
15. If there are multiple generators that have the highest offer price and are dispatched, all of them are referred to as marginal generators.



(a) Hypothetical dispatch curve



(b) Rightward shift in the dispatch curve due to additional wind (W).



(c) Shift in generator i's residual demand curve (D_i^r) due to the additional wind (W)

Figure 4: Hypothetical electricity dispatch curves and the effect of wind generation on marginal fossil fuel generator.

Note: c_i denotes generator i's offer/bid price of supplying electricity. Vertical dotted line denotes the inelastic demand for electricity (D). W is the wind integrated to the grid due to transmission expansion, and S_i denotes the supply curve of generator i.

the demand for electricity (D^S) and wind generation (q_w) are invariant to changes in p, the slope of i's residual demand curve depends only on the production decisions of its competitors. Therefore,

$$\frac{\partial^2 D_i^r(p, q_w; \mathrm{K})}{\partial p \partial \mathrm{K}} = -\frac{\partial^2 Q_f(q_w, p)}{\partial p \partial q_w} \cdot \frac{\partial q_w}{\partial \mathrm{K}}$$

Let $\eta_f = \frac{\partial Q_f(q_w,p)}{\partial p}$ (> 0) denote the slope of the aggregate (marginal) fossil fuel generators supply curve. Rearranging,

$$\frac{\partial^2 D_i^r(p, \mathrm{K})}{\partial p \partial \mathrm{K}} = -\frac{\partial \eta_f}{\partial q_w} \cdot \frac{\partial q_w}{\partial \mathrm{K}} \tag{10}$$

The slope of the generator supply curves at the margin determines the slope of the dispatch curve at the margin. Therefore, (10) shows that changes in the slope of the dispatch curve due to additional wind will affect generator *i*'s residual demand curve. This leads to the following proposition:

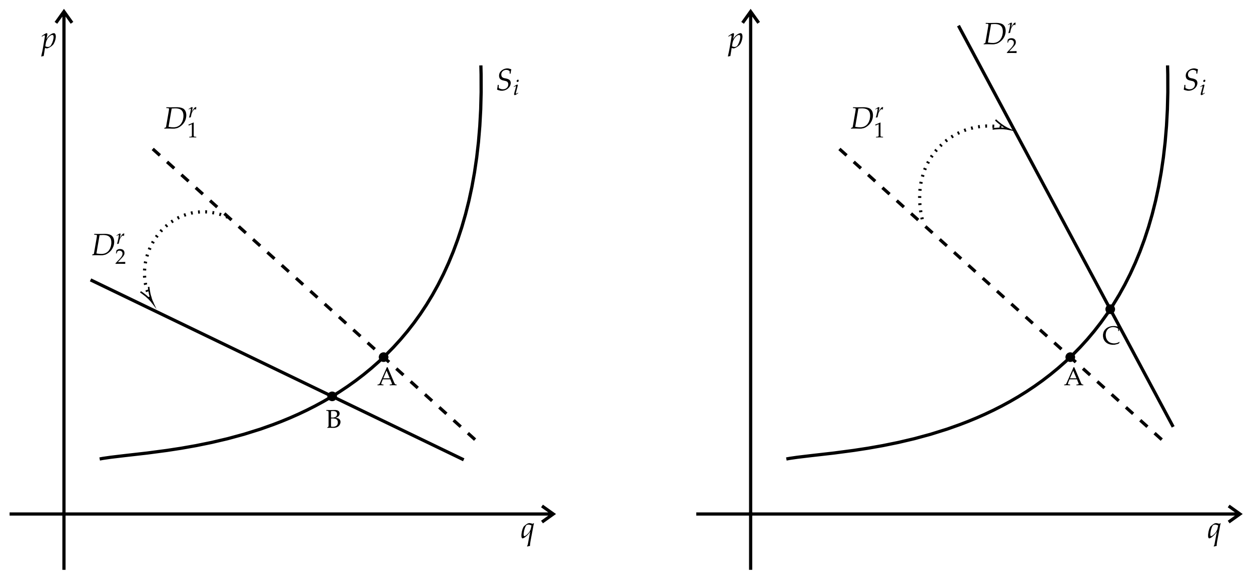
Proposition 3 *The impact of transmission expansion on the slope of the marginal generator's residual demand curve is ambiguous.*

As shown in Figure 4b, integration of wind shifts the dispatch curve to the right. Heterogeneity in the cost of electricity generation from fossil fuel sources could lead to generator(s) with steeper or flatter supply curves operating at the margin. Figure 5 shows that this would lead to the rotation of residual demand curve of generator *i*.

A flatter dispatch curve due to additional wind would result in a flatter residual demand curve as shown in Figure 5a. In this case, generator *i* moves from point A to point B which is at the more elastic region of its offer curve, thus reducing its ability to set higher markups. However, we could expect a steeper dispatch curve especially during the periods of high demand. Thus in turn would result in a clockwise rotation of generator *i*'s residual demand curve as shown in Figure 5b. In this case, the generator moves from point A to point C of its offer curve. Since point C is associated with the steeper region of the offer curve than point A, this enhances its ability to set higher markups.

Therefore, $\frac{\partial \eta_f}{\partial q_w}$ could be weakly positive or negative. This translates to Equation (10) being weakly negative or positive meaning a more inelastic or elastic residual demand curve respectively. Substituting the expressions for ΔDisplacement from Equation (8) and ΔSlope from Equation (10) in Equation (7):

$$\frac{1}{p - c_i} \cdot \frac{\partial (p - c_i)}{\partial \mathrm{K}} = \left[\frac{1}{Q_i^{net}} \cdot \frac{\partial Q_i^{net}}{\partial q_w} + \frac{1}{\partial D_i^r / \partial p} \cdot \frac{\partial \eta_f}{\partial q_w} \right] \cdot \frac{\partial q_w}{\partial \mathrm{K}} \tag{11}$$



(a) Anti-clockwise rotation of residual demand curve as a result of flatter dispatch curve at the margin.

(b) Clockwise rotation of residual demand curve as a result of steeper dispatch curve at the margin.

Figure 5: Rotation of fossil fuel generator's residual demand curve post integration of wind due to transmission expansion.

Note: D_1^r and D_2^r denote the residual demand curves of generator i pre and post transmission expansion respectively, and S_i denotes the supply curve of generator i.

Equation (11) shows that the overall effect of transmission expansion on generator i's markups can be broken down into two pieces. First is the effect of wind generation on markups represented by the two terms in the square brackets in Equation (11). Second is the effect of expansion in transmission capacity on wind generation. Equation (11) can alternatively be expressed as:

$$\frac{\partial(p - c_i)}{\partial K} = \underbrace{\frac{\partial(p - c_i)}{\partial q_w}}_{\gtreqless 0} \cdot \underbrace{\frac{\partial q_w}{\partial K}}_{>0} \tag{12}$$

Thus, the effect of transmission expansion on markups is driven by the effect of wind generation on markups and the extent to which transmission expansion integrates the electricity generated from wind. From Equation (12), $\frac{\partial q_w}{\partial K}$ simply acts as a multiplier that scales up the effect of wind generation on fossil fuel markups.

4.3 Empirical Strategy

In this section, I estimate the impact of transmission expansion (K) on fossil fuel generator markups based on the relationship between transmission lines and markups described in Equation 12. I run the following regressions to estimate the empirical analogues of Equation 12:

$$y_{it} = \alpha_h \cdot w_t + f(\mathrm{D}_t|\lambda) + \kappa_i + \delta_{hmy} + \epsilon_{it} \tag{13}$$

$$w_t = \beta_h \cdot crez_d + \gamma \cdot max_t + \eta_{hm} + \omega_t \tag{14}$$

where, y_{it} is the markup set by marginal generator i at hour t of the sample. Markup is defined as $(p-c)_{it}$ where p is the Locational Marginal Price (LMP) and c is the marginal cost of generator i at period t. Wind generation (GWh) in hour t is denoted by w_t, and $crez_d$ is the percentage completion of CREZ transmission project at day d of the sample. The parameters of interest are α_h which measures the impact of wind generation on markups, and β_h which measures the impact of transmission expansion on wind generation. Thus,

$$\alpha_h \approx \frac{\partial(p-c_i)}{\partial q_w}, \quad \beta_h \approx \frac{\partial q_w}{\partial \mathrm{K}} \tag{15}$$

I use a wide variety of controls to account for potential confounding factors in Equation 13 and Equation 14. I use a quadratic polynomial of system wide electricity demand D_t in Equation 13 to account for variation in markups driven by spikes in electricity demand.[16] In Equation 14, I use the maximum predicted generation (max_t) of electricity from wind at hour t to control for the maximum energy production possible from wind at period t. [17] This is a useful control because it not only incorporates the generating capacity and technology of the wind generator but it also takes into account the real time meteorological conditions that could affect the amount of power generated through wind farms.

As shown in Figure 6 the actual electricity generated from wind (w_t) closely tracks the maximum predicted wind generation (max_t) for each hour from 2011 to 2014. The difference between the two curves arises due to inadequate transmission capacity needed

16. Using zonal demand levels instead of system wide demand does not change the results.

17. Maximum predicted generation is technically referred to as the High System Limit (HSL) by ERCOT. HSL for a generation resource is defined as the maximum sustained energy production capability of that entity. HSL is established by the generator itself and is continuously updated in Real-Time.

to transport the power to demand centers. Therefore, this gap is the amount of wind generation curtailed by ERCOT so as to maintain grid stability. However, with the CREZ expansion in 2013 we see the gap between the maximum and actual wind generation decreasing with the lowest difference observed across all hours of 2014.

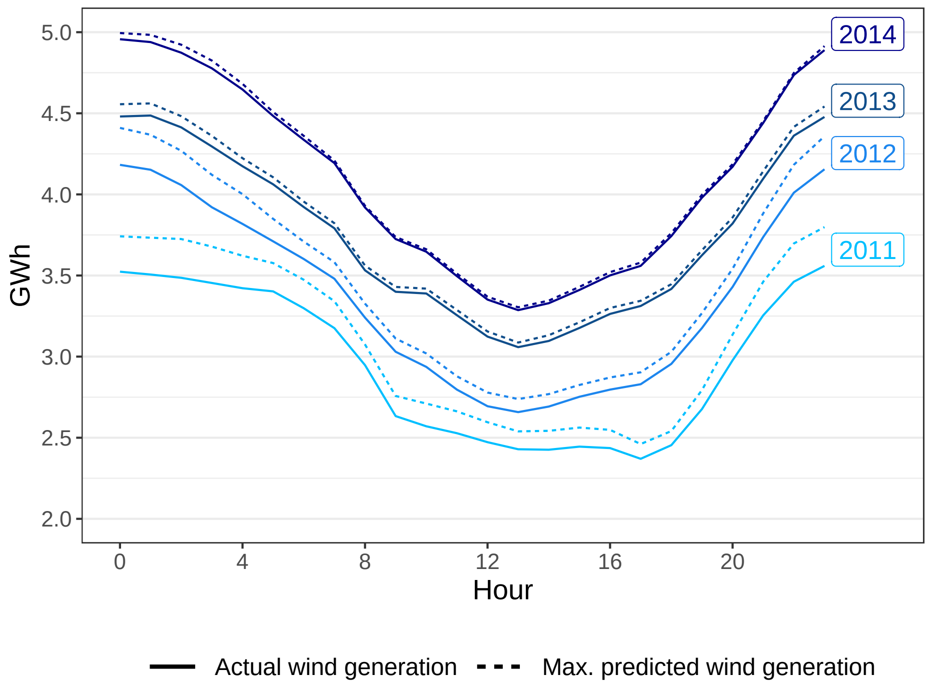


Figure 6: Hourly averages of actual wind generation (w_t) and maximum predicted wind generation (max_t) of wind generation from 2011 - 2014.

Note: max_t is the maximum energy production capability of the generator at period t. It is established by the generator itself and is continuously updated in Real-Time.

I use a battery of fixed effects to control for unobserved determinants of markups that could be correlated with wind generation. In Equation 13, I use generator fixed effects (κ_i) to control for any generator specific heterogeneity in markups. I use hour by month by year fixed effects (δ_{hmy}) to control for seasonality exhibited by the electricity market in Texas. This seasonality arises due to varying wind pattern at different hours of the day over the months in a year. For example, wind generation in Texas tends to be higher during the night than during the day. Similarly, wind flow is typically higher during the spring months than winter and summer months. Similarly, I use hour-by-month fixed effects (η_{hm}) in Equation 14 to control for seasonality in wind generation. ϵ_{it} and ω_t are the random error terms in Equation 13 and Equation 14 respectively.

The identifying variation for α_h in Equation 13 comes from the within generator variation in markups caused by changes in wind generation across hours h within a month m in a given year y. For example, α_{16} is the identified from deviations in markups from generator specific averages across all 16:00 hours within a month, in a given year. Similarly, the identifying variation for β_h in Equation 14 comes from variation in wind generation caused by daily transmission expansion across same hours in a given month.

Under the identifying assumption that the control variables and fixed effects account for confounding factors, α_h captures the unbiased effect of wind generation on generator markups and β_h is the unbiased effect of CREZ expansion on wind generation. Therefore, the estimator of the impact of CREZ on markups is, $\hat{\theta}_h = \hat{\alpha}_h \times \hat{\beta}_h$. Standard errors in Equation 13 are clustered at the generator level. I use Newey West auto-correlation corrected standard errors with a seven day lag structure for estimates in Equation 14.

4.4 Results

I first discuss the results of the effect of wind generation on generator markups in Figure 7, followed by the impact of CREZ expansion on integrating wind generation in Figure 8. Figure 7 shows the coefficient estimates ($\hat{\alpha}_h$) of the magnitude of the decrease in fossil fuel markups (\$/MWh) due to additional GWh of wind energy to the grid. We see that on average the drop in markups is strongest in magnitude at the on-peak hour of 16:00, about \$9/MWh. The coefficient estimates are smallest for the off-peak hours. Due to low electricity demand and high wind generation during the off-peak hours, fossil fuel generators typically operate on a smaller net demand curve as compared to the on-peak hours, thereby lowering their incentives to set high markups. In other words, the impact of additional wind in lowering fossil fuel markups is higher at the on-peak hours than at the off-peak hours.

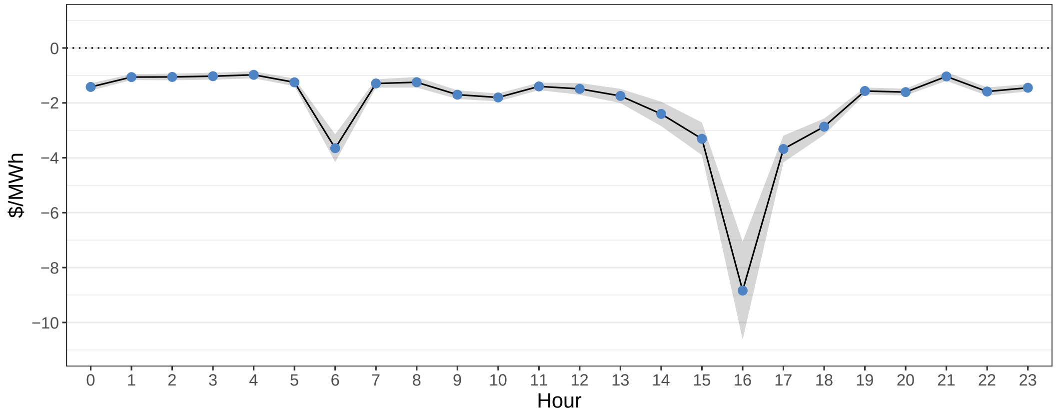


Figure 7: Coefficient estimates $(\hat{\alpha}_h)$ of the effect of addition of a GWh of wind energy on generator markups ($/MWh) and the 95 percent confidence intervals.

Figure 8 shows the impact of CREZ expansion on wind generation at each hour of the day. The effect is highest for the off-peak hours and lowest at the on-peak hours. [18] The coefficient estimates imply that keeping the stock of generating capacity fixed, CREZ integrated about 0.22 GWh of wind at 23:00 and 0:00, and about 0.10 GWh during the on-peak hours of 15:00 to 18:00. The hourly pattern of the coefficient estimates $(\hat{\beta}_h)$ closely follows the hourly wind flow pattern in Texas where the wind flow is strongest in the evening compared to the day. This reflects that availability of transmission capacity is instrumental in integrating higher levels of wind generation in the Texas electricity market.

Recall that the overall impact of CREZ expansion on markups (θ) is given by the product of the effect of wind generation on markups (α_h) and the impact of CREZ on integrating wind generation (β_h). Figure 9a shows that the drop in markups due to CREZ is strongest at 16:00, about $0.88/MWh. This is followed by 6:00 (about $0.53/MWh) which stands out from other hours in the earlier part of the day possibly because it marks the end of the off-peak hours of weekday in ERCOT. Compared to total wind power integrated at hour 0:00, CREZ only led to the integration of about half that amount at 16:00 ($\sim$ 0.10 GWh), but the subsequent drop in markups at 16:00 is about 2.5 times that at 0:00.

18. The on-peak hours in ERCOT are defined as the hours ending in 7:00 to 22:00 CPT from Monday through Friday. I use this definition to discuss the results of my analysis as well.

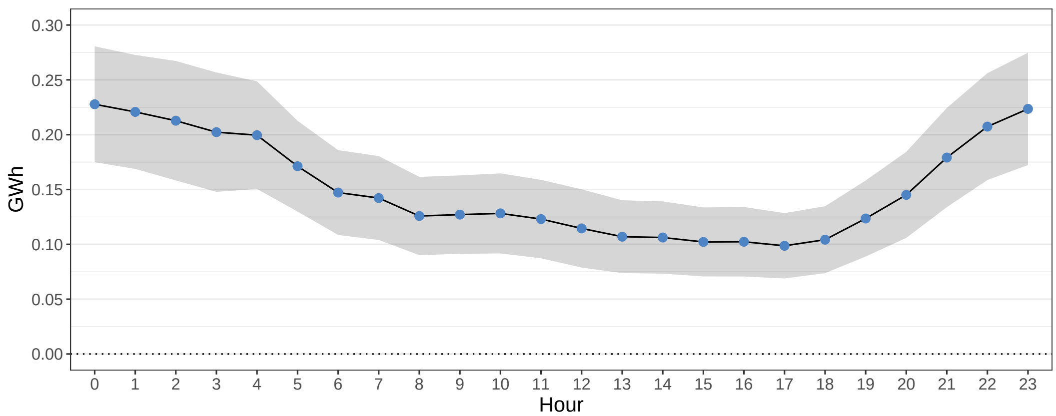


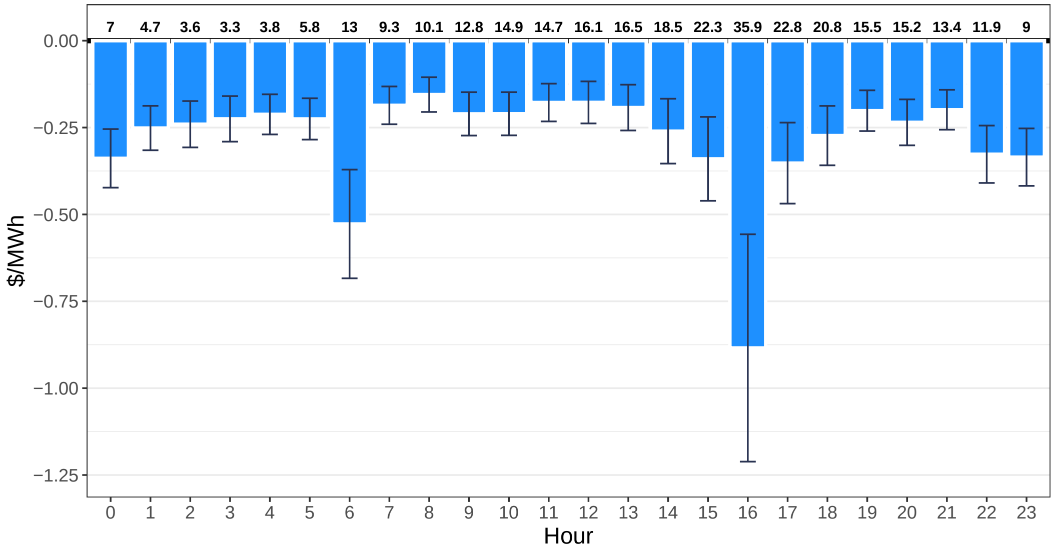
Figure 8: Coefficient estimates $(\hat{\beta}_h)$ for the effect of CREZ expansion $(crez_d = 1)$ on hourly wind generation (GWh) and the 95 percent confidence intervals.

To provide a better sense of the magnitudes of $\hat{\theta}$ in Figure 9a, I present the semi-elasticity of markups in response to CREZ expansion in Figure 9b.[19] We see a clear distinction between the semi-elasticity of markups between off-peak v.s. on-peak hours. The magnitude of the semi-elasticity is highest for hours before 7:00 with the maximum decrease of 6.8 percent at hour 3:00. However, the percentage drop in markups for the on-peak hours (7:00 to 22:00) is less than 3 percent mainly because of the lower proportion of wind added to the grid during these hours.

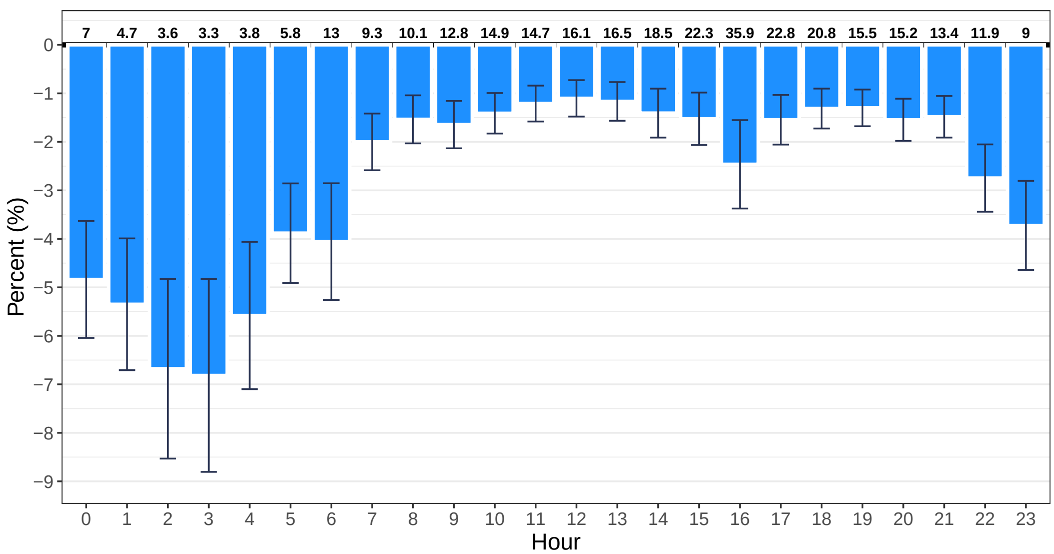
Figure 10 shows the estimates of percentage change in on-peak markups (Figure 9a) against the average wind generation in those hours. This shows the variation in the estimated impact of CREZ on markups across low and high wind generation for on-peak hours. While the point estimates remain almost stable from 2.6 GWh to 3.4 GWh of wind generation, there is a significant drop at periods of high wind. This indicates that the impact of CREZ in reducing markups is strongest when the wind generation is high. This follows from the evidence in Figure 8 that CREZ expansion led to higher integration of wind to the grid. As suggested from the theoretical model, this would in turn shrink the generator's net-demand curve thereby reducing its ability to set high markups. [20]

19. I calculate semi-elasticity values by dividing the estimates in Figure 9a with the average markup at each hour.

20. This pattern of drop in markups is true for off-peak hours as well with the similar explanation.



(a) Effect of CREZ completion ($crez_d = 1$) on markups ($/MWh) and the associated 95 percent confidence intervals.



(b) Semi-elasticity of markups for CREZ completion ($crez_d = 1$) for each hour and the associated 95 percent confidence intervals.

Figure 9: Short-run impact of CREZ expansion on realized markups.

Note: Figure 9a shows the estimates and 95 percent confidence intervals of $\hat{\theta}_h = \hat{\alpha}_h \times \hat{\beta}_h$, where $\hat{\alpha}_h$ is the hourly impact of wind generation on markups from Figure 7 and $\hat{\beta}_h$ is the hourly impact of CREZ expansion on wind integration from Figure 8. Figure 9b is the semi-elasticity estimates corresponding to Figure 9a. Average markups for the sample are shown above the x axis.

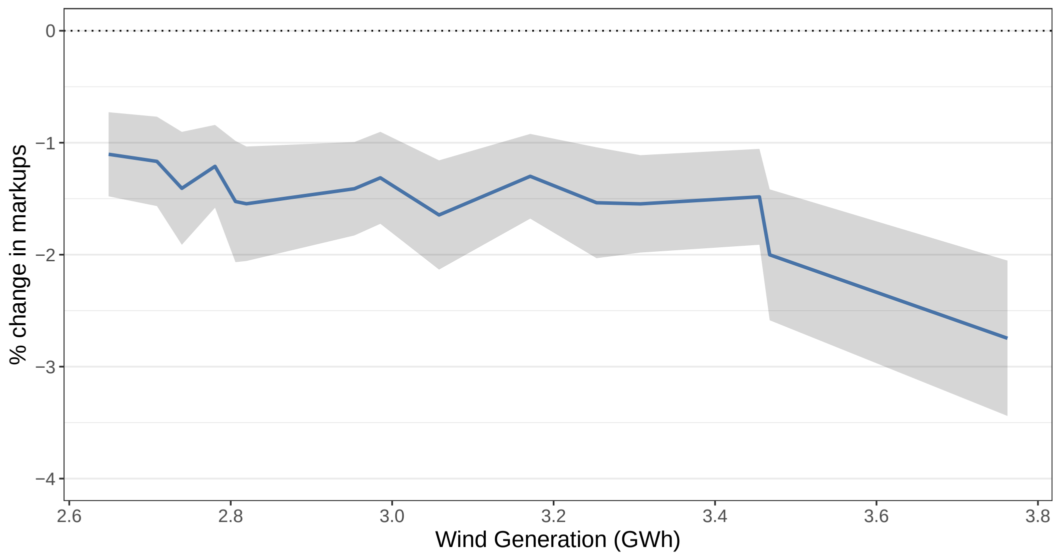


Figure 10: Percentage change in on-peak hour markups for varying levels of average wind generation

Note: This figure plots the estimates of percentage change in markups for on-peak hours (7:00 to 22:00) from Figure 9b against the average wind generation in those hours for the sample, August 2011 to December 2014.

4.5 Change in producer surplus from CREZ expansion

How do these changes in markups translate to gains or loss of producer surplus? In the short-run, marginal generators gain producer surplus in the form of excess rents from the purchasers of electricity like retailers by exercising market power. While the retail rates of electricity paid by end-use consumers remains fixed in the short-run, these excess rents are passed down from the retailers to the consumers in the long-run.

I conduct a counterfactual exercise to estimate the changes in annual rents collected by marginal fossil fuel generators due to lower markups as a result of transmission expansion. Using the parameter estimates from Equation 14, I first compute the counterfactual wind generation ($\widetilde{w}_t$) in the absence of CREZ expansion (i.e. $crez = 0$),

$$\widetilde{w}_t = \hat{\gamma} \cdot max_t + \hat{\eta}_{hm} + \hat{\omega}_t \tag{16}$$

I substitute $\widetilde{w}_t$ in the estimated Equation 13 to compute the counterfactual markups ($\widetilde{y}_{it}$) in the absence of CREZ expansion. The magnitude of increase in rents collected by generators, or more simply the change in surplus (ΔS) from the absence of CREZ expansion is:

$$\Delta S \approx \Delta(p-c) \times \widetilde{Q} \tag{17}$$

where, $\Delta(p-c)$ is the change in markups and $\widetilde{Q}$ is the power produced by the marginal generators in the absence of transmission expansion. I make two simplifying assumptions to compute ΔS. First, I assume that the gap between actual wind generation (w_t) and the counterfactual wind generation without CREZ ($\widetilde{w}_t$) is met by the power generated by marginal fossil fuel generators. In other words, this means that the wind generation integrated by grid expansion would have been met by the fossil fuel generators in the absence of the expansion. Second, I assume constant marginal costs, thus the change in markups is due to changes in the wholesale price of electricity (or LMP), for each generator. Therefore, $\Delta(p-c) = \widetilde{y}_{it} - y_{it} = p_{(\text{crez}=0)} - p_{(\text{crez}=1)}$.

I compute the total electricity produced by marginal generators without CREZ as:

$$\widetilde{Q}_t = Q_t + (w_t - \widetilde{w}_t) \tag{18}$$

where, Q_t is the observed hourly generation from the marginal generators and $w_t - \widetilde{w}_t$ measures the wind generation integrated by CREZ for each hour of the sample. For simplicity, I aggregate the generator data at the hourly level. This abstracts away from any distributional changes in the supply of electricity from generators in the absence of CREZ. Capturing these effects would require estimating the generator supply function which is beyond the scope of this paper.

The counterfactual analysis finds that marginal generators would have accrued about \$110 million over the course of my sample in the absence of CREZ expansion. Since over 80 percent of CREZ expansion occurred throughout 2013, I use counterfactual profit values from the year 2014 to measure the annual surplus changes. I find that CREZ led to approximately \$44 million annual reduction in transfers from retailers to marginal generators in the short-run and consumers of electricity in the long-run.

Note that the markup analysis only considers pricing behavior of the marginal fossil fuel generators. Thus the reduction in annual transfers is only for these marginal generators. Further this is the impact of wind integrated to the grid due to transmission expansion and not the system wide wind generation. the long-run, we expect higher wind capacity and thereby higher wind generation as a result of CREZ. Therefore, the annual benefits due to lower markups can be expected to increase as a result of higher wind capacity in the long-run.

5 Short-run: Impact of CREZ expansion on emissions

As shown in Section 4, the addition of wind to the grid would shift the electricity dispatch curve to the right. Further, the intermittent nature of wind generation is likely to affect which fossil fuel generator operates at the margin and therefore the emissions. In this section I examine how integration of wind due to CREZ expansion affected the emissions from the fossil fuel generator(s) at the margin at different hours of the day.

The closest empirical study in economics in this regard is Fell et al. (2021), where authors study how lower grid congestion as a result of CREZ enhanced the value of total wind generation measured by lower emissions. By contrast, I focus on how CREZ integrated more wind to the grid (keeping the generating capacity fixed) and the subsequent impact on emissions from marginal fossil fuel units in the short-run. The findings from this section are therefore complimentary to Fell et al. (2021).

The variation in the types of marginal generators over the course of a day makes such an analysis informative. For example, coal fired generators typically operate at the margin during the night whereas natural gas generators are the marginal units during the day since they are quicker to ramp up or down to meet any sudden changes in demand. The additional electricity from wind in the night could therefore displace high polluting coal generators from the margin with significant implications in terms of emissions. I run the following regression to estimate the impact of additional wind on marginal emissions:

$$E_{zt} = \rho_{zh} \cdot w_t + f(D_{zt,t-1}|\lambda) + \alpha_z + \delta_{hmy} + \epsilon_{zt} \tag{19}$$

where, E_{zt} is the total emissions from fossil fuel generators at the margin in zone z and w_t is the wind generation at hour t of the sample. The parameter of interest is ρ_{zh} which measures the impact of an additional GWh of system wide wind generation on the marginal emissions in zone z at hour h. I restrict my analysis to the four main load zones in Texas: West, North, South, and Houston since these contain all the marginal generators affected by wind generation added as a result of CREZ. Figure 11 shows these zones along with the geographic distribution of marginal coal and natural gas generators in the sample.

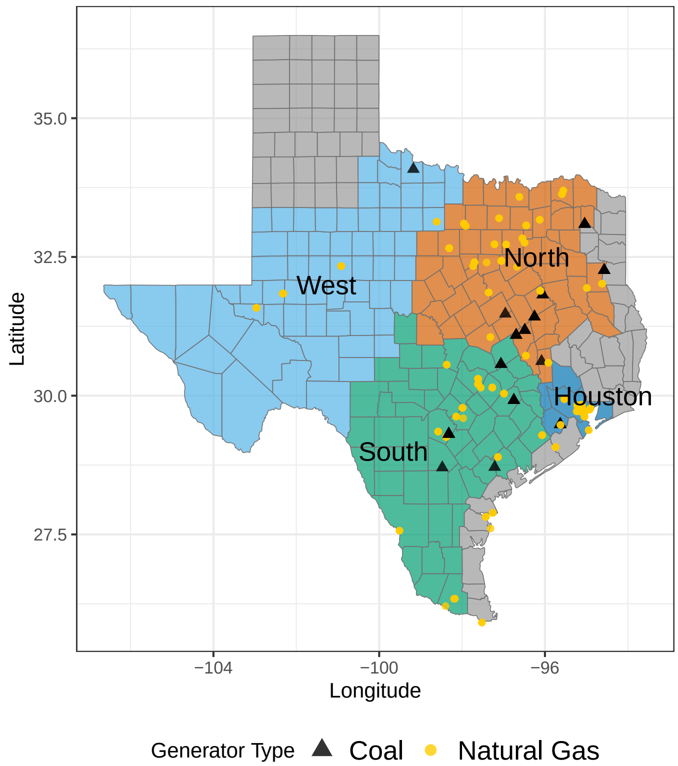


Figure 11: The four Texas zones and the locations of marginal coal and natural gas generators used in the emissions analysis

Marginal generators typically respond to changes in demand of electricity over the course of the day by ramping up or down. I use a cubic polynomial of contemporaneous and lagged demand of electricity $D_{zt,t-1}$ at the zone level to control for the variation in marginal emissions due to changes in the demand. Fixed effects δ_{hmy} control for average emission levels at hour h in month m in year y. Conditioning on these averages controls for seasonal patterns in wind generation that could also be correlated with variation in emissions. To account for baseline level of emissions across the zones, I use zone fixed effects α_z. Standard errors are clustered at the daily level to account for serial correlation.

5.1 Results

5.1.1 Impact on marginal carbon emissions

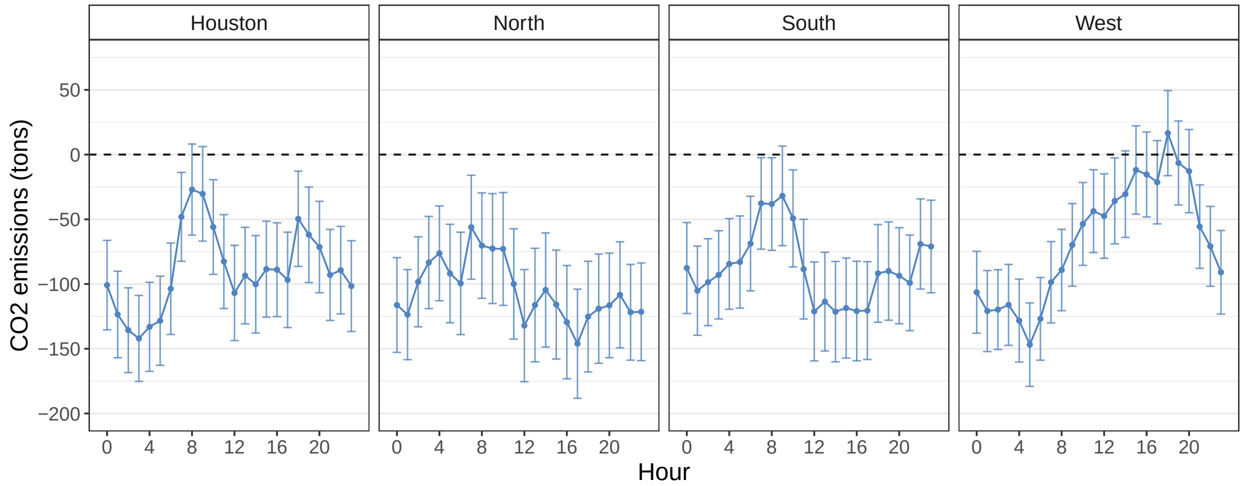
Figure 12a shows the average changes in the marginal carbon emissions (tons) for each hour of the day across the four zones in response to an additional GWh of wind energy. There is a clear decrease in emissions across all the zones throughout the day with significant spatial heterogeneity. The magnitude of decline in emissions is highest between the hours of 12:00 to 20:00 in North, South, and Houston. However, this pattern is different for the wind rich West, wherein the decline in emissions is highest at the night when the flow of wind is strongest.

The pattern in Figure 12a could be the result of the heterogeneity in the types of generators at the margin at different times of the day. To explore this, I estimate Equation 19 separately for the sample of marginal emissions from coal and natural gas. The coefficient estimates are shown in Figure 12b. Two key insights emerge. First, the hourly pattern of estimates for coal is very similar to the pattern in Figure 12a, suggesting that the carbon emissions are mainly driven by emissions from coal generators. Second, the drop in emissions from marginal natural gas generators is mostly stable and negative over the hours across all the four zones. This would shift the emissions estimates from coal downwards when aggregated by fuel type giving rise to the pattern in Figure 12a.

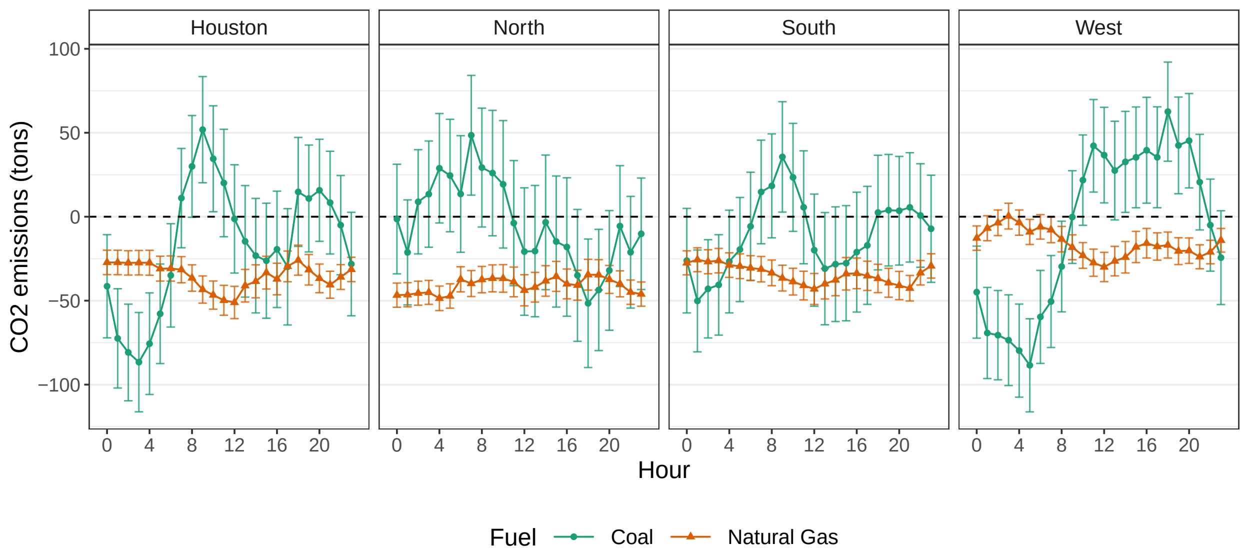
The coefficient estimates for coal generators suggests that electricity from wind has a significant effect in lowering emissions from coal generators at the margin during the night. However, we can notice the rise in emissions from coal units during the early hours of the day especially in Houston and West. This could be a consequence of intermittent wind generation during the early hours of the day leading to ramping up of coal fired power plants to meet the demand.

5.1.2 Impact on marginal local pollution (SO_2 and NOx)

To estimate the impact of hourly wind generation on damages from local pollutants, I use SO_2 and NOx emissions (tons) from marginal generators as the dependent variable in Equation 19. Figure 13a shows the coefficient estimates for SO_2 and NOx. The pattern of SO_2 emissions is very similar to that of carbon emissions from coal generators in



(a) Impact of additional wind generation on marginal CO_2 emissions



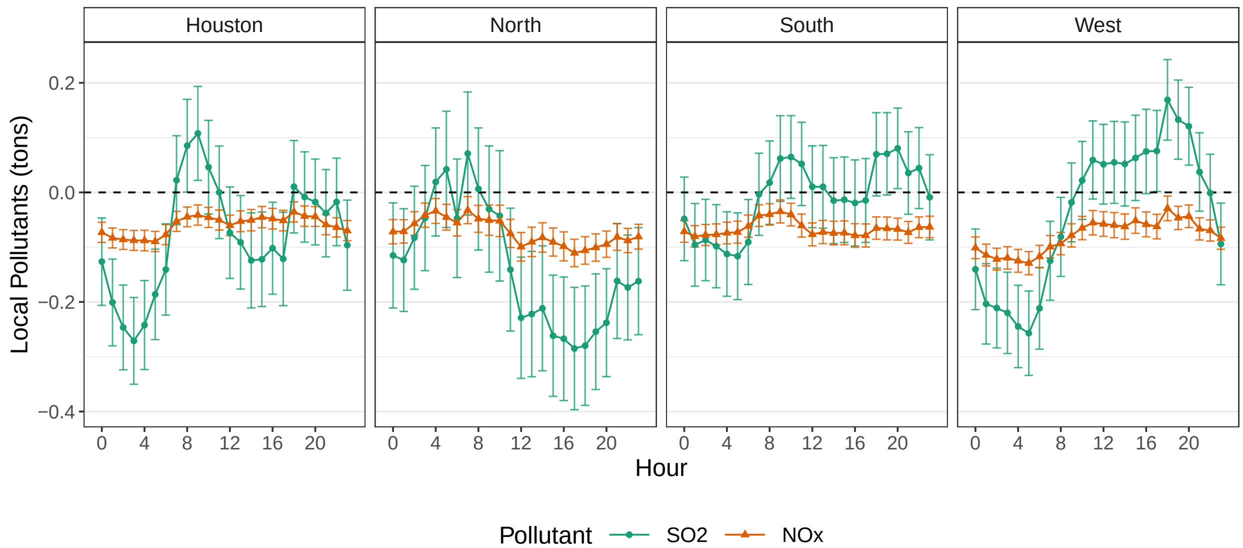
(b) Impact of additional wind generation on CO_2 emissions from coal and natural gas marginal generators

Figure 12: Short-run impact of wind generation on tons of CO_2 emissions.

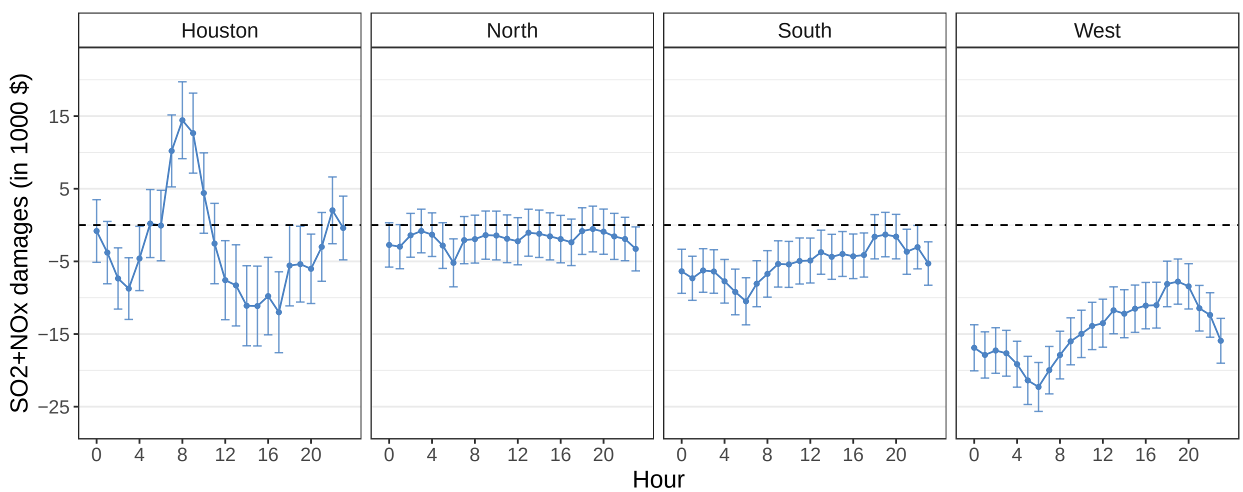
Figure 12b.[21] This is because SO_2 is a byproduct from burning of coal in power plants due to the presence of sulphur impurities. SO_2 emissions from natural gas power plants are low because of low amounts of sulphur in pipeline quality natural gas. NOx on the

21. I present the estimates for the effect of wind generation on tons of SO_2 and NOx from coal and natural gas generators in Figure E6 in Appendix.

other hand is released from burning of any fossil fuel due to the mixing of fuel and air (EPA 1998).



(a) Impact of additional wind generation on local pollutants (SO_2 and NOx) in physical units



(b) Impact of additional wind generation on damages (2020 $) from local pollutants (SO_2 and NOx)

Figure 13: Short-run impact of wind generation on emissions from local pollutants (SO_2 and NOx).

Figure 13b uses county-specific marginal damage estimates from Holland et al. (2016) to reflect the $ value of damages from local pollution (SO_2 and NOx).

Since the health impacts of local pollutants vary across space due to differences in population, I use estimates of county-specific marginal damages due to SO_2 and NOx from Holland et al. (2016) to calculate the dollar value of damages due to emissions from each generator. I then aggregate these damages at the zonal level. Figure 13b shows the coefficient estimates using the sum of damages from SO_2 and NOx (2020 $) as the dependent variable in Equation 19. These coefficients measure the impact of additional wind generation on the damages from SO_2 and NOx across the four zones for each hour of the day.

Figure 13b shows evidence of significant heterogeneity in damages avoided from local pollutants across zones. For South and West zones, additional wind leads to decline in damages from SO_2 and NOx across all hours, whereas the effect is statistically insignificant for the North. In case of Houston, we see a significant rise in local emissions during the early hours of the day. This is similar to the rise in carbon emissions and is indicative of the ramping up of coal generators during the early hours of the day to meet the demand.

Zooming in on the marginal generators within West and Houston, we observe that the estimates for SO_2 and carbon emissions for coal are driven by the only coal power plants in these zones. In Houston, the coal emissions are due to W.A. Parish Coal Plant (four generators with total capacity of 2.7 GW) whereas in West the emissions are due to Oklaunion Power Plant (single generator with 720 MW capacity).[22] The increase in emissions in the day suggests that during the periods of low wind generation post 8:00 AM, availability of transmission capacity tends to promote power ramping up of coal generators located near the population centers to meet the demand. These ramping effects are shown to undercut the emissions reductions from wind, especially when operating at low levels of efficient generation (Lew et al. 2012). Furthermore, these emissions are a cause of concern especially since the polluting generators are located near major population centers.

5.1.3 Value of damages avoided due to CREZ expansion

I calculate the value of marginal carbon emissions avoided due to wind integrated from CREZ expansion as:

22. Figure E4 in Appendix E shows the location of various coal and natural gas fired marginal generators in the sample from 2011 to 2014 along with ERCOT Zones and CREZ counties.

$$D_z(\$) = \sum_{h=0}^{24} \tau \times \beta_h \times \rho_{zh} \tag{20}$$

where, D_z is the zonal daily average of damage (in 2020 \$) due to marginal carbon emissions in zone z. I assume social cost of carbon, τ as \$44 per ton of CO_2 emissions (US Interagency Working Group on Social Cost of Carbon 2014), β_h is the hourly average wind generation added due to CREZ in the short-run estimated in Equation 14, and ρ_{zh} is the impact of additional GWh of wind generation on marginal emissions. For local pollution, I simply multiply the coefficient estimates in Figure 13b with β_h and aggregate over the hours to get the value of average daily damage avoided.

Table 2: Average daily damages avoided from marginal generators due to CREZ

	Damages Avoided (2020 \$)			
Zone	CO2	SO2 + NOx	Total	Percent (%)
Houston	15,169	8,710	23,879	16
North	16,700	7,173	23,873	16
South	13,776	20,044	33,820	23
West	12,276	55,267	67,543	45
Total	57,921	91,194	149,115	100

Notes: This table reports the daily average of damages from carbon and local pollutants avoided from marginal generators due to additional wind integrated from CREZ expansion for each Zone.

Table 2 reports the daily value of damages avoided from marginal emissions due to CREZ expansion for each zone.[23] We notice a decline in damages from carbon emissions across all the zones in the short-run. The total value of daily carbon emissions avoided is about \$58,000 with three fifths of the share coming from North and the South zone, and a fifth each from Houston and West. The story is a bit different for local pollutants. While the total daily damages avoided is about \$91,000, the reduction is mostly concentrated

23. The coefficient estimates of hourly averages of damages avoided for each zone due to CREZ are presented in Figure E7 in Appendix E. The pattern for carbon emissions and local pollution is similar to Figure 12a and Figure 13b respectively.

in the West followed by South, North, and Houston. The total daily damages avoided from CO_2, SO_2 and NOx emissions is approximately $150,000 which translates to about $54 million annually.

6 Long-run: Impact of CREZ announcement on investment in wind energy

The CREZ transmission expansion project was selected by the Public Utilities Commission of Texas (PUCT) in consultation with ERCOT after a multi-year process in July 2008 (NREL 2008).[24] It was aimed to accommodate 18.5 GW of total wind power- 6.9 GW by the end of 2008 and a projected 11.5 GW by 2012, by building 3,600 miles of 345 kV electricity transmission lines between existing and new substations throughout the Panhandle, West, and East of Texas at a projected cost of $4.95 billion (PUCT 2009).[25]

Wind developers site their projects in regions with availability and access to transmission capacity and locate near the electrical substations to deliver their power to the grid.[26] In the data I only see the counties where these substations were located and thus I call them 'CREZ counties'.[27] I refer to July 2008 as the "announcement date" as it provides the first most accurate information of transmission siting in the CREZ project. The specific technical details of the transmission expansion - the cost breakdown, expected completion dates, and the transmission service providers responsible for the expansion was released in October 2010 in CREZ Progress Report (RS&H 2010).

Figure 14 shows a cluster of wind projects located within and near CREZ counties post 2008.[28] While there is an increasing trend of wind energy development in Texas, some of this capacity could a long term response towards CREZ expansion beyond the projected 2012 capacity addition. To parse out whether CREZ counties saw higher levels

24. Refer Appendix B for a discussion on the planning behind CREZ expansion.

25. Electrical or Transmission substations typically serve as the terminal points for high voltage transmission lines as well as serve as the hub for nearby generating plants to deliver their power to the grid.

26. Appendix C presents a simple conceptual model to build intuition on a wind developer's choice of siting its wind project.

27. I do not have access to exact location of these substations because it is restricted data for the purposes of national security.

28. There is also a cluster of wind farms in coastal Texas. This is because of superior wind quality in this region which could be profitable for wind developers.

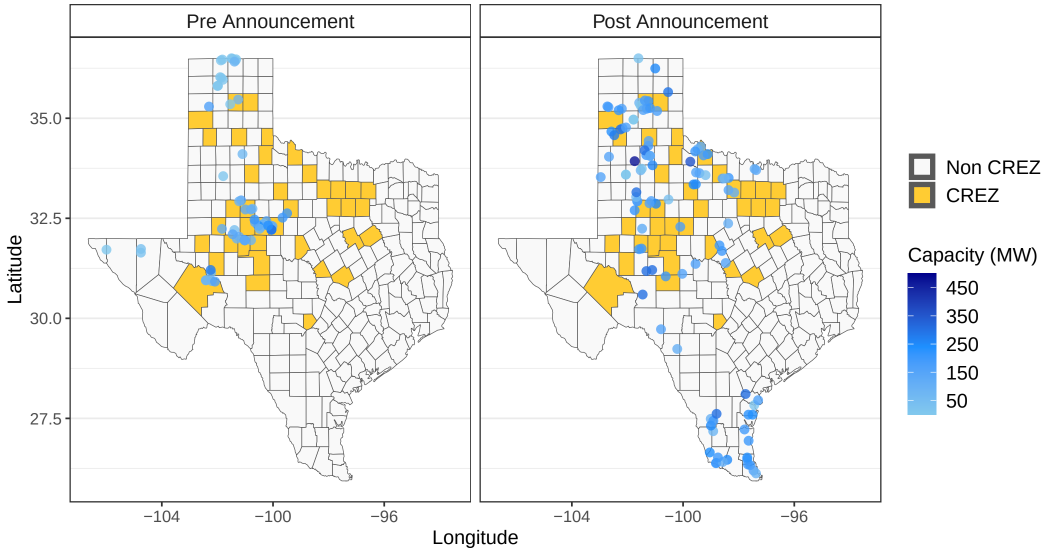


Figure 14: Location and Nameplate Capacity (MW) of wind projects Pre and Post CREZ announcement in July 2008.

Note: This figure shows wind farms in Texas Pre-CREZ Announcement (Jan 2001 - Jul 2008) and Post-CREZ Announcement (Aug 2008 - Dec 2019) samples.

of wind investment over the long run, I estimate the following specification:

$$y_{it} = \alpha + \beta \cdot crez_i + \mathbf{X}'\Pi + \epsilon_{it} \tag{21}$$

where, y_{it} is the outcome of interest. I use total wind capacity in county i in year t, average wind capacity of the project (total nameplate capacity/total number of projects in the county), and total number of turbines in county i in year t as the dependent variables for this analysis. The variable $crez_i$ is a binary variable that specifies whether county i is a CREZ county.

The analysis is restricted to annual county level observations from 2012 through 2019 to estimate the additional wind added beyond the projected period of CREZ planning. This excludes wind projects that were already in development or were perhaps sited in CREZ counties just prior to the grid expansion announcement in late 2008. Since project planning and development typically takes a few years, this allows for the addition of wind capacity in response to transmission expansion.[29]

29. Generator interconnection is one of the first steps towards wind project development (AWEA 2019). The period between signing generator interconnection agreement and commercial operation is about 2-3 years for a typical wind project in Texas.

I use a battery of control variables and fixed effects summarized by vector **X** in Equation (21). I use wind turbine class, capacity factor, and cubic polynomial of average wind speed to flexibly control for wind resource quality of a county. These variables are aggregated at the county level from 2km by 2km grid data from NREL's Wind Integration National Datatset (WIND) toolkit (Draxl et al. 2015). I use average yearly wind project cost data from Lawrence Berkeley's Wind Technologies Report, land price data, and median land acreage compiled by the Real Estate Center at Texas A&M University to control for project costs.

To control for demographic factors that could influence CREZ transmission siting and location choice for wind projects I use median household income in 2007 and average population over 2007 to 2010. I use average farm size in a county to account for variation in wind investment due to turbine dis-amenities.[30] This data comes from the USDA Census of Agriculture. Cities and counties often enact regulations for wind projects that are sited in their jurisdiction. These regulations commonly known as setbacks or wind ordinances, specify limits on factors like the size of wind turbines, height of turbines, noise, maximum capacity. The presence of a wind ordinance could affect investment in wind capacity in a county and could also be correlated with siting of transmission infrastructure. I include an indicator variable specifying whether the county (or a city in the county) has a wind ordinance.[31] I use the publicly available dataset on wind ordinances from WINDExchange for this variable.

To control for Load Zone specific characteristics I use Zone fixed effect and a cubic polynomial for time trend to control for increasing trend in wind generation across all counties. I use fixed effect for the years 2012 and 2013 to control for a sudden decline in wind installations due to Production Tax Credit (PTC) expiration in late 2012 and the

30. The rationale behind these variables is that urban areas tend to have higher opposition towards transmission and wind project siting (Andrade and Baldick 2016). Further it is harder to site wind farms in areas with small farms (Winikoff and Parker 2019). Household income, population, and average farm size for other years is highly correlated with the 2007 variables that I use in the analysis. Therefore, including values of these variables for other years in the sample does not change the results.

31. Most counties in Texas do not have wind ordinances for large wind projects (i.e. projects bigger than 10 MW). Out of 254 counties, I only find cities in five counties, namely Dallas, Ellis, Kleberg, Taylor, and Wichita to have enacted a wind ordinance for both smaller and bigger wind projects.

subsequent extension in early 2013. Standard errors are clustered at the county level to account for serial correlation at the county level.

A key concern in Equation (21) is the endogeneity of $crez_i$ due to the selection of regions with superior wind quality and historically higher levels of wind capacity to site CREZ substations and transmission lines. To the extent that I attempt to account for these factors by including a rich array of control variables, the concern of a lack of common support amongst counties still remains. I address these concerns by implementing a matching strategy to obtain unbiased estimate of the impact of CREZ expansion on wind investment.

6.1 Matching Strategy

The objective of the matching exercise is to construct a control group of counties that are comparable to the treated counties on a wide set of observable characteristics. Comparing the counterfactual outcomes from the control group, conditional on confounding factors would provide the unbiased impact of transmission expansion. However, making a causal claim requires the validity of the conditional independence assumption (CIA):

$$\mathbb{E}(\epsilon_{it}|\mathbf{X}, crez_i = 1) = \mathbb{E}(\epsilon_{it}|\mathbf{X}, crez_i = 0) \tag{22}$$

where, ϵ_{it} is the unobserved component of dependent variable of interest (y_{it}) - wind capacity, total turbines, and average project size. Under the assumption that the unobserved component (ν_i) of a county that affects the treatment status is time invariant, using county fixed effect would eliminate the selection bias. However, since the treatment variable is assigned at the county level and at the beginning of the sample, I cannot include county fixed effects.

Instead, I assume that ν_i can be approximated using some flexible function of observable county characteristics $\mathbf{Z}$, i.e. $\nu_i = f(\mathbf{Z})$. Therefore, validating CIA involves comparing counties with exactly the same combination of characteristics, such that $\mathbb{E}(\epsilon_{it}|f(\mathbf{Z}), \mathbf{X}, crez_i = 1) = \mathbb{E}(\epsilon_{it}|f(\mathbf{Z}), \mathbf{X}, crez_i = 0)$. This would provide an estimate of the unbiased effect of the treatment. However, the presence of continuous variables in $\mathbf{Z}$ and a finite sample make it impossible to compare counties based on an exact fit of $f()$.

I use Coarsened Exact Matching (CEM) introduced by Iacus et al. (2012) to obtain the set of counties comparable on observable dimensions which includes both continuous and discrete variables. I divide the sample of counties across CREZ (treated) and non-CREZ (control) groups and then match the counties across the two groups based on observable characteristics using CEM. I use a wide variety of pre-treatment observable covariates to account for factors that could have influenced CREZ siting as well as investment in wind energy post 2012. These factors include historical wind capacity, wind resource quality, average land price and acreage, wind ordinance, and county level demographic characteristics.

For wind resource quality, I use wind speed (m/s), capacity factor, and wind turbine class designation from NREL (Draxl et al. 2015). I use average land price over 2007-2010 and median land acreage to account for variation in project costs due to land prices across the counties. To account for bargaining power and community opposition (mainly from urban areas) in citing of wind projects and transmission lines I use average farm size in 2007, median household income in 2007, and average population of a county over 2007-2010. Finally, I perform exact matching on ERCOT load zones to capture regional differences across load zones in the Texas electricity market. [32]

Table 3 provides the balance table of these observable characteristics for pre- and post-matched samples. As evident, CEM provides a well balanced group of treated and control counties that look identical on all observable dimensions. Counties that do not lie in the common support of observable characteristics used in matching are discarded from the sample. Therefore, the control group comprises of 30 counties and the treated group comprises of 13 counties. Figure 15 shows the map of treated and control counties. Most of the control counties (light yellow) are adjacent to the treated counties (dark yellow).

32. Amongst the set of observable dimensions: wind capacity as of 2008, wind speed, capacity factor, average land price over 2007-2010, median land acreage, average farm size in 2007, median household income in 2007, and average population over 2007-2010 are continuous whereas wind turbine class and Zone are discrete variables. Each category within wind turbine class is matched exactly whereas I use the following structure for exact matching on Zone: {{Panhandle, West}, North, Coastal, Houston, South, None}.

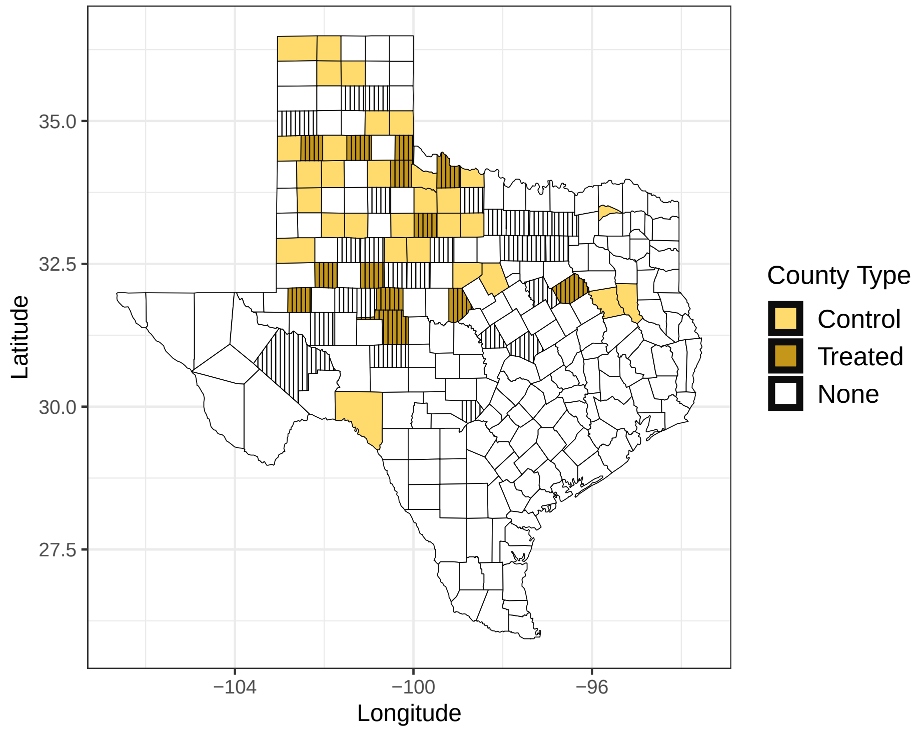


Figure 15: Treated and Control counties obtained using Coarsened Exact Matching.

Note: Hatched counties depict the CREZ counties in the overall sample. Unshaded hatched and non-hatched counties are discarded from the sample used in the analysis as they lie outside of the common support of observable characteristics.

For the regression analysis on the counties obtained by matching, I use the same set of control variables as described in Equation 21. The key assumption is that conditional on the vector of controls **X**, there are no unobservables that affect the outcome variable and treatment status $(crez_i = 1)$. Therefore, conditional on matching the counties on **Z**, selection into CREZ is "as-good-as" random. Thus, the OLS regression of Equation 21 on the matched sample gives the unbiased impact of CREZ on wind investment in the long-run.

6.1.1 Results

Table 4 reports the regression results of the baseline specification with total nameplate capacity (MW), total turbines, and average project capacity (MW) in a county as the dependent variables respectively. These regressions use the full set of control variables, i.e. cubic polynomial of time trend, controls for wind resource quality, project costs, county demographics, fixed effects for wind ordinance, load zone, and Production Tax Credit. I

Table 3: Balance Table of key observables for Pre- and Post-Matching Sample

Variables	Pre-Matching			Post-Matching		
	Means Treated [CREZ = 1]	Means Control [CREZ = 0]	p-value	Means Treated [CREZ = 1]	Means Control [CREZ = 0]	p-value
Wind Capacity as of 2008 (MW)	158.599	5.579	0.000	5.581	4.264	0.138
Wind Speed (m/s)	7.923	7.348	0.000	7.887	7.891	0.619
Capacity Factor	0.449	0.413	0.000	0.437	0.439	0.949
Wind Turbine Class = 1	0.000	0.005	–	0.000	0.000	–
Wind Turbine Class = 2	0.692	0.393	–	0.837	0.837	–
Wind Turbine Class = 3	0.308	0.603	–	0.163	0.163	–
Avg. Land Price (2007-2010)	284.684	424.427	0.000	228.424	231.216	0.929
Median Land Acreage	560.184	779.632	0.032	360.746	351.736	0.161
ERCOT Zone: Coastal	0.000	0.051	–	0.000	0.000	–
ERCOT Zone: Houston	0.000	0.028	–	0.000	0.000	–
ERCOT Zone: None	0.000	0.107	–	0.000	0.000	–
ERCOT Zone: North	0.308	0.220	–	0.163	0.163	–
ERCOT Zone: Panhandle	0.179	0.136	–	0.302	0.371	–
ERCOT Zone: South	0.026	0.252	–	0.000	0.000	–
ERCOT Zone: West	0.487	0.206	–	0.535	0.466	–
Avg. Farm Size in 2007	1,595.667	1,724.206	0.418	1,183.140	1,262.035	0.118
Median Income in 2007	43,133.130	39,739.930	0.000	35,789.190	35,574.620	0.837
Avg. Population (2007-2010)	171,282.000	83,280.770	0.002	28,917.870	20,612.030	0.026
Total Units	312	1,712		104	240	

Notes: This table presents balance test of key pre-treatment observable characteristics of a county. Each unit is a county-year observation. Pre-Matching sample includes all county-year observations. Post-Matching sample is selected using Coarsened Exact Matching (CEM).

also include the interaction of group fixed effects with the time trend to allow for time varying unobserved factors that could affect specific matching groups.

The results for total nameplate capacity indicate a significant increase in wind capacity in CREZ counties. Column (1) in Table 4 shows that transmission expansion led to approximately 73 MW higher wind capacity in treated counties over 2012 - 2019. The semi-elasticity indicates a 202.3 percent increase in wind capacity for CREZ counties. In a similar vein, Column (2) shows that treated counties on average had about 40 more turbines than the control counties with a 'semi-elasticity' of 245 percent. Both of these results are statistically significant at 5 percent critical level.

Table 4: Effect of CREZ expansion on wind investment - matching results

	Dependent variable		
	Total Nameplate Capacity (MW)	Total Turbines	Avg. Capacity of a project (MW)
	(1)	(2)	(3)
CREZ	72.640***	39.419***	32.756*
	(26.499)	(13.075)	(19.093)
Mean Dep. Variable	35.907	16.067	26.951
Semi-elasticity (%)	202.3	245.3	121.5
Controls	✓	✓	✓
Group × Trend FE	✓	✓	✓
Matching Weights	✓	✓	✓
Sample	Matched	Matched	Matched
Observations	344	344	344
R^2	0.467	0.476	0.426

Notes: This table reports the result of baseline regressions on the matching sample. The sample is a balanced panel of 13 treated (CREZ) and 30 control (non-CREZ) counties from 2012-2019 obtained using CEM. The independent variable is a binary variable indicating whether a county received CREZ transmission infrastructure or not. All specifications include cubic polynomial of time trend and controls for wind quality, project cost, county level regulation and demographics. Wind controls include power curve, capacity factor, and cubic polynomial of wind speed. Project Cost Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include FE for PTC and wind ordinance in a county. Demographic controls include average farm size (acres) in 2007, median household income in 2007, and average population over 2007 to 2010. I also include group by trend fixed effects to allow for time varying unobserved factors affecting matching groups. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Column (3) examines whether the size of a wind project varies differentially with county type. Everything else equal, we might expect wind developers to build bigger wind projects near sites that allow access to transmission capacity and therefore a positive coefficient. The coefficient estimate lends weak evidence in favor of this hypothesis. I find that CREZ counties were associated with 33 MW bigger wind projects, however, the coefficient estimate is only significant at 10 percent critical level.

In order to contextualize these estimates, I compute the value of carbon emissions avoided due to wind investment as a result CREZ expansion. I use an emissions rate of 0.601 tons of CO_2 avoided for each MWh of on-shore wind in Texas (EPA 2021). Assuming the capacity factor of wind in Texas as 34.57 percent, wind added due to CREZ avoided roughly 5.34 million tonnes of CO_2 emissions from the power sector in Texas in 2019. Using a social cost of carbon of \$51/ton for 2019 (US Interagency Working Group on Social Cost of Carbon 2021), the value of total reduction in carbon emissions in 2019 in Texas is about \$271 million.[33]

6.1.2 Threats to identification

Selection on unobservables:
The key threat to identification in matching is the selection of CREZ counties based on unobservable characteristics that would violate the Conditional Independence Assumption (CIA). While I cannot test CIA directly, I provide institutional evidence and robustness checks to support its validity in this context.

CREZ planning process involved discussions with various stakeholders like wind developers, county officials, transmission service providers, and interested landowners (Cohn and Jankovska 2020). The final locations were selected based on their wind energy potential and to accommodate the existing stock of wind capacity (Lasher 2008, 2014). Several of the wind quality variables account for the wind energy potential of a county. Pre CREZ wind capacity compares counties based on existing stock of wind capacity which was a key factor in selection of CREZ counties.

33. The total value of damages prevented from emissions is likely to be much higher if we include local pollutants. However, calculating this will require computing the SO_2 and NOx offsets due to additional wind across space in 2019. Such an analysis is beyond the scope of this paper.

One of the unobservable factors is whether certain counties lobbied for or again siting of CREZ lines. While opposition is likely not a major concern for West Texas due to low land costs and minimal community opposition, it is certainly a concern for East and South Texas where some of the lines were closer to urban areas (Andrade and Baldick 2016). Cohn and Jankovska (2020) describe cases where certain counties were opposed to transmission siting and objected with the PUCT during the planning process. I run the matching algorithm by excluding these 'contesting' counties from the original sample.[34] The regression results on the new matched sample are reported in Appendix F.2 and are similar to the baseline estimates in Table 4.

On the other hand, certain counties in the Panhandle region expressed interest with the PUCT for CREZ investment. This was in part due to an already declining population and economic loss in these counties in the years preceding CREZ expansion (Cohn and Jankovska 2020). As before, I run the matching algorithm by excluding these 'enthusiastic' counties from the original sample.[35] The regression results on the new matched sample are reported in Appendix F.2 and are similar to the baseline estimates in Table 4.

I also conduct a series of robustness checks in Appendix F.3 to explore how the coefficient estimates change by excluding some control variables, group fixed effects, and matching weights. The results are similar to the estimates in Table 4.

Anticipation to CREZ announcement:

A potential source of bias in measuring the causal impact could be the anticipation amongst wind developers to CREZ announcement in 2008. This would be reflected as a spike in investment in wind projects within CREZ counties in the years leading upto the transmission expansion announcement. Using the data on generator interconnection in Texas, I verify the existence of such an anticipation effect in Appendix D. The analysis does not show existence of any anticipation to the announcement of grid expansion two and four years prior to the announcement date.

Multi-phase wind projects and extensions:

Another threat to identification could be if projects within CREZ counties prior to 2008 saw subsequent extensions shortly after 2012. This would be a selection issue in the sense

34. These 'contesting' counties are: Kendall, Gillespie, Newton, Kimble, Kerr, Mason, and Schleicher.

35. These 'enthusiastic' counties are: Dallam, Sherman, Oldham, Swisher, Lipscomb, Parmer, Lamar, Hall, Deaf Smith.

that a county gets selected to site CREZ infrastructure because of the likely development of a project extension in the future. To address this concern I examine the occurrence of post 2012 extensions of wind projects that started operating before 2008 within CREZ counties. Figure E8 in Appendix shows that existence of multi-phase wind projects and project extensions are not a cause of concern.

7 The link between short- and long-run effects on wind curtailment in Texas

Regulators in electricity markets typically curtail renewable resources during the periods of congestion in order to maintain grid stability.[36] In Texas, lack of adequate transmission capacity to transport electricity from wind farms in the west has been the primary source of wind curtailment, reaching to about 17 percent of total wind generation in 2009 (Bird et al. 2014). Figure 16 shows that CREZ expansion led to a significant decline in wind curtailments post 2014. With generation capacity fixed in the short-run, availability of transmission capacity led to integration of wind that would otherwise be curtailed. The short-run analysis (see Figure 8) finds that CREZ expansion led to integration of wind across all hours of the day, most significantly at the night when wind is strongest.

Another key observation from Figure 16 is the rise in the level and frequency of curtailments since 2016. By the end of 2018, these curtailments were higher than the pre grid expansion levels in 2012. This is elaborated in Figure 17, wherein average hourly curtailments in 2018 were higher than curtailments in the year after CREZ in 2014 as well as pre CREZ levels in 2012. The long-run analysis (see Table 4) shows that locations that received investment in CREZ infrastructure saw higher levels of wind investments in the long run. Even through wind capacity in Texas has been increasing, there has not been any major grid expansion projects in Texas post CREZ. The steady rise in curtailment could be an implication of the localized investment in wind energy in the west coupled with inadequate transmission capacity.

36. Wind curtailment is defined as the reduction in electricity generated from a wind generator below the level that it could have produced given available resources (Bird et al. 2014). For example, if a wind generator is estimated to produce 100 MW of electricity in period t but is finally scheduled to produce 80 MW, the corresponding wind curtailment is said to be 20 MW. Wind curtailment is typically involuntary to the generator and is carried out by ERCOT to maintain grid stability.

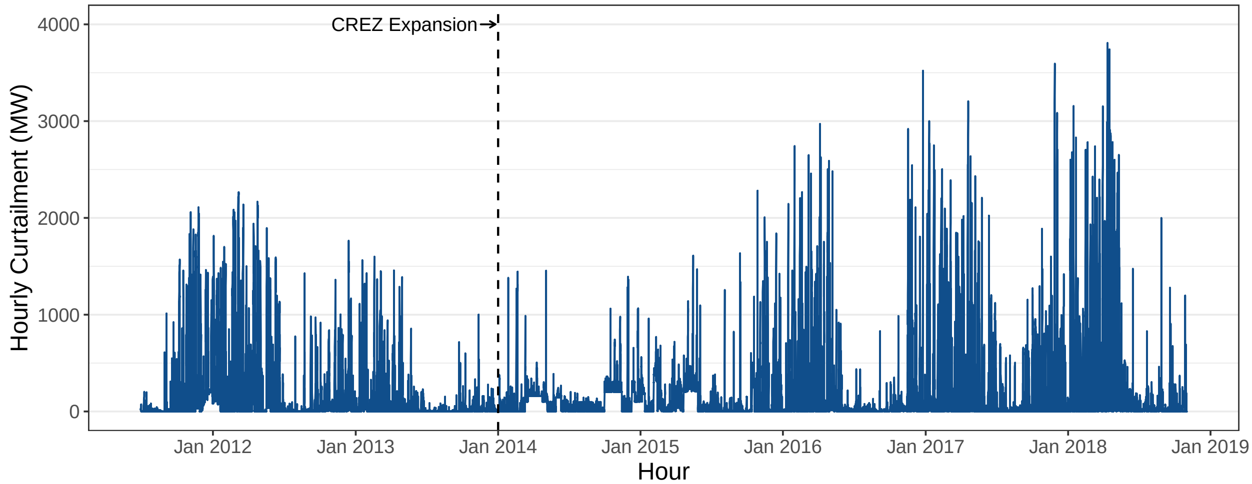


Figure 16: Hourly wind curtailment in Texas

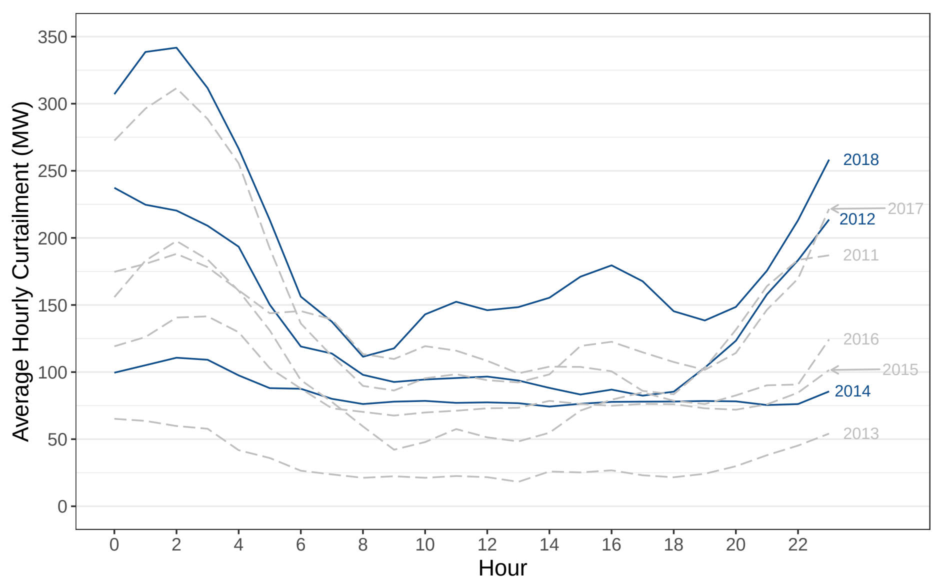


Figure 17: Average hourly wind curtailment from 2011 to 2018

Note: This figure shows average hourly wind curtailments for each hour from 2011 to 2018. For clarity, solid lines highlight the curtailment pattern pre CREZ expansion (2012), post CREZ expansion (2014), and for the latest year (2018) in the sample.

I provide descriptive evidence by comparing curtailments between wind farms located near and those located farther from the regions impacted by CREZ expansion. I estimate the following series of equations for off-peak ($\in$ [22:00 - 7:00)) and on-peak hours ($\in$ [7:00 - 22:00)) separately:

$$y_i = \sum_{k=2011}^{2018} \gamma_k \cdot \mathbb{1}\{\text{in/adjacent to CREZ}\} + \mathbf{X}'\Gamma + \delta_{dm} + \epsilon_i \quad (23)$$

I use curtailment for each wind farm i as the dependent variable y_i.[37] The key explanatory variable is an indicator specifying whether the wind farm is within or adjacent to a CREZ county. I vary the coefficient estimate by year of the sample to capture the long-run effects. Therefore, the parameter of interest γ_k measures the average percentage difference in curtailment between wind farms near CREZ counties and those located elsewhere for the off-peak and on-peak demand hours in 2011 to 2018.

I control for average project costs in a year common to all projects in Texas and quarter of the sample time trend to account for changes in curtailment due to rise in wind generation over time. I use day by month fixed effects to account for seasonality in wind generation. The standard errors are clustered at the wind generator level to account for serial correlation in curtailments across the wind farms.

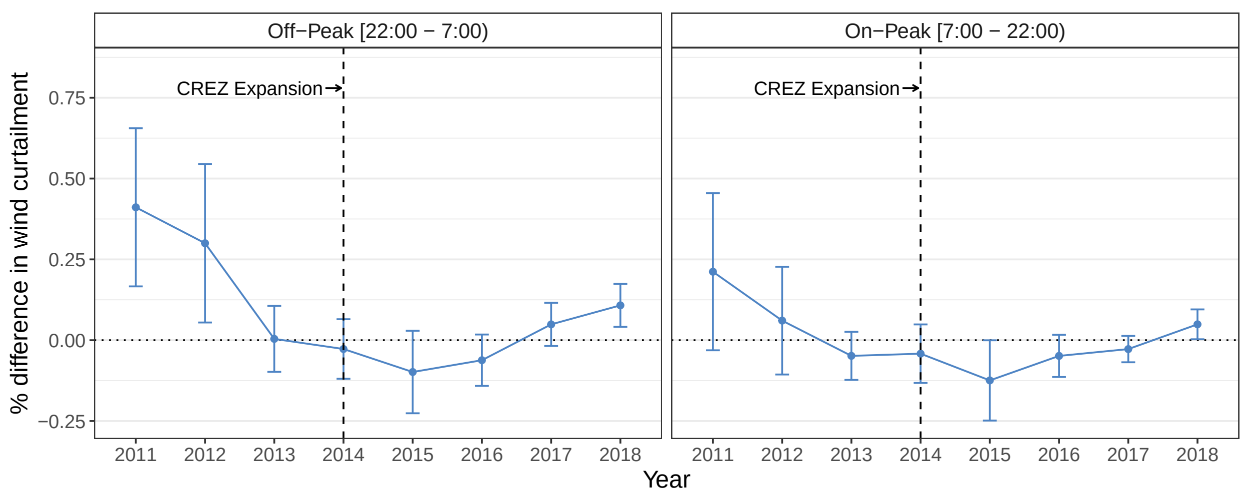


Figure 18: Percentage difference in curtailments between wind farms near CREZ counties and those in other regions

Note: This figure shows the percentage change in curtailment between wind farms near CREZ counties and wind farms in other regions for off-peak and on-peak hours over 2011 to 2018. Each panel is the set of coefficient estimates of the years (2011 to 2018) corresponding to regression equation for the particular time of use (off-peak/on-peak).

37. I use inverse hyperbolic sine (IHS) transformation of the dependent variable to account for the significant mass of zeros in the dependent variable.

Figure 18 shows the percentage difference in curtailment between wind farms near CREZ counties and wind farms in other regions for off-peak and on-peak hours over 2011 to 2018. Curtailments in wind farms near CREZ counties were significantly higher than curtailments in wind farms in other regions in the years leading upto the transmission expansion in 2014 especially during the off-peak hours. For instance, curtailment was on average about 25 and 35 percent higher in wind farms near CREZ counties during off-peak hours in 2011 and 2012 respectively. The difference in curtailments is statistically insignificant for at least two years post CREZ expansion which is consistent with the finding that CREZ decreased curtailment by integrating wind to the grid.

However, wind farms near CREZ counties saw higher curtailments, about 12 percent for off-peak hours and 6 percent for on-peak hours in 2018.[38] This difference is both economically and statistically significant. This result is indicative of a negative impact of localized investment in wind energy but inadequate transmission capacity. The rising wind capacity in West Texas but fixed transmission capacity could be concerning since the resulting curtailments could in turn erode some of the short-run benefits of transmission expansion.

8 Discussion and Policy Implications

Efforts to combat climate change in the US have largely focused on expanding the solar and wind generating capacity. A key factor in ensuring that the power generated through these sources is fully utilized is the availability of transmission lines that could carry the electricity to demand centers. Using the CREZ transmission expansion in Texas as the case study, this paper studies the short- and long-run impacts of large scale grid expansion. I examine the impact of grid expansion on markups and emissions from marginal fossil fuel generators in the short-run and wind investment in the long-run.

To study the short-run impact on markups, I write a uniform auction based model for the marginal generator based on Ryan (2021). I extend this model by including a renewable sector which is connected by the demand centers through electricity transmission lines. The main innovation of my model is to show that the impact of grid expansion on markups is mainly due to the displacement of net-demand curve and the changes

38. I plan to extend this analysis to 2019 and 2020 in the near future.

in slope of the electricity dispatch curve. I then estimate the relationship between grid expansion and markups derived from this model in my empirical analysis.

The short run analysis suggests that CREZ had a moderate effect on lowering markups. The decline in markups is greatest at periods of high wind generation, varying from 1 percent to 7 percent. These lower markups prevented about $44 million in annual rents accrued by marginal generators from power retailers in the short-run. Further, CREZ prevented about $54 million in annual damages from marginal emissions. I find an increase in emissions as a result of ramping up of marginal coal generators due to wind intermittency during the early hours of the day and is most pronounced in the West and Houston region of Texas.

Next, I estimate the magnitude of long-run investment in wind energy in response to grid expansion. I use coarsened exact matching to address the endogeneity issue of citing of CREZ lines. OLS regressions on the matched sample suggests that counties with CREZ transmission infrastructure saw significant investment in wind capacity (+202%) over 2012 to 2019. A back of the envelope calculation shows that the wind capacity added due to CREZ prevented approximately $271 million worth of carbon emissions in Texas in 2019.

The results in this paper have several policy implications. First, the short-run results indicate that the market and non-market benefits of transmission expansion are substantial and comparable in magnitude. Second, utility scale energy storage can mitigate some of the negative impacts of wind intermittency. Storage can reduce wind curtailment and use the stored electricity at peak demand when the wind generation is low. This could lower markups and enhance the benefits of transmission expansion. Storage can also address the rise in emissions due to ramping-up of coal generators by smoothing the supply of electricity especially when wind generation is low.

Third, this study quantifies the value of investment in transmission expansion in terms of its impact on integrating wind generation in the short-run and higher investment in wind capacity in the long-run. These responses are important to consider while planning grid expansion projects as they could have significant market and non-market consequences. I provide descriptive evidence that while CREZ expansion led to decline in curtailments following the expansion, wind farms near CREZ counties saw higher curtailments in the long-run due to oversupply of wind in this region. Grid congestion and curtailments would undo some of the estimated gains from transmission expansion.

These findings open up several avenues for future research. A key issue with renewable sources is their intermittent nature. As discussed before, utility scale energy storage can be a useful step to address some of the concerns highlighted in this paper. Karaduman (2020) is an important first empirical analysis looking at the private incentives for investment in energy storage. More research is needed to understand the impacts of the interaction between grid expansion and utility scale storage.

Renewable intermittency could have dynamic effects on the costs of electricity generation from fossil fuel plants which could translate to higher market power (Jha and Leslie 2021). While the short-run analysis in this paper does not account for such dynamic changes in markups due to generator ramp-up, it is a worthwhile extension that would provide a more precise impact of grid expansion on generator markups.

References

Andrade, Juan, and Ross Baldick. 2016. "Estimation of transmission costs for new generation." Energy Institute, University of Texas at Austin.

AWEA. 2019. *US Wind Industry Annual Market Report.* Technical report. American Wind Energy Association, Washington DC (United States).

Billo, Jeff. 2017. *The Texas Competitive Renewable Energy Zone Process.* Electric Reliability Council of Texas.

Bird, Lori, et al. 2014. *Wind and solar energy curtailment: Experience and practices in the United States.* Technical report. National Renewable Energy Lab.(NREL), Golden, CO (United States).

Birge, John R, et al. 2018. "Limits to Arbitrage in Electricity Markets: A case study of MISO." *Energy Economics* 75:518–533.

Borenstein, Severin, et al. 2000. "The competitive effects of transmission capacity in a deregulated electricity industry." *The Rand Journal of Economics* 31 (2): 294.

Borenstein, Severin, et al. 2002. "Measuring market inefficiencies in California's restructured wholesale electricity market." *American Economic Review* 92 (5): 1376–1405.

Borenstein, Severin, et al. 2008. "Inefficiencies and market power in financial arbitrage: a study of California's electricity markets." *The Journal of Industrial Economics* 56 (2): 347–378.

Bushnell, James B, et al. 2008. "Vertical arrangements, market structure, and competition: An analysis of restructured US electricity markets." *American Economic Review* 98 (1): 237–66.

Cohn, Julie, and Olivera Jankovska. 2020. *Texas CREZ Lines: How Stakeholders Shape Major Energy Infrastructure Projects.* Technical report. Baker Institute for Public Policy, Rice University.

Cullen, Joseph. 2013. "Measuring the environmental benefits of wind-generated electricity." *American Economic Journal: Economic Policy* 5 (4): 107–33.

Davis, Lucas, and Catherine Hausman. 2016. "Market impacts of a nuclear power plant closure." *American Economic Journal: Applied Economics* 8 (2): 92–122.

Doshi, Gaurav, and Xiaodong Du. 2021. "Transmission Integration and the Market for Congestion Revenue Rights." *The Energy Journal* 42 (5).

Draxl, Caroline, et al. 2015. "The wind integration national dataset (wind) toolkit." *Applied Energy* 151:355–366.

EIA. 2019. "Electricity Data Browser." US Energy Information Administration. Data retrieved from: https://www.eia.gov/electricity/data/browser/.

EPA. 1998. *AP 42, Fifth Edition, Volume I Chapter 1: External Combustion Sources.* Technical report. Retrieved from: https://www.epa.gov/air-emissions-factors-and-quantification/ap-42-fifth-edition-volume-i-chapter-1-external-0.

———. 2021. *Avoided emissions and generation tool (AVERT).* U.S. Environmental Protection Agency (EPA) Office of Air and Radiation Climate Protection Partnerships Division, Washington D.C. Data retrieved from: https://www.epa.gov/avert/download-avert/.

ERCOT. 2008. *CREZ Transmission Optimization Study.* Electric Reliability Council of Texas, TX (United States), April. https://www.nrc.gov/docs/ML0914/ML091420467.pdf.

———. 2021. "Fact Sheet." Electric Reliability Council of Texas. Retrieved from: http://www.ercot.com/content/wcm/lists/219736/ERCOT_Fact_Sheet_1.19.21.pdf.

Fell, Harrison, and Jeremiah X Johnson. 2021. "Regional disparities in emissions reduction and net trade from renewables." *Nature Sustainability* 4 (4): 358–365.

Fell, Harrison, and Daniel T Kaffine. 2018. "The fall of coal: Joint impacts of fuel prices and renewables on generation and emissions." *American Economic Journal: Economic Policy* 10 (2): 90–116.

Fell, Harrison, et al. 2021. "Emissions, transmission, and the environmental value of renewable energy." *American Economic Journal: Economic Policy* 13 (2): 241–272.

Gonzales, Luis E, et al. 2022. "The Value of Infrastructure and Market Integration: Evidence from Renewable Expansion in Chile." Working Paper.

Hernández, Cristián. 2018. "Resource Misallocation in an Oligopoly Environment: Evidence from Texas' Electricity Market." Working Paper.

Holland, Stephen P, et al. 2016. "Are there environmental benefits from driving electric vehicles? The importance of local factors." *American Economic Review* 106 (12): 3700–3729.

Hortacsu, Ali, and Steven L Puller. 2008. "Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market." *The RAND Journal of Economics* 39 (1): 86–114.

Iacus, Stefano M, et al. 2012. "Causal inference without balance checking: Coarsened exact matching." *Political analysis:* 1–24.

Ito, Koichiro, and Mar Reguant. 2016. "Sequential markets, market power, and arbitrage." *American Economic Review* 106 (7): 1921–57.

Jha, Akshaya, and Gordon Leslie. 2021. "Start-up Costs and Market Power: Lessons from the Renewable Energy Transition." Working Paper.

Joskow, Paul L, and Jean Tirole. 2000. "Transmission rights and market power on electric power networks." *The Rand Journal of Economics:* 450–487.

———. 2005. "Merchant Transmission Investment." *The Journal of Industrial Economics* 53 (2): 233–264.

Kaffine, Daniel T, et al. 2013. "Emissions savings from wind power generation in Texas." *The Energy Journal* 34 (1).

Karaduman, Omer. 2020. "Economics of grid-scale energy storage." Working Paper.

LaRiviere, Jacob, and Xueying Lu. 2020. "Transmission constraints, intermittent renewables and welfare." Working Paper.

Larson, Eric, et al. 2021. *Net-Zero America: Potential Pathways, Infrastructure, and Impacts, interim report.* Technical report. Retrieved from: `https://netzeroamerica.princeton.edu/the-report`. Princeton University, Princeton, NJ.

Lasher, Warren. 2008. "The development of competitive renewable energy zones in Texas." In *2008 IEEE/PES Transmission and Distribution Conference and Exposition,* 1–4. IEEE.

———. 2014. "The Competitive Renewable Energy Zones Process." In *Quadrennial Energy Review Public Meeting: State, Local and Tribal Issues.* US Department of Energy, Santa Fe, NM.

Lew, Debra, et al. 2012. *Impacts of wind and solar on fossil-fueled generators.* Technical report. National Renewable Energy Lab.(NREL), Golden, CO (United States).

Mercadal, Ignacia. 2018. "Dynamic Competition and Arbitrage in Electricity Markets: The Role of Financial Traders." Available at SSRN 3281886.

Meyer, Robinson. 2021. "Unfortunately, I Care About Power Lines Now." Retrieved from: `https://www.theatlantic.com/science/archive/2021/07/america-is-bad-at-building-power-lines-lets-fix-that-transmission-climate/619591/`, *The Atlantic.*

New York Times. 2016. "Making Way for Wind Power." Editorial. Retrieved from: `https://www.nytimes.com/2016/04/05/opinion/making-way-for-wind-power.html`.

Novan, Kevin. 2015. "Valuing the wind: renewable energy policies and air pollution avoided." *American Economic Journal: Economic Policy* 7 (3): 291–326.

NREL. 2008. "Texas $4.9 Billion Transmission Plan to Tap Wind." Retrieved from: `https://www.nrel.gov/news/program/2008/620.html`, *National Renewable Energy Laboratory.*

PUCT. 2009. *Docket 35665, PUC CADM: Final Order.* Public Utility Commission of Texas, Austin, TX (United States), March.

RS&H. 2010. *CREZ Progress Report No. 1.* Technical report. Public Utility Commission of Texas, TX (United States).

Ryan, Nicholas. 2021. "The Competitive Effects Of Transmission Infrastructure In The Indian Electricity Market." *American Economic Journal: Microeconomics* 13 (2): 202–242.

Saravia, Celeste. 2003. "Speculative Trading and Market Performance: The Effect of Arbitrageurs on Efficiency and Market Power in the New York Electricity Market." University of California Berkeley CSEM Working Paper 121.

Temple, James. 2017. "How to Get Wyoming Wind to California, and Cut 80% of U.S. Carbon Emissions." Retrieved from: `https://www.technologyreview.com/2017/12/28/146566/how-to-get-wyoming-wind-to-california-and-cut-80-of-us-carbon-emissions/`, *MIT Technology Review.*

US Interagency Working Group on Social Cost of Carbon. 2014. *Technical Support Document: Technical update of the social cost of carbon for regulatory impact analysis under executive order 12866.* Technical report. American Council for an Energy Efficient Economy, Washington, DC.

———. 2021. *Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide: Interim Estimates under Executive Order 13990.* Technical report. American Council for an Energy Efficient Economy, Washington, DC.

Winikoff, Justin, and Dominic Parker. 2019. "Farm Size, Spatial Externalities, and Wind Energy Development." Working Paper.

Woerman, Matt. 2019. "Market size and market power: Evidence from the Texas electricity market." Energy Institute Working Paper 298.

Appendix

A Data Sources and Sample Construction

A.1 Data and sample for markup analysis

In this section, I describe the sample construction for the short-run analysis. The hourly generator level sample used in the short-run analysis on the effect of CREZ expansion on markups uses data from three sources - ERCOT Report 13029, EIA Form 860, and EPA's CEMS Data. A brief description of these data sources is as follows:

ERCOT Report 13029 This report includes the offer price and the name of the entity submitting the offer for the highest-priced offer selected or dispatched by the Security Constrained Economic Dispatch (SCED) two days after the applicable operating day. It identifies all the entities that submitted the highest-priced offers selected for each SCED run (in case of multiple entities). SCED is the market clearing process in ERCOT and occurs at every 15 minutes. Therefore, this data is at 15 minute intervals for August 2011 to December 2014. I aggregate this data at the hourly level and all the generators that appear in this data in a specific hour are regarded as marginal generators for that hour. Apart from the identity of the generation resource, this dataset also includes the Locational Marginal Price (LMP) resolved at the resource node for that generator. This acts as the wholesale price corresponding to the marginal generator.

EIA Form 860 This is an annual dataset of all the power plants and generators operating in the US. This data contains information like EIA code of the power plant and generator(s), plant name, location, generator technology, prime mover, main energy source, regulatory status of the power plant, nameplate capacity, operating month and year, planned retirement year, operating status etc.

CEMS Data This is an hourly level data of all the fossil fuel generators at least 25 MW in size. It contains information on hourly emissions (CO_2, NOx, and SO_2), hourly generation, and heat input. The generators are identified using ORISPL Code.

For my sample period, ERCOT Report 13029 contains about 300 fossil fuel generators that operate at the margin at some instance. Since I do not observe the EIA Plant Code or Generator ID in ERCOT Report 13029, I manually match each of the 300 fossil fuel generators to the corresponding generators in the EIA Form 860. I am able to successfully match most of the generators in the ERCOT data to EIA Data.

The next part of sample construction is to match the generator data in EIA to hourly generator data in CEMS. The generator identifiers in CEMS are the ORISPL Code and Unit ID. ORISPL Code corresponds directly to the EIA Plant Code for most cases. I verify and correct ORISPL Codes in case of any discrepancy. Similarly, Unit ID in CEMS data corresponds directly to generator id in EIA Form 860. However, I verify and correct all the cases where there is any discrepancy.

A.2 CREZ Transmission Expansion Data

I use Transmission Project Information Tracking (TPIT) Reports obtained from ERCOT to assemble the dataset on CREZ transmission expansion. These reports contain detailed information on various electricity transmission projects in Texas. I specifically focus on new transmission lines built as a part of CREZ project. These reports provide the length of each transmission line (in miles) along with their in-service dates. I also see the counties where the terminals of each specific line lies. These terminals are usually existing or new electrical substations. The data on the exact location of these substations is restricted since it is considered a matter of national security, thus, I only see the county where these substations are located.

Following counties are classified as 'CREZ' counties in my data: Archer, Bell, Borden, Briscoe, Brown, Carson, Castro, Childress, Coke, Collin, Cottle, Dallas, Deaf Smith, Denton, Dickens, Ector, Glasscock, Gray, Haskell, Hill, Jack, Kendall, Lampasas, Martin, Mitchell, Navarro, Nolan, Parker, Pecos, Schleicher, Scurry, Shackelford, Sterling, Tarrant, Taylor, Tom Green, Upton, Wilbarger, Wise.

B Institutional Details

B.1 Real-time electricity market

Real-time market operations mainly refers to the operating hour and the hour immediately preceding the operating hour. ERCOT collects the status of all the transmission infrastructure from Transmission Service Providers and identifies transmission constraints and forecasts demand at various points of the network for the operating hour. This information is made available to the supply side of the market that comprises of the generating firms.

To participate in the market, each firm submits offer curves for all the generators that it owns. These offer curves are monotonically increasing vectors of price-quantity pairs based on the demand and grid information provided by ERCOT. Firms enjoy great flexibility to specify and alter their offer curves which can be different for different hours of the day. They can input up to ten price-quantity pairs and alter their offer curve up to the hour preceding the operating hour. This allows a firm to update its strategy when more information on various factors like demand, transmission constraints, or strategies of competitors is available.

The demand side of the market is comprised of retailers and load serving entities who submit demand for energy at various locations in the operating hour. Equipped with the information on supply, demand, and transmission constraints, ERCOT deploys a market clearing process that occurs every 5 minutes. This process identifies least cost generating resources that would meet the electricity demand at various locations in the system while respecting transmission constraints and the capacity limits of the generating resources. Apart from matching supply to demand, a major task of this process is to prevent the system from exceeding operational limits thus maintaining the reliability of the network. This market clearing process generates market clearing prices called Locational Marginal Price which is the location specific wholesale price of electricity.

B.2 Details of CREZ Expansion Planning

The process of identifying the locations and cost of CREZ began following the enactment of the Texas Senate Bill 20 in 2005. In April 2008, ERCOT submitted a transmission optimization study that delineated four scenarios of transmission expansion (ERCOT

2008). These scenarios were expected to integrate the existing wind capacity of 6.9 GW by the end of 2008 and varying levels of projected wind capacities to be added until 2012. These scenarios differed widely in total cost and amount of wind the resulting transmission infrastructure could accommodate by 2012. Scenario 1A was expected to cost $2.95 billion and accommodated 5.15 GW of additional wind; Scenario 1B, was deemed more scaleable with a cost of $3.78; Scenario 2 was projected to cost $4.95 billion and accommodate 11.5 GW; Scenario 3 would accommodate 17.9 GW at a cost of $6.38 billion; and Scenario 4 would accommodate 17.5 GW wind with a total cost of $5.75 billion. These scenarios were evaluated based on three main objectives in ERCOT's transmission optimization study:

1. All of these scenarios would integrate existing wind capacity of 6.9 GW in West Texas.

2. The overall wind curtailment due to transmission congestion would be no more than 2 percent (curtailment as a share of total wind generation). For each scenario, curtailments on existing and planned wind facilities upto 2012 were considered.

3. ERCOT adopted an incremental approach to transmission planning that would essentially "overlay" the new CREZ lines on the existing grid in West Texas. In other words, the new system would not even be indirectly connected to the existing grid in West Texas. This was done in order to prevent widespread congestion and overloads in the existing low voltage system due to additional wind generation in the West and Panhandle region.

C Conceptual model of location choice

This section presents a simple conceptual model to build intuition on a wind developer's location choice for its wind project. Wind developer i choose location j to site their wind projects in order to maximize present value of annual profits written as:

$$\pi_{ij} = p_i \mathbb{E}(Q_j) - F_{ij} - OM_{ij} \tag{24}$$

where, p_i is the per MWh price that the wind farm receives, $\mathbb{E}(Q_j)$ is the expected electricity production from the wind farm which is a function of wind resource quality and the number and types of turbines. F_{ij} are the fixed costs and OM_{ij} are the operations and maintenance costs.

The location choice is dependent on availability and access to transmission lines K at site j. Access to transmission lines is necessary for the wind farm to be able to deliver its electricity to the grid. Therefore, for two locations with similar wind quality, profits would be higher at the location with better access and availability of transmission lines,

$$\therefore \mathrm{K}_j > \mathrm{K}_{j'} \implies \pi_{ij}(\mathrm{K}_j) > \pi_{ij'}(\mathrm{K}_{j'}) \tag{25}$$

Next, the developer considers how far to locate from the electrical substation corresponding to the grid. [39] To see this, consider the profit function in Equation 24:

$$\pi_{ij} = p_i \mathbb{E}(Q_j) - \underbrace{[C_i + \kappa_j \cdot l]}_{\text{fixed costs}} - OM_{ij} \tag{26}$$

The fixed costs is a combination of two main components. The first is C_i, fixed costs incurred in building the wind project (like purchasing wind turbines), and second is the cost of constructing a spur transmission line, denoted by $\kappa_j \cdot l$. Spur transmission line is a relatively short transmission line that connects the generator to the bulk transmission grid (Andrade and Baldick 2016). The cost of building spur lines is borne by the developer of the project. The schematic in Figure 19 illustrates the cost allocation of spur lines and bulk transmission lines between developer and end use consumers of electricity in Texas.

39. Electrical (step-up) substations increase the voltage of electricity generated by power plants in order to make it efficient for transmission using long distance transmission lines. Therefore, these substations typically serve as the point of injection of electricity from the power plants into the grid.

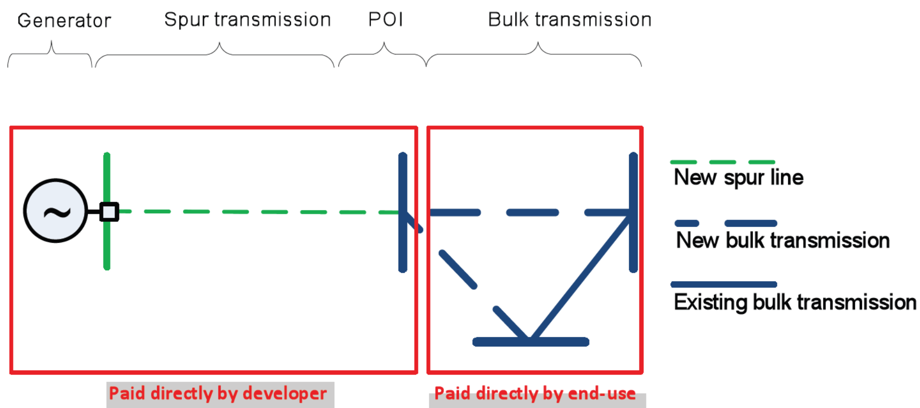


Figure 19: Illustration of transmission cost allocation in Texas for a new generation project. Source: Andrade and Baldick (2016)

The length of a spur line in Equation 26 is denoted by l and κ_j is a positive cost multiplier which summarizes the costs associated with building a unit length of spur line (of a specific voltage) at location j. These costs are mainly due to land prices, terrine features, and generation technology (example wind, coal, natural gas). Partially differentiating π_{ij} with respect to length l shows that profits are decreasing in spur line length, i.e.

$$\frac{\partial \pi_{ij}}{\partial l} = -\kappa_j < 0 \tag{27}$$

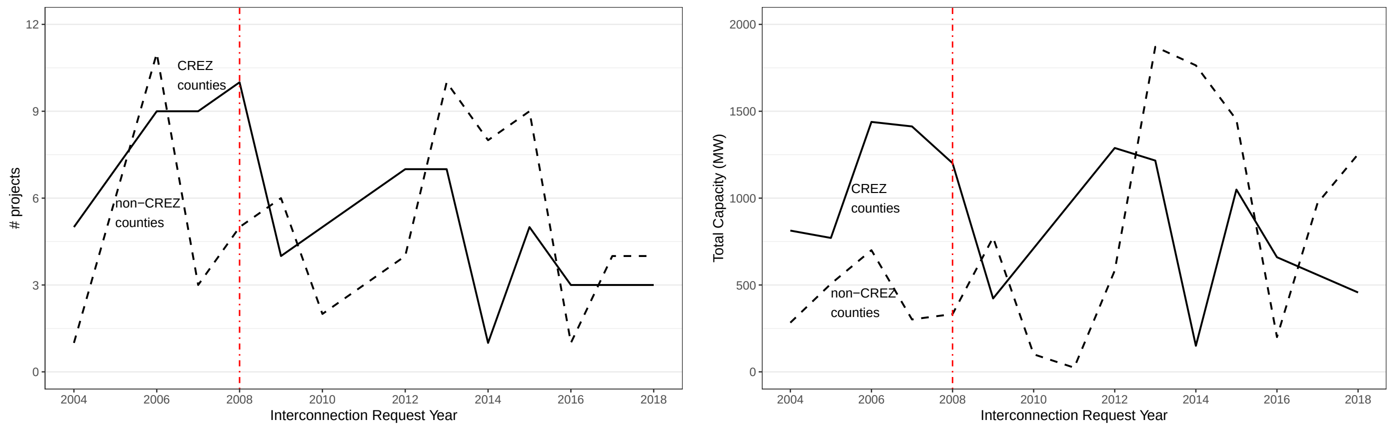
therefore, wind developers have an incentive to locate near the substation associated with the bulk transmission grid in order to maximize profits (or minimize costs). The simplified model shows that wind developers site their project in a region with access and availability to the grid, and then tend to locate near the grid substations to minimize the costs of building the spur transmission line.

D Anticipation Effects

In this section, I examine whether there was an anticipation amongst wind developers to invest in wind projects in the period leading upto the announcement of CREZ transmission expansion in late 2008. Existence of such an anticipation could lead to biased estimates of the impact on CREZ announcement on wind investment in Section 6.1. The direction of the bias is expected to be downwards since the coefficient estimate would not capture the wind investment in periods before the announcement.

To examine the anticipation effects, I use information on generator interconnection as a measure of changes in wind project planning in ERCOT since the latter is usually unobserved or hard to measure. Wind developers usually sign the interconnection agreement if they expect to build a project at a particular site and this is usually one of the first steps in the process of building a wind project (AWEA 2019).I use interconnection data from EIA Form 860 for the years 2004 - 2012 and Generator Interconnection Status (GIS) Reports from ERCOT for the years 2013 - 2019 to get the date when a wind project signed the interconnection agreement. I match these data with the wind project data from EIA 860 and AWEA to get information on project level characteristics. The matched dataset comprises of 147 projects that signed the interconnection agreement between 2004 and 2018. In terms of successful matches, this represents about 87 percent of the existing wind projects in Texas between 2004-2018.

Figure 20 shows the number of projects and the total capacity of projects located in CREZ and non-CREZ counties that signed the interconnection agreements over 2004 - 2018. Any anticipation effect of transmission expansion would be marked by a spike in the number of projects signing the interconnection agreement mainly in CREZ counties in the years leading upto grid expansion announcement in 2008. We might also expect a rise in the total capacity of projects signing the interconnection agreements prior to 2008. However, from Figure 20a and Figure 20b we do not notice any clear pattern in either the number of project or the total capacity for the years leading upto 2008 in both CREZ and non-CREZ counties.



(a) Total # projects signing the interconnection agreement

(b) Total capacity (MW) of projects signing the interconnection agreement

Figure 20: # projects and wind capacity in the ERCOT interconnection queue over 2004 - 2018

Note: Solid line is corresponding to CREZ counties and dashed line is corresponding to non-CREZ counties. Dashed vertical line indicates the year of CREZ announcement.

I estimate specifications to test the existence of an anticipation effect after controlling for confounding factors that could influence generator interconnection. Specifically, I estimate versions of the following specification:

$$y_{it} = \beta \cdot \mathbb{1}\{year \in [k,\ 2008]\} + \alpha_i + \mathbf{X}'\Pi + \epsilon_{it} \tag{28}$$

where, y_{it} is the inverse hyperbolic sines (IHS) of number of projects or the total nameplate capacity of projects that signed the interconnection agreement in county i in year t. The independent variable of interest $\mathbb{1}\{year \in [k,\ 2008]\}$ is an indicator for the range of years from k to 2008, denoting the anticipation period. I consider two versions of this variable - $k = 2006$, i.e. $\mathbb{1}\{year \in [2006,\ 2008]\}$ and $k = 2004$, i.e. $\mathbb{1}\{year \in [2004,\ 2008]\}$ as the anticipation period. I estimate Equation 28 separately for CREZ and non-CREZ counties.

I use a rich set of covariates to control for confounding factors. I use county fixed effects denoted by α_i and a vector of county and demographic controls summarized by $\mathbf{X}$. This includes a linear time trend, cubic polynomial of county specific wind speed, capacity factor of wind generation, median land acerage, real price of land, indicator for whether the county has a wind ordinance, average farm size (acres) in 2007, median household income, and log of population. To account for correlation in interconnection queue across counties, I cluster the error ϵ_{it} at the county level.

Table D1 reports the results of OLS regression of Equation 28 with [2006, 2008] as the anticipation period. Column (5) is the baseline specification for the sample using CREZ counties and Column (6) is the baseline specification for the sample using non-CREZ counties. Panel A shows the results for IHS of the number of projects in interconnection as the dependent variable. The coefficient estimates suggest that anticipation effect for both CREZ and non-CREZ counties is positive but statistically and economically insignificant. Restricting the sample to counties obtained using matching (Panel A.2) in the long-run analysis does not change the results by much with the exception of the estimate for non-CREZ counties. I find a weak positive effect with an elasticity of 8 percent, however the coefficient is only significant at 10 percent critical level.

Panel B shows the results for IHS of the total capacity of projects in interconnection as the dependent variable. I find a positive anticipation effect for CREZ counties but it is not statistically significant in the baseline specification. Interestingly, the coefficient estimate for non-CREZ counties is negative but the magnitude is economically and statistically insignificant. Restricting to the counties in matching sample (Panel B.2) flips the pattern with CREZ counties showing a negative anticipation effect and non-CREZ counties showing a positive anticipation effect. However, none of these effects are statistically indistinguishable from zero.

Table D2 reports the results of OLS regression of Equation 28 with [2004, 2008] as the anticipation period. Column (5) and Column (6) are the baseline specifications for the samples using CREZ counties and non-CREZ counties respectively. Similar to Table D1, the coefficient estimates do not reveal any evidence of anticipation effects during the years 2004 to 2008 for both CREZ and non-CREZ counties. Therefore, based on the results from this analysis I rule out the possibility of an anticipation effect in the form of an increase in the number and capacity of wind projects in the ERCOT interconnection queue in the years leading upto CREZ announcement in late 2008.

Table D1: Anticipation of CREZ announcement for the years 2006 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Dependent variable: IHS (# projects in interconnection queue)					
	A.1 All counties in Texas					
Year $\in$ [2006, 2008]	0.102*	0.002	0.102*	0.002	0.066	0.002
	(0.054)	(0.008)	(0.055)	(0.009)	(0.059)	(0.010)
Elasticity	0.107	0.002	0.107	0.002	0.068	0.002
R^2	0.016	0.000	0.137	0.116	0.145	0.117
	A.2 Restricting to counties in the matching sample					
Year $\in$ [2006, 2008]	0.004	0.065	0.004	0.065	0.004	0.077*
	(0.054)	(0.044)	(0.055)	(0.045)	(0.056)	(0.044)
Elasticity	0.004	0.067	0.004	0.067	0.004	0.080
R^2	0.000	0.017	0.064	0.081	0.085	0.092
	B. Dependent variable: IHS (Total capacity (MW) in interconnection queue)					
	B.1 All counties in Texas					
Year $\in$ [2006, 2008]	0.454*	−0.021	0.454*	−0.021	0.304	−0.002
	(0.242)	(0.035)	(0.250)	(0.037)	(0.287)	(0.043)
Elasticity	0.575	−0.020	0.575	−0.02	0.356	−0.002
R^2	0.012	0.0001	0.137	0.123	0.145	0.124
	B.2 Restricting to counties in the matching sample					
Year $\in$ [2006, 2008]	−0.018	0.158	−0.018	0.158	−0.013	0.244
	(0.264)	(0.151)	(0.273)	(0.156)	(0.281)	(0.154)
Elasticity	−0.018	0.172	−0.018	0.172	−0.013	0.276
R^2	0.000	0.004	0.072	0.063	0.097	0.079
County FE			✓	✓	✓	✓
Time Trend					✓	✓
Wind Controls					✓	✓
County Controls					✓	✓
Sample	CREZ	non-CREZ	CREZ	non-CREZ	CREZ	non-CREZ

Notes: This table reports the results of regressions analyzing the anticipation effect of CREZ announcement for the years 2006 to 2008. Sample specifies whether the estimation sample is CREZ counties or non-CREZ counties. Panels A.1 and B.1 use all the counties in the data. Total observations in 'CREZ' and 'non-CREZ' Sample in A.1 and B.1 is 585 and 3,225 respectively. Panels A.2 and B.2 restrict the observations to the counties obtained in the matching sample. Total observations in 'CREZ' and 'non-CREZ' Sample in A.2 and B.2 is 195 and 450 respectively. The independent variable is an indicator variable for the years in 2006 to 2008. Time Trend is a linear time trend variable. Wind Controls include capacity factor and cubic polynomial of wind speed. County Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include median land acreage, real land price, indicator for the presence of wind ordinance, average farm size (acres) in 2007, median household income in 2007, and log of population. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Table D2: Anticipation of CREZ announcement for the years 2004 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	A. Dependent variable: IHS (# projects in interconnection queue)					
	A.1 All counties in Texas					
Year $\in$ [2004, 2008]	0.090*	−0.003	0.090*	−0.003	0.090	−0.003
	(0.046)	(0.006)	(0.048)	(0.006)	(0.065)	(0.009)
Elasticity	0.094	−0.003	0.094	−0.003	0.095	−0.003
R^2	0.017	0.0001	0.138	0.116	0.147	0.117
	A.2 Restricting to counties in the matching sample					
Year $\in$ [2004, 2008]	−0.031	0.026	−0.031	0.026	−0.043	0.063
	(0.043)	(0.028)	(0.044)	(0.029)	(0.087)	(0.039)
Elasticity	−0.031	0.026	−0.031	0.026	−0.042	0.065
R^2	0.003	0.004	0.067	0.068	0.087	0.083
	B. Dependent variable: IHS (Total capacity (MW) in interconnection queue)					
	B.1 All counties in Texas					
Year $\in$ [2004, 2008]	0.394*	−0.044*	0.394*	−0.044	0.443	−0.016
	(0.215)	(0.027)	(0.222)	(0.027)	(0.319)	(0.040)
Elasticity	0.482	−0.043	0.482	−0.043	0.557	−0.016
R^2	0.013	0.001	0.137	0.124	0.147	0.125
	B.2 Restricting to counties in the matching sample					
Year $\in$ [2004, 2008]	−0.194	0.006	−0.194	0.006	−0.264	0.205
	(0.221)	(0.106)	(0.229)	(0.109)	(0.435)	(0.153)
Elasticity	−0.176	0.006	−0.176	0.006	−0.232	0.227
R^2	0.005	0.000	0.077	0.059	0.100	0.075
County FE			✓	✓	✓	✓
Time Trend					✓	✓
Wind Controls					✓	✓
County Controls					✓	✓
Sample	CREZ	non-CREZ	CREZ	non-CREZ	CREZ	non-CREZ

Notes: This table reports the results of regressions analyzing the anticipation effect of CREZ announcement for the years 2004 to 2008. Sample specifies whether the estimation sample is CREZ counties or non-CREZ counties. Panels A.1 and B.1 use all the counties in the data. Total observations in 'CREZ' and 'non-CREZ' Sample in A.1 and B.1 is 585 and 3,225 respectively. Panels A.2 and B.2 restrict the observations to the counties obtained in the matching sample. Total observations in 'CREZ' and 'non-CREZ' Sample in A.2 and B.2 is 195 and 450 respectively. Time Trend is a linear time trend variable. Wind Controls include capacity factor and cubic polynomial of wind speed. County Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include median land acreage, real land price, indicator for the presence of wind ordinance, average farm size (acres) in 2007, median household income in 2007, and log of population. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

E Supplementary Figures

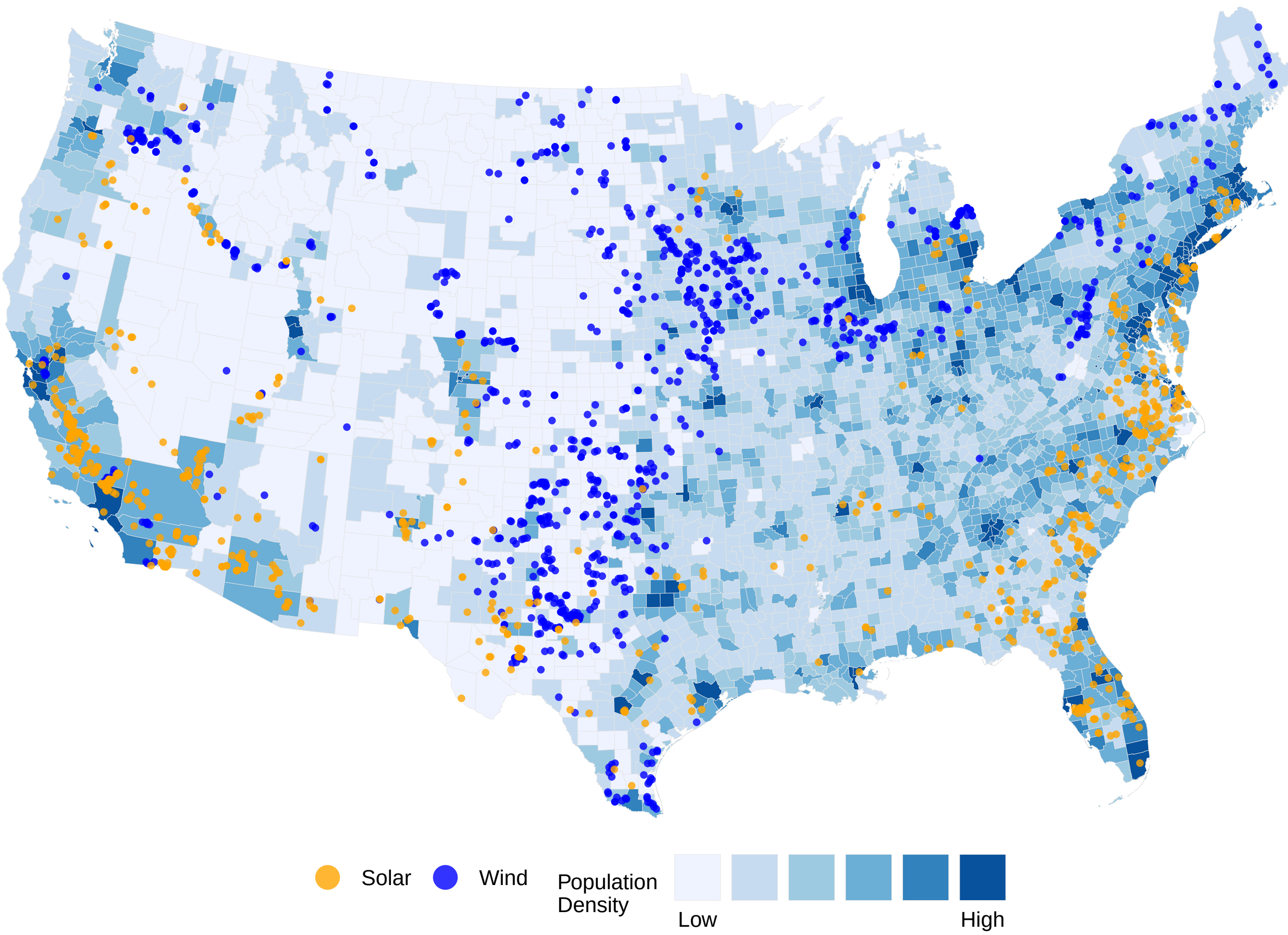
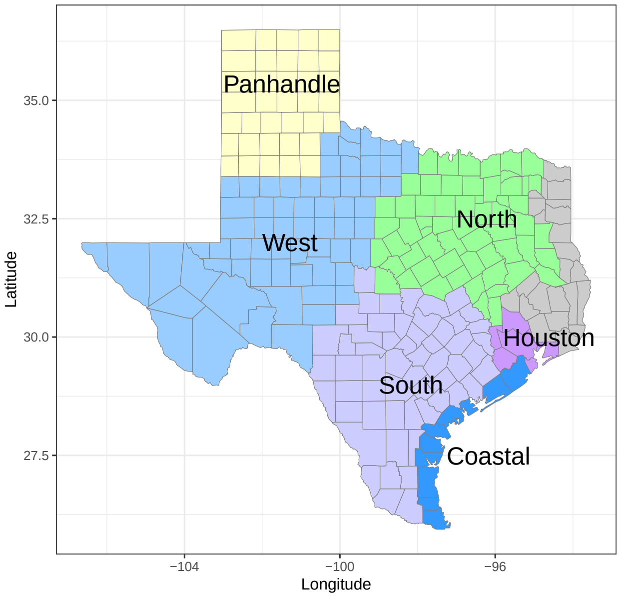
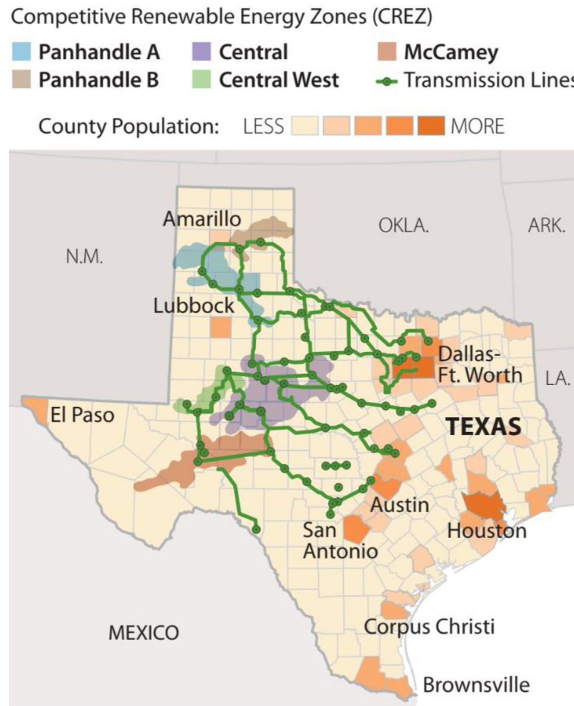


Figure E1: All solar and wind projects with $\geq$ 10 MW of nameplate capacity that started operation post 2001.

Note: The county level population density is based on 2014 data from US Census Bureau. Population density bins are: [0, 10], (10, 50], (50, 100], (100, 500], (500, 1,000], (1000, 72,000]. This figure shows that most utility scale wind and solar power plants are located far from the demand centers.



(a) ERCOT Zones Map



(b) CREZ lines and county level population. Source: US EIA

Figure E2: ERCOT Zones and CREZ transmission expansion

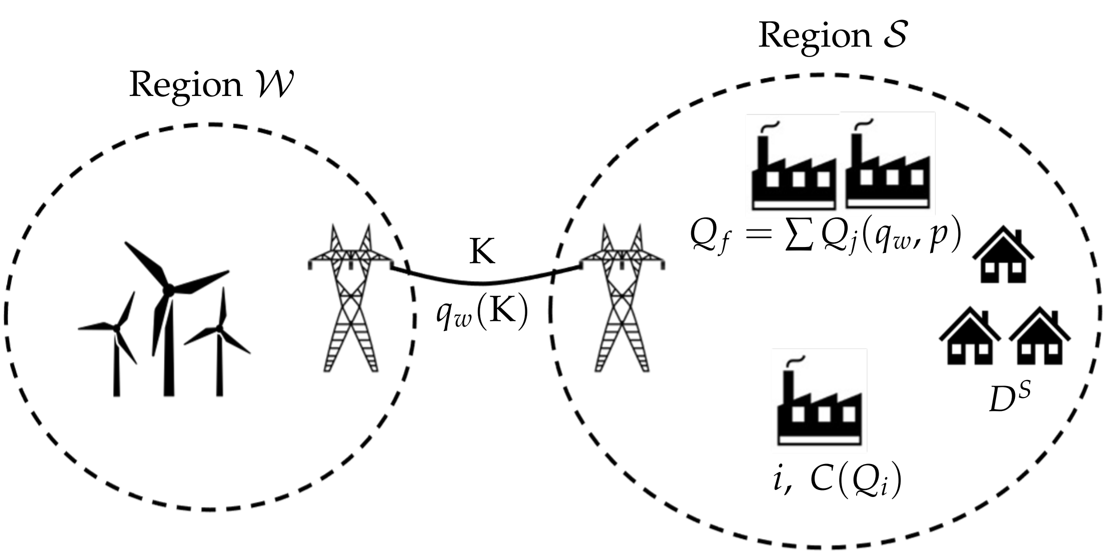


Figure E3: Theory model setup

Note: K denotes the transmission capacity between Regions $\mathcal{W}$ and $\mathcal{S}$, $q_w(\mathrm{K})$ is the amount of wind generation transported into region $\mathcal{S}$. D^S is the inelastic demand for electricity, $C(Q_i)$ is generator i's cost of generating electricity, and Q_f is the total electricity generated by other fossil fuel generator's.

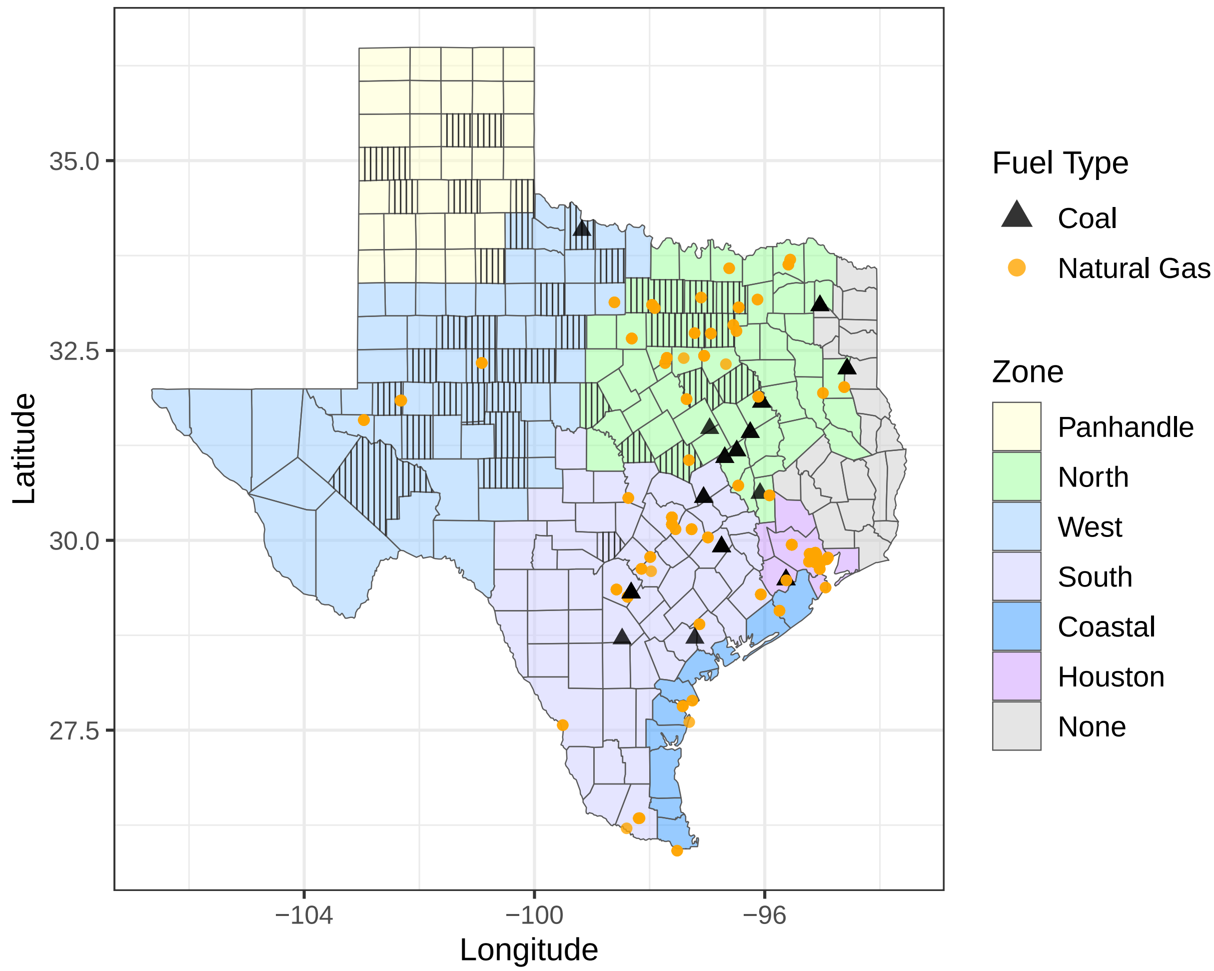


Figure E4: Coal and natural gas fired generators operating at the margin in sample from 2011 - 2014. Hatched counties denote the counties that received CREZ transmission expansion.

E.1 Robustness results for the impact of wind generation on markups

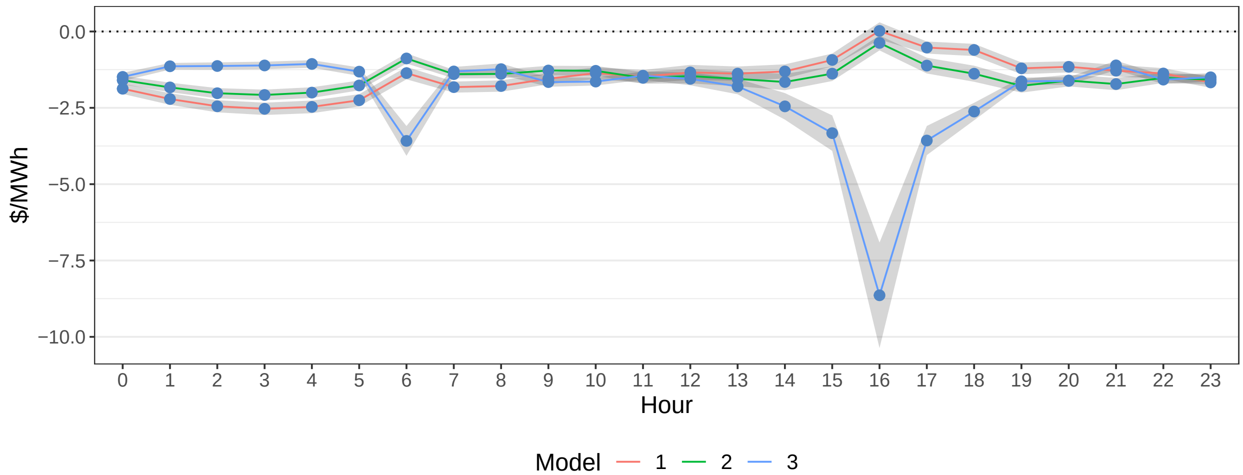


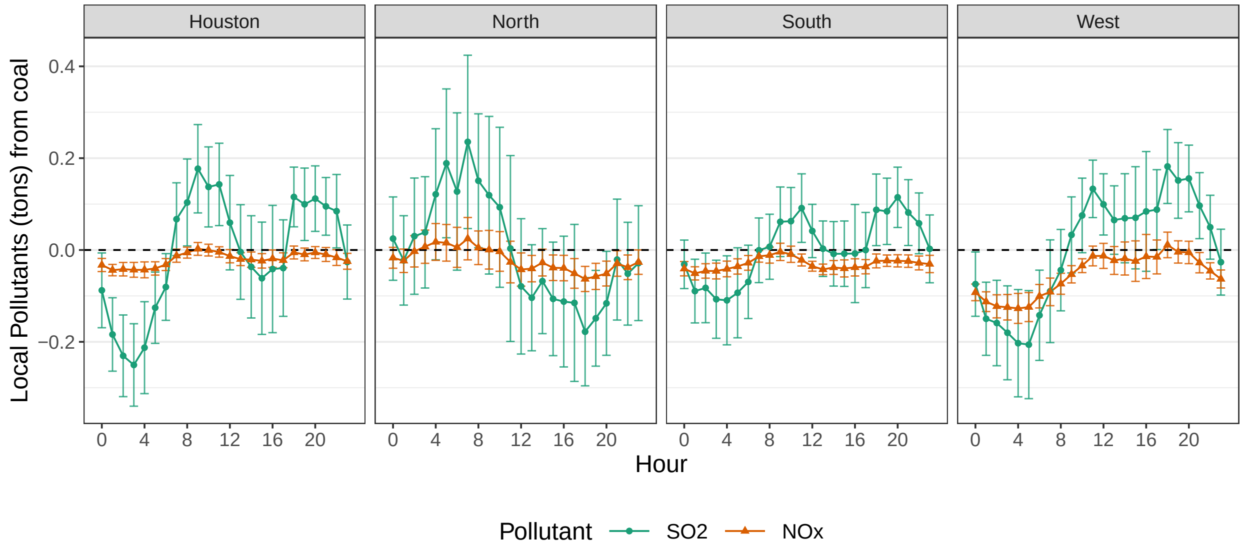
Figure E5: Effect of integration of 1 GWh of wind energy on marginal fossil fuel generator markups ($/MWh)

Sample: Hourly data from August 2011 to December 2014. 95 percent confidence intervals shown as shaded bands. Standard errors clustered at the generator level.

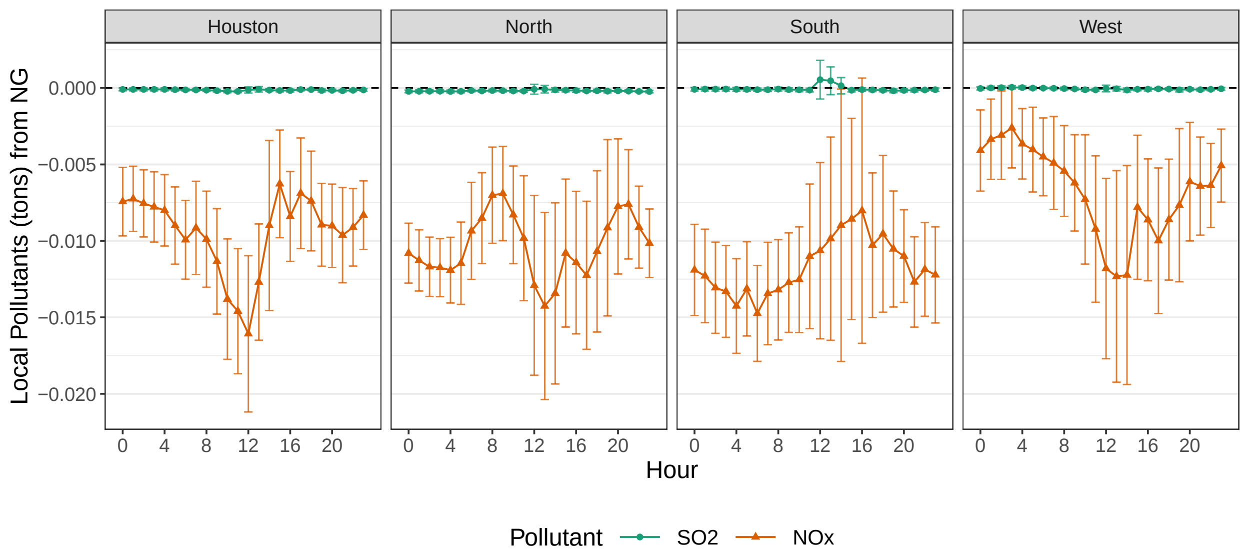
Model Specifications:

	(1)	(2)	(3)
Generator FE	✓	✓	✓
Load and Load^2		✓	✓
Hour × Month × Year FE			✓
Number of FE	284	284	1244
Observations	619,864	619,864	619,864
R^2	0.141	0.152	0.253

E.2 Wind generation and local pollution from marginal generators



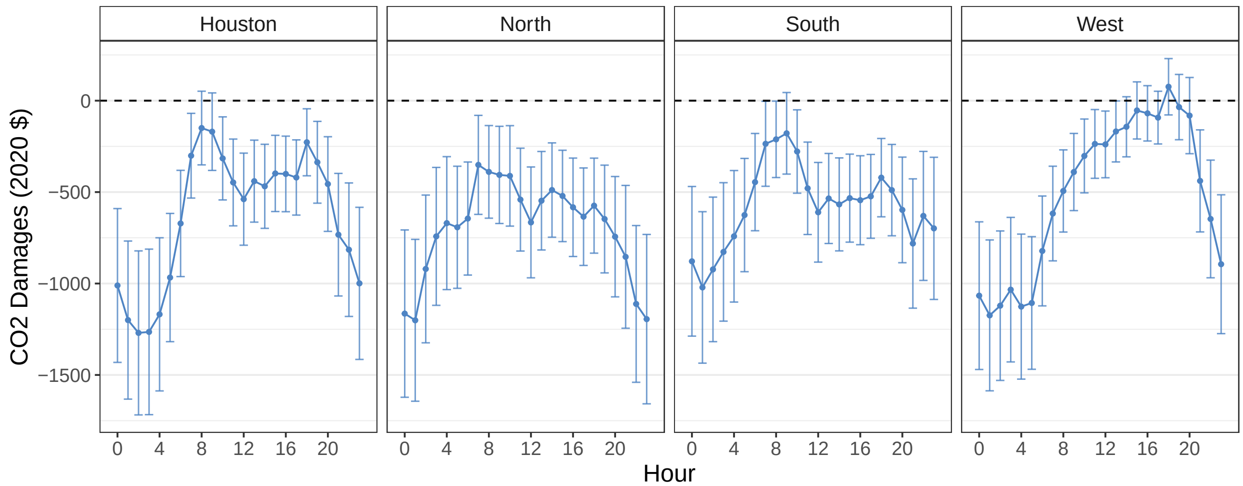
(a) Impact of wind generation on local pollutants (SO_2 and NOx) from coal generators



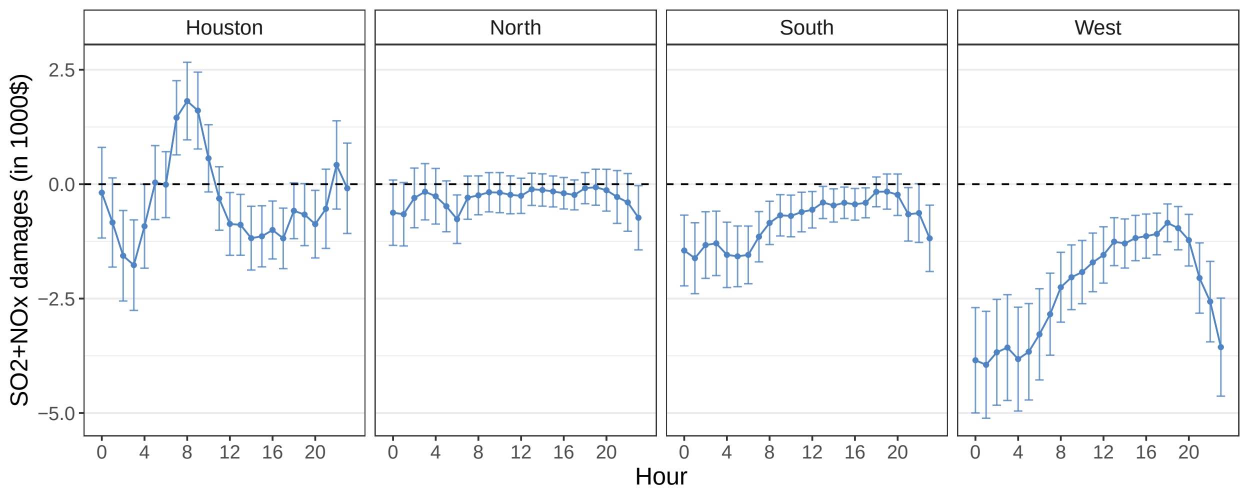
(b) Impact of wind generation on local pollutants (SO_2 and NOx) from natural gas generators

Figure E6: Short-run impact of wind generation on local pollutants (SO_2 and NOx) by generator type

E.3 Total damages from CO_2 and local pollutants for each hour



(a) Damages due to global pollution (CO_2)



(b) Damages due to local pollution (SO_2 and NOx)

Figure E7: Hourly averages of the marginal damages (2020 $) avoided due to CREZ expansion for each zone over 2011 - 2014.

E.4 Existence of multi-phase wind projects and project extensions

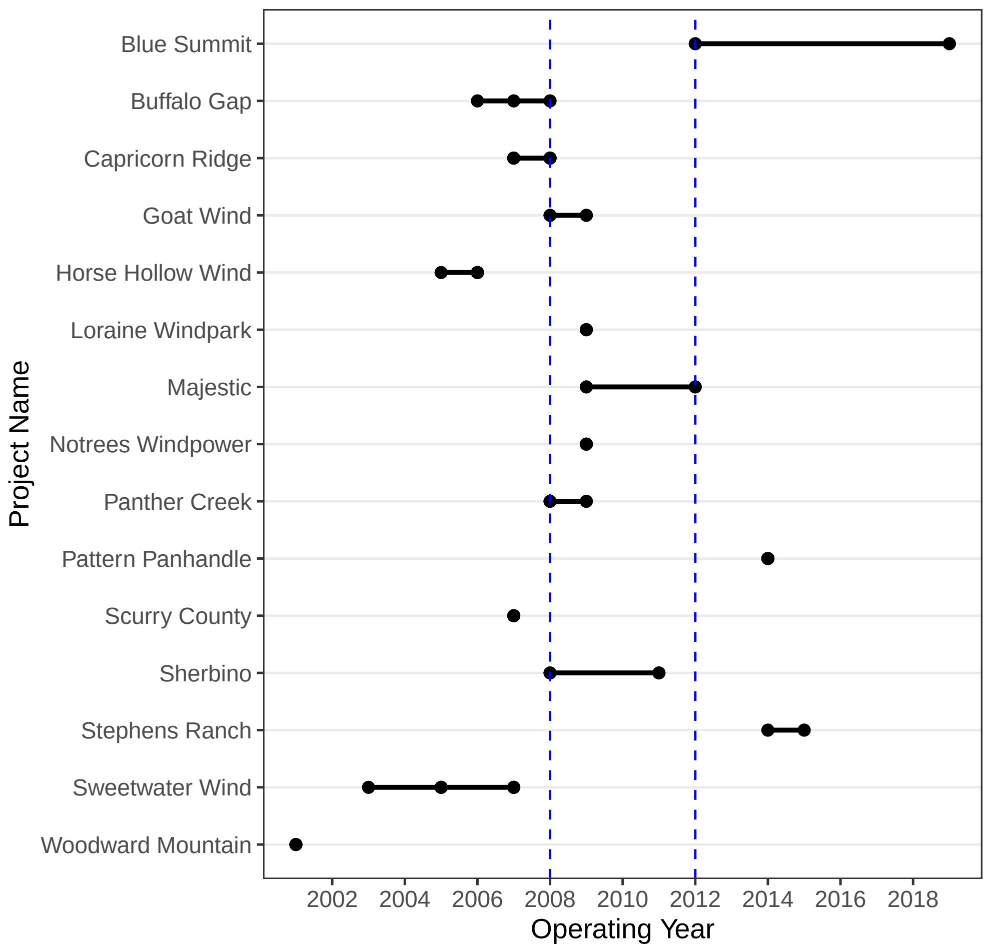


Figure E8: Wind projects with multiple phases and extensions

Note: This figure presents projects with multiple phases or extensions within CREZ counties. Each dot represents at least one phase. Projects with single dots (Loraine Windpark, Notrees Windpower, Pattern Panhandle, Scurry County, and Woodward Mountain) have multiple phases completed in the same year. There are 37 individual projects within 15 "main projects" shown in this figure. The selection issue arises if a line segment intersects both the dotted vertical lines for the years 2008 and 2012. From the figure, we do not see any instance of such a situation. However, wind projects under Majestic and Sherbino warrant more attention. The first phase of Majestic was completed in 2009 and the second one was completed in 2012. This is not a cause of concern since the first phase started operating post CREZ announcement in 2008 and only the second phase is counted in the dependent variable(s). In case of Sherbino, although the first phase was completed in 2008, the second phase was completed in 2011 and is therefore not included in the dependent variable(s).

F Supplementary Tables

F.1 Descriptive Statistics

Table F1: Descriptive statistics of key variables used in the short-run analysis

	2011		2012		2013		2014	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Marginal Cost ($/MWh)	17.19	14.13	12.97	12.16	18.48	17.88	20.71	19.39
Markups ($/MWh)	12.20	33.10	12.76	41.79	12.15	76.53	12.59	36.09
Load (GWh)	35.30	8.24	36.16	7.59	37.02	7.62	38.05	7.93
Wind Generation (GWh)	2.47	1.59	2.96	1.73	3.30	1.95	3.88	2.43
CREZ progress	0.06	0.01	0.11	0.06	0.61	0.22	1.00	0.00

This table reports the annual means and standard deviation (SD) of key variables used in the short-run analysis in Section 4. Note that marginal cost and markups is at the hourly generator level, load and wind generation are the hourly system level. CREZ progress is the ratio of cumulative addition of transmission lines (at the daily level) to total length of transmission lines built in CREZ.

Table F2: Effect of CREZ completion on hourly wind generation (GWh)

	Dependent variable: Hourly Wind Generation (GWh)		
	(1)	(2)	(3)
crez			
$\times \mathbb{1}\{\text{hour} = 0\}$	1.722 (0.206)***	0.170 (0.024)***	0.228 (0.027)***
$\times \mathbb{1}\{\text{hour} = 1\}$	1.706 (0.207)***	0.165 (0.024)***	0.221 (0.027)***
$\times \mathbb{1}\{\text{hour} = 2\}$	1.621 (0.208)***	0.160 (0.025)***	0.213 (0.028)***
$\times \mathbb{1}\{\text{hour} = 3\}$	1.489 (0.207)***	0.156 (0.024)***	0.202 (0.028)***
$\times \mathbb{1}\{\text{hour} = 4\}$	1.336 (0.209)***	0.166 (0.023)***	0.200 (0.025)***
$\times \mathbb{1}\{\text{hour} = 5\}$	1.163 (0.208)***	0.171 (0.022)***	0.171 (0.021)***
$\times \mathbb{1}\{\text{hour} = 6\}$	0.992 (0.207)***	0.169 (0.021)***	0.147 (0.020)***
$\times \mathbb{1}\{\text{hour} = 7\}$	0.827 (0.207)***	0.169 (0.020)***	0.142 (0.020)***
$\times \mathbb{1}\{\text{hour} = 8\}$	0.505 (0.210)***	0.161 (0.019)***	0.126 (0.018)***
$\times \mathbb{1}\{\text{hour} = 9\}$	0.286 (0.213)**	0.151 (0.018)***	0.127 (0.018)***
$\times \mathbb{1}\{\text{hour} = 10\}$	0.216 (0.215)*	0.146 (0.018)***	0.128 (0.019)***
$\times \mathbb{1}\{\text{hour} = 11\}$	0.047 (0.214)	0.138 (0.018)***	0.123 (0.018)***
$\times \mathbb{1}\{\text{hour} = 12\}$	−0.113 (0.211)	0.130 (0.017)***	0.115 (0.018)***
$\times \mathbb{1}\{\text{hour} = 13\}$	−0.193 (0.207)	0.127 (0.017)***	0.107 (0.017)***
$\times \mathbb{1}\{\text{hour} = 14\}$	−0.147 (0.203)	0.129 (0.017)***	0.106 (0.017)***
$\times \mathbb{1}\{\text{hour} = 15\}$	−0.059 (0.200)	0.131 (0.017)***	0.102 (0.016)***
$\times \mathbb{1}\{\text{hour} = 16\}$	0.038 (0.200)	0.134 (0.017)***	0.102 (0.016)***
$\times \mathbb{1}\{\text{hour} = 17\}$	0.105 (0.201)	0.138 (0.018)***	0.099 (0.015)***
$\times \mathbb{1}\{\text{hour} = 18\}$	0.313 (0.206)**	0.149 (0.018)***	0.104 (0.016)***
$\times \mathbb{1}\{\text{hour} = 19\}$	0.597 (0.205)***	0.160 (0.019)***	0.124 (0.018)***
$\times \mathbb{1}\{\text{hour} = 20\}$	0.844 (0.198)***	0.168 (0.020)***	0.145 (0.020)***
$\times \mathbb{1}\{\text{hour} = 21\}$	1.177 (0.196)***	0.179 (0.021)***	0.179 (0.023)***
$\times \mathbb{1}\{\text{hour} = 22\}$	1.513 (0.199)***	0.188 (0.023)***	0.207 (0.025)***
$\times \mathbb{1}\{\text{hour} = 23\}$	1.676 (0.204)***	0.182 (0.023)***	0.224 (0.026)***
High System Limit		✓	✓
Hour × Month FE			✓
Observations	29,205	29,205	29,205
R^2	0.051	0.992	0.992

This table reports the coefficient estimates of Equation 14. The dependent variable is total wind generation (GWh) at hour t. The coefficient of interest are the interaction of CREZ progress (*crez*) and indicator of the hour. All regressions use hourly data from August 2011 to December 2014. Newey-West Autocorrelation corrected standard errors with a 7 day lag structures reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

F.2 Robustness checks for matching on unobservables

F.2.1 Results excluding 'contesting' counties

Table F3: Effect of CREZ expansion on wind investment - matching results

	Dependent variable		
	Total Nameplate Capacity (MW)	Total Turbines	Avg. Capacity of a project (MW)
	(1)	(2)	(3)
CREZ	72.640***	39.419***	29.671*
	(26.499)	(13.075)	(15.423)
Mean Dep. Variable	35.907	16.067	26.951
Semi-elasticity (%)	202.3	245.3	110.1
Controls	✓	✓	✓
Group × Trend FE	✓	✓	✓
Matching Weights	✓	✓	✓
Sample	Matched	Matched	Matched
Observations	344	344	344
R^2	0.400	0.411	0.353

Notes: This table reports the result of regressions excluding 'contesting' counties (Kendall, Gillespie, Newton, Kimble, Kerr, Mason, and Schleicher) from the sample before using Coarsened Exact Matching to obtain the matched sample. The independent variable is a binary variable indicating whether a county received CREZ transmission infrastructure or not. All specifications include cubic polynomial of time trend and controls for wind quality, project cost, county level regulation and demographics. Wind controls include power curve, capacity factor, and cubic polynomial of wind speed. Project Cost Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include FE for PTC and wind ordinance in a county. Demographic controls include average farm size (acres) in 2007, median household income in 2007, and average population over 2007 to 2010. I also include group by trend fixed effects to allow for time varying unobserved factors affecting matching groups. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***$p<0.01$;**$p<0.05$;*$p<0.1$

F.2.2 Results excluding 'enthusiastic' counties

Table F4: Effect of CREZ expansion on wind investment - matching results

	Dependent variable		
	Total Nameplate Capacity (MW)	Total Turbines	Avg. Capacity of a project (MW)
	(1)	(2)	(3)
CREZ	78.277***	42.508***	31.496*
	(28.030)	(13.617)	(16.666)
Mean Dep. Variable	36.636	16.484	26.761
Semi-elasticity (%)	213.661	257.9	117.6
Controls	✓	✓	✓
Group $\times$ Trend FE	✓	✓	✓
Matching Weights	✓	✓	✓
Sample	Matched	Matched	Matched
Observations	312	312	312
R^2	0.414	0.433	0.347

Notes: This table reports the result of regressions excluding 'enthusiastic' counties (Dallam, Sherman, Oldham, Swisher, Lipscomb, Parmer, Lamar, Hall, Deaf Smith) from the sample before using Coarsened Exact Matching to obtain the matched sample. The independent variable is a binary variable indicating whether a county received CREZ transmission infrastructure or not. All specifications include cubic polynomial of time trend and controls for wind quality, project cost, county level regulation and demographics. Wind controls include power curve, capacity factor, and cubic polynomial of wind speed. Project Cost Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include FE for PTC and wind ordinance in a county. Demographic controls include average farm size (acres) in 2007, median household income in 2007, and average population over 2007 to 2010. I also include group by trend fixed effects to allow for time varying unobserved factors affecting matching groups. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***$p<0.01$;**$p<0.05$;*$p<0.1$

F.3 Robustness check results for different specifications for matching regression

Table F5: Effect of CREZ on total wind capacity (MW)

	Dependent variable: Total Nameplate Capacity (MW)			
	(1)	(2)	(3)	(4)
CREZ	43.041*	60.425**	71.670***	72.640***
	(22.676)	(27.899)	(26.194)	(26.499)
Time Trend	✓	✓	✓	✓
Wind Controls	✓	✓	✓	✓
Project Cost Controls	✓	✓	✓	✓
Regulatory Controls	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
FE	Zone	Group	Group	Group $\times$ Trend
Sample	OLS	Matched	Matched	Matched
CEM Weights			✓	✓
Mean Dep. Variable	33.069	35.907	35.907	35.907
Observations	2,024	344	344	344
R^2	0.218	0.339	0.390	0.467

Notes: The dependent variable is total turbines in a county in year t. The independent variable is a binary variable indicating whether a county is CREZ or not. OLS Sample is a balanced panel of 253 Texas counties from 2012-2019. Matched Sample is a balanced panel of 13 treated (CREZ) and 30 control (non-CREZ) counties from 2012-2019 obtained using CEM. Time Trend is a cubic polynomial of linear time trend variable, Wind Controls include power curve, capacity factor, and cubic polynomial of wind speed. Project Cost Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include FE for PTC and wind ordinance in a county. Demographic controls include average farm size (acres) in 2007, median household income in 2007, and average population over 2007 to 2010. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Table F6: Effect of CREZ on Total Turbines in a County

	Dependent variable: Total Turbines in a County			
	(1)	(2)	(3)	(4)
CREZ	23.358**	34.451**	39.826**	39.419***
	(11.855)	(15.718)	(15.467)	(13.075)
Time Trend	✓	✓	✓	✓
Wind Controls	✓	✓	✓	✓
Project Cost Controls	✓	✓	✓	✓
Regulatory Controls	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
FE	Zone	Group	Group	Group × Trend
Sample	OLS	Matched	Matched	Matched
CEM Weights			✓	✓
Mean Dep. Variable	15.928	16.067	16.067	16.067
Observations	2,024	344	344	344
R^2	0.206	0.347	0.408	0.476

Notes: The dependent variable is total turbines in a county in year *t*. The independent variable is a binary variable indicating whether a county is CREZ or not. OLS Sample is a balanced panel of 253 Texas counties from 2012-2019. Matched Sample is a balanced panel of 13 treated (CREZ) and 30 control (non-CREZ) counties from 2012-2019 obtained using CEM. Time Trend is a cubic polynomial of linear time trend variable, Wind Controls include power curve, capacity factor, and cubic polynomial of wind speed. Project Cost Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include FE for PTC and wind ordinance in a county. Demographic controls include average farm size (acres) in 2007, median household income in 2007, and average population over 2007 to 2010. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Table F7: Effect of CREZ on Average Capacity (MW) of a wind project in a County

	Dependent variable: Average Capacity (MW) of a project			
	(1)	(2)	(3)	(4)
CREZ	10.620*	26.500	32.722*	32.756*
	(10.721)	(19.046)	(18.832)	(19.093)
Time Trend	✓	✓	✓	✓
Wind Controls	✓	✓	✓	✓
Project Cost Controls	✓	✓	✓	✓
Regulatory Controls	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
FE	Zone	Group	Group	Group × Trend
Sample	OLS	Matched	Matched	Matched
CEM Weights			✓	✓
Mean Dep. Variable	19.99	26.951	26.951	26.951
Observations	2,024	344	344	344
R^2	0.196	0.313	0.345	0.426

Notes: The dependent variable is the average capacity of a wind project in a county in year t. The independent variable is a binary variable indicating whether a county is CREZ or not. OLS Sample is a balanced panel of 253 Texas counties from 2012-2019. Matched Sample is a balanced panel of 13 treated (CREZ) and 30 control (non-CREZ) counties from 2012-2019 obtained using CEM. Time Trend is a cubic polynomial of linear time trend variable, Wind Controls include power curve, capacity factor, and cubic polynomial of wind speed. Project Cost Controls include average wind project cost, real land price, and median land acreage. Regulatory Controls include FE for PTC and wind ordinance in a county. Demographic controls include average farm size (acres) in 2007, median household income in 2007, and average population over 2007 to 2010. Robust Standard Errors clustered at the county level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1