Wiring America: Market and Environmental Effects of Electricity Grid Expansion*

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Abstract

This paper examines the impact of transmission expansion on market power and emissions from fossil fuel generators in wholesale electricity markets. The analysis proceeds by first isolating the impact of transmission expansion on integrating wind energy, followed by the effect of wind integration on markups and emissions from marginal producers. Utilizing the context of a large-scale grid expansion project in Texas, I find annual benefits of approximately $313 million due to lower market power and emissions. These findings underscore the significant economic benefits of transmission expansion, a key policy to achieve decarbonization in the US.

JEL Classifications: L11, Q40, Q41, Q53.
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1 Introduction

Investment in electricity transmission is crucial to fully realize the benefits of renewable energy and achieve ambitious energy policy targets. Because most wind and solar farms in the US are located far from demand centers, high-capacity transmission lines are necessary to move this electricity over long distances. Inadequate transmission impedes integration of electricity from renewable sources (Joskow and Tirole 2005) and enhances the market power by fossil fuel generators (Borenstein, Bushnell, and Stoft 2000).[1]

In this paper I study the short-run impact of large scale grid expansion on fossil fuel market power and emissions. I develop an estimator that proceeds in two steps: first, isolating the impact of transmission expansion on integrating wind energy by lowering curtailment,[2] followed by estimating the effect of wind integration on market power and marginal emissions. This is the first paper to analyze market power and emissions through this mechanism in a nodal wholesale electricity market.[3] I answer the research questions in the context of a large-scale transmission expansion project called Competitive Renewable Energy Zones (CREZ) in Texas.

I write a model of optimal bidding to understand how transmission expansion affects a fossil fuel generator's incentives in setting markups. The model includes a geographically distinct renewable sector which is connected to the demand centers and the fossil fuel sector through high capacity transmission lines. I develop this model in the context of a uniform auction in a nodal market wherein the generator participates by bidding on the price and quantity of electricity. I focus on the case of a marginal generator because its optimal bid determines the wholesale electricity price at the node. The corresponding markup set by the generator is the 'realized markup.'

My model yields insights on how transmission expansion affects realized markups. In the short run with the stock of generating capacity fixed, transmission expansion integrates wind energy into the grid by lowering curtailment. This affects a marginal fossil fuel generator in two ways: (1) by displacing energy production, characterised by an inward shift of the residual demand, and (2) by changing the slope of the residual

1. This issue has also been covered widely in popular news outlets, pointing out the imminent necessity to build transmission lines in order to dramatically cut carbon emissions and achieve ambitious energy targets (New York Times 2016; Meyer 2021).

2. Wind curtailment is the reduction in electricity generated from a wind generator below the level it could have produced given available resources, in this case availability of electricity transmission capacity (Bird, Cochran, and Wang 2014).

3. In a nodal electricity market the market clearing process occurs at each node instead of a zone as in a zonal market. Depending on binding constraints at a given period, there could be several marginal entities and corresponding market clearing prices associated with different nodes in the entire market. When no binding constraints exist, prices are uniform across all the nodes.

demand. A flatter residual demand curve implies lower ability to set markups whereas a steeper residual demand curve enhances the potential for higher markups.

Using detailed generator level bidding and generation data, I follow Ito and Reguant (2016) to calculate the residual demand curve for each marginal generator at the node specific market clearing price. I then conduct empirical tests of the aforementioned findings from the theoretical model. I show negative relationship between wind generation and residual demand, and a positive relationship between transmission expansion and the slope of residual demand. Finally, consistent with the theory, I find that a steeper residual demand curve is associated with larger markups.

The theoretical model shows that the overall impact of grid expansion on markups is driven by the extent to which grid expansion integrates electricity from wind and the impact of this additional wind on markups. The finding motivates the empirical strategy for the analysis. I use a fixed effects model to estimate the empirical analogs of the relationship between transmission expansion and markups. In the first step, I estimate the effect of transmission expansion on wind integration (by lowering curtailment), followed by the impact of wind generation on hourly markups. The empirical specifications flexibly control for confounding factors like electricity demand and seasonal variation that could be correlated with wind generation and markups.

I utilize hourly generator level data on generation, prices, and emissions from August 2011 to December 2014, along with detailed temporal data on the rollout of CREZ transmission expansion from the Public Utilities Commission of Texas. I combine these data with information on fuel prices and generator heat rate to construct marginal cost of generation, generator characteristics from EIA Form 860, and hand collected generator specific ownership data for heterogeneity analysis.

The empirical analysis shows that the CREZ expansion led to moderate decline in markups with the magnitude of decline strongest at the peak demand hours. A counterfactual analysis shows that the incidence of market power would have led to about $2.8 billion worth of excess rents over the sample period in the absence of transmission expansion. This translates to about a $190 million annual reduction in excess rents collected by fossil fuel generators from electricity consumers due to lower markups. These transfers are policy relevant, as they can translate to lower retail rates and optimal electricity consumption in medium to long-run.

I conduct two main heterogeneity analyses to understand the drivers of these results. First, I show that most of the decline in markups are due to natural gas generators operating at the margin of electricity supply curve during peak demand hours. Second, I find that firms with ownership of generators across different fuel types show larger declines in markups than firms with ownership of generator(s) of a single fuel type. This effect is especially higher at the peak hours, indicating the impact of greater market competition due to transmission expansion.

Next, I study the impact of CREZ expansion on hourly emissions across generators. I find that CREZ led to an approximately $123 million worth of annual decline in emissions, with the majority of the decline from carbon emissions followed by SO_2 and NOx emissions from marginal producers in West and Houston region. Using generator level regressions, I show that most of these benefits are due to lower emissions from large coal generators in Houston and West during off-peak hours. However, some of the benefits of lower emissions are offset by ramping up of coal generators in peak-hours due to wind intermittency.

Incidence of market power and emissions from the fossil fuel sector in electricity markets are central policy issues. Analyzing these issues within the context of energy transition is useful for understanding policies like grid expansion that could speed up the transition (Gonzales, Ito, and Reguant 2023; Doshi 2024). While transmission expansions are expensive endeavors, the benefits accrue over time. The analysis shows annual benefits of about $313 million dollars due to lower market power and emissions from marginal producers. These estimated benefits are in conjunction additional benefits, such as enhanced grid reliability and lower transmission congestion.[4] Therefore, these estimates are lower-bound numbers.

The findings from this paper also provide insights for grid expansion in other wholesale markets in the US. The theoretical model and the empirical strategy can be applied to markets such as Midwest ISO and Southwest Power Pool where transmission expansion could integrate renewable resources into the grid and lead to large reductions in both emissions and market power associated with the fossil fuel sector. This analysis can be informative for wholesale electricity markets beyond US undergoing energy transition with investments in large scale grid expansion.

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 post-deregulation electricity markets have found that market power contributes to high wholesale prices (Borenstein, Bushnell, and Wolak 2002) and misallocation of generating resources due to sub-optimal

4. Transmission lines are said to be congested when they operate at maximum capacity. Some of the main reasons for transmission congestion are insufficient transmission capacity and spike in demand due to weather conditions. Recent literature has shown evidence of lower market power and lower emissions as a result of to lower grid congestion in Texas post transmission expansion (Fell, Kaffine, and Novan 2021; Woerman 2023).

bidding behavior (Hortacsu and Puller 2008; Hernández 2018). The existence of market power in sequential electricity markets causes a lack of arbitrage, which results in price premia across markets (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, Mansur, and Saravia 2008).

Second, I contribute to the 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 more competition and mitigates the effects of market power (Borenstein, Bushnell, and Stoft 2000; Joskow and Tirole 2000, 2005). Recent empirical literature has looked at role of transmission constraints in exacerbating the market power exercised by generating firms (Ryan 2021). I make theoretical and empirical contributions to this literature by estimating changes in markups from marginal producers in response to transmission expansion in a nodal wholesale electricity market.

Third, I add to the literature in economics looking at the nexus between transmission expansion, wind energy, and emissions in electricity markets. This also builds upon studies estimating the impact of renewable generation in lowering emissions (Kaffine, McBee, and Lieskovsky 2013; Novan 2015). The closest empirical study that looks at the link between grid expansion and emissions is Fell, Kaffine, and Novan (2021). However, there is one key difference. Fell, Kaffine, and Novan (2021) focus on how CREZ expansion enhanced the environmental value of wind by lowering congestion. By contrast, this paper focuses on a different mechanism- marginal emissions avoided due to lower wind curtailment as a result of transmission expansion. To the extent that these two papers are different, the findings on emissions are complimentary.

Finally, I contribute to the recent empirical literature looking at various market level impacts of CREZ expansion. These studies show evidence of lower wholesale prices (LaRiviere and Lyu 2022), lower costs of hedging congestion risk (Doshi and Du 2021), and evidence of long-run investment in wind energy due to grid expansion (Doshi 2024).

Outline. The remainder of this paper is organized as follows. Section 2 describes the institutional context along with the CREZ expansion project. Section 3 presents the theoretical model of fossil fuel markups followed by a description of the data and summary statistics in Section 4. Section 5 and Section 6 presents the empirical strategy and results for the markups and emissions respectively. Section 7 provides a simple welfare analysis followed by a concluding discussion in Section 8.

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. ERCOT schedules the dispatch of generators in order to meet demand for electricity at all times, and oversees more than 46,500 miles of electricity transmission and 700 generators serving electricity demand from over 26 million consumers over the state of Texas. 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). Figure 1a 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, while most of the fossil fuel capacity and demand centers are located in the East and South.

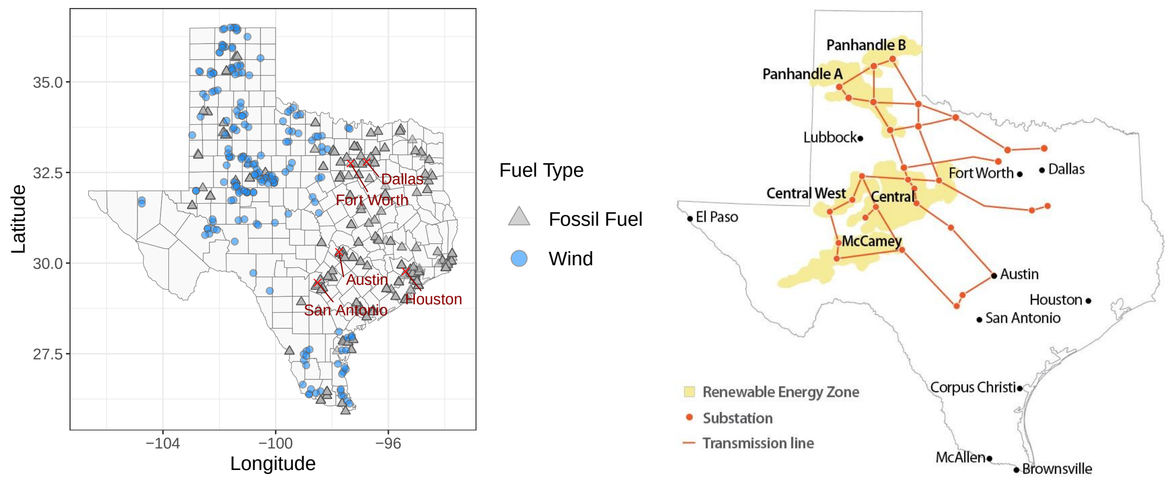
2.2 Competitive Renewable Energy Zones

Competitive Renewable Energy Zones (CREZ) was a large-scale transmission expansion project aimed at integrating electricity generation from wind farms located in the West to the major demand centers in the East (Figure 1b). The project, commissioned in 2008 by the Public Utilities Commission of Texas, was aimed at accommodating 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 wind generators (Billo 2017). These 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 placed in service by December 2013 (Lasher 2014).

2.3 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 the participation of various market participants, including generators, retailers, transmission service providers, and distributors. ERCOT manages the efficient operation of the real-

Figure 1: ERCOT Zones and CREZ transmission expansion



(a) Wind farms and fossil fuel generators

(b) CREZ lines and substations

Note: Figure 1a shows the geographic distribution of various electricity generators in Texas. Fossil Fuel generators include coal, natural gas, petroleum, and other gas based generators. Petroleum and other gas based generators are only 2 percent of total generators in Texas. Red triangles mark the locations of the five biggest population centers in Texas. Figure 1b shows the location of the CREZ transmission lines. Source: ERCOT

time market, including scheduling the dispatch of generators to meet the demand at all times using a series of sequential auctions.

Electricity transmission enables the flow of electricity from the generating units to the demand centers. Generators are scheduled to dispatch in an increasing order of electricity generating costs. Thus, renewable 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.

Transmission lines operate under certain capacity limits that need to be maintained. Inadequate transmission capacity between the West and other parts of Texas can lead to congestion, thereby preventing the export of electricity from the wind-rich West to demand centers in the East. Binding transmission constraints could cause ERCOT to schedule electricity from local fossil fuel generators, resulting in emissions that would otherwise be offset by wind-based electricity. Additionally this could incentivize fossil fuel generators to exert market power by charging markups over their marginal cost of production.[5] Transmission expansion is a key public policy investment aimed at relieving transmission congestion and integrating renewable generators into the grid.

5. Please refer to Appendix B for an example that illustrates this phenomenon.

3 A Model of Optimal Fossil Fuel Markups

The theoretical model 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) and Ryan (2021), but extend these by including a renewable sector that is geographically distinct from the demand centers and the fossil fuel sector. The renewable sector is connected to the demand centers via high capacity transmission lines. In what follows, I derive the optimal markup rule for a fossil fuel generator and provide intuition on how it is affected by the transmission expansion.

3.1 Model Setup

In this model, I focus on the pricing decision of a profit-maximizing fossil fuel generator i located in region $\mathcal{E}$. 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.

The generator faces uncertainty over the offer schedules $\mathcal{E}_{-i} = (b_{-i}, Q_{-i})$ from other competitive fossil fuel generators $(-i)$ in $\mathcal{E}$.[6] Generator i's optimization problem is:

$$\max_{b_i, Q_i} \mathbb{E}_{\mathcal{E}_{-i}} \left[p \cdot Q_i(p) - C_i(Q_i(p)) \right] \tag{1}$$

Market demand in $\mathcal{E}$ is denoted by $D^{\mathcal{E}}$ and is assumed to be perfectly inelastic. Generator i faces a downward-sloping residual demand curve $D_i^r(p, q_w; \mathrm{K})$ comprised of demand for electricity $D^{\mathcal{E}}$, electricity generated from wind farms denoted by $q_w(K)$, and electricity generated from infra-marginal fossil fuel producers, $Q_{-i}(p; K)$.

Regions $\mathcal{E}$ and $\mathcal{W}$ are connected by transmission lines K which enable the export of electricity from wind farms in $\mathcal{W}$. Thus, q_w is a function of available transmission capacity K. I express Q_{-i} as $s \times p$, where s is the slope of generator i's residual demand curve. The inherent assumption is that infra-marginal producers are willing to produce electricity as long as p is above their marginal costs, $c_{-i}(q) = q/p$. This micro-foundation

6. For simplicity, I abstract away from any forward positions that generator i might have. Appendix C shows an extension of this model which considers the forward position. Key findings and the intuition does not change.

is similar to the one in Ito and Reguant (2016).[7] Thus, $D_i^r(p, q_w; K)$ is,

$$\begin{aligned} D_i^r(p, q_w; \mathrm{K}) &= D^{\mathcal{E}} - q_w(K) - Q_{-i}(p, q_w; K) \\ &= D^{\mathcal{E}} - q_w(K) - sp \end{aligned} \tag{2}$$

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 $Q_i(p, q_w; K)$ depend on the optimal bid price b_i that solves the generator i's problem:

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

Taking a first-order condition with respect to b_i and rearranging,

$$\implies \mathbb{E}_{\mathcal{E}_{-i}} \left[\frac{\partial p}{\partial b_i} \left(D_i^r(p, q_w; K) + \frac{\partial D_i^r(p, q_w; K)}{\partial p} \left[p - C_i'(D_i^r(p, q_w; K)) \right] \right) \right] \bigg|_{p=b_i} = 0 \tag{3}$$

$\frac{\partial p}{\partial b_i}$ is the slope of the market-clearing bid price and is equal to one if the bid is marginal and zero otherwise. I focus on the marginal generator, whose optimal bid b_i determines the market-clearing price. For simplicity, I assume constant marginal cost, i.e., $C_i'(D_i^r(p, q_w; K)) = c_i$, as well as full information on other generators' strategy. Equation (22) reduces to,

$$p - c_i = \frac{D_i^r(p, q_w; K)}{-\partial D_i^r(p, q_w; K)/\partial p} \tag{4}$$

Equation 4 shows that the 'realized markups' is a function of residual demand and its slope (which is a negative quantity). The numerator measures how generator i's production decision affects markups. The denominator shows that with a flatter residual demand curve, generator will find it optimal to set lower markups, whereas a steeper residual demand implies higher markups.

7. Wind-based electricity generation incurs zero marginal cost and is always scheduled to dispatch first. I assume $D^{\mathcal{E}} > q_w$ which ensures that fossil fuel generators are scheduled to dispatch in order to meet the remaining demand of $D^{\mathcal{E}} - q_w$ units of power. Another assumption is that of a downward sloping residual demand for generator i, i.e. $\frac{\partial D_i^r(p, q_w; K)}{\partial p} = -s,\ s > 0$. Both of these assumptions are consistent with the data and the empirical context.

3.2 Model illustration and predictions

For intuition on the model predictions, consider the hypothetical electricity dispatch curve shown in Figure 2a. 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 of generators arranged in increasing order of the offer price. The dotted vertical line (D) is the demand for electricity and is assumed to be fixed in the short run. Generators are dispatched in increasing order of the offer price until the demand is met. The generator(s) dispatched with the highest offer price is the marginal generator, which determines the wholesale price of electricity. In this case, generator i submits the highest offer price c_4 and is thus the marginal generator. Note that I assume the marginal generator to remain fixed throughout this analysis.

Next, to characterize the effect of transmission line (K) expansion on markups, I perform a comparative statics exercise by partially differentiating Equation (4) with respect to K. Simplifying and expressing the resulting expression as a percentage change in markups:

$$\frac{\partial (p - c_i)/(p - c_i)}{\partial K} = \underbrace{\left[\frac{1}{D_i^r(p, q_w; K)} \cdot \frac{\partial D_i^r(p, q_w; K)}{\partial K} \right]}_{\Delta\text{Displacement}} - \underbrace{\left[\frac{1}{\partial D_i^r(p, q_w; K)/\partial p} \cdot \frac{\partial^2 D_i^r(p, q_w; K)}{\partial p \partial K} \right]}_{\Delta\text{Slope}} \tag{5}$$

ΔDisplacement. The first term in Equation 5 shows that changes in transmission capacity K can affect markups due to a *displacement* of generator i's residual demand.

$$\frac{\partial D_i^r(p, q_w; K)}{\partial K} = \frac{\partial D_i^r(p, q_w; K)}{\partial q_w} \cdot \frac{\partial q_w}{\partial K} \tag{6}$$

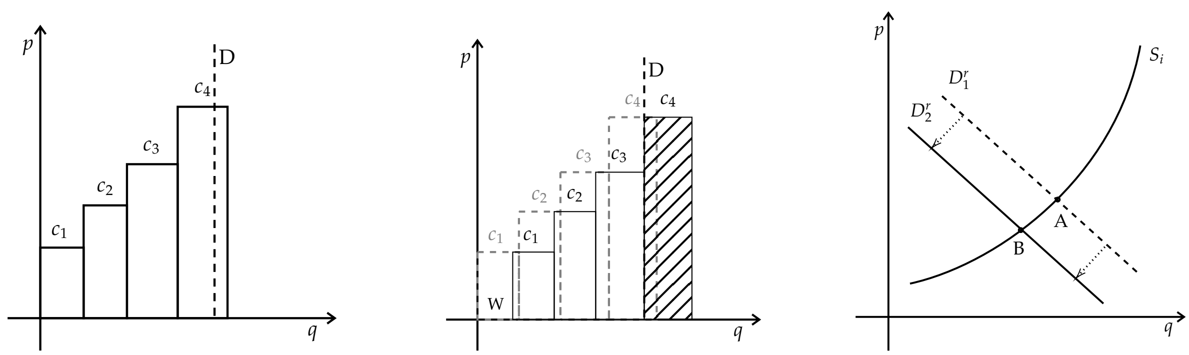
With the stock of wind generating capacity fixed in the short run, $\frac{\partial q_w(K)}{\partial K} (\geq 0)$ is the amount of wind integrated into the grid due to transmission expansion. This additional wind q_w displaces electricity generated from i, shown as the hatched area in Figure 2b. This can be summarized as:

Result 1 *Integration of wind due to transmission expansion leads to a displacement of a marginal generator's residual demand curve.*

$$\frac{\partial D_i^r(p, q_w; K)}{\partial q_w} < 0 \tag{7}$$

Thus, electricity from wind shifts the dispatch curve to the right, displacing power by generator i. This is reflected as an inward shift of i's residual demand curve, which in turn reduces its ability to set higher markups. As shown in Figure 2c, with the generator moving from point A to point B of its offer curve after wind integration. Compared to point A, point B is associated with a flatter region of the offer curve, thereby lowering the markups.

Figure 2: Hypothetical electricity dispatch curves and the effect of wind generation on marginal fossil fuel generator



(a) Hypothetical dispatch curve

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

(c) Shift in residual demand curve due to the additional wind

Notes: c_i denotes generator i's offer/bid price to supply electricity. The vertical dotted line in Figure 2a and Figure 2b denotes the demand for electricity (D), which is inelastic in the short run. q_w is the wind integrated into the grid due to transmission expansion, and S_i denotes the supply curve of generator i.

ΔSlope. This term measures how changes in transmission capacity affect the slope of generator i's residual demand curve.

$$\frac{\partial D_i^r(p, q_w; K)}{\partial p} = -\frac{\partial Q_{-i}(p, q_w; K)}{\partial p} \tag{8}$$

Taking the derivative with respect to K,

$$\frac{\partial^2 D_i^r(p, q_w; K)}{\partial p \partial K} = -\frac{\partial s}{\partial K} \tag{9}$$

Heterogeneity in the cost of electricity generation could lead to steeper or flatter electricity dispatch curves at the margin.[8] For example, during periods of low demand, the dispatch curve tends be more elastic (flatter) whereas during periods of high demand, the dispatch curve is typically inelastic (steeper). This can be summarized as:

Result 2 *The impact of transmission expansion on the slope of the marginal generator's residual demand curve is ambiguous.*

The above finding is characterized by the direction of the change in slope of residual demand with respect to transmission expansion, i.e. the sign of $\frac{\partial s}{\partial K}$

1. In the first case, a flatter dispatch curve results in a more elastic residual demand, i.e. $\frac{\partial s}{\partial K} \geq 0 \Rightarrow \frac{\partial^2 D_i^r(p,q_w;K)}{\partial p \partial K} \leq 0$. This in turn reducing generator i's ability to set higher markups.

2. In the second case, steeper dispatch curve results in a more inelastic residual demand curve, and $\frac{\partial s}{\partial K} \leq 0 \Rightarrow \frac{\partial^2 D_i^r(p,q_w;K)}{\partial p \partial K} \geq 0$. This in turn enhances the generator's ability to set markups.[9]

3.3 Summary of main findings

Substituting the expressions for ΔDisplacement and ΔSlope in Equation 5, and simplifying yields,

$$\frac{\partial(p - c_i)}{\partial \mathrm{K}} = \underbrace{\frac{\partial(p - c_i)}{\partial q_w}}_{\gtreqless 0} \cdot \underbrace{\frac{\partial q_w}{\partial \mathrm{K}}}_{>0} \tag{10}$$

Equation (10) summarizes the findings from the theoretical model. It shows that the overall effect of transmission expansion on realized markups in the short run is driven by two factors. The first is the effect of wind generation on markups, measured by $\frac{\partial(p-c_i)}{\partial q_w}$. The second is the extent to which transmission expansion integrates wind energy into the grid by reducing curtailment, measured by $\frac{\partial q_w}{\partial \mathrm{K}}$. In the empirical strategy below, I estimate the empirical analogues of each of the two components of Equation (10). The overall effect of grid expansion on markups is the product of these two components.

8. Note that the slope of electricity dispatch curve is characterized by $s = \frac{\partial Q_{-i}}{\partial p}$

9. Figure D2 in the Appendix illustrates this point graphically by characterizing $\frac{\partial s}{\partial K}$ as rotations of generator i's residual demand curve. Figure D2a shows the case where $\frac{\partial s}{\partial K} \geq 0$ leads to a counter-clockwise rotation of the residual demand, whereas Figure D2b corresponds to $\frac{\partial s}{\partial K} \leq 0$ which leads to a clockwise rotation of the residual demand.

4 Data and Descriptive Statistics

I assemble multiple datasets at the generator level for the short run analysis of markups and emissions, from 2011 to 2014. Most of this data comes from publicly available sources, including ERCOT, the Energy Information Administration (EIA), and the Environmental Protection Agency (EPA).

4.1 Identifying marginal generators

I use publicly available data from ERCOT Report 13029 to identify the price-setting (marginal) generators and the corresponding market clearing price at every 15 minutes of the sample. This report identifies all the entities that submitted the highest-priced offers for each instance of market clearing process. Note that because Texas electricity market is a nodal market, there could be multiple marginal generators, especially during periods of high congestion. I aggregate this data at the hourly level, therefore all the generators that appear in this data in a specific hour are the marginal generators for that hour.

4.2 Markups

Markups are defined as $p - c$, where p is the Locational Marginal Price (LMP) and c is the marginal cost of production. LMP is the price of supplying one MWh of electricity at a particular location. The other component of markup is the marginal cost of production. As common in the literature, I construct marginal cost as the sum of two main components: fuel costs and emissions permit costs for SO_2 and NOx.[10]

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 by the heat rate of

10. Under the US 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. The marginal cost c_{it} of generator i in period t is:

$$c_{it} = \underbrace{\mathrm{HR}_{it} \cdot p_t^{\mathrm{fuel}}}_{\text{fuel costs}} + \underbrace{\mathrm{ER}_{it}^{\mathrm{SO_2}} \cdot p_t^{\mathrm{SO_2}} + \mathrm{ER}_{it}^{\mathrm{NO}_x} \cdot p_t^{\mathrm{NO}_x}}_{\text{emissions permit costs}}$$

where HR_i is the generator level heat rate at period t, p_t^{fuel} is input price of fuel, $\mathrm{ER}_{it}^{SO_2}$ is the generator level emission rate of SO_2 at period t, ER_{it}^{NOx} is the generator level emission rate of NOx at period t, and $p_t^{\mathrm{SO_2}/\mathrm{NO}_x}$ are the allowance prices.

the generator.[11] I use hourly electricity generation data at the generator level from ERCOT and heat input data from EPA's Continuous Emissions Monitoring system (CEMS). Finally, I compute emissions permit costs using daily data on NOx and SO_2 allowance prices from S&P Global Market Intelligence. Using hourly emissions data from CEMS, I calculate the emissions rate for SO_2 and NOx by taking the ratio of emissions to net generation.

4.3 Global and local emissions

Another outcome of interest 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. Because the impact of local pollutants varies across space due to differences in population densities, I use estimates of county-specific marginal damages due to an additional ton of SO_2 and NOx from Holland et al. (2016).[12] I combine these county-specific damage estimates with SO_2 and NOx emissions from each generator to compute the dollar value of damages from these pollutants.

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

4.5 Other data

I collect data on other covariates like hourly electricity demand from ERCOT.[13] I also collect data on fossil fuel generator characteristics from EIA Form 860. I compliment this data with hand collected information on generator ownership for the heterogeneity analysis of market power outlined in Section 5.

11. EIA defines heat rate as the amount of energy used by a power plant to produce 1 KiloWatt hour (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.

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

13. Figure D1 shows hourly average of electricity demand in ERCOT by season for the sample period. Electricity demand exhibits a consistent seasonal pattern with the peak during afternoon hours in summer and fall.

4.6 Descriptive Statistics

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 and the remaining 30 percent are coal units. The average coal generator in my sample is almost three times the capacity of an average natural gas generator. Coal generators are also much more polluting than natural gas. Damages from carbon emissions from coal generators are about \$332/MWh, about 3 times as that of 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 are on average \$100 compared to \$0.76 for natural gas generators.

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

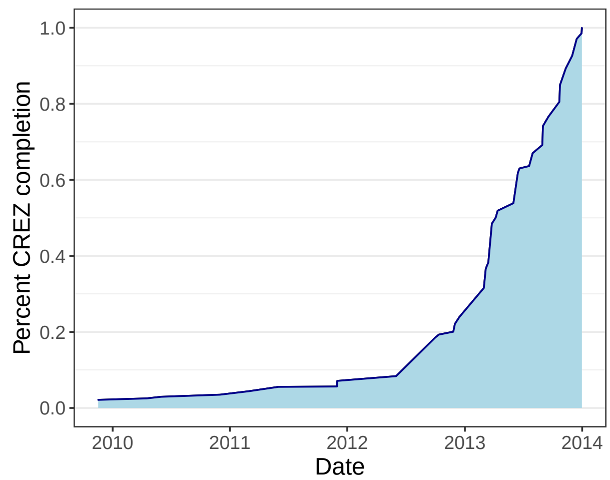
	Coal		Natural Gas	
	Mean	Std. Dev.	Mean	Std. Dev.
Nameplate Capacity (MW)	602.37	200.99	189.93	86.53
Marginal Cost (\$/MWh)	21.83	21.04	15.50	14.22
Realized Markups (\$/MWh)	4.18	31.97	16.58	60.40
CO_2 damages (\$/MWh)	332.23	335.13	104.14	117.32
SO_2 & NOx damages (\$/MWh)	102.40	138.37	0.76	2.87

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. 33.12% of generator-hour observations are from coal generators and 66.88% are natural gas generators. Damages (in 2020 \$) computed using SCC of \$185/ton for CO_2 emissions (Rennert et al. 2022) and county-specific estimates from Holland et al. (2016) for SO_2 and NOx emissions.

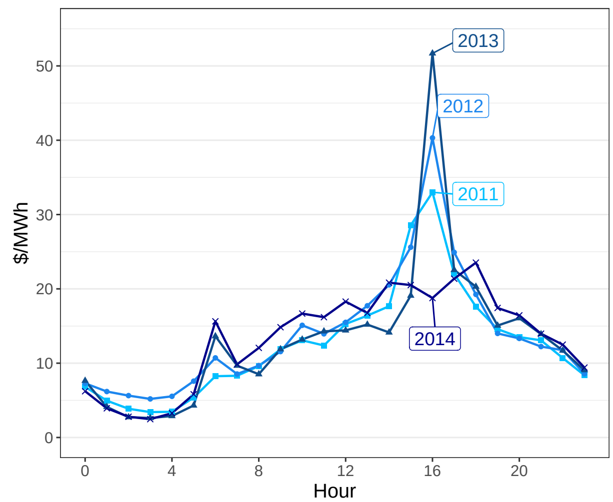
While the average marginal cost of coal generators is about \$6/MWh higher than the marginal cost of natural gas generators, the average markup set by a marginal natural gas generator is about four times that of a coal generator. This is because coal generators tend to operate at the margin during the night, 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.

Figure 3b shows the hourly variation in markups, which is not apparent from Table 1. 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 across the peak afternoon hours, perhaps most significantly at 4 PM. While CREZ expansion would have contributed to this drop, there are other contributing confounding factors as well.

Figure 3: CREZ expansion and average hourly markups



(a) Daily progress of CREZ expansion.



(b) Average hourly realized markups ($/MWh)

Note: Figure 3a shows the cumulative share of CREZ lines (miles) completed each day from 2010 to 2014. Figure 3b shows the average hourly realized price-cost markups set by marginal fossil fuel generators (2011 - 2014, N = 619,864).

5 Empirical strategy and results of markup analysis

In this section, I first present empirical tests for the three main results from the theory section, (1) the displacement of fossil fuel generator's residual demand curve due to wind integration, (2) association between transmission expansion and slope of residual demand, and (3) the association between the slope of residual demand and markups. I then outline the empirical strategy to analyze the impact of transmission expansion on markups followed by results and the heterogeneity analysis.

5.1 Empirical tests of theoretical predictions

The first result I test is that integration of wind is associated with an inward shift of fossil fuel generator's residual demand. This is the *displacement effect* shown in Figure 2c. In the data, I observe the production commitments of marginal units at the market clearing prices at each node. I run the following regression to test this result:

$$q_{it} = \alpha + \beta w_t + \phi \mathbf{X}_{it} + \epsilon_{it} \tag{11}$$

where q_{it} is the residual demand of generator i in period t and w_t is the total wind generation. For the control variables, I include electricity demand at period t, generator fixed effects, and month by year fixed effects summarized by the vector $\mathbf{X}$. The parameter of interest β measures the within generator effect of additional wind on residual demand.

Next, I test the second result, the *slope effect* from the theory section which states that transmission expansion can have an ambiguous effect on the slope of generator i's residual demand. Following Ito and Reguant (2016), I use generator-level data to directly calculate the slope of residual demand curve at the market clearing price for each marginal generation i at each hour t of the sample. I run the following regression to test this result:

$$s_{it} = \alpha + \gamma crez_t + \phi \mathbf{X}_{it} + \epsilon_{it} \tag{12}$$

where s_{it} is the slope of the generator i's residual demand curve at the market clearing price and $crez_t$ measures the share of CREZ lines completed in period t. I include quadratic polynomial of demand, generator fixed effects, and hour by month by year fixed effects in $\mathbf{X}$. The parameter of interest γ is the within generator association between transmission expansion and the slope of residual demand.

Finally, I test the link between the slope and the realized markups. As I describe in the theoretical section, a flatter residual demand reduces generator's ability to set markups whereas a steeper residual demand enhances it. I run the following regression to analyze the association between slope of residual demand and markups:

$$(p - c)_{it} = \alpha + \delta s_{it} + \phi \mathbf{X}_{it} + \epsilon_{it} \tag{13}$$

where $(p - c)_{it}$ are the realized markups and s_{it} is the slope of the generator i's residual demand at the market clearing price. I control for quadratic polynomial of demand, generator fixed effects, and hour by month by year fixed effects in $\mathbf{X}$. The parameter of interest δ describes how the slope of residual demand is associated with realized markups.

Table 2 shows the coefficient estimates of β, γ and δ from Equations (11), (12) and (13). Column (1) shows that an increase in wind generation is associated with a decline in marginal generator's residual demand. This finding serves as a test for Result 1 from the theory section. Column (2) finds that transmission expansion is associated with a flatter residual demand and is consistent with the result in Figure D2a. In Column (3), I show that an increase in the slope of residual demand is associated with higher markups. This result is consistent with the prediction that a steeper residual demand enhances a generator's ability to set higher markups.

Table 2: Empirical tests of residual demand, slope of residual demand, and markups

	Dependent variable		
	Residual demand	Slope of residual demand (MWh/$)	Realized markups ($/MWh)
	(1)	(2)	(3)
Wind generation (GWh)	-6.028***		
	(0.681)		
Transmission (%)		−1.857***	
		(0.254)	
Slope of residual demand (MWh/$)			16.635***
			(0.012)
Mean of dependent variable	320.70	269.59	12.47
Observations	619,864	619,864	619,864

Notes: This table shows the estimation results of Equations (11), (12) and (13). Column (1) tests for the displacement effect, i.e. a negative association between wind generation and residual demand of marginal generator. Column (2) tests for the association between transmission expansion and the slope of residual demand, and Column (3) tests whether a steeper residual demand is associated with higher realized markups. All regressions control for electricity demand, and include generator fixed effects. Specification in Column (1) includes month × year fixed effects, Columns (2) and (3) include hour × month × year fixed effects. These fixed effects control for seasonal variation and generator specific heterogeneity. Standard errors are clustered at the generator level. Significance: ***p<0.01;**p<0.05;*p< 0.1

5.2 Empirical Strategy

The findings from the theoretical model motivate the empirical strategy, wherein I estimate the empirical analogues of the relationship between transmission expansion and realized markups. This analysis proceeds by estimating, (1) the impact of transmission expansion on wind integration, and (2) the association between wind integration and fossil fuel markups.

5.2.1 Impact of wind generation on markups

I use the following specification to estimate how integration of wind into the grid affects markups:

$$y_{it} = \alpha_h \cdot w_t + f(\mathrm{D}_t) + \kappa_i + \delta_{hmy} + \epsilon_{it} \tag{14}$$

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.[14] Wind generation (GWh) at hour t is denoted by w_t. The parameter of interest is α_h, which measures the change in realized markups as a result of additional wind generation for each hour h. Thus,

$$\alpha_h \equiv \frac{\partial(p - c_i)}{\partial q_w}$$

I use a wide variety of controls to account for potential confounding factors in Equation 14. I use a quadratic polynomial of system-wide electricity demand D_t to account for variation in markups driven by spikes in electricity demand. I use generator fixed effects (κ_i) to control for any generator-specific heterogeneity in markups. Finally, I use hour by month by year fixed effects (δ_{hmy}) to control for seasonality in the Texas electricity market. This seasonality arises due to varying wind patterns 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 the winter and summer months.

The identifying variation for α_h 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 identified from deviations in markups from generator-specific averages across all 16:00 hours (4 PM) within a month, in a given year. Standard errors are clustered at the generator level to account for correlation in markups at the unit level.

5.2.2 Impact of CREZ expansion on wind integration

Next, I estimate the impact of CREZ expansion on wind integration into the grid by reducing wind curtailment. I run the following specification:

$$w_t = \beta_h \cdot crez_t + \gamma \cdot max_t + \eta_{hm} + \xi_t \tag{15}$$

where w_t is the wind generation (GWh) in hour t and $crez_t$ is the percentage completion of CREZ transmission lines. The parameter of interest is β_h, which measures the integration of wind energy into the grid as a result of CREZ expansion. Thus,

$$\beta_h \equiv \frac{\partial q_w}{\partial K}$$

14. Note that there could be multiple marginal generators at a given hour of the sample. This is because I aggregate 15 minute market clearing data to hourly level, and because ERCOT is a nodal market which could lead to multiple marginal generators especially during periods of high congestion. Therefore, using generator fixed effects allow me to look at the within-generator effect on markups.

I use the maximum predicted generation (max_t) of electricity from wind at hour t to control for the maximum energy production from wind at a given period. This variable incorporates the generating capacity and technology, and the real-time meteorological conditions that can affect the wind generation at hour t.[15]

I use hour-by-month fixed effects (η_{hm}) in Equation 15 to control for seasonality in wind generation. Thus, conditional on predicted wind generation (max_t) and fixed effects, β_h identifies the additional wind energy integrated into the grid as a result of transmission expansion. The identifying variation comes from changes in wind generation caused by transmission expansion across the same hours in a given month. I use Newey West auto-correlation corrected standard errors with a seven-day lag structure in Equation 15. Under the identifying assumption that the fixed effects and controls 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.

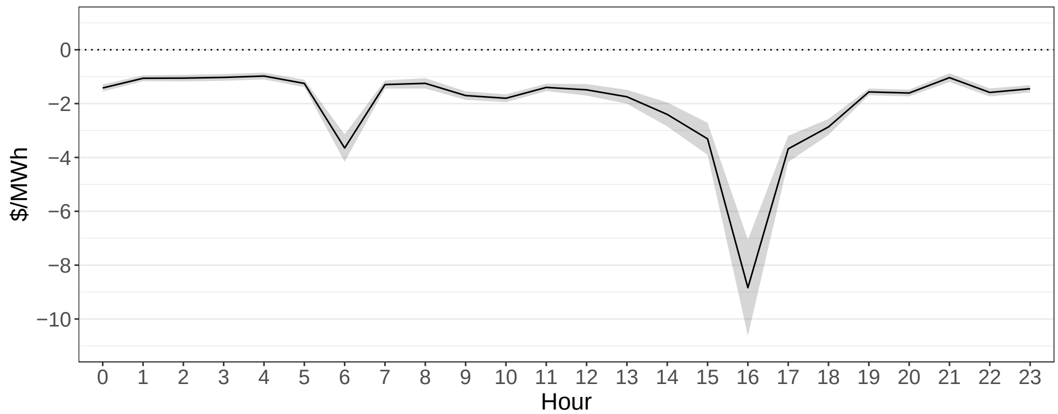
5.3 Results: impact of transmission expansion on markups

Figure 4 shows the coefficient estimates of $\hat{\alpha}_h$ from Equation 14, i.e., the change in fossil fuel markups due to additional wind in the grid. On average, the drop in markups is strongest in magnitude at the peak demand hour at 4 PM, about \$9/MWh. The coefficient estimates are smallest for the off-peak hours. Due to low electricity demand and high wind generation during off-peak, fossil fuel generators typically operate on a smaller and flatter net demand curve as compared to on-peak hours, thereby lowering their ability to set high markups.

Figure 5 presents the coefficient estimates of $\hat{\beta}$ Equation 15, i.e., the effect of CREZ expansion on wind generation. The coefficient estimates show that keeping the stock of generating capacity fixed in the short-run, transmission expansion led to higher wind generation by reducing curtailment. Wind integration is highest during off-peak, about 0.22 GWh between 10 pm to midnight which is almost twice the amount during the peak demand hours between 3:00 and 6:00 PM. This hourly pattern of $(\hat{\beta}_h)$ closely follows

15. ERCOT refers to maximum predicted generation as the High System Limit (HSL). HSL for a generation resource is defined as the maximum sustained energy production capability of that entity. HSL is determined by the generator itself and is continuously updated in real time. As shown in Figure D3, 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 w_t and max_t arises due to inadequate transmission capacity between generation and demand centers. Therefore, this difference 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.

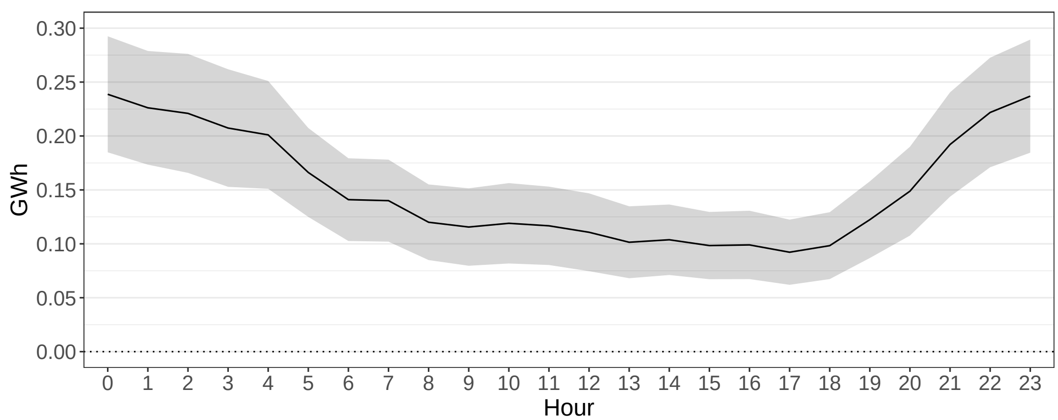
Figure 4: Effect of additional wind energy on realized markups



Notes: This figure shows the coefficient estimates ($\hat{\alpha}_h$) from Equation 14. Each point estimate is the hourly marginal impact of wind energy on generator markups ($/MWh). 95 percent confidence intervals constructed from standard errors clustered at the generator level.

the hourly wind flow pattern in Texas, where the wind flow is strongest in the night compared to the day.

Figure 5: Impact of CREZ expansion on integrating wind energy into the grid



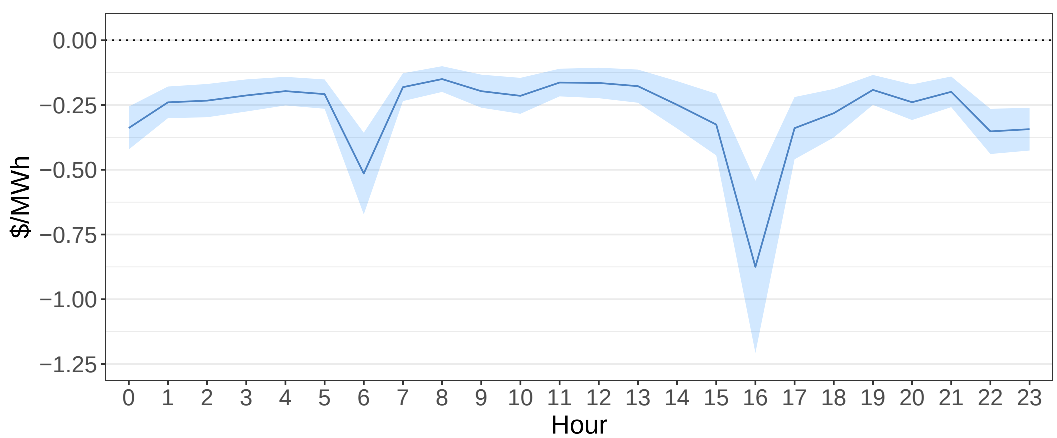
Notes: This figure shows the coefficient estimates ($\hat{\beta}_h$) from Equation 15. Each point estimate measures the effect of CREZ expansion ($crez_d = 1$) on hourly wind integration due to lower curtailment. 95 percent confidence intervals constructed from Newey-West auto-correlation corrected standard errors with a 7-day lag structure.

Next, I combine the estimates of the association between wind generation and markups (α_h) and the impact of transmission expansion on wind (β_h) to derive the association between transmission expansion and realized markups. From the theoretical model, this relationship is given by:

$$\underbrace{\frac{\partial(p-c)}{\partial \mathrm{K}}}_{\hat{\theta}} = \underbrace{\frac{\partial(p-c)}{\partial q_w}}_{\hat{\alpha}} \times \underbrace{\frac{\partial q_w}{\partial \mathrm{K}}}_{\hat{\beta}} \tag{16}$$

Figure 6 shows the coefficient estimates of $\hat{\theta}$ for each hour of the day. The decline in markup is highest during the peak hours between 3 and 5 PM, and the beginning of peak hour period at 6 AM.[16] Thus the impact of transmission expansion in lowering market power is most salient during the periods of high demand. These results also provide support to the theoretical finding that transmission enhances the value of additional wind especially during the peak periods. As shown in the empirical tests, this is operating with wind displacing fossil fuel generator's residual demand curve (Column (1) in Table 2) and additional transmission reducing the slope of residual demand (Column (2) in Table 2).

Figure 6: Impact of CREZ expansion on realized markups ($/MWh)



Notes: This figure shows the estimates of $\hat{\theta}$ in Equation 16 which measures the impact of transmission expansion on realized markups. These hourly estimates combine the estimates $\hat{\alpha}$ ($\equiv \frac{\partial p-c}{\partial q_w}$) from Equation 14 and $\hat{\beta}$ ($\equiv \frac{\partial q_w}{\partial K}$) from Equation 15.

16. Peak hours in ERCOT are defined as the 16-hour time block from hours ending 7:00 AM to 10:00 PM CDT on weekdays. This is also the period of higher average markups. For example, average markup in my sample is about 13$/MWh for both 6 AM (hour ending 7 AM) and 9 PM (hour ending 10 PM). Average markups are highest at 4 PM, about 36$/MWh. Average markup for peak-hours is 17$/MWh and 6$/MWh for off-peak hours.

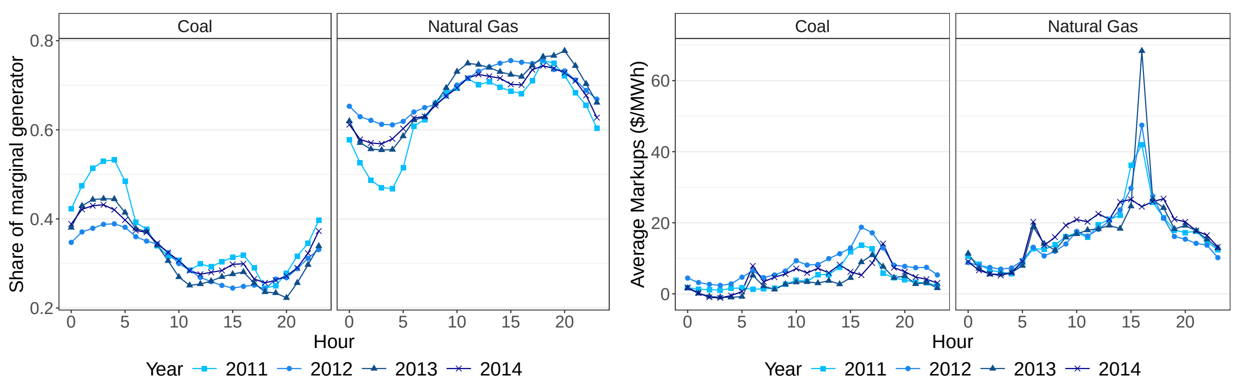
5.4 Markup Heterogeneity Analysis

In this section, I explore heterogeneity in the markups by two main dimensions of fossil fuel generators- fuel type and generator ownership. I first begin by documenting patterns of heterogeneity in the data followed by the empirical analysis.

5.4.1 Heterogeneity by Fuel type

Figure 7a shows the average share of marginal coal and natural gas generators from 2011 to 2014. The overall profile is about the same over the years with a higher share of coal generators at the margin during the off-peak hours than at the peak hours. A higher share of natural gas generators are typically at the margin during peak hours than at the off-peak. This in turn translates to the average markup profile by these generators as shown in Figure 7b. Natural gas generators set higher markups during the peak hours with a sharp decline in 2014.

Figure 7: Share of marginal generators and average markups by fuel type



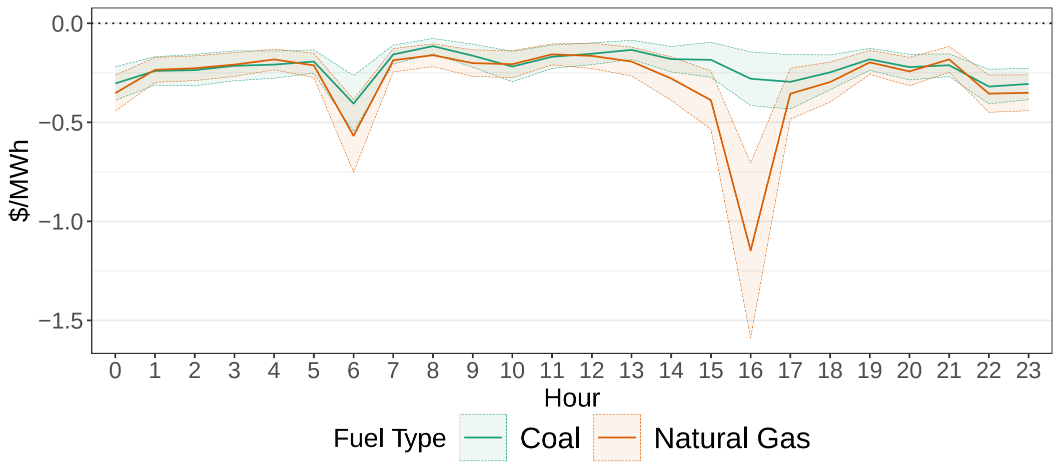
(a) Share of marginal generator by fuel type

(b) Average markups by fuel type

I estimate the main empirical specification in Equation 14 separately for coal and natural gas generators, and combine them with the estimates wind integration from CREZ. Figure 8 shows the coefficient estimates on the decline in markups due to CREZ by generator fuel type and the associated 95 percent confidence intervals. The decline in markups is similar in magnitude across most hours except near the peak demand hour of 4 PM, where there is a sharp decrease in markups from natural gas generators.

Figure 8 provides evidence that the decline in markups is mainly driven by natural gas generators. This finding is consistent with the theoretical model which shows that an inward shift in marginal generator's residual demand curve in turn reduces the realized markups. With a higher share of natural gas units operating at the margin during peak

Figure 8: Impact of CREZ expansion on realized markups by generator fuel type



Notes: This figure shows the coefficient estimates of the association between transmission expansion and realized markups for coal and natural gas generators. These estimates are obtained by running the regressions in Equation 14 separately for coal and natural gas separately and combining them with estimates from Equation 15. Corresponding 95 percent confidence intervals for the hourly estimates shown in the shaded bands.

hours, the effect of transmission expansion is therefore most pronounced for the natural gas units.

5.4.2 Heterogeneity by common generator ownership

Next, I analyse heterogeneity by firm ownership portfolio. Several firms in Texas own both natural gas and coal generators, and a few firms that own wind and fossil fuel generators. In similar spirit to Ito and Reguant (2016), I refer to firms with generator ownership across different fuel types as dominant firms and firms that own generators of single fuel type (coal, natural gas, or wind) as fringe firms.[17]

Using hand collected data on generator ownership, I find seven dominant firms (including public utilities) with a portfolio comprising of both coal and natural gas plants. By contrast, the number of fringe firms (with either coal or natural gas plants) in my sample are 114. There is also some overlap in fossil fuel and wind generator ownership during my sample. As of 2015 in my sample, four dominant firms own fossil fuel generators and wind farms whereas 38 fringe firms primarily own wind farms. Table 3

17. For the analysis in this section, I restrict to generators (coal, natural gas, and wind) operating before 2015. I also exclude petroleum and other fossil fuel generators since they represent a very small share of the overall generating capacity.

reports total nameplate capacity and the share of capacity across dominant and fringe firms by fuel type. [18]

Table 3: Common generator ownership across multiple fuel types

A. Common ownership across coal and natural gas generators

	Coal		Natural Gas	
	Total Capacity (GW)	Share (%)	Total Capacity (GW)	Share (%)
Dominant Firms	18.66	73.38	24.45	27.71
Fringe Firms	6.77	26.62	63.78	72.29

B. Common ownership across fossil fuel and wind generators

	Fossil Fuel		Wind	
	Total Capacity (GW)	Share (%)	Total Capacity (GW)	Share (%)
Dominant Firms	3.26	3.58	0.78	8.73
Fringe Firms	110.39	96.42	13.54	91.27

Notes: This table reports total nameplate capacity (GW) and the share of total capacity of generators for firms with common ownership across different fuel types. Dominant firms are the firms with generator ownership across multiple fuel types whereas fringe firms own generators with a single fuel type. Panel A. shows this classification for coal and natural gas generators, and Panel B. shows this classifications for fossil fuel and wind generators. Dominant firms (including utilities) in Panel A. are City of San Antonio, Lower Colorado River Authority (LCRA), Luminant Generation Company, NRG Energy, South Texas Electric Cooperative, Southwestern Electric Power Company, and Xcel Energy. Dominant firms in Panel B. are Duke Energy, El Paso Electric Company, Exelon Corporation, and Valero Energy Corporation.

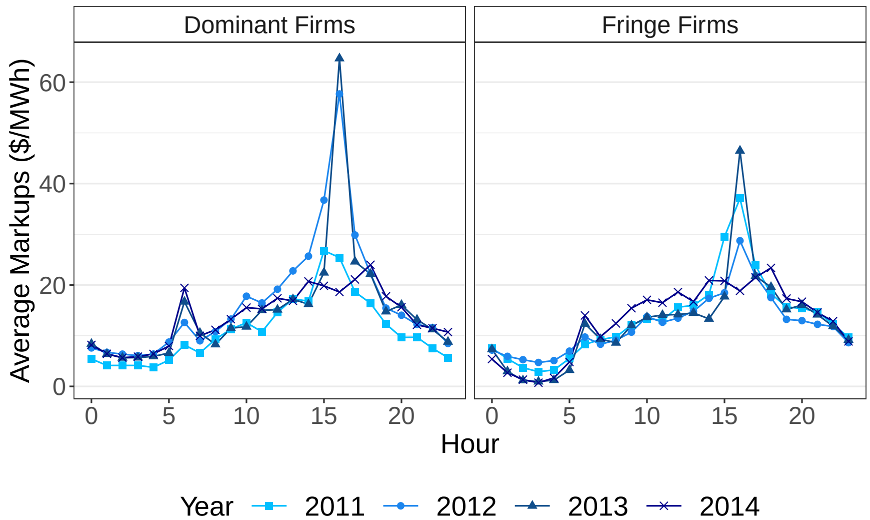
Three interesting observations emerge from Table 3. First, a handful of dominant firms (Panel A) own a large share of coal generating capacity along with a quarter of natural gas capacity. Second, fringe firms make up the lion share of both natural gas and wind generating capacity in Texas. Third, there is a greater overlap of common ownership across coal and natural gas units than across fossil fuel and wind. The latter point is due to the presence of numerous, often regional wind farm developers and owners that specialize in wind energy operations.

For the purpose of this analysis, I take the union of dominant firms from the two panels in Table 3. Dominant firms with multiple generators could potentially coordinate pricing strategy across multiple units to set higher markups, especially during periods

18. The seven dominant firms that own both natural gas and coal generators in my sample are: City of San Antonio, Lower Colorado River Authority (LCRA), Luminant Generation Company, NRG Energy, South Texas Electric Cooperative, Southwestern Electric Power Company, and Xcel Energy. The four dominant firms that own fossil fuel and wind generators are: Duke Energy, El Paso Electric Company, Exelon Corporation, and Valero Energy Corporation

of high congestion. Figure 9 confirms that the average hourly markups in the raw data were slightly higher for the dominant firms especially during the peak demand hours. This is perhaps most pronounced for the pre-transmission expansion years of 2012 and 2013.

Figure 9: Average markups by generator ownership portfolio



Note: This figure shows realized markups for dominant and fringe firms during 2011 - 2014 (N = 619,864). I classify firms with common ownership portfolio across coal, natural gas, and wind as dominant firms, and firms with only natural gas, coal, or wind generator(s) as fringe firms.

I analyze the heterogeneity in the impact of wind integration due to CREZ on realized markups by firm ownership type. To that end, I estimate specifications that allow the marginal effect of wind integration to vary by firm type (dominant v.s. fringe) and by peak v.s. off-peak hours.[19] Table 4 shows the coefficient estimates of these specifications.

Table 4 shows a negative association between wind integration and realized markups, with the marginal effect of wind larger during peak hours. The preferred specification in Column (3) shows a decline in realized markups for both dominant and fringe firms. On average, the decline in markups is slightly higher in magnitude for dominant firms during the periods of peak demand. This result follows from transmission expansion leading to greater market integration and thus higher competition amongst generators. A consequence of greater competition is flatter residual demand which is associated with lower markups, as illustrated in the theory and empirically tested in Section 5.1. To that end, higher market integration and competition has a larger effect of reducing market power of firms with multiple marginal (or peaker) units.

19. Peak period in Texas is defined as the hours ending in 7:00 AM to 10:00 PM CPT.

Table 4: Heterogeneity analysis by firm ownership type

	Markups ($/MWh)		
	(1)	(2)	(3)
Wind (GWh)	-1.244***	-1.926***	-1.350***
	(0.049)	(0.078)	(0.067)
Wind × Peak	-1.083***		-0.922***
	(0.101)		(0.095)
Wind × Dominant firm		0.082	0.307**
		(0.152)	(0.123)
Peak × Dominant firm			1.053
			(0.728)
Wind × Peak × Dominant firm			-0.478**
			(0.198)
Observations	619,864	619,864	619,864
R^2	0.251	0.250	0.251

Notes: This table shows the coefficient estimates for the association between wind integration and markups by firm type (dominant firm v.s. fringe firm) and across peak and off-peak hours. Peak is an indicator specifying whether the period is an on-peak hour or off-peak hour. Dominant is an indicator specifying whether the generator is owned by a dominant firm. All specification control for quadratic polynomial electricity demand, generator fixed effects, and hour by month by year fixed effects. Sample is hourly marginal generators from August 2011 to December 2014. Standard errors are clustered at the generator level. Significance: ***p<0.01;**p<0.05;*p< 0.1

6 Empirical strategy and results of emissions analysis

In this section, I examine how wind integration due to CREZ affected marginal emissions. Variation in fuel type and emission intensity of generators at the margin over the course of a day makes it informative to study which generators respond due to wind integration at different hours. Coal-fired generators typically operate at the margin at night, whereas natural gas generators are marginal during the day since they are quicker to ramp up or down to meet any sudden changes in demand. Greater wind integration could therefore displace generation from highly-polluting coal generators at the margin and thereby reduce emissions.

The main specification is similar to Equation 10 for markup analysis:

$$e_{it}^{zp} = \gamma_h^{zp} \cdot w_t + f(D_{t,t-1}) + \alpha_i^{zp} + \delta_{hmy}^{zp} + \epsilon_{it}^{zp} \tag{17}$$

where e_{it}^{pz} is the emissions of pollutant p from generator i at the margin in period t and zone z and w_t is the wind generation at hour t of the sample. The parameter of interest γ_h^{pz} measures the association between hourly additional wind generation and hourly marginal emissions of pollutant p in zone z at hour h. I run this regression separately for the four zones in Texas: West, North, South, and Houston; and three main pollutants, denoted by $p \in \{\mathrm{CO_2}, \mathrm{SO_2}, \mathrm{NOx}\}$.

I use a quadratic polynomial of contemporaneous and lagged demand for electricity summarized in $D_{t,t-1}$ to control for the variation in marginal emissions due to changes in demand. I include hour-by-month-by-year fixed effects δ_{hmy}^{zp} in each specification to control for month and year specific average emission levels at hour h in month m in year y. I also include generator fixed effects α_i^{zp}, so $\hat{\gamma}_h^{zp}$ is the within generator association between wind integration and emissions. Standard errors are clustered at the daily level to account for serial correlation.

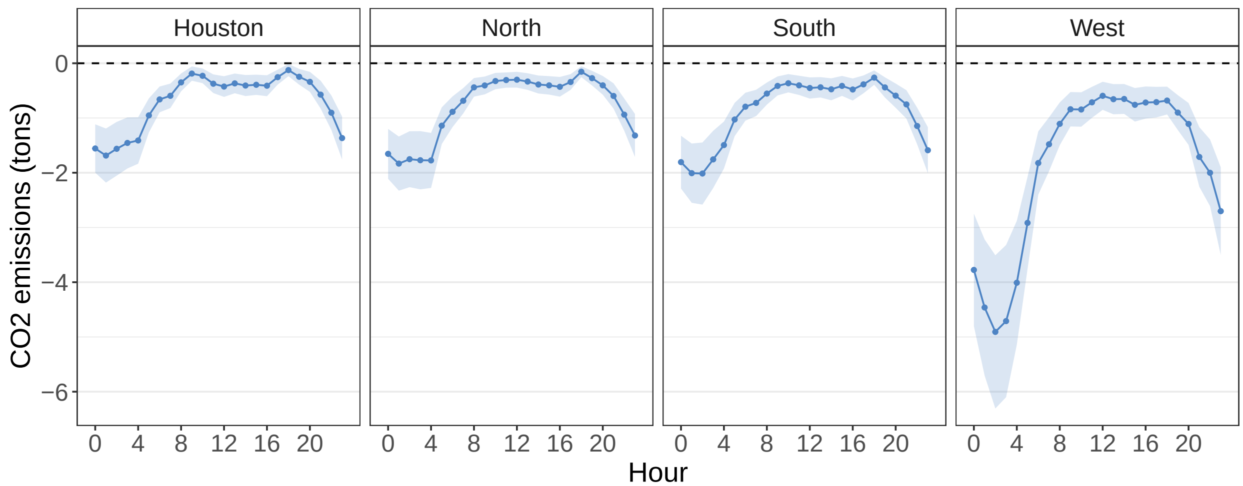
6.0.1 Transmission expansion and marginal carbon emissions

I combine zone specific coefficient estimates for CO_2 from Equation 17 with the hourly estimates of wind integration from Equation 15. The result, shown in Figure 10a is the within generator estimate of hourly change in marginal carbon emissions in zone z in response to CREZ expansion. There is a clear decline in carbon emissions across all the zones throughout the day due to wind integrated post transmission expansion. The decline is most pronounced during off-peak hours when wind integration is highest.

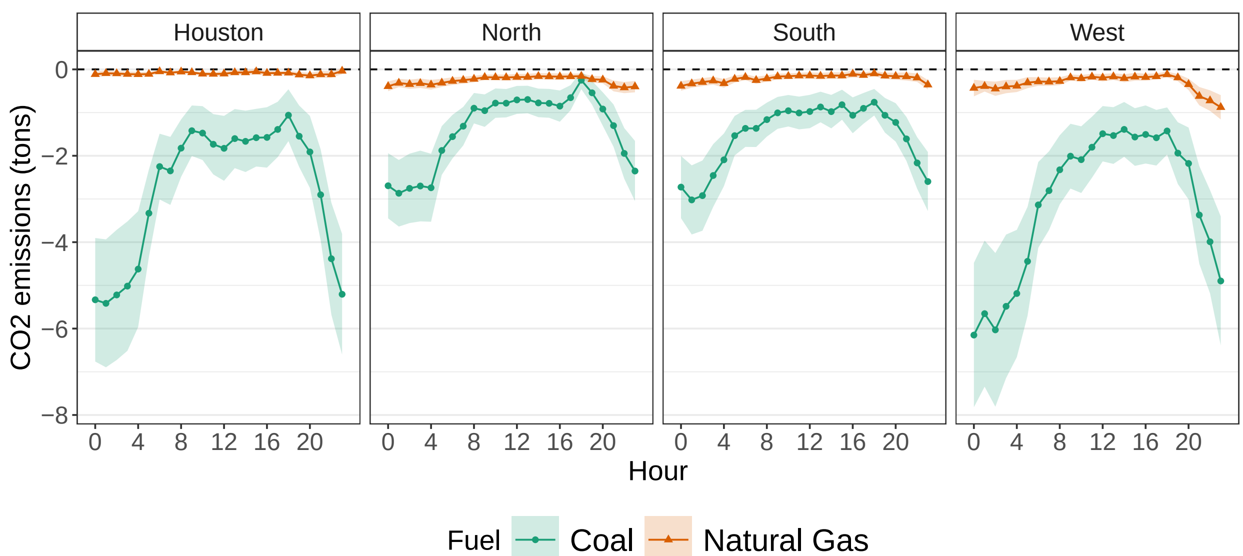
Figure 10b breaks down the effect by generator fuel type. Two key insights emerge. First, the decline in carbon emissions is mainly driven by decline in emissions from coal generators primarily during the off-peak hours. This is consistent with the generation pattern in Texas, where coal generators operate at the margin during the off-peak. Second, the displacement of coal generators and thus the reduction in emissions is most significant in Houston and West Texas.

While wind integration lowers emissions from coal generators, rise in emissions during early hours of the day as a consequence of wind intermittency could enhance damages especially in populated regions like Houston. These emissions are the result of ramping up of fossil fuel generators to meet the demand during periods of low wind generation. These ramping effects are shown to undercut the emissions reductions from

Figure 10: Transmission expansion and marginal carbon emissions



(a) Reduction in marginal carbon emissions due to CREZ expansion



(b) Reduction in marginal carbon emissions estimates by generator fuel type

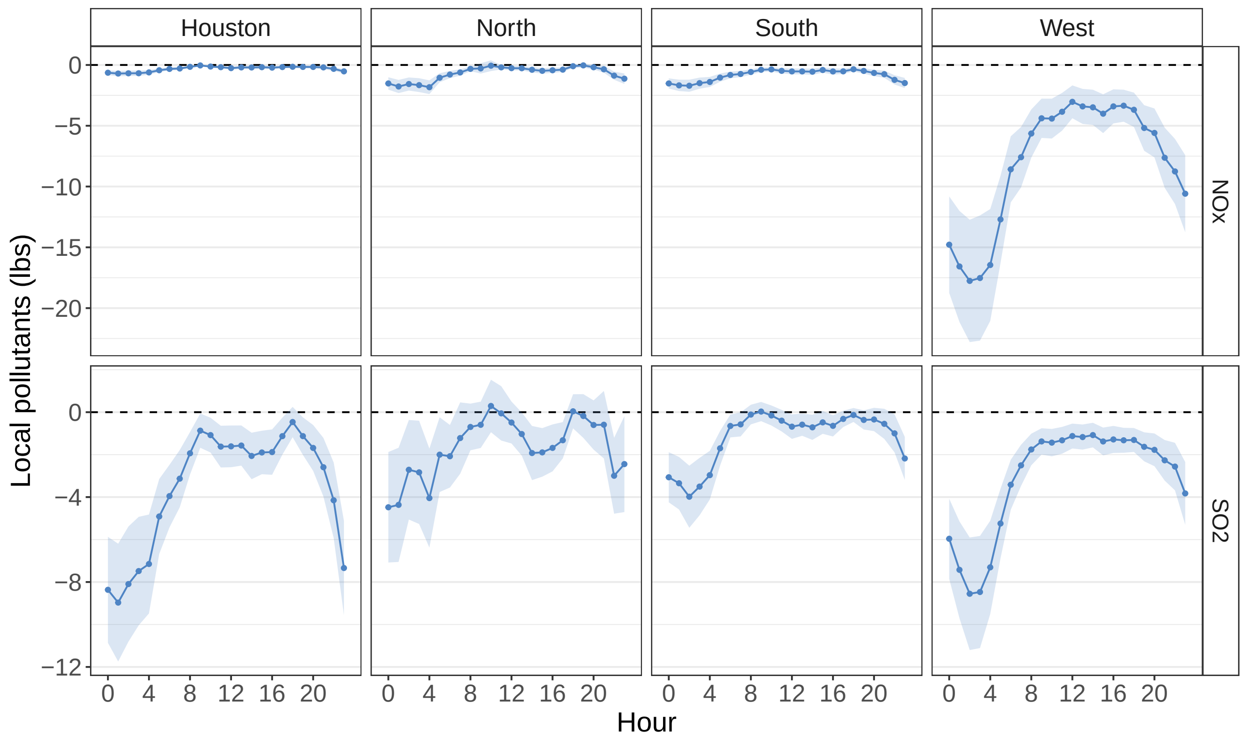
Note: This figure shows the product of hourly coefficient estimates of the association between wind generation and carbon emissions from Equation 17, and coefficient estimates of wind integration due to CREZ expansion from Equation 15. Shaded ribbons show the associated 95 percent confidence intervals.

wind, especially with generators operating at low levels of efficient generation (Lew et al. 2012).

6.0.2 Transmission expansion and local emissions (SO_2 and NOx)

Next, I estimate the association between transmission expansion and local emissions (SO_2 and NOx) from marginal fossil fuel generator. As with carbon emissions, I combine estimates of γ_h^z for SO_2 and NOx with the hourly integration estimates from Equation 15. Figure 11 shows the resulting hourly coefficient estimates for NOx and SO_2, and the four zones.

Figure 11: Transmission expansion and change in local emissions (NOx and SO_2)



Note: This figure shows the product of hourly coefficient estimates of the association between wind generation and local emissions (NOx and SO_2) from Equation 17, and coefficient estimates of wind integration due to CREZ expansion from Equation 15. Shaded ribbons show the associated 95 percent confidence intervals.

The pattern of coefficient estimates of SO_2 in Figure 11 is similar to carbon emissions from coal generators in Figure 10b. Presence of sulphur impurities leads to SO_2 emissions as a byproduct of burning coal in power plants, giving rise to this pattern in Figure 11. SO_2 emissions from natural gas power plants are low because of low amounts of sulphur in pipeline-quality natural gas. NOx, on the other hand, is released from burning of any fossil fuel due to the mixing of fuel and air (EPA 1998).[20]

Perhaps more interesting is the pattern of SO_2 emissions in Houston and West. The pattern of emissions in these regions is very similar to pattern of marginal carbon emissions from coal generators in Figure 10b. In Houston, the dominant coal power plant is W A Parish whereas Oklaunion is the dominant coal power plant in West. I refer to these two coal power plants 'dominant' because they are the main source of emissions in these two regions.[21] The pattern in Figure 11 could be suggestive of excess emissions due to ramping up of generators to meet the demand. To explore this phenomenon, I estimate specifications allowing for the marginal effect of wind generation to vary by plant type i.e. dominant coal plant v.s. natural gas and by time of day i.e. on-peak v.s. off-peak hours. I run these regressions separately for Houston and West:

$$e_{it} = \alpha_{peak} \cdot \textit{dominant coal pp} \times w_t + \Lambda \mathbf{X}_{ihmy} + \epsilon_{it} \tag{18}$$

where e_{it} is SO_2 emissions from generator i in period t, *dominant coal pp* is an indicator specifying whether generator i is part of the dominant coal power plant. I include quadratic polynomial of contemporaneous and lag of demand, generator, and hour-by-month-by-year fixed effects in $\mathbf{X}_{ihmy}$. The parameter of interest, α_{peak} measures how the marginal effect of wind differs between the dominant coal plant and natural gas plants at on-peak v.s. off-peak hours. Figure 12 shows the coefficient estimates from Equation 18.

Figure 12 shows that the majority of emissions reduction in Houston and West is driven by reduction in emissions from the two dominant coal power plants in these regions during the off-peak hours. Interestingly, natural gas plants in both these regions show a slight increase in emissions during the off-peak hours. This suggests that while wind generation displaces highly polluting coal power plants, intermittency could lead to excess emissions from ramp-up of gas generators. [22]

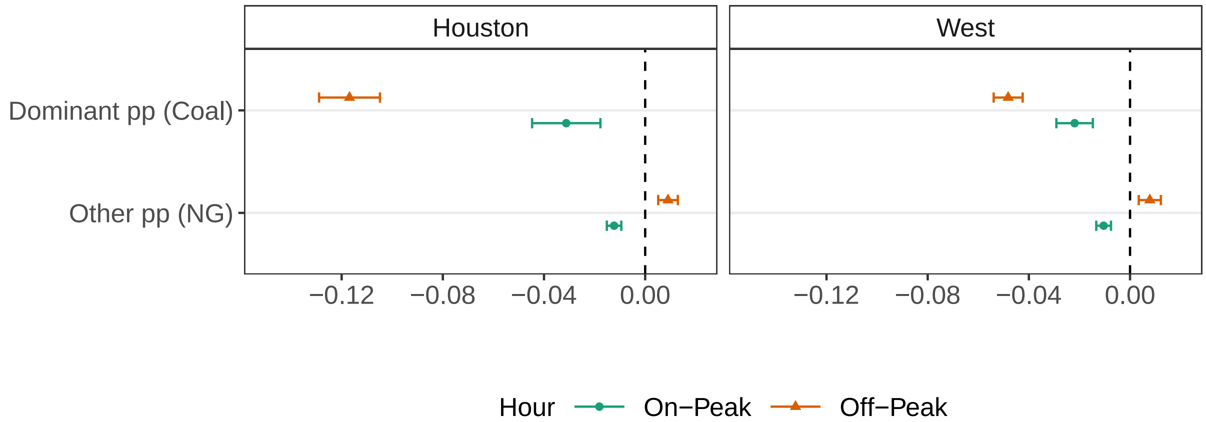
Relatedly, I also find lower emission reduction from coal plants during peak hours compared to off-peak. This is indicative of excess emissions from coal plants due to

20. Figure D5 and Figure D6 in Appendix breaks down local emissions by generator fuel type and shows that the pattern of SO_2 and NOx emissions estimates in Figure 11 are driven by coal generators, whereas local emissions from natural gas generators are grazing zero.

21. A power plant typically comprises of multiple generators mostly of single fuel type. In my data, I see 16 natural gas power plants and one coal power plant (W A Parish) in Houston. By comparison, for West I see 4 different natural gas power plants and one coal power plant (Oklaunion) in West. All of these power plants have at least one generator that is at the margin of the dispatch curve.

22. The analysis of NOx emissions by power plant type shows a very similar pattern as in Figure 12 with the exception that the estimates are larger for West than Houston. This is also apparent from the pattern of hourly NOx emissions reduction in Figure 11.

Figure 12: SO_2 emissions and wind generation in Houston and West by power plant type



Note: This figure shows the coefficient estimates and 95 percent confidence intervals of the slope of SO_2 emissions with respect to wind generation (lbs/MWh) from Equation 18 by power plant type and hour of use. Dominant pp in Houston comprises of coal generators in W A Parish power plant, and Other pp is the 16 natural gas power plants. Dominant pp in West comprises of coal generators in Oklaunion power plant, and Other pp is the 4 natural gas power plants. Sample for Houston emissions regression is all generator-hour pairs in Houston from 2011-2014 (N = 132,080). Sample for West emissions regression is all generator-hour pairs in West from 2011-2014 (N = 39,120).

ramp-up effects especially during early peak hours when wind is intermittent. This finding is consistent with the evidence from Fell, Kaffine, and Novan (2021), who show lower emission reduction from wind in periods with higher grid congestion. Thus availability of transmission capacity can in turn contribute to excess emissions if it leads to ramping-up of coal plants to meet demand. These ramp-up effects can offset part of the benefits from emissions reductions due to greater wind integration during off-peak periods.

7 Evaluating welfare effects of transmission expansion

7.1 Market impact- producer surplus due to market power

In the short run, producers of electricity earn rents from the purchasers of electricity by exercising market power. With a downward sloping demand curve in the medium to long-run (Deryugina, MacKay, and Reif 2020), these excess rents can lead to welfare losses as a result of greater than optimal retail rates of electricity paid by end-use consumers, and consequently sub-optimal consumption of electricity.

I conduct a simple counterfactual exercise to calculate the producer surplus accrued by fossil fuel generators due to higher markups in the absence of CREZ expansion. This analysis proceeds in two steps. First, using the parameter estimates from Equation 15, I compute the counterfactual wind generation (w_t^c) in the absence of CREZ expansion. Next, I substitute w_t^c in the estimated Equation 14 to compute counterfactual markups, $\widehat{(p-c)}$. The producer surplus in period t from the absence of transmission expansion is the product of counterfactual markups and the electricity generated by fossil fuel producers in the counterfactual scenario (Q^c) i.e. $S_t \approx \widehat{(p-c)}_t \times Q_t^c$.

I make a simplifying assumption to compute Q_t^c. I assume that the set of marginal generators remains the same in the counterfactual scenario of no CREZ expansion. In other words, I assume that the difference between actual wind generation (w_t) and the counterfactual wind (w_t^c) is met by the same set of marginal producers as in the factual scenario. Therefore, counterfactual generation by marginal producers is simply ${Q^c}_t = Q_t + (w_t - w_t^c)$.

This counterfactual analysis finds that the incidence of greater market power due to absence of transmission expansion would have led to about $2.8 billion worth of excess rents over the sample of this study. This is approximately $190 million more than the surplus collected by marginal producers in the base scenario.[23] Assuming that this decline in markups (due to transmission expansion) is reflected as lower wholesale prices at each power plant, implies a reduction of approximately $223 million worth of annual decline in excess rents collected by producers.[24] This decline in 'excess rents' is essentially a reduction in transfers from retailers to generators in the short run and from consumers to producers in the long run.[25]

7.2 Environmental benefits- value of damages avoided

Next, I calculate the aggregate value of emissions avoided due wind integrated as a result of CREZ expansion. To that end, I estimate zone specific estimates of Equation 17

23. Figure D4 in Appendix shows the box plot of excess rents in the counterfactual scenario of no transmission expansion against the excess rents in the factual scenario for each year of the sample.

24. This calculation assumes total demand of electricity to remain the same which is not unreasonable given the inelastic nature of electricity demand in the short-run.

25. Note that these welfare numbers focus primarily on changes in surplus due to higher wind integration and does not include welfare gains due to other mechanisms. For example, Woerman (2023) identifies markups due to temperature induced transmission congestion and finds about $540 million worth of annual rent transfer from consumers to producers. To the extent that transmission expansion could lower market power due to other sources, the welfare figures I estimate are conservative estimates of overall welfare gains due transmission expansion.

on data aggregated at zone-hour level for each pollutant.[26] These estimates measure the reduction in emissions in response to additional wind generation. The avoided damages are therefore the product of aggregated emissions estimates (impact of additional wind on emissions) and the amount of wind integrated due to CREZ, estimated in Equation 15. I use social cost of carbon, $185 per ton of CO_2 emissions to convert the amount carbon emissions avoided to dollar value (Rennert et al. 2022). For local emissions, I use county specific damage estimates ($/lbs) of SO_2 and NOx from Holland et al. (2016).

Aggregating the hourly damage estimates I find $244,000 worth of daily carbon emissions avoided and $91,000 worth of SO_2 and NOx avoided per day. Therefore, the value of total emissions avoided is approximately $123 million annually.[27] Note that the avoided damage values in my calculation are primarily a result of lower wind curtailment as the subsequent wind integration due to transmission expansion. However, there could be additional environmental benefits. For example, Fell, Kaffine, and Novan (2021) show that CREZ increased the value of wind generation in ERCOT by over $240 million due to lower grid congestion. Aggregating these two figures would imply total annual environmental benefits of approximately $360 million.

8 Conclusion

A critical factor in fully utilizing the benefits of renewable energy is the availability of electricity transmission lines. Using the CREZ transmission expansion in Texas as a case study, this paper shows that transmission expansion led to lower market power and emissions from marginal fossil fuel producers with about $313 million worth of annual benefits. As consistent with the theoretical model of fossil fuel firm behavior, these effects are strongest for marginal generators operating at the peak demand hours.

While CREZ expansion was a $6.8 billion investment funded through the Transmission Cost Recovery Factor, a component in the retail rate of electricity paid by consumers in Texas (Fink et al. 2011; Dorsey-Palmateer 2020), there are both public and private benefits of this investment. On the public front, this includes lower grid congestion and decline in market power, amongst others. This translates to efficient dispatch of electricity, lower wholesale and retail prices of electricity, and therefore welfare gains in the medium to long-run. From the private side, this includes greater investments in renew-

26. Figure D7 and Figure D8 in the Appendix provides zone specific estimates of the association between wind generation and carbon emissions and local emissions respectively. The hourly pattern is very similar to the within-generator estimates reported in Figure 10 and Figure 11. Figure D9 provides zone level estimates with marginal damage ($) as the dependent variable.

27. Table E1 in Appendix shows the break-down of the daily estimates by zone and pollutant.

able energy (Gonzales, Ito, and Reguant 2023; Doshi 2024) which in turn creates public benefits due to lower emissions.

Because transmission expansions are costly public undertakings that take several years of planning and execution, quantifying these effects is useful to assess the economic value of these investments. Several of such investments are being considered in different parts of the US like the Midwest and the Southwest (Puppel 2021; Kite 2022). The findings from this paper can provide insights about the effects of transmission expansion in other wholesale electricity markets. Alternatively, these results also highlight the forgone benefits and environmental costs from delays in grid expansion.

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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, and operating status.

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.

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.

B.3 Transmission congestion and market power

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.[28]

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

28. 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.

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.

C Theoretical model accounting for firm forward position

C.1 Theoretical model including generator's forward position

Here, I extend the theoretical model presented in Section 3 to consider the forward position by the marginal generator. Recall, that I model the effect of transmission expansion on the markups set by a fossil fuel generator operating in a nodal wholesale electricity market.

C.1.1 Model Setup

Consider two geographically distinct regions: West, denoted by $\mathcal{W}$ and East, denoted by $\mathcal{E}$. West ($\mathcal{W}$) is comprised of wind farms and East ($\mathcal{E}$) is comprised of fossil fuel generators that serve a large demand center. Electricity transmission capacity (K) enables export of electricity generated by wind in $\mathcal{W}$ to demand centers in $\mathcal{E}$.

Generator i is a profit-maximizing fossil fuel generator i located in $\mathcal{E}$. It 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.

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

$$\max_{b_i, Q_i} \mathbb{E}_{\mathcal{E}_{-i}} \left[p \cdot Q_i(p) - C_i(Q_i(p)) + (p^F - p) Q_i^F \right] \tag{19}$$

The last term in Equation 19 is the payoff from the forward position that is resolved in the real-time market.

Market demand in $\mathcal{E}$ is denoted by $D^{\mathcal{E}}$ and is assumed to be perfectly inelastic. Generator i faces a downward-sloping residual demand curve $D_i^r(p, q_w; \mathrm{K})$ comprised of demand for electricity $D^{\mathcal{E}}$, electricity generated from wind farms denoted by $q_w(K)$, and electricity generated from infra-marginal fossil fuel producers, $Q_{-i}(p, q_w; K)$.[29] Mathematically, D_i^r can be written as,

$$D_i^r(p, q_w; \mathrm{K}) = D^{\mathcal{E}} - q_w - Q_{-i}(p, q_w; K) \tag{20}$$

29. Wind-based electricity generation incurs zero marginal cost and is always scheduled to dispatch first. I assume $D^{\mathcal{E}} > q_w$ which ensures that fossil fuel generators are scheduled to dispatch in order to meet the remaining demand of $D - q_w$ units of power.

Note that because regions $\mathcal{E}$ and $\mathcal{W}$ are connected by transmission lines K, I express q_w is a function of available transmission capacity K. Further, similar to the micro-foundation in Section 3, I express Q_{-i} as $s \times p$, where s is the slope of generator i's residual demand curve. The inherent assumption is that infra-marginal producers are willing to produce electricity as long as p is above their marginal costs, $c_{-i}(q) = q/p$. This micro-foundation is similar to the one in Ito and Reguant (2016). Thus, $D_i^r(p, q_w; K)$ is,

$$\begin{aligned} D_i^r(p, q_w; \mathrm{K}) &= D^{\mathcal{E}} - q_w(K) - Q_{-i}(p, q_w; K) \\ &= D^{\mathcal{E}} - q_w(K) - sp \end{aligned} \tag{21}$$

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:

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

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

$$\implies \mathbb{E}_{\mathcal{E}_{-i}} \left[\frac{\partial p}{\partial b_i} \left(Q_i^{net}(p, q_w) + \frac{\partial D_i^r(p, q_w)}{\partial p} \left[p - C_i'(D_i^r(p, q_w)) \right] \right) \right] \Bigg|_{p=b_i} = 0 \tag{22}$$

Equation (22) is the optimal pricing rule for generator i, which sets price equal to marginal cost plus a markup term. $\frac{\partial p}{\partial b_i}$ is the slope of the market-clearing 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., $C_i'(D_i^r(p, K)) = c_i$, as well as full information on other generators' strategy. Equation (22) reduces to

$$p - c_i = -\frac{Q_i^{net}(p, q_w)}{\partial D_i^r(p, q_w)/\partial p} \tag{23}$$

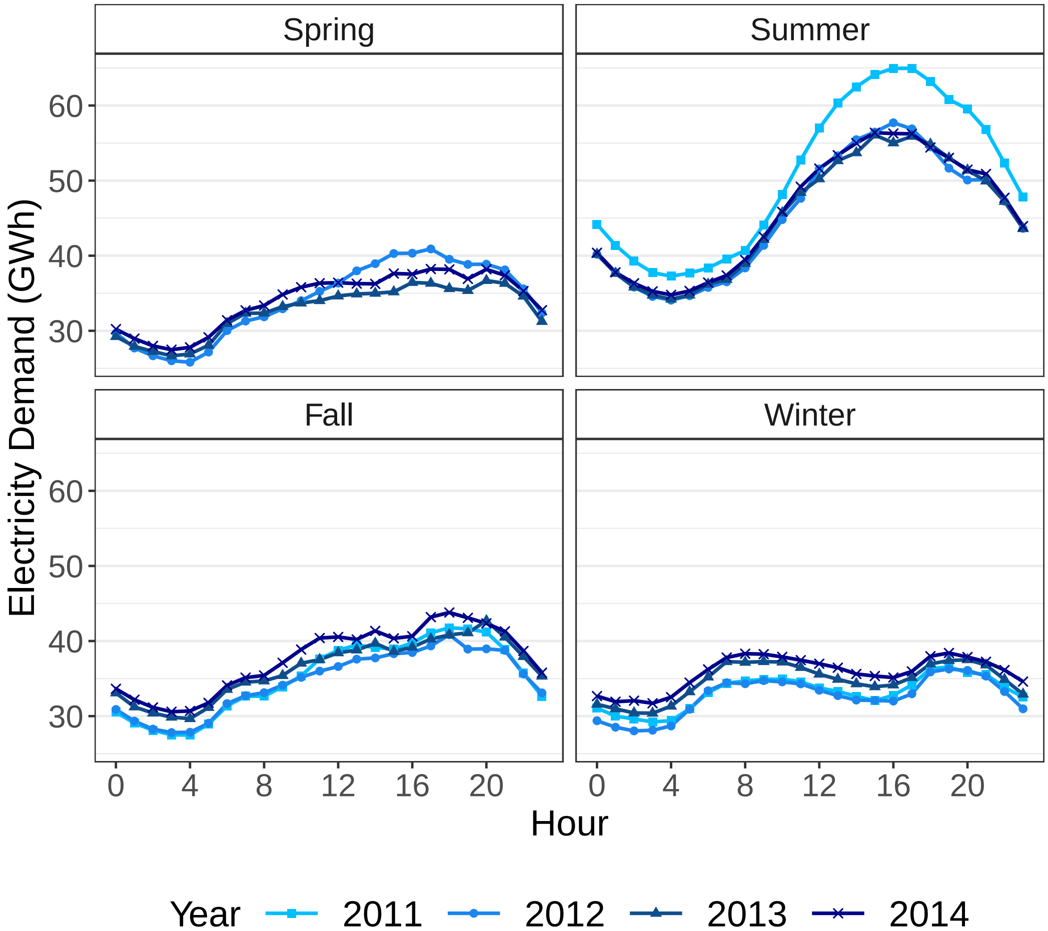
Equation 4 shows that the 'realized markups' are dependent on the net production of electricity and the slope of its residual demand curve, which is a negative quantity. The numerator measures the extent to which a generator's production decision affects the markups. With $Q_i^{net} > 0$, the generator is a net seller, implying that it produces more than its position 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 less than the marginal cost for the electricity generated.

The denominator is the slope of residual demand curve, which determines the ability of the generator to set markups. A flatter residual demand curve implies that the generator will find it optimal to set lower markups, whereas a steeper residual demand curve implies higher markups.

Comparative statics of Equation 23 proceeds by taking a partial derivative of $p - c_i$ with respect to transmission expansion K and rearranging the resulting terms. The results (and the model predictions) obtained are identical to the ones obtained in Section 3. Therefore, for the sake of brevity I skip the derivations of the *displacement* and *slope* effects for Equation 23.

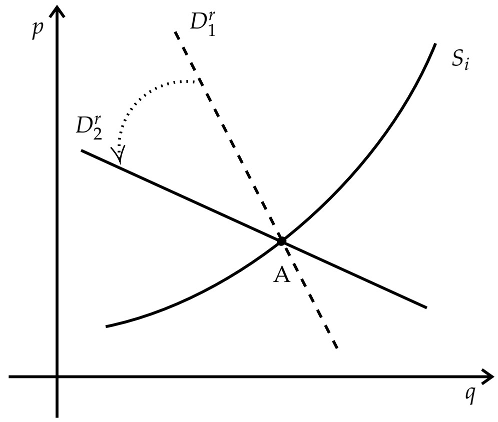
D Supplementary Figures

Figure D1: Hourly average of electricity demand by season from 2011 - 2014

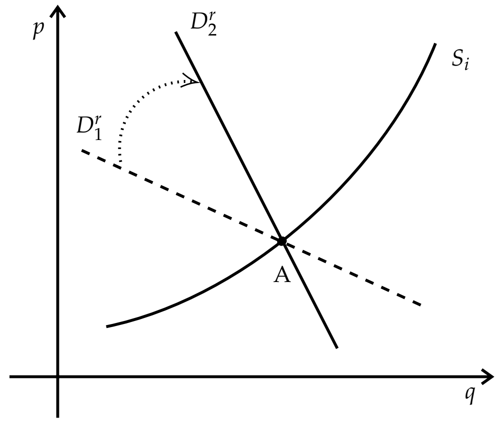


Notes: This figure shows hourly average electricity demand (GWh) in ERCOT by season. Spring is the months of March, April, and May; Summer is the months of June, July, and August; Fall is the months of September, October, and November; Winter is the months of December, January, and February. Due to data limitations the panel for Spring does not show 2011.

Figure D2: Rotation of generator i's residual demand curve post transmission expansion



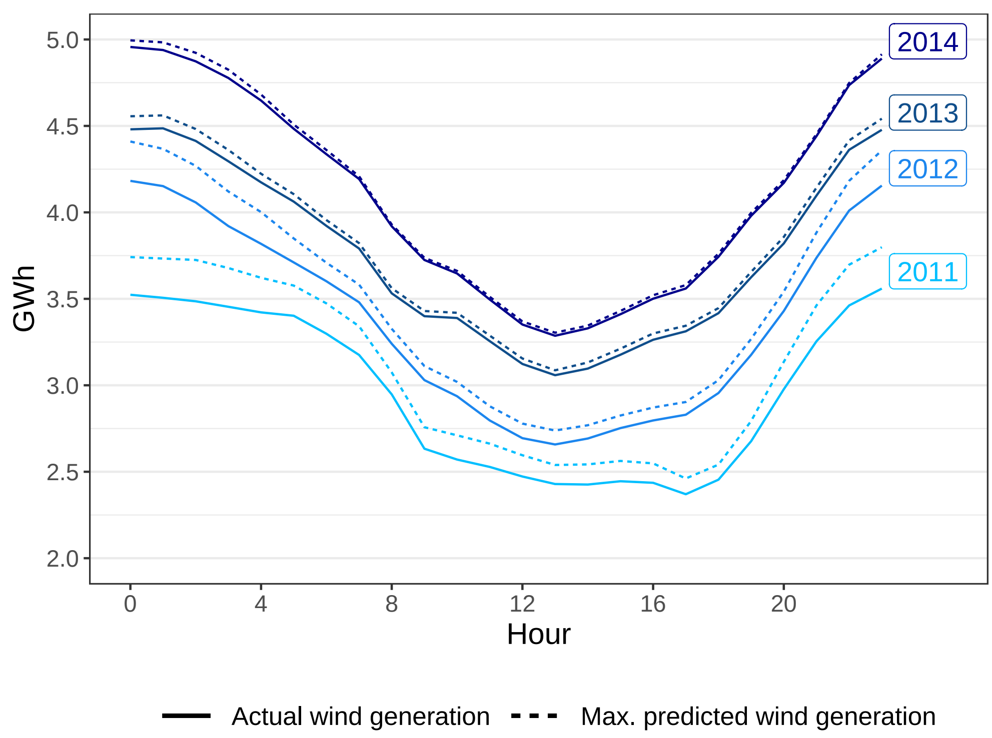
(a) $\partial s/\partial K \geq 0$: flatter residual demand curve



(b) $\partial s/\partial K \leq 0$: steeper residual demand curve

Notes: 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. Counterclockwise rotation of residual demand curve in Figure D2a occurs due to a flatter dispatch curve at the margin, whereas clockwise rotation as shown in Figure D2b is a result of a steeper dispatch curve at the margin.

Figure D3: Hourly averages of actual wind generation (w_t) and maximum predicted wind generation (max_t) from 2011 - 2014



Notes: 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.

Figure D4: Producer surplus due to markups in the factual scenario and counterfactual scenario of no transmission expansion

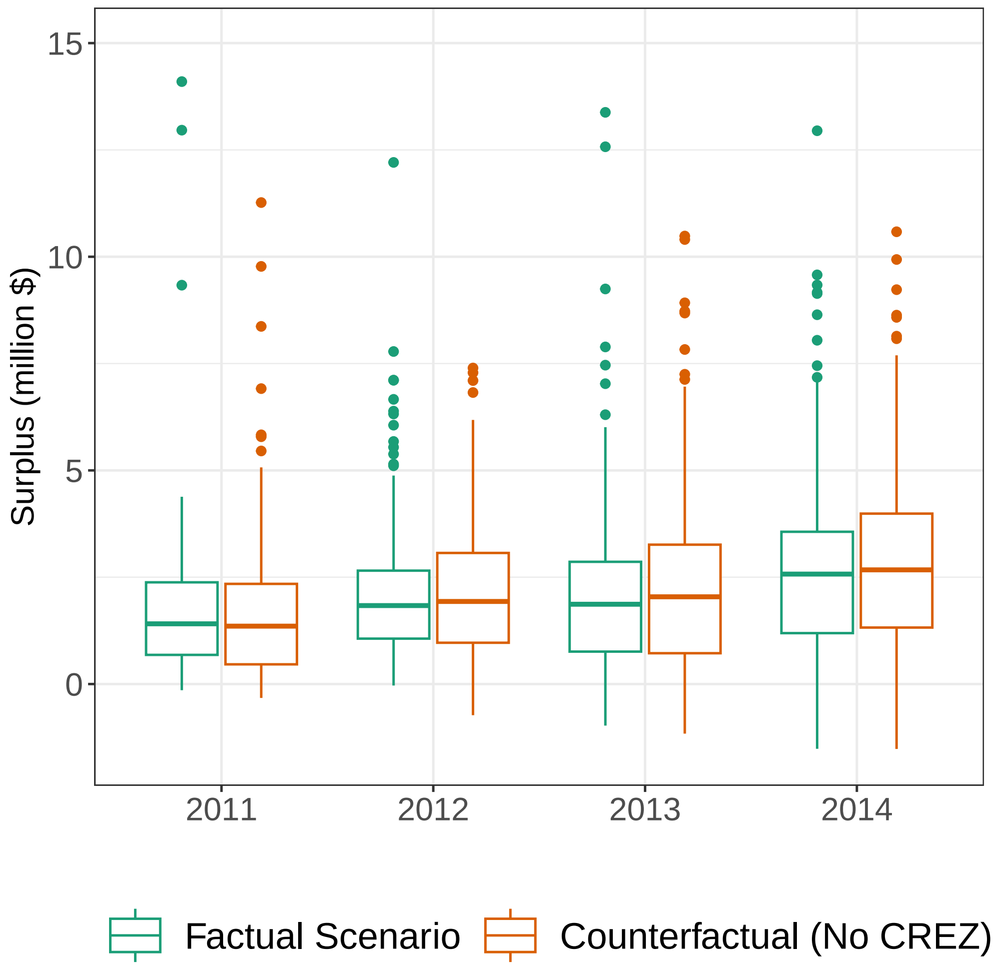
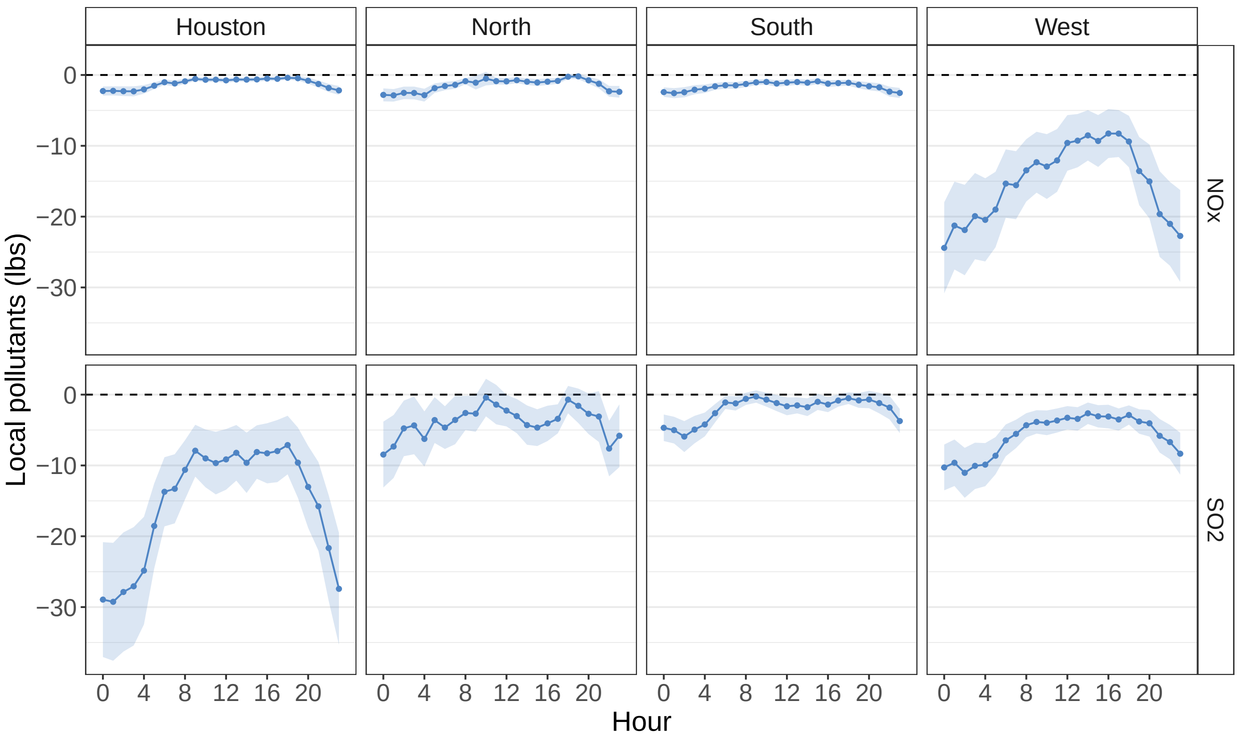
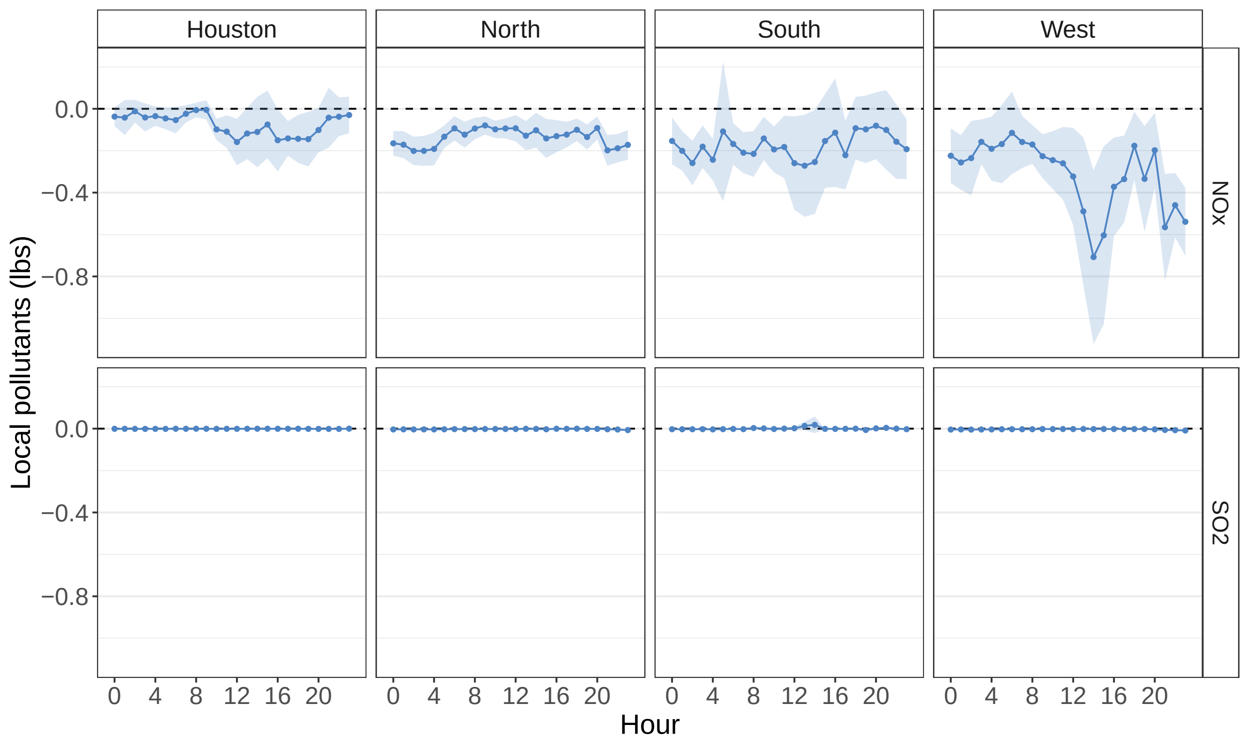


Figure D5: Transmission expansion and local emissions (NOx and SO_2) from coal generators



Note: This figure shows the product of hourly coefficient estimates of the association between wind generation and local emissions (NOx and SO_2) from Equation 17 (for the sample of coal generators), and coefficient estimates of wind integration due to CREZ expansion from Equation 15. Shaded ribbons show the corresponding 95 percent confidence intervals.

Figure D6: Transmission expansion and local emissions (NOx and SO_2) from natural gas generators



Note: This figure shows the product of hourly coefficient estimates of the association between wind generation and local emissions (NOx and SO_2) from Equation 17 (for the sample of natural gas generators), and coefficient estimates of wind integration due to CREZ expansion from Equation 15. Shaded ribbons show the corresponding 95 percent confidence intervals.

Figure D7: Zonal estimates of marginal effect of wind on carbon emissions (tons)

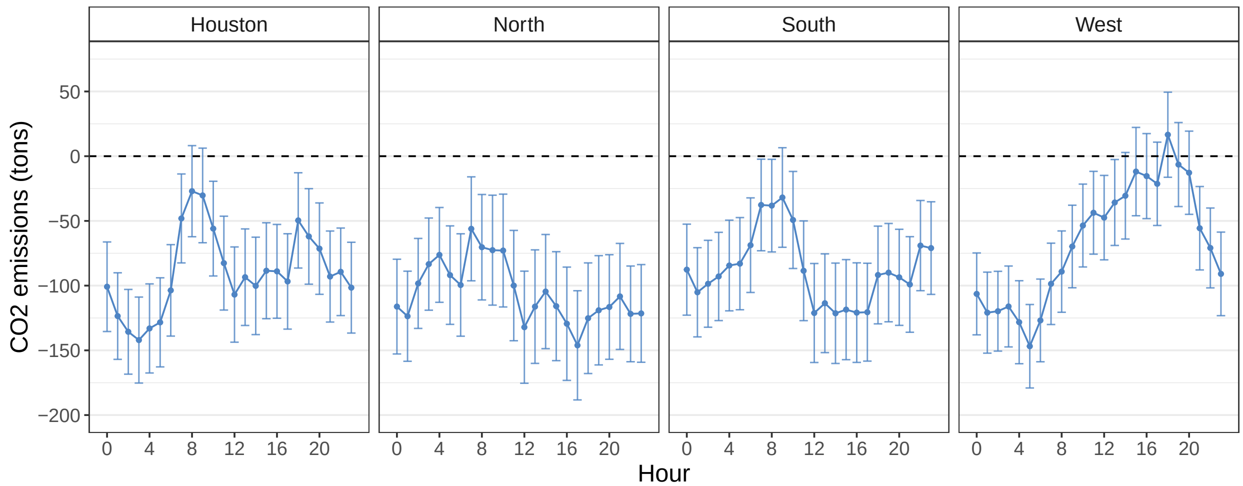


Figure D8: Zonal estimates of marginal effect of wind on local emissions (tons)

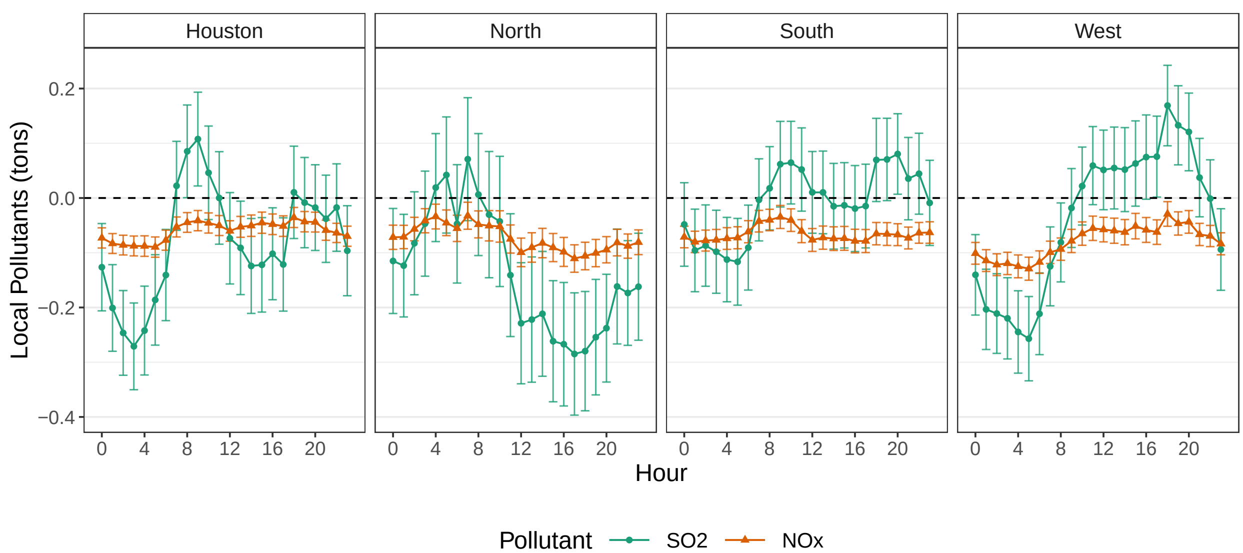
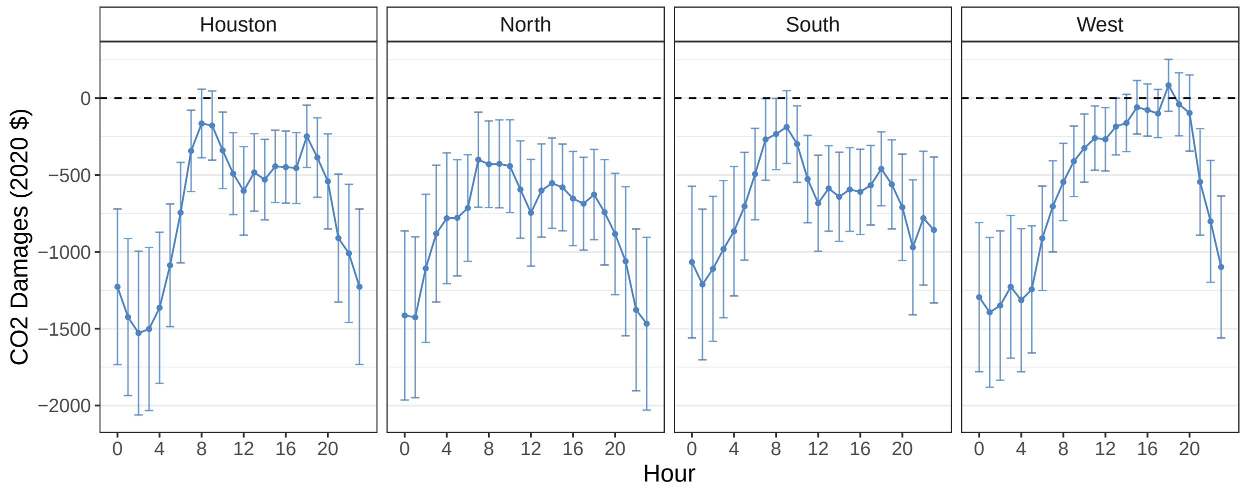
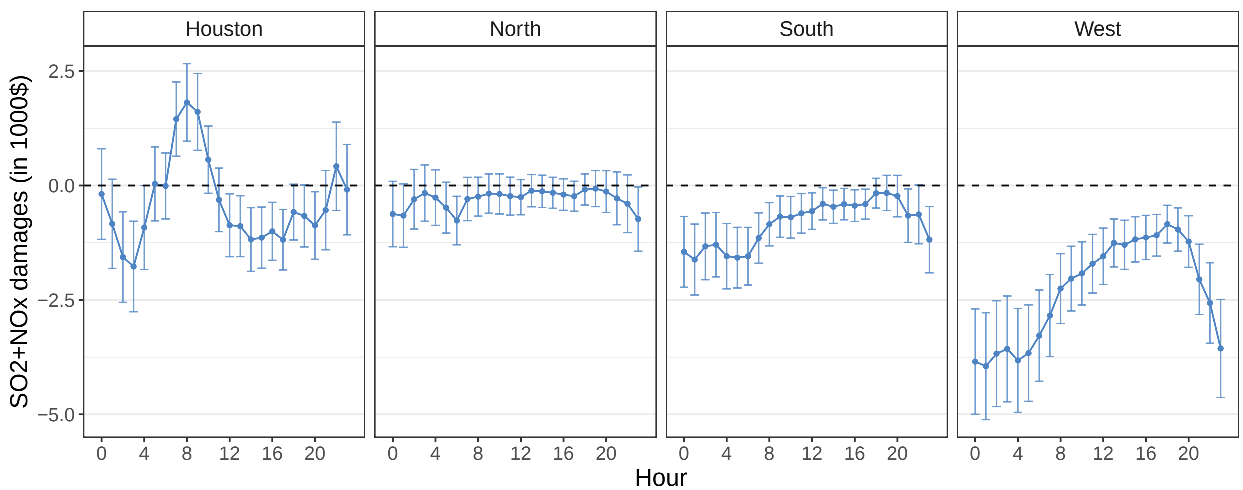


Figure D9: Hourly averages of the marginal damages (2020 $) avoided due to CREZ expansion for each zone over 2011 - 2014.

(a) Damages due to global pollution (CO_2)



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



E Supplementary Tables

Table E1: Average daily damages avoided from marginal generators due to CREZ

	Damages Avoided (2020 $)			
Zone	CO_2	SO_2 + NOx	Total	Percent (%)
Houston	64,178	8,710	72,888	22
North	70,328	7,173	77,501	23
South	57,974	20,044	78,018	23
West	52,010	55,267	107,277	32
Total	244,491	91,194	335,685	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.