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Does electricity get cheaper and cleaner with more wind in ERCOT?

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ABSTRACT

In this paper we utilize nodal market operation and price data in Texas to revisit two empirical questions: (1) How does wind integration change the energy price? (2) Has wind displaced emission from thermal generation? We find that for every additional 1,000 MW of wind generation in a Real-Time 15-minutes settlement interval would suppress nodal prices at non-wind resources by $1.5/MWh to $4.5/MWh. We also find additonal wind generation results in higher emission in CO_2, SO_2 and NO_X during both on-peak and off-peak hours.

Keywords: Renewables, Electricity market, Electricity price, emission

JEL codes: L94, L98, Q42, Q48, Q51, Q53, Q58

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1. Introduction

The production of electricity has heavily relied on fossil fuels such as coal and natural gas. With the prospect of transitioning to a low carbon intensity power system and owing to various policy incentives or subsidies, zero-emission intermittent renewable resources have rapidly penetrated into the bulk electric grid and changed the generation fuel mix in various power markets worldwide. As the share of renewables in the power system continue to increase, grid operator faces new operational challenges such as renewable energy forecast errors, net load ramps, low inertia, and need for variable ancillary services. Many engineering studies have devoted significant efforts in addressing these operational risks while meeting the policy objective of accommodating more renewable energy into bulk electric power system.[1]

On the other hand, increasing penetration of renewable energy also brings economic and environmental impact to power system. Comparing with a rich strand of engineering-economic studies that utilize security constrained economic dispatch models to simulate the price and emission impact of increasing renewables (see, e.g., Bladick, 2012; Deng et al., 2015), there are also growing *ex post* statistical analyses on the past effects of integrating renewable energy. A strand of literature, mostly focusing on European counties, investigated the effect of expanding renewables on market price or production cost (see, e.g. Würzburg et al., 2013; Cludius et al., 2014; Clò et al., 2015; Dillig et al., 2016; and Denny et al., 2017). These studies in general found that increasing renewable energy would reduce power market prices or total system production costs. Another stand of literature has tried to empirically identify the short-term operational impact of renewables in displacing carbon emissions (see, e.g. Cullen, 2013; Kaffine et al., 2013; Wheatley, 2013; Novan, 2015; Thomson et al., 2017) These studies are system-specific however often found that emission savings may be less than expected values.

Aiming to make several contributions to the existing literature as well as ongoing policy discussion, we use the example of the Electric Reliability Council of Texas (ERCOT) market and try to re-visit the following questions: (1) How does wind integration change the energy price? (2) Has wind displaced emission from thermal generation? As mentioned in earlier studies (Cullen, 2013; Kaffine et al., 2013 and Novan, 2015), ERCOT provides an unique setting for investigating the above questions, because Texas was the largest producer of wind power in the U.S., and the ERCOT grid is relatively isolated from the rest of the interconnections in the U.S.

[1] See, e.g. Andrade et al, 2017; Mahoney et al, 2012; Wu et al., 2015.

Our research adds values to extant studies in several ways. First, we cover a period (2011 to 2016) with explosive development of wind capacity and increase in wind generation. Installed wind capacity within ERCOT footprint reached 18.9 GW by end of 2016, and wind generation output fulfilled 15.1% of ERCOT load year-round and set a new record of 47% instantaneous wind penetration in the year.[2] Second, in terms of the price impact of renewable energy, the majority of existing empirical studies are based on hourly Day-Ahead spot prices in European power markets. Our study utilizes 15-minutes Real-Time (RT) security constrained economic dispatch (SCED) reports and ***nodal*** settlement point prices in ERCOT, which consists of over 45 million observations between 2011 and 2016. The high granular nature of RT nodal market data allows us to capture intra-hourly, intra-daily, and seasonal fluctuations of wind generation output and to identify its impact to RT nodal prices at non-wind thermal generation plants. Third, for investigating the emission replacement effect of wind integration, we depart from previous studies that have also investigated ERCOT market (Cullen, 2013; Kaffine et al., 2013 and Novan, 2015) by: (i) proposing multi-stage fixed-effects estimation method; and (ii) identifying the relationship between real-time price and emission caused by electricity generation.

Our study finds that wind generation has not effectively displaced fossil-fueled generation in ERCOT, particularly during on-peak hours in summer months, although the installed wind capacity increased from 11 GW to 18.9 GW during the analysis period. For the price effect of wind, our analyses suggest that every 1,000 MW wind addition in a 15-minute real-time settlement interval would suppress settlement point prices at non-wind resource nodes by \$1.5/MWh to \$4.5/MWh, depending on peak/off-peak seasons and hours in a day. Finally, our multi-stage regression analysis indicates that on-peak generation is dirtier per MWh emissions than expected. In other words, when the price of electricity is the highest during the day, the emissions from a MWh of electricity generated is greater than in a per MWh during the off-peak hours when mostly the coal plants are operating.

The remainder of the paper is organized as follows. In Section 2 we provide background information on ERCOT market and review recent empirical studies that have investigated the price and emission impact of integrating renewables. In Section 3 we describe our data and empirical models. We present the empirical results in Section 4 and conclude in Section 5.

2. Background and literature review

[2] See ERCOT, *Grid Information – Generation*. Accessed at http://www.ercot.com/gridinfo/generation

2.1 Electric Reliability Council of Texas (ERCOT)

Among all organized wholesale electricity markets in the U.S., ERCOT has the most aggressive addition in wind power during 2011 and 2016. Installed wind capacity increased from 9.8 GW in 2011 to 18.9 GW in 2016. Annual wind generation output hence increased from 28 million MWh to 53 million MWh during this period, and accounted for 15.1% of ERCOT generation in 2016.[3] It is worth noting that high wind installed capacity and production numbers benefit from the state's Competitive Renewable Energy Zone (CREZ) initiative that induced the investment of $6.9 billion in nearly 3,600-miles of new transmission lines with roughly 18,500-MW of capacity to accommodate abundant wind resources in the state. CREZ was completed in end of 2013, which fully unlocked the wind potential in West Texas and Panhandle.[4] On the other hand, abundant and cheap unconventional shale gas for power generation was also reshaping the landscape of electric industry during the same period. Cheap natural gas not only flooded Texas power grid, but also further enhanced the downward pressure on wholesale energy prices. As shown in Figure 1, between 2011 and 2016, wind penetration has increased from 9% to 16% while the annual average natural gas Henry Hub spot price was below $4 per million Btu (mmBtu) and was below $3/mmBtu in 2012, 2015 and 2016, except for 2014. Annual average wholesale prices in ERCOT hence have decreased from $45/MWh in 2011 to $22/MWh in 2016, despite growing demand.

To address several evolving risks to grid operation due to rapidly penetration of wind energy, ERCOT added a new "Reliability Risk Desk" in its control room, which went live in January 2017. In addition to raising challenges to grid operation, there were also wide-spreading concerns on the revenue adequacy among conventional thermal generators. Several stakeholders were urging the Public Utility Commission of Texas to futher reform price formation in ERCOT market.[5] In contrary, the potential benefits of emission savings because of increasing wind generation draw much less attention in the state. Municipals were reported to sign long-term power purchase agreement with independent renewable energy producers to take advantage of low energy price, rather than to "save the planet."[6]

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[3] See ERCOT, *Grid Information – Generation*. Accessed at http://www.ercot.com/gridinfo/generation

[4] See The Competitive Renewable Energy Zones Process. Access at https://energy.gov/sites/prod/files/2014/08/f18/c_lasher_qer_santafe_presentation.pdf

[5] See a report filed with the Public Utility Commission of Texas in May 2017, which urged the Commission to address several price formation and market reform issues. Accessed at http://interchange.puc.state.tx.us/WebApp/Interchange/Documents/40000_669_939373.PDF

[6] See The Guardian, "Texas city opts for 100% renewable energy – to save cash, not the planet." Dated March 28, 2015. Accessed at https://www.theguardian.com/environment/2015/mar/28/georgetown-texas-renewable-green-energy

2.2 Literature review

The potential impact of integrating wind on energy price, or the "merit-order-effect," has been widely discussed. Furthermore, every MWh of electricity produced by wind turbines in theory would displace generation from conventional fossil fuel generators, and hence offset emissions. As ex-post data from power systems operation continue becoming available, there is growing number of empirical studies that utilize econometric techniques to identify these price and emission impacts of integrating renewables into power grid. Cullen (2013) and Denny et al. (2017) both illustrated that the benefit of econometric analyses is that studies can be conducted based on publicly available generator or grid operational data, without requiring proprietary information for sophisticated unit commitment dispatch models. Denny et al. (2017) further showed that for identifying the price effect of integrating wind, econometric method and unit commitment model yield highly comparable results based on their sample Ireland market. Siler-Evans et al. (2012) study shows the variation in marginal emissions factors across different RTOs in the United States. Their study has shown that replacing electricity demand in regions where generation is coal-intensive would result-in higher emissions reductions.

On the other hand, Holttinen et al. (2015) commented that emission saving estimates based on historical data may have more pitfalls in methodology than estimates based on dispatch simulations. Another drawback of econometric analyses is that the results in general cannot be used for forecasting the impact of new renewable capacity addition in the future, or applied to a different market as analyses are system-specific.

In Table 1, we list recent empirical studies (published after 2011) on investigating the effect of integrating renewables on wholesale market prices.[7] The majority of studies are based on Day-Ahead spot prices in different European countries, which consists of only one price in each hourly settlement period in a trade zone or country. Several studies further aggregated hourly prices into daily average values. The only exception is Woo et al. (2011), which is based on ERCOT Real-Time 15-minutes price data from January 2007 to May 2010 in four zones (Houston, North, South and West). Nonetheless, ERCOT has transitioned from zonal market to nodal market since December 2010, which featured locational marginal pricing for generation resource. In terms of empirical strategy, most studies utilize either

[7] Würzburg et al (2013) provided a comprehensive review on empirical studies that investigated various power markets among European countries between 2004 and 2010. Nonetheless, the penetration of renewable energy was relatively small comparing with today's level when those studies were being conducted. Hence we did not include those studies in our literature review.

ordinary least square (OLS) or time series regressions. Dillig et al. (2016) is the only exception, in which the author reconstructed marginal cost curves for hypothetical scenarios of no renewable energy presence in system. Despite heterogeneity among study period, data, and empirical strategies, these studies in general found integrating renewables would suppress or lower wholesale energy price.

In Table 2, we survey recent empirical studies (published after 2011) on investigating the effect of integrating renewables on emission reduction. Cullen (2013) was considered as the first-of-kind econometric analysis that estimated emissions offset by wind power from observed operational data. Cullen first estimated how wind generation affect the electricity production from conventional thermal plants, then calculated the resulting average reduction in emissions by multiply the generation output avoided from each fossil plant with average emission rates. Kaffine et al. (2013) and Novan (2015) on the other hand directly estimated the average impact of wind generation on the actual level of emissions from fossil fuel generators. Wheatley (2013) and Thomson et al. (2017) provided different approaches by estimating changes in the emission factor (in tCO_2/MWh or in kg CO_2eq/kWh) in European countries. The results of these studies differ in terms of magnitude but often found that the estimated emission savings could be lower than expected or hypothetical values.

In this paper, we utilize a rich Texas market dataset to re-examine the price and emission impact of integrating more wind generation into Texas grid. Our study differs from existing studies in several key ways. First, we utilize ERCOT Real-Time 15-minutes ***nodal*** operational and price data between 2011 and 2016. In contrary, existing studies mostly are based on hourly ***zonal*** market price data. Zarnikau et al. (2014) have found that after ERCOT transitioned into nodal market, the averages of locational marginal prices under the nodal market are about 2% lower than the balancing energy prices that would occur under the previous zonal market structure. The high granularity nature of our data also allows us to separate nodal prices by generation resource type (i.e. wind versus non-wind), and to estimate the impact of intra-hourly wind intermittence or seasonal variation on nodal prices in non-wind generation resources. Second, after ERCOT moved to nodal market, generation resources in general were financially settled by nodal or locational marginal price (LMP), unless otherwise settled through bilateral contracts. In theory, LMP represents the least cost to service the next increment of demand at that location (node) consistent with all power system transmission and generation constraints, as represented by Lagrange multiplier corresponding to the real power balance constraint at a node (Liu et al., 2009; Douglas and Popova, 2011). Hence any change in electricity injection or withdrawal at any node will in principle affect

LMPs at every other node on the same grid. Given the nodal setting of the data, our estimation implicitly accounts for unobserved transmission characteristics or constraints and its impact to nodal prices.

3. Data and empirical model

Our dataset consists of (i) Real-Time dispatch and Settlement Point Price for every 15-minute interval at each Resource Node, from 2011 to 2016;[8] (ii) hourly observations of total emissions in pounds of SO_2 and NO_X and short tons of CO_2 of each fossil generation resource in ERCOT (2014-2016).

3.1 ERCOT Real-Time dispatch and nodal price data

We obtained the following public reports from the ERCOT to construct our main dataset, including (i) 60-Day DAM Disclosure Reports (Day-Ahead Hourly); (ii) 60-Day SCED Disclosure Reports (Real-Time 15-minutes); and (iii) Settlement Point Prices at Resource Nodes (Real-Time 15-minutes). For each generation resource, we identify the name of its Resource Node, resource type, operational status, dispatched and metered output (in MW), and corresponding Settlement Point Price in real-time for every 15-minute interval, from 2011 to 2016. We then aggregate the metered generation output at all wind resource nodes to get 15-minutes ERCOT-wide wind generation output; and sum metered generation output at all resource nodes as proxy to 15-minutes ERCOT-wide load. Based on aggregated ERCOT wind generation and load, we calculated 15-minutes wind penetration level (%) by dividing wind generation with load.

In Table 3 we provide summary statistics of ERCOT load and wind generation through 2011 to 2016. We break our dataset into six sub-groups based on season in a year and hour in a day when generating summary statistics.[9] First, in terms of load, ERCOT had extreme hot weather in 2011 and boosted demand for air conditioning in the year. Average load growth returned to normal in 2012 and kept growing through 2016 in all sub-groups, roughly 4,000 MW for every 15-minutes interval. During peak load summer (Jun-Sept) and winter months (Dec-Feb), maximum load grows even faster than average load at both on-peak and off-peak hours. Second, in terms of wind generation, average 15-minutes output really

[8] For definition of Resource Node and Settlement Point Price, please see ERCOT Glossary at http://www.ercot.com/glossary/

[9] We follow ERCOT terminology for data breakdown: Within a year, June to September are Peak Load Summer Months; December to February are Peak Load Winter Months, and the rest (Mar.-May; Oct.-Nov.) are off-peak load months. Within a week, hours ending in 7am to 22pm from Monday through Friday are On-Peak Hours, and the rest hours in a week are considered as Off-Peak Hours.

took off since 2014 after the completion of CREZ, particularly during off-peak hours in off-peak load months.

To visualize the relationship between load and wind generation at different hours in a day and in different months within a year, we plot the distribution of wind penetration level in Figure 2 through Figure 4. In general, we observe a similar pattern: wind penetration is low (below 10%) during on-peak hours (particularly between 12 p.m. and 6 p.m.) and higher during off-peak hours, in all seasons. However, as the installed wind capacity doubled from 9 GW in 2011 to 18.9 GW in 2016, and along with the completion of CREZ lines in end of 2013, we observe that the number of higher wind penetration hours (above 20%) began to increase, and also to migrate, from off-peak to peak hours in a day, and from off-peak months to either peak load summer or winter months in a year. Hours with high wind penetration (above 40%), albeit in a limited fashion, began to show up since 2015.

In Table 4 we report summary statistics of Settlement Point Prices at resource nodes by six sub-groups. Within each sub-group, we further separate prices at wind resource nodes from prices at non-wind resource nodes (including coal, nuclear, natural gas, hydro plants). Average nodal prices, at either wind or non-wind resource nodes, are higher during peak load summer months than in other months within a year, which is consistent of the load pattern in ERCOT. Average nodal prices at non-wind resources in general are also higher than average prices at wind resource nodes. Interestingly, negative prices also occur at non-wind resource nodes, and larger than negative prices at wind resources in terms of magnitude prior than 2013. Furthermore, we also noticed that the maximum price at non-wind resources have also decreased significantly since 2014, along with the pattern of natural gas price.[10]

3.2 ERCOT Emission data

We obtained emission data, including CO_2, NO_X, and SO_2 emitted from qualifying facilities in Texas, from Environmental Protection Agency (EPA) Continuous Emissions Monitoring Systems database. Emission data is hourly observation at facility level, from 2014 to 2016. In Table 5 we provide summary statistics.

3.3 Empirical model

Wind generation and price impact

To estimate the impact of wind generation on nodal prices at non-wind resources, we use the general model:

[10] In Appendix 1 we provide summary statistics of natural gas prices.

$$Price_{i,t} = \beta_1 \cdot L_t + \beta_2 \cdot W_t + \beta_3 \cdot NG_t + u_i + \emptyset \cdot Z_t + \varepsilon_{i,t} \quad (1)$$

Where i indexes each non-wind Resource Node and t indexes each 15-minutes observations during 2014 to 2016; and

L_t = Aggregate 15-minutes ERCOT load (MW)

W_t = Aggregate 15-minutes ERCOT wind generation (MW)

NG_t = Natural gas price (\$/mmBtu)

u_i = Resource Node dummy

Z_t = Vector of time dummies.

The coefficient of interests, β_1 through β_3, represents the average change in Settlement Point Price at non-wind Resource Node caused by changes in load, wind generation, and natural gas price respectively. We include u_i or Resource Node Dummy to control for fixed effect at a generation resource. The vector of Z_t includes a group of dummy variables associated with time, i.e. Year dummy, Month dummy, Year-Month dummy, or Day dummy variables, to control for any yearly, seasonal or daily patterns in the ERCOT grid.

Wind generation and emission impact

To estimate the relationship between the real-time price of electricity and emissions, we use the following systems of equations. We specify hourly emissions as system of equations to account for the reverse causality relationship between dependent and independent variables (i.e., endogeneity). Our estimation strategy is three stage least squares estimation, where in each equation there are endogenous variables on both left and right sides of the equation. Based on our empirical assessment, this estimation method is more efficient than traditional Ordinary Least Squares (OLS) estimation.

$$Price_{i,t} = \alpha_1 \cdot Price_{i,t-1} + \alpha_2 \cdot NG_t + \alpha_3 \cdot Coal_t + u_i + \emptyset \cdot Z_t + \delta_{i,t} \quad (2.1)$$

$$Net\ Load_t = \alpha_1 \cdot \widehat{Price}_{i,t} + \alpha_2 \cdot \widehat{Price}^2_{i,t} + u_i + \emptyset \cdot Z_t + \theta_{i,t} \quad (2.2)$$

$$Emission_{i,t} = \alpha_1 \cdot \widehat{Price}_{i,t} + \alpha_2 \cdot \widehat{Net\ Load}_t + \alpha_3 \cdot W_t + u_i + \emptyset \cdot Z_t + \varepsilon_{i,t} \quad (2.3)$$

Where i indexes each emission facility and t indexes each hourly observations during 2014 to 2016; and

$Net\ Load_t$ = ERCOT Hourly Net Load (MW)

NG_t = Natural gas price (\$/mmBtu)

$Coal_t$ = Coal price (\$/mmBtu)

W_t = Aggregate Hourly ERCOT wind generation (MW)

u_i = Resource Node dummy

$Z_t =$ Vector of time dummies

The first-stage of the system predicts real-time price of electricity ($Price_{i,t}$) using lagged real-time price ($Price_{i,t-1}$), natural gas prices (NG_t) and coal prices ($Coal_t$). The second-stage of the system predicts hourly net load, i.e. ERCOT load minus generation from wind, using predicted real-time price ($\widehat{Price}_{i,t}$) from the first-stage and squared real-time prices ($\widehat{Price}^2_{i,t}$). In the third-stage of the system, we predict hourly emissions using predicted real-time price ($\widehat{Price}_{i,t}$), hourly net load ($\widehat{Net\ Load}_{i,t}$), and wind generation ($W_t$).

We also estimated this system of equations for on-peak and off-peak hours to identify the relationship between real-time price, electricity load and emissions when the price of electricity is highest and lowest during the day.

4. Results

4.1. Impact on ERCOT 15-minutes real-time non-wind resource nodal prices

In Table 5 we report coefficient estimates of L_t, W_t and NG_t variables, by conducting regressions separately for each six of sub-groups, based on our general model in Equation (1). In columns (1) to (3), we use monthly natural gas price sold to electric power consumers in Texas for NG_t; and from columns (4) to (6), we instead use EIA daily Henry Hub natural gas spot price. For each natural gas price, we have three set of regressions by gradually introducing dummies in the vector of Z_t: in column (1) and (4), we do not include any time dummies; in columns (2) and (5), we include Year dummy, Month dummy and Year-Month dummy, to control for yearly, monthly, and year-month specific trends; finally in columns (3) and (6), we include Day dummy, to capture any trend that changes on daily basis.

In all regressions, the sign of our coefficient estimates are consistent with our expectations. For the coefficient estimates of L_t, all estimates are consistently positive and significant, suggesting that as demand increase, wholesale energy price at resource nodes on average would also increase. On the other hand, the coefficient estimates of W_t are consistently negative and significant, suggesting that as wind generation increases system-wide, settlement point prices at resource nodes on average would decrease. The coefficient estimates of NG_t are also generally positive and significant, which is consistent with the ERCOT operational data that natural gas plants fulfill over 40% or ERCOT load.

Comparing the magnitude of coefficient estimates between panels, we further shows how wind penetration level affect settlement point price at non-wind resource nodes at different time horizon. First, during Peak Load Summer Months, wind penetration has higher impact in reducing nodal prices in On-Peak hours then in Off-Peak hours, when we compare results in Panel A with Panel B. We find the similar pattern for all other off-peak load months by comparing Panel E with Panel F. However for Peak Load Winter Months (Panel C and Panel D), wind penetration has higher impact in reducing nodal prices in Off-Peak hours. Second, among all panels, increasing the same MW of wind generation at a 15-minutes interval would lower average non-wind nodal prices to the most extent during Peak Load Summer Months at On-Peak Hours. This is interesting given that we have lowest wind production level during this time horizon (see Panel A in Table 3). In contrary, increasing one MW of wind generation at a 15-minutes interval would have least impact on suppressing non-wind nodal prices during Peak Load Winter Months at On-Peak Hours.

We then investigate if using different natural gas price would affect our coefficient estimates for load and wind. By comparing column (1) with column (4), we find that using either monthly or daily natural gas price have minimal impact to the coefficient estimates for L_t and W_t. The magnitude of coefficients in general are similar to each other between columns (1) and (4). We also find the same similarity between columns (2) and (5), and columns (3) and (6), when we gradually introduce dummies in the vector of Z_t. Finally we examine the impact of introducing different dummies in the vector of Z_t to our coefficient estimates of L_t, W_t and NG_t variables. During peak load summer months (Panel A and B), using different time dummies have minimal impact to coefficient estimates for L_t, however would change coefficient estimates for W_t and NG_t more significantly (for instance, comparing columns (2) and (3) with column (1)). For other months (Panel C through Panel F), introducing time dummies would change coefficient estimates of all three variables L_t, W_t and NG_t. There is also no consistent trend of how the coefficient estimates would change in terms of magnitude. For wind variable W_t, in most cases using Day dummy (columns (3) and (6)) would result in largest estimate in absolute value (Panel A through Panel E). However the coefficient estimates for NG_t are often larger when introducing a set of Year dummy, Month dummy and Year-Month dummy (see columns (2) and (5)) except in Panel E.

4.2. Impact on emission in ERCOT footprint

We present the preliminary results for the estimated coefficients for ERCOT in Table 7. The estimated coefficients on the first-stage of the regression equation predicts real-time price of electricity as function of price in the previous hour and input prices including natural gas and coal. We found that increase in these prices increases hourly electricity prices. The estimated coefficients on the second-stage of the regression equation predicts hourly net load as function of settlement price, predicted in the first-stage, and the square of settlement price.

We found that increase in the price of electricity increases net load. This is due to the relationship between price and supply of electricity. Estimated coefficients on the third-stage of the regression equation predicts CO2, SO2 and NOX emissions as function of predicted electricity net load, price and wind generation. Our findings show that the direction of the relationship between hourly price of electricity and emissions is negative indicating that a marginal increase hourly price of electricity (i.e., an incremental increase in $/MWh) is associated with a decrease in average CO2, SO2 and NOX emissions. During off-peak hours, generators often rely on base-load fuel sources such as coal, while during on-peak hours, electricity generation relies on alternative fuel sources such as natural gas. During peak hours, cost of electricity is higher and the generation mix is dirtier relative to the off-peak hours. A marginal increase in electricity price during off-peak hours decreases CO2 emissions by 0.5 short tons, SO2 emissions by 1.2 pounds and NOX emissions by 1.2 pounds, on average. In addition, we found a statistically significant relationship between the net hourly load and real-time market price. In addition, the estimated coefficients on the net hourly load is positive and statistically significant indicating that increasing hourly load generation increases CO2, SO2 and NOX emissions.

Another interesting finding is the impact of wind generation on hourly emissions from electricity generation. We found that marginal increase in wind generation (i.e., an additional MW generation) increases emissions from CO2 by 0.006 short tons, SO2 by 0.022 pounds and NOX by 0.01 pounds during on peak hours. During off-peak hours, marginal increase in wind generation increases emissions from CO2 by 0.004 short tons, SO2 by 0.03 pounds and NOX by 0.009 pounds.

We also examined the relationship between real-time price, hourly load and emissions for NRG and Luminant, one of the biggest generators in ERCOT region.[11] We present the estimated regression coefficients in Table 8. We found similar results to overall ERCOT estimations, except for the impact of wind generation on emissions from Luminant generators. We found that marginal increase in wind generation during off-peak hours decreases CO2 emissions by about 0.02 short tons, SO2 emissions by about 0.08 pounds and NOX emissions by about 0.01 pounds.

5. Conclusion and policy discussion

In the interest of moving towards a cleaner, more reliable and resilient energy economy, there is a clear and urgent need to understand the effect of integrating renewable

[11] Luminant a subsidiary of Vistra Energy (formerly TUX), is a competitive power generation business.

resources into the power system as such penetration is undertaking an unprecendented pace. Using the unique example of ERCOT, which is one of the largest electricity markets in the United States with considerable amount of wind capacity, this paper provides empirical evidence on the impacts of increasing wind on wholesale energy prices. We find that increaing wind prodcution would generally suppress nodal prices at non-wind resources. However the magnitude of impact is different in terms of season in a year, and hours in a day.

In addition, this paper shows the dynamic relationship between renewable and non-renewable resources in electricity generation and its effects on carbon emissions. Our preliminary results show that higher electricity prices is associated with lower emissions from electricity generation. This could be explained by the use of cleaner resources during peak hours that are more expensive, while the use of dirtier resources during off-peak hours such as coal. Our preliminary results also show that increasing wind generation does not necessarily decreases emissions during on and off-peak emissions.

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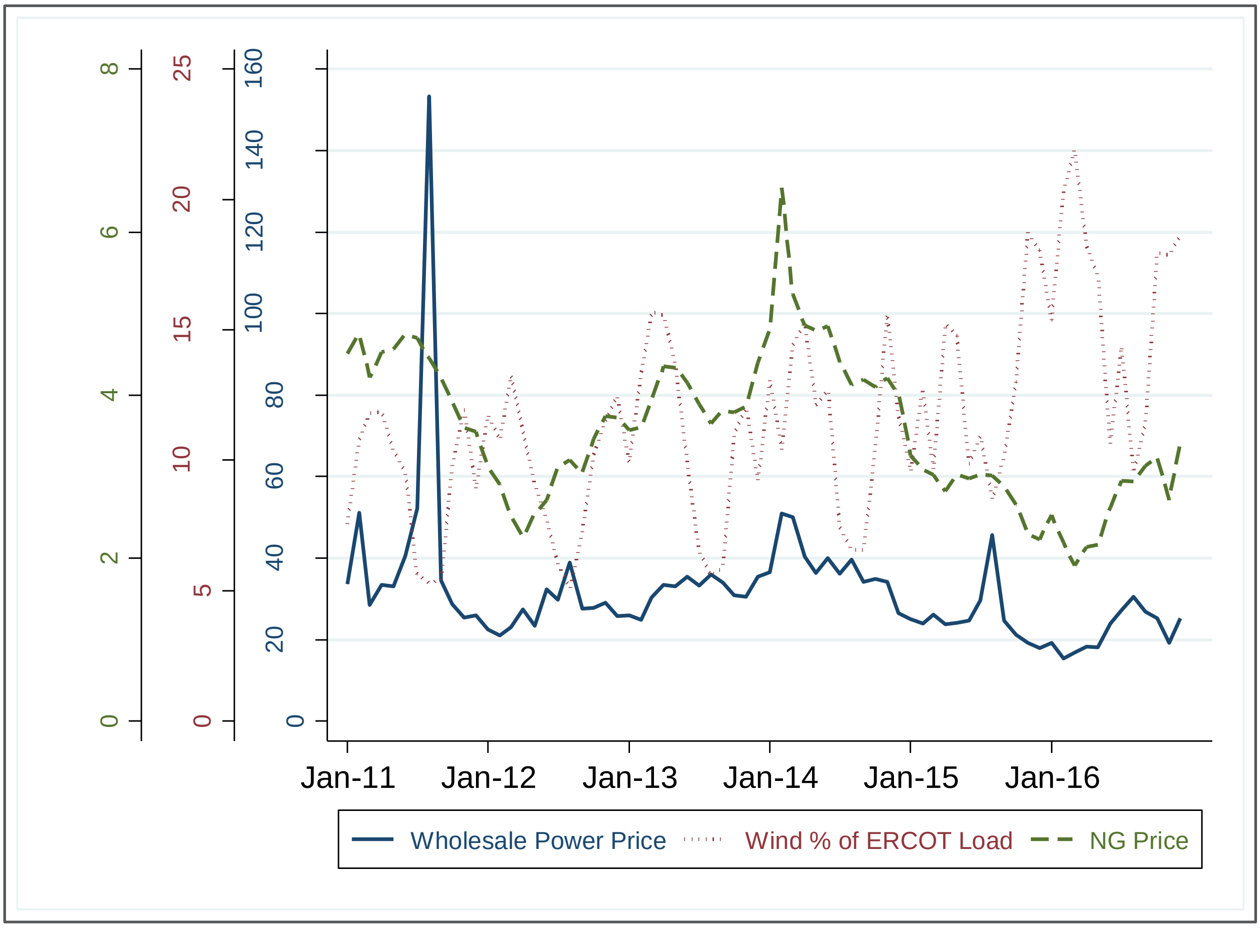
Figure 1: ERCOT Monthly Average Wholesale Energy Price, Wind Penetration and Henry Hub Natural Gas Price (2011 to 2016)



Data sources: ERCOT for energy price, load, and wind generation output; U.S. EIA for daily natural gas Henry Hub spot price.

Figure 2: ERCOT Wind Penetration: June to September

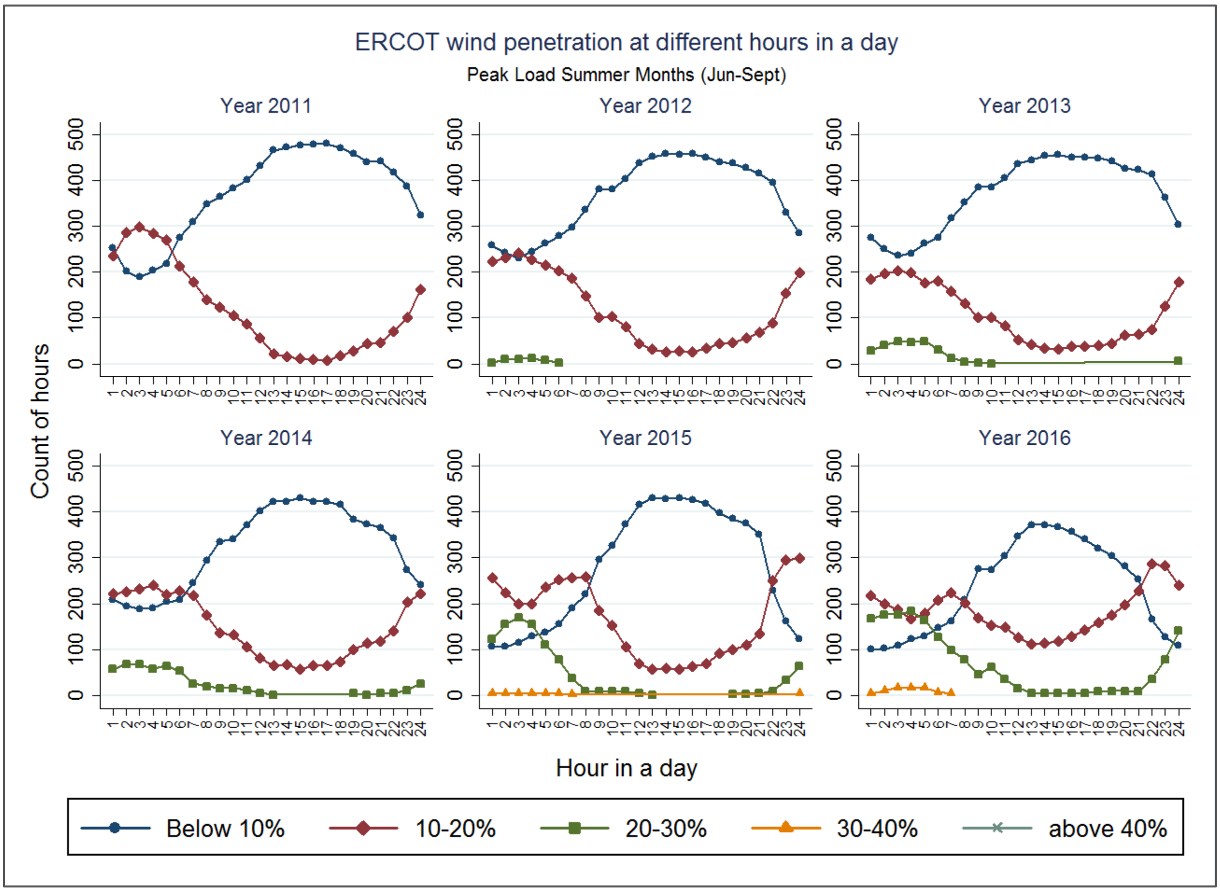


Figure 3: ERCOT Wind Penetration: December to February

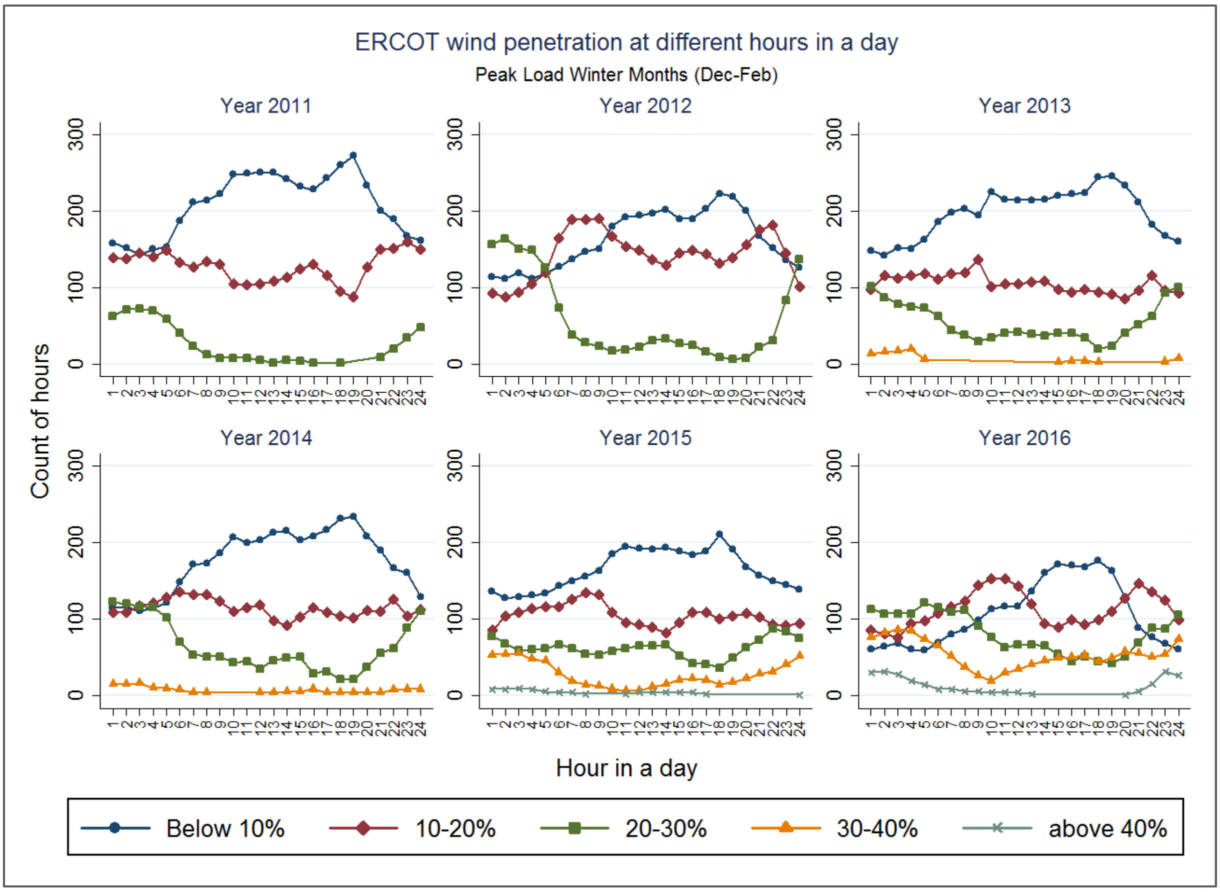


Figure 4: ERCOT Wind Penetration: March to May; October to November

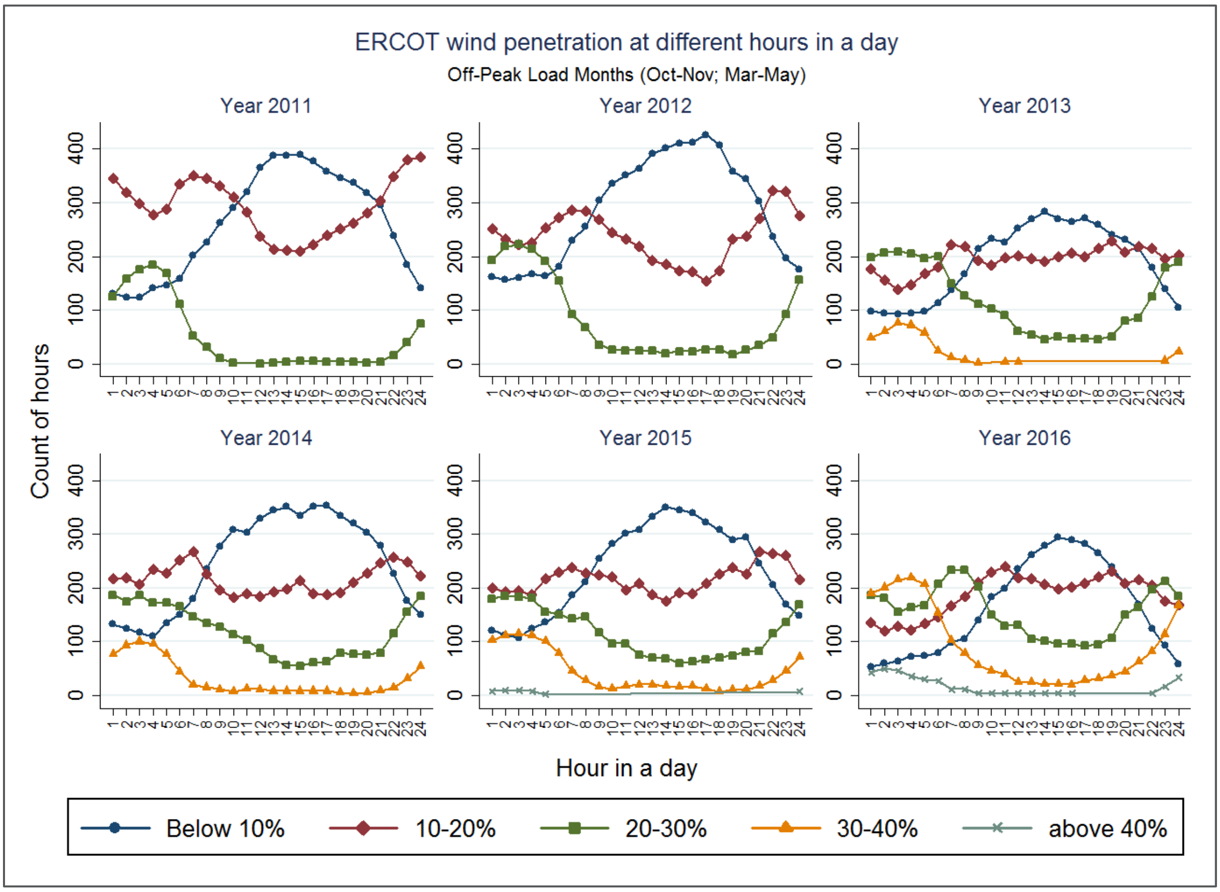


Table 1: Recent empirical studies on renewable energy and its impact on wholesale price

Region	Reference	Price Data	Data Period	Data Frequency	Estimation Method
Germany	Cludius et al. (2014)	Day-Ahead	2008-2012	Hourly	OLS regression
	Dillig et al. (2016)	Day-Ahead	2011-2013	Hourly	Marginal cost curve
Ireland	Denny et al. (2017)	4 day ex-post	2009	Hourly	Time series regression
Italy	Clò et al. (2015)	Day-Ahead	2009-2013	Daily	Time series regression
Netherlands	Mulder et al. (2013)	Day-Ahead	2006-2011	Daily	Time series regression
Spain	Gelabert et al. (2011)	Day-Ahead	2005-2009	Daily	Time series regression
	Gil et al. (2012)	Day-Ahead	2007-2010	Hourly	OLS regression
Texas	Woo et al. (2011)	Real-Time Zonal	2007-2010	15-minutes	Time series regression

Table 2: Recent empirical studies on renewable energy and its impact on emission

Region	Reference	Data Period	Data Frequency	Estimation Method
Great Britain	Thomson et al. (2017)	2009-2014	Half-Hourly	Time series regression
Ireland	Wheatley (2013)	2011	Half-hourly	Time series regression
Texas	Cullen (2013)	2005-2007	15-minutes	OLS regression
	Kaffine et al. (2013)	2007-2009	Hourly	OLS regression
	Novan (2015)	2007-2011	Hourly	OLS regression

Table 3: Summary Statistics of ERCOT Load and Wind Generation (MW)

Year		2011	2012	2013	2014	2015	2016
Panel A: Peak Load Summer Months (June – Sept); On-peak Hours (7am to 10pm Mon-Fri)							
Load	Mean	52,595	50,493	51,065	50,914	53,051	54,223
	Median	53,983	50,970	51,751	51,383	53,789	55,219
	Min	30,685	32,068	29,667	30,809	33,245	33,453
	Max	67,635	65,845	66,831	65,858	68,939	71,389
Wind Generation	Mean	2,390	2,497	2,692	3,320	3,629	4,748
	Median	2,065	2,108	2,267	2,792	3,296	4,220
	Min	60	7	5	45	183	112
	Max	6,899	8,327	8,968	9,897	10,386	13,308
Panel B: Peak Load Summer Months (June – Sept); Off-peak Hours (11pm to 6am Mon-Fri; Sat. and Sun.)							
Load	Mean	42,013	39,673	40,176	40,432	42,341	43,576
	Median	39,950	37,672	38,148	38,365	40,331	41,666
	Min	25,104	25,945	24,811	26,465	27,376	27,723
	Max	64,309	61,213	61,866	63,037	65,888	66,941
Wind Generation	Mean	3,342	2,983	3,232	3,887	4,997	5,906
	Median	3,399	2,720	2,887	3,606	4,880	5,800
	Min	30	9	86	113	405	214
	Max	7,316	7,581	9,048	10,036	11,380	13,801
Panel C: Peak Load Winter Months (Dec – Feb); On-peak Hours (7am to 10pm Mon-Fri)							
Load	Mean	36,845	34,603	36,688	39,253	39,338	38,113
	Median	34,711	33,882	35,162	37,397	37,658	37,343
	Min	29,069	28,243	29,287	28,942	29,646	29,903
	Max	57,384	46,889	53,374	58,257	57,444	57,977
Wind Generation	Mean	2,785	3,373	3,270	3,676	3,967	5,474
	Median	2,363	3,148	2,777	3,129	3,304	4,913
	Min	50	35	77	91	55	130
	Max	7,110	8,584	9,282	10,844	12,849	14,362
Panel D: Peak Load Winter Months (Dec – Feb); Off-peak Hours (11pm to 6am Mon-Fri; Sat. and Sun.)							
Load	Mean	32,184	30,641	32,707	34,121	34,847	34,467
	Median	31,258	30,281	31,889	32,888	34,017	33,788
	Min	22,626	23,203	23,343	24,179	25,227	24,982
	Max	57,695	46,618	53,385	57,662	57,227	57,564
Wind Generation	Mean	3,226	4,055	3,744	4,470	5,287	6,966
	Median	3,211	4,232	3,358	4,244	4,935	6,684
	Min	98	34	53	73	40	773
	Max	7,023	8,062	9,443	10,941	13,799	15,979
Panel E: Off-Peak Load Months (Mar-May; Oct-Nov); On-peak Hours (7am to 10pm Mon-Fri)							
Load	Mean	36,431	37,298	37,351	38,306	38,945	40,032
	Median	35,033	35,875	35,690	36,793	37,969	38,431

Year		2011	2012	2013	2014	2015	2016
	Min	25,853	25,303	28,367	28,658	28,283	28,830
	Max	56,825	59,013	56,086	58,313	59,238	59,634
Wind Generation	Mean	3,365	3,332	4,323	3,878	4,569	5,733
	Median	3,413	3,163	4,276	3,380	3,967	5,382
	Min	87	27	235	12	110	296
	Max	7,380	7,992	9,650	10,765	12,937	14,069
Panel F: Off-Peak Load Months (Mar-May; Oct-Nov); Off-peak Hours (11pm to 6am Mon-Fri; Sat. and Sun.)							
Load	Mean	30,289	30,421	30,851	31,949	32,196	32,615
	Median	29,219	29,195	30,291	31,090	31,402	31,732
	Min	22,357	22,527	23,241	23,357	24,266	24,801
	Max	54,641	51,325	51,555	53,695	53,618	54,024
Wind Generation	Mean	3,851	3,948	4,839	5,046	5,050	6,992
	Median	4,220	4,078	5,164	4,897	4,882	7,232
	Min	130	61	190	121	38	246
	Max	7,027	8,377	9,548	10,652	12,729	15,008

Notes: This table reports 15-minutes mean, min, max and median ERCOT load, wind generation from 2011 to 2016, measured in MW based on Real-Time Security Constrained Economic Dispatch (SCED) reports.

Table 4: Summary Statistics of Resource Node Real-Time Settlement Point Prices

Year		2011	2012	2013	2014	2015	2016
Panel A: Peak Load Summer Months (June – Sept); On-peak Hours (7am to 10pm Mon-Fri)							
Wind	Mean	97.49	41.91	42.40	39.85	32.74	29.60
	Median	41.50	28.55	35.22	36.71	25.89	24.57
	Min	-188.3	-480.1	-313.7	-251	-152.8	-251
	Max	3,061	5,848	4,900	5,725	2,711	4,789
	Observation	392,600	386,728	438,480	465,785	591,055	673,599
None-Wind	Mean	122.6	41.06	44.19	40.94	37.62	33.64
	Median	44.47	29.10	36.72	38.44	26.99	26.09
	Min	-4,470	-2,957	-517.7	-251	-251	-251
	Max	3,001	4,145	4,900	6,740	4,937	2,197
	Observation	988,278	822,090	854,458	800,416	914,420	944,032
Panel B: Peak Load Summer Months (June – Sept); Off-peak Hours (11pm to 6am Mon-Fri; Sat. and Sun.)							
Wind	Mean	30.94	22.66	27.20	30.21	20.58	21.50
	Median	26.09	19.47	23.94	27.53	19.07	18.48
	Min	-926.4	-145.2	-134.3	-251	-245.5	-72.74
	Max	3,000	2,912	1,115	3,069	583.2	871.2
	Observation	495,701	506,758	575,008	597,937	757,102	860,632
None-Wind	Mean	39.02	22.87	28.57	31.51	21.73	24.60
	Median	28.01	19.89	24.59	28.02	19.43	18.86
	Min	-3,438	-385.9	-2228	-251	-251	-251
	Max	3,297	1,938	1,562	3,503	3,521	2,329
	Observation	910,292	854,707	860,426	815,342	940,215	943,437
Panel C: Peak Load Winter Months (Dec – Feb); On-peak Hours (7am to 10pm Mon-Fri)							
Wind	Mean	42.33	19.76	25.91	37.99	21.32	19.27
	Median	26.15	21.84	24.54	27.86	20.12	18.19
	Min	-741.4	-598.3	-608.3	-146.8	-251	-251
	Max	3,528	1,685	1,718	5,310	3,429	993.0
	Observation	264,642	294,944	315,643	325,915	378,801	478,615
None-Wind	Mean	58.13	23.63	28.33	47.88	23.39	21.49
	Median	28.10	22.63	25.20	29.97	21.35	18.92
	Min	-4,454	-4,470	-3,257	-251	-251	-251
	Max	5,126	1,238	3,426	7,286	3,421	5,863
	Observation	449,968	401,565	438,512	475,359	510,387	479,353
Panel D: Peak Load Winter Months (Dec – Feb); Off-peak Hours (11pm to 6am Mon-Fri; Sat. and Sun.)							
Wind	Mean	29.18	17.46	24.94	32.21	18.71	16.24
	Median	22.83	18.97	22.87	24.69	18.28	16.65
	Min	-1,509	-1,822	-251	-141.6	-251	-251
	Max	3,571	1,016	1,320	5,131	3,421	674.8
	Observation	339,282	392,857	390,953	410,208	485,565	644,885
None-Wind	Mean	40.87	21.68	28.50	39.61	22.64	18.23
	Median	24.31	20.31	23.74	25.85	19.32	16.98

Year		2011	2012	2013	2014	2015	2016
	Min	-4,278	-4,468	-1,793	-178.9	-251	-63.40
	Max	5,046	1,003	3,429	7,213	1,539	682.8
	Observation	505,509	479,701	503,978	503,695	574,212	561,690
Panel E: Off-Peak Load Months (Mar-May; Oct-Nov); On-peak Hours (7am to 10pm Mon-Fri)							
Wind	Mean	26.54	33.98	36.68	41.61	25.23	21.97
	Median	25.87	23.06	26.83	32.76	21.90	18.30
	Min	-1,049	-584.5	-1,601	-188.1	-251	-209.4
	Max	3,001	5,159	4,569	6,812	3,368	3,544
	Observation	452,499	510,231	492,169	573,081	705,843	844,590
None-Wind	Mean	34.20	31.93	39.05	48.21	27.33	26.53
	Median	28.13	23.92	28.77	34.48	22.82	19.30
	Min	-3,369	-3,387	-4,000	-251	-251	-251
	Max	3,001	3,685	3,421	6,812	3,439	4,672
	Observation	758,468	828,290	632,284	782,099	815,975	911,881
Panel F: Off-Peak Load Months (Mar-May; Oct-Nov); Off-peak Hours (11pm to 6am Mon-Fri; Sat. and Sun.)							
Wind	Mean	18.76	19.47	26.51	32.19	18.97	13.94
	Median	21.73	17.93	23.72	26.89	18.26	14.64
	Min	-387.2	-273.9	-927.2	-120.6	-251	-251
	Max	2,999	3,000	4,717	5,044	3,366	1,508
	Observation	573,773	627,284	605,086	754,255	895,767	1,087,129
None-Wind	Mean	28.69	23.73	29.79	37.38	22.74	16.72
	Median	24	19.57	24.63	27.78	18.79	15.24
	Min	-8,169	-2,257	-4,919	-251	-251	-251
	Max	3,042	3,000	4,247	5,299	3,381	3,515
	Observation	814,013	854,687	665,908	849,797	924,772	953,284

Notes: This table reports the mean, median, min, max of ERCOT Resource Node Real-Time 15-minutes Settlement Point Prices (in $/MWh).

Table 5: Summary Statistics of Emission (2014-2016)

	2014	2015	2016
CO2 (Short Tons)			
Observation	677,142	696,469	676,442
Mean	383	352	356
Std. Dev.	460	406	418
Min	-	-	-
Max	3,416	3,460	3,452
SO2 (Pounds)			
Observation	679,431	698,480	678,358
Mean	1,011	745	724
Std. Dev.	2,849	2,274	2,142
Min	-	-	-
Max	29,871	31,736	30,168
NOX (Pounds)			
Observation	679,431	698,480	678,358
Mean	360	309	314
Std. Dev.	617	524	537
Min	-	-	-
Max	12,268	6,465	9,154

Table 6: The Effect of Load, Wind Generation and Natural Gas Price on Non-wind Resource Node Real-Time Settlement Point Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Peak Load Summer Months (June – Sept); On-peak Hours (7am to 10pm Mon-Fri)						
Load	0.00173***	0.00174***	0.00165***	0.00173***	0.00173***	0.00165***
	(4.26e-06)	(4.44e-06)	(4.92e-06)	(4.28e-06)	(4.50e-06)	(4.92e-06)
Wind Gen	-0.00261***	-0.00253***	-0.00445***	-0.00262***	-0.00249***	-0.00445***
	(1.22e-05)	(1.29e-05)	(2.64e-05)	(1.22e-05)	(1.30e-05)	(2.64e-05)
NG Price	6.575***	13.49***	6.254***	7.163***	11.39***	1.589
	(0.0471)	(0.191)	(0.425)	(0.0507)	(0.267)	(9.197)
Panel B: Peak Load Summer Months (June – Sept); Off-peak Hours (11pm to 6am Mon-Fri; Sat , Sun)						
Load	0.00103***	0.00106***	0.000983***	0.00103***	0.00105***	0.000983***
	(2.15e-06)	(2.25e-06)	(2.63e-06)	(2.17e-06)	(2.28e-06)	(2.63e-06)
Wind Gen	-0.00134***	-0.00145***	-0.00220***	-0.00138***	-0.00148***	-0.00220***
	(6.25e-06)	(6.87e-06)	(1.26e-05)	(6.27e-06)	(6.95e-06)	(1.26e-05)
NG Price	6.473***	9.588***	3.315***	7.258***	8.759***	-1.438
	(0.0260)	(0.107)	(0.277)	(0.0282)	(0.161)	(0.940)
Panel C: Peak Load Winter Months (Dec – Feb); On-peak Hours (7am to 10pm Mon-Fri)						
Load	0.00215***	0.00233***	0.00258***	0.00193***	0.00219***	0.00258***
	(1.34e-05)	(1.40e-05)	(2.69e-05)	(1.43e-05)	(1.53e-05)	(2.69e-05)
Wind Gen	-0.00122***	-0.00148***	-0.00183***	-0.00134***	-0.00148***	-0.00183***
	(2.29e-05)	(2.36e-05)	(4.05e-05)	(2.37e-05)	(2.45e-05)	(4.05e-05)
NG Price	8.047***	12.41***	2.482**	8.155***	5.161***	0.495
	(0.0565)	(0.246)	(0.991)	(0.0587)	(0.174)	(3.280)
Panel D: Peak Load Winter Months (Dec – Feb); Off-peak Hours (11pm to 6am Mon-Fri; Sat , Sun)						

	(1)	(2)	(3)	(4)	(5)	(6)
Load	0.00245***	0.00254***	0.00324***	0.00240***	0.00259***	0.00324***
	(1.54e-05)	(1.60e-05)	(2.49e-05)	(1.58e-05)	(1.64e-05)	(2.49e-05)
Wind Gen	-0.00163***	-0.00189***	-0.00334***	-0.00176***	-0.00193***	-0.00334***
	(2.69e-05)	(2.85e-05)	(4.25e-05)	(2.72e-05)	(2.91e-05)	(4.25e-05)
NG Price	5.312***	15.46***	-1.038	4.772***	-5.748***	-1.988
	(0.0714)	(0.304)	(1.355)	(0.0747)	(0.243)	(1.465)
Panel E: Off-Peak Load Months (Mar-May; Oct-Nov); On-peak Hours (7am to 10pm Mon-Fri)						
Load	0.00178***	0.00278***	0.00253***	0.00168***	0.00223***	0.00253***
	(7.71e-06)	(9.03e-06)	(1.30e-05)	(7.76e-06)	(9.37e-06)	(1.30e-05)
Wind Gen	-0.00213***	-0.00280***	-0.00328***	-0.00198***	-0.00265***	-0.00328***
	(1.45e-05)	(1.52e-05)	(2.80e-05)	(1.46e-05)	(1.52e-05)	(2.80e-05)
NG Price	9.651***	14.38***	125.6***	12.14***	34.00***	-0.471
	(0.0442)	(0.191)	(0.376)	(0.0425)	(0.150)	(2.306)
Panel F: Off-Peak Load Months (Mar-May; Oct-Nov); Off-peak Hours (11pm to 6am Mon-Fri; Sat , Sun)						
Load	0.00198***	0.00225***	0.00198***	0.00192***	0.00198***	0.00198***
	(7.92e-06)	(8.33e-06)	(1.01e-05)	(8.06e-06)	(8.58e-06)	(1.01e-05)
Wind Gen	-0.00206***	-0.00202***	-0.00191***	-0.00202***	-0.00212***	-0.00191***
	(1.34e-05)	(1.40e-05)	(2.47e-05)	(1.36e-05)	(1.42e-05)	(2.47e-05)
NG Price	7.820***	12.49***	2.115***	9.232***	29.07***	0.972
	(0.0424)	(0.182)	(0.488)	(0.0428)	(0.173)	(1.112)
Monthly NG price for power generator	X	X	X			
Daily Henry Hub spot price				X	X	X
Month##Year Fixed Effect		X			X	
Day Fixed Effect			X			X
Resource Node Fixed Effect	X	X	X	X	X	X

	(1)	(2)	(3)	(4)	(5)	(6)

Note: This table report coefficient estimates of dependent variables ERCOT Load, ERCOT Wind Generation, and NG Price in baseline equation (1). In column (1) to (3), we use EIA monthly natural gas price sold to electric power consumers in Texas; from column (4) to (6), we use EIA daily Henry Hub natural gas spot price. Additionally we add Month, Year, Month-Year fixed effects in columns (2) and (4), and add Day fixed effects in columns (3) and (6). All regressions have Resource Node fixed effect.

Table 7: Regression Results on the Relationship between Emissions, Hourly Net Load and Settlement Price during On-Peak and Off-Peak Hours

ERCOT	**CO2**		**SO2**		**NOX**	
	On-Peak	Off-Peak	On-Peak	Off-Peak	On-Peak	Off-Peak
Equation 1: Hourly Price						
Lagged Settlement Price	0.994***	0.932***	0.995***	0.937***	0.995***	0.937***
	2004.23	554.04	2095.86	570.38	2095.86	570.26
NG Price	0.296**	1.569***	0.371***	1.518***	0.373***	1.546***
	2.9	8.15	3.63	7.91	3.65	8.06
Coal Price	0.593	-13.07***	-0.202	-13.50***	-0.185	-13.24***
	0.39	(-4.64)	(-0.13)	(-4.81)	(-0.12)	(-4.71)
Constant	-2.864	0	-1.611	0	-1.656	0
	(-1.05)	(.)	(-0.59)	(.)	(-0.60)	(.)
Equation 2: Hourly Net Load						
Settlement Price	57.39***	71.30***	55.77***	71.11***	54.50***	70.21***
	75.92	115.76	76.47	117.76	74.99	116.58
Settlement Price Sq.	-0.0130***	-0.0390***	-0.0126***	-0.0397***	-0.0122***	-0.0387***
	(-64.00)	(-75.43)	(-64.57)	(-77.09)	(-62.96)	(-75.58)
Constant	27558.3***	23415.1***	23137.7***	24552.2***	22138.1***	24837.5***
	206.74	209.69	175.14	187.88	167.93	215.46
Equation 3: Hourly Emissions						
Hourly Net Load	0.0536***	0.0560***	0.193***	0.229***	0.0480***	0.0556***
	21.31	26.04	16.7	21.47	23.24	29.25
Settlement Price	-0.518***	-1.413***	-1.922***	-6.419***	-0.384***	-1.210***
	(-11.19)	(-18.23)	(-9.42)	(-16.98)	(-10.53)	(-17.90)
Wind Generation	0.00647*	0.00375	0.0217	0.0285**	0.00963***	0.00831***
	2.47	1.79	1.79	2.74	4.46	4.48
N	71,576	147,606	71,706	148,208	71,706	148,208

Note: We excluded the time-fixed effects dummies from the results table.

Table 8: Regression Results for NRG and Luminant on the Relationship between Emissions, Hourly Net Load and Settlement Price during On-Peak and Off-Peak Hours

NRG	**CO2**		**SO2**		**NOX**	
	On-Peak	Off-Peak	On-Peak	Off-Peak	On-Peak	Off-Peak
Equation 1: Hourly Price						
Lagged Settlement Price	0.997***	0.958***	0.997***	0.958***	0.997***	0.958***
	12149.44	1226.54	12149.42	1226.58	12149.34	1226.77
NG Price	-0.0511***	0.278**	-0.0472**	0.212*	-0.0462**	0.229*
	(-3.46)	2.61	(-3.20)	1.99	(-3.13)	2.14
Coal Price	0.570**	4.791**	0.554*	5.648***	0.668**	0.731
	2.63	3.08	2.55	3.63	3.07	0.47
Equation 2: Hourly Net Load						
Settlement Price	48.32***	59.78***	50.96***	62.99***	49.83***	71.93***
	22.73	35.23	23.87	36.99	23.52	42.01
Settlement Price Sq.	-0.0102***	-0.0365***	-0.0110***	-0.0404***	-0.0107***	-0.0512***
	(-17.64)	(-21.23)	(-18.89)	(-23.36)	(-18.48)	(-29.37)
Constant	26171.6***	22085.5***	28996.5***	32516.6***	24644.3***	21416.0***
	71.5	68.88	67.32	99.62	57.08	58.6
Equation 3: Hourly Emissions						
Net Hourly Load	0.177***	0.154***	0.871***	0.723***	0.0976***	0.120***
	26.6	39.4	23.27	31.73	26.91	34.39
Settlement Price	-1.536***	-3.190***	-8.024***	-16.57***	-0.677***	-1.350***
	(-11.43)	(-22.08)	(-10.63)	(-19.79)	(-9.19)	(-10.59)
Wind Generation	0.0385***	0.0295***	0.135***	0.0768***	0.0239***	0.0318***
	5.78	7.76	3.59	3.45	6.59	9.28
Constant	0	-5698.7***	0	-26244.8***	0	-4679.5***
	(.)	(-25.45)	(.)	(-20.16)	(.)	(-23.48)
N	8761	17531	8761	17531	8761	17531

Note: We excluded the time-fixed effects dummies from the results table.

Luminant	**CO2**		**SO2**		**NOX**	
	On-Peak	Off-Peak	On-Peak	Off-Peak	On-Peak	Off-Peak
Equation 1: Hourly Price						
Settlement Price	0.993***	1.007***	0.997***	1.012***	0.997***	1.012***
	2102.35	634.11	1972.62	702.11	1972.6	701.98
NG Price	-0.174	0.312*	0.508**	0.413*	0.475**	0.308
	(-1.63)	2.07	3.25	2.31	3.03	1.73
Coal Price	1.889	4.822*	-2.106	4.08	-0.852	8.517**
	1.19	2.16	(-0.91)	1.55	(-0.37)	3.23
Equation 2: Hourly Net Load						
Settlement Price	63.76***	154.6***	46.37***	125.8***	42.98***	125.3***
	28.87	50.4	27.03	49.67	25.29	49.49
Settlement Price Sq.	-0.0148***	-0.184***	-0.0103***	-0.141***	-0.00934***	-0.141***
	(-25.55)	(-35.92)	(-23.01)	(-35.40)	(-21.13)	(-35.19)
Constant	20520.9***	0	18216.8***	17478.5***	18185.5***	19934.6***
	47.42	(.)	34.2	42.47	32.71	46.23
Equation 3: Hourly Emissions						
Hourly Net Load	0.0480***	0.0336***	0.137***	0.149***	0.0622***	0.0359***
	12.67	13.6	4.35	6.37	11.36	8.83
Settlement Price	-0.361***	-0.765***	-1.782***	-9.194***	-0.389***	-1.744***
	(-5.55)	(-4.82)	(-4.21)	(-8.07)	(-5.28)	(-8.81)

Wind Generation	0.000825	-0.0159***	-0.0556	-0.0792***	0.00179	-0.0147***
	0.23	(-6.85)	(-1.74)	(-3.54)	-0.33	(-3.80)
Constant	-854.5***	0	-507.6	0	-1017.1***	0
	(-5.45)	(.)	(-0.38)	(.)	(-4.44)	(.)
N	6250	12537	6380	13139	6380	13139

Appendix 1: Summary Statistics of Natural Gas Price ($/mmBtu)

Year	2011	2012	2013	2014	2015	2016
Using monthly natural gas price to power generator in Texas						
June – Sept	4.530	3.020	3.875	4.395	2.975	2.910
Dec – Feb	4.270	3.247	3.857	5.123	2.860	2.720
Mar-May; Oct-Nov	4.162	2.902	4.062	4.640	2.764	2.434
Using daily Henry Hub spot price						
June – Sept	4.225	2.773	3.619	4.118	2.765	2.807
Dec – Feb	3.903	2.839	3.642	4.671	2.563	2.636
Mar-May; Oct-Nov	3.863	2.693	3.870	4.403	2.543	2.211

Notes: This table reports mean natural gas price from two datasets published by the U.S. Energy Information Administration.