Transmission Constraints, Intermittent Renewables and Welfare

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Abstract

We use the roll-out of a large transmission expansion in Texas' electricity market to measure the market impacts of the transmission expansion on benefits of increased renewable capacity. We find large market benefits leading to a payback period of roughly 14 years. However, total welfare improvements from reduced congestion depend on how global non-market externalities are internalized by regional policy makers: accounting for non-market externalities reduces the payback period of this project from 14 to less than 9 years. We discuss the finding's implications for the welfare of regional decisions to build transmission capacity for the U.S. wholesale electricity market.

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1 Introduction

To mitigate non-market externalities and decrease reliance on imported fossil fuels, the U.S. federal and various state governments have subsidized both solar and wind electricity generation capacity for the past 10 years in various ways. The most widely used direct subsidy to private developers to date in terms of total electricity generation is the federal production tax credit (PTC) for wind electricity generation.[1] The PTC is a large volumetric based subsidy whereby each Megawatt Hour (MWh) of electricity produced entitles the renewable asset owner to a deductible federal tax credit, regardless of the location and wholesale price of the electricity generated. Total federal payments of the PTC in 2015 were roughly $4.4 billion.[2] Driven by both market conditions and the PTC, in 2015 wind generation was 5.5% of domestic electricity production, roughly 5 times solar generation and almost 80% of hydroelectric generation according to the Energy Information Administration.

The structure of electricity markets leads to at least one potential channel for inefficiency from the PTC. Electricity is both homogeneous and non-storable. As a result, electricity which is produced at one location must be moved via transmission lines to locations where it is consumed. If there is insufficient transmission capacity there can be congestion constraints leading to price discrepancies in the wholesale price of electricity over space (Joskow and Tirole (2005) and Davis and Hausman (2016)). Popular press has reported how increases in wind capacity are straining the grid and advocates argue that wind farms require more transmission to fully benefit investors, ratepayers and federal taxpayers.[3]

There is reason to believe that transmission line construction cannot be provided ef-

[1] See `https://www.eia.gov/analysis/requests/subsidy/`. Renewable Portfolio Standards (RPSs) are common policies at the state level and implicitly subsidize renewables. Investment Tax Credits (ITCs) are common for solar investment.

[2] The PTC for the U.S. was $.023/kWh of generation through 2016 declining to $.0184/kWh for generation constructed after 2017. See IRS form 8835 (`https://www.irs.gov/pub/irs-pdf/f8835.pdf`) or this more general description: `http://programs.dsireusa.org/system/program/detail/734`. Among all the states, Texas has the largest wind capacity at roughly 2.5 times the next closest states (California and Iowa). In Texas, wind generation accounted for 10 percent of electricity generation in 2015 (See: `https://tinyurl.com/kmtadrm`).

[3] Outlets like MIT Technology Review (`goo.gl/6s7JDE`), Reuters (`goo.gl/6s7JDE`) and NPR (`goo.gl/qHVZwC`) all have been covering this issue recently.

ficiently by the market: they have high fixed costs and low marginal costs, similar to telephone lines, and therefore prone to natural monopolies (Joskow and Tirole (2005)). As a result, regional electricity entities like Independent System Operators (ISOs) often plan and facilitate their construction passing the cost on to market participants. Thus the PTC presents a regulatory federalism issue: the PTC didn't include a complementary federal policy which explicitly optimized the electricity transmission grid in response to new wind capacity. Taken effect in 2016, Federal Energy Regulatory Commission (FERC) order number 1000 implicitly acknowledges this challenge and requires that impacted utilities and other regional stakeholders "must consider transmission needs driven by public policy requirements established by state or federal laws or regulations".[4]

This paper estimates the economic benefits of building new large scale transmission capacity conditional on large increases in wind capacity facilitated by a second best policy like the PTC. To do so we combine a new theoretical model and structural research design. In the theoretical model, we extend the electricity transmission constraint framework in Joskow and Tirole (2005) to wind generation. The Joskow and Tirole (2005) model considers a simple transmission system with two nodes: one with excess demand (net demand) which serves as an importer, and the other with excess supply (net supply) which serves as an exporter. Unconstrained transmission capacity allows trade between the two nodes until nodal prices are equal. Deviations from a single network price imply congestion in the model. In a straightforward extension, we add intermittent renewable generation to the model and show how the shadow cost of any transmission constraint changes with increased intermittent renewable generation. We also show how increases in transmission capacity decrease price differences between exporting and importing regions when renewables generate.

In the empirical section we use quasi-experimental variation in the construction of a large ∼$7 billion transmission expansion in ERCOT (Texas' electricity grid) to estimate economic benefits of the expansion. The expansion was called the Competitive Renewable Energy Zones (CREZ) project and added significant transmission capacity between wind generation locations in west Texas and load centers in the south, central and east Texas.

[4]See `https://www.ferc.gov/industries/electric/indus-act/trans-plan.asp`.

CREZ construction occurred mainly between 2011 and 2014. We use hourly wind generation, hourly wholesale real time and day ahead price data, and hourly load data from 2011-2016 to estimate how wind generation impacts price discrepancies (e.g., through shifts in the net demand and net supply curves) across space as more CREZ lines are completed.

Identification comes from both the timing of incremental completion of the CREZ expansion over the five years in our sample and inclusion of hour-month-year and day-of-sample fixed effects. Our identifying assumption is that variation in CREZ construction across the same hour of a day (e.g., 6am) within a month. Put another way, we rely on changes in the completion of CREZ lines in the same hour of a day within a month being exogenous to net supply and net demand shifts. We present evidence in support of this identifying assumption by showing how price gaps across ERCOT systematically close as a function of CREZ completion.

The key empirical feature in our approach is that we directly estimate the slopes of the net supply and net demand curves in ERCOT and combine them with the theoretical model of congestion and wind generation. The parameters combined with the structure in the theoretical model allows us to construct congestion costs for each hour in our data and compare them to a counterfactual in which wind generation would be traded freely until prices between generation centers in West ERCOT and load centers in North ERCOT, South ERCOT and Southeastern ERCOT (e.g., Houston) are equal.[5] We leverage the unique spatial distribution of wind and load centers and regulatory history in ERCOT to combine the theoretical and empirical models to perform the analysis in addition to robustness checks.[6] Our approach is far more transparent and parsimonious than a research design which uses an engineering simulation of the ERCOT market. A simulation research design focusing on CREZ and wind generation would need to simulate the entire ERCOT transmission network, the market behavior of each market participant and the algorithm used to allocate production as a function of bids and load. While this model

[5] In this sense we build on other structural work like Borenstein, Bushnell, and Wolak (2002).

[6] Texas is an ideal case study for three main reasons: First, ERCOT has the largest share of wind generation in the country. Second, ERCOT has a sufficient history of wind generation data to identify the model. Third, ERCOT is its own electricity interconnection meaning that imports and exports between Texas and other states are minimized.

might capture some complexities like network loop flows, we provide evidence that our more parsimonious approach is sufficient for evaluating CREZ impacts.

Consistent with transmission constraints preventing trade, our results show a price gap of ∼\$5/MWh in 2011 before much of CREZ was completed and a ∼\$.50/MWh price gap in 2015 after CREZ was mostly finished. The decrease in price dispersion is an economic benefit: electricity production costs decrease on the whole due to more trade. The main channel for the benefits is the additional electricity traded between the West and other higher production cost areas of ERCOT thereby equalizing marginal producers' costs over space. Using hourly data we show that traded wind generation is the primary driver of the decreased price dispersion. The reason wind generation in particular matters is that wind generation occurs in locations where there is little demand for electricity. Thus transmission lines are required to bring that electricity to more valuable load centers. We calculate that annual wholesale electricity market benefits from CREZ conditional on extant wind generation is roughly \$500M/year due to reduced transmission constraint loss from increased trade.

Since electricity production has unpriced negative externalities (CO2 and other air pollutants) we perform a back of the envelope calculation for benefits of mitigated fossil fuel generation from increased trade of wind electricity. To do so we use the technique developed in Zivin, Kotchen, and Mansur (2014) and updated in Holladay and LaRiviere (2017) to calculate marginal hourly forgone emissions in ERCOT due to additional transmission capacity. This technique complements the more granular emissions work of Fell, Kaffine, and Novan (2017) to size the non-market impacts of CREZ's construction through increased trade of wind generation. If 10% of generation from wind was curtailed in this period due to transmission capacity constraints the non-market impacts of CO2 alone using a price per ton estimate of \$37 are roughly \$115M/year. That number ignores other unpriced pollutants like PM 2.5, making it a lower bound. Adding in non-market benefits of roughly \$200M/year in Fell, Kaffine, and Novan (2017) implies annual non-market benefits of roughly \$300M/year. In sum, we estimate annual benefits of CREZ conditional on installed wind capacity at roughly \$800M/year. Thus, we find that the gains from CREZ depends on the valuation for non-market benefits and lead to a payback period of less than 9 years.

There are notable asymmetries in the incidence of CREZ. Our net supply and net demand parameters imply that west ERCOT ratepayers saw their wholesale electricity prices increase while ratepayers in the rest of ERCOT saw their rates decrease. Thus the mechanism for how transmission projects are paid for across ratepayers becomes important. Conversely, generators in west ERCOT received higher wholesale prices while generators in the rest of ERCOT earned decreased wholesale prices. In ERCOT wind blows at night implying that baseload generators took the brunt of CREZ's price decreases in ERCOT outside of the West. For example, in late 2017 ERCOT approved the decommissioning of ∼4,000 MWh of coal fired generation. While it is beyond the scope of this paper to make causal statements about retirement decisions, the decision to retire those plants was certainly not helped by CREZ. Importantly, these incidence measures are transfers from one set of stakeholders to another so they don't factor in our benefit cost analysis. In sum, we find evidence that generators in west ERCOT benefit from CREZ whereas generators in other ERCOT regions lose.

The policy implications of this paper speak directly to the policy debate playing out in the popular press on transmission line construction. Our estimates indicate that the benefits of additional transmission in ERCOT has a payback period of roughly 14 years when not accounting for carbon and something closer to 9 years when valuing carbon at standard worldwide values of $37/ton. Insofar as these ERCOT results are externally valid, the social gains from additional transmission ride very much on how CO2 and air pollution reductions are valued by ISOs. At a high level, the key metric for external validity is the spatial correlation of renewable generation and load. The results are likely to hold in Iowa where generation is relatively large compared to load. In California, roof top solar has tighter spatial correlation meaning that transmission capacity might be less important.

This paper adds to a growing literature on renewable energy policy in the U.S. There is a large literature on environmental impacts or possible environmental impacts of wind generation (Cullen (2013), Novan (2015), Holladay and LaRiviere (2017)). Our work focuses on a different question: market inefficiencies brought about by policies aimed at increasing renewable generation. As a result, our work is more in line with how renewables have impacted or can interact with various market conditions (Callaway, Fowlie, and McCormick

(2018), Gowrisankaran, Reynolds, and Samano (2016) and Cullen and Reynolds (2017)). While don't investigate investment dynamics empirically like Cullen and Reynolds (2017) and instead focus on transmission expansion's impact on extant capacity, we do discuss the implications of transmission expansion on investment decisions. The only other economics paper to study CREZ we are aware of is Fell, Kaffine, and Novan (2017) which identifies how wind generation substitutes for different types of fossil fuel generation in the rest of ERCOT before, during and after CREZ's construction and focuses on non-market implications of CREZ.

Our contribution, however, is primarily on transmission constraints and the economics of the electricity sector and the challenges of layered national and regional energy policy. In terms of net supply and net demand, Borenstein, Bushnell, and Wolak (2002) focuses on imported electricity into California to evaluate the relative efficiency of California's restructured electricity markets. More broadly, there is a large literature on how deregulation and market power impacts strategic bidding behavior of market participants (Puller (2007), Bushnell, Mansur, and Saravia (2008), Mansur (2008), Fowlie (2009), Ito and Reguant (2016), Mercadal (2018)). Further, ERCOT in particular has received attention related to strategic bidding behavior and efficiency (Hortacsu and Puller (2008) and Hortacsu, Luco, Puller, and Zhu (2017)).

Our research design approach doesn't address strategic bidding and market power structurally; transmission constraint loss can be reduced directly through increased trade or indirectly through reduced market power from increased trade. We discuss implications of market power and also perform robustness checks by trimming our sample to periods were market power is the least likely to occur but we don't disentangle to relative import of increased trade versus reductions in market power from increased trade. The closest paper to ours is Davis and Hausman (2016) which addresses the impacts of changes in transmission constraints, among other market outcomes, due to a nuclear plant shutdown. We are not aware of any empirical work in the economics literature which evaluates the market and non-market welfare impacts of new transmission construction.

The rest of the paper is organized as follows. Section 2 describes the theoretical model framework. Section 3 introduces basic background about the CREZ project. Section 4 introduces datasets used in this paper. Section 5 shows level impacts of wind generation on electricity prices in ERCOT and impacts of wind generation on electricity price discrepancies across geographical regions. Section 6 calculate transmission constraint loss associated with wind generation and discusses incidence of the CREZ project. Section 7 concludes.

2 Theoretical Model

We use the Joskow and Tirole (2005) framework to define the shadow cost of a transmission constraint then add intermittent renewables to their model. Their model starts with the simplest possible transmission network: a system with two nodes. Node "A" can export electricity to a population center in node "B". Both node A and node B have generation capacity but in node B, load is often much larger than in node A. In this case it is optimal for node A to export electricity to node B until prices in the A and B are identical. Thus node A is an exporting node and node B is an importing node. Only if there are transmission constraints will there be a discrepancy in prices.

We now formalize the intuition above and extend it so that the node A also has wind generation capacity. First consider node A in isolation. Consistent with renewable electricity being must take, the price of electricity in node A is determined by "net load". We define net load in node A as load minus wind generation ($L_t^A - W_t$) for any period t. Following Joskow and Tirole (2005), we assume that the price of electricity in node A is equal to linear marginal costs of fossil fuel generation: $P_t^A = a_A + b_A(L_t^A - W_t)$. Similarly, the price of electricity in node B which is assumed to have no wind generation is also equal to linear marginal costs: $P_t^B = a_B + b_B L_t^B$. Note that if there is market power in node B, slope coefficient b_B encompasses information on both marginal costs and exercised market power of suppliers.

In both nodes, then, electricity has a positive price determined by the costs of the marginal fossil fuel electricity generator. For example, $L_t^A - W_t$ must be supplied by fossil fuel generators at node A and L_t^B must be supplied by fossil fuel generators at node B. The linear slope coefficient defines how increases in fossil fuel generation map to wholesale prices at each node.

In this model, an increase in wind generation decreases the price of electricity at market settlement point near wind farms (e.g., node A). Conditional on load, inelastic demand of electricity and must take wind generation implies estimating the price impacts of increased wind generation recovers the shape of the marginal cost curve. The magnitude of the decrease is an empirical question we estimate in the next section.

Now allow trade so that node A can export electricity to node B. For convenience and consistent with the subsequent data, assume that $P_t^A < P_t^B$ in the absence of trade. In that case, node A always exports a weakly positive amount of electricity by assumption. The marginal cost of exporting a given amount of electricity, Q_t from node A to node B is a function of load, wind generation and costs parameters in node A which we call the "net supply curve": $P_t^A = a_A + b_A(L_t^A - W_t) + b_A Q_t$. In the context of traded electricity Q_t, the term $b_A(L_t^A - W_t)$ shifts the intercept of node A's supply function up and down but does not impact the slope since wind is must take.[7]The net supply curve is upward sloping if we plot P_t^A as a function of Q_t since the marginal cost of generating more electricity from fossil fuels is increasing in the amount of exports.

Node B's demand function for imported electricity from node A is downward sloping in the price charged by node A and the intercept is a function of their own load and cost parameters. We thus define the net demand function as: $P_t^B = a_B + b_B L_t^B - b_B Q_t$. Here, b_B represents the cost of node B to procure electricity internally.[8] As a result, node B's net demand function is downward sloping to reflect the opportunity cost of imports either through additional domestic fossil fuel production at the node B, or the cost of importing from a third party which is not part of the explicit model. Without barriers to trade, prices in node A and node B will be equal in equilibrium.

Lastly, assume there is also a transmission capacity K. The transmission capacity K means there can be violations of the law of one price between node A and node B. This is represented in Figure 1 which shows how adding wind generation to the Joskow and Tirole (2005) model impacts the shadow cost of transmission constraints. $Q = K^*$ is the unconstrained level of trade but K is the constrained level of trade and η is the resultant price discrepancy between node A and B. The figure also shows how capacity constraints

[7]A richer model might include a slight readjust of the merit order when the wind blows which would affect the slope. That additional complexity is second order to our focus here.

[8]In a more complicated network, the marginal costs of electricity generators at other nodes also determines the slope of the net demand curve. This could also be the implicit cost of reducing load to avoid blackouts.

lead to losses through decreased trade (the shaded triangle) we call a transmission constraint loss (TCL). This loss is not necessarily a deadweight loss, however, since the costs of adding transmission capacity may outweigh the gains.

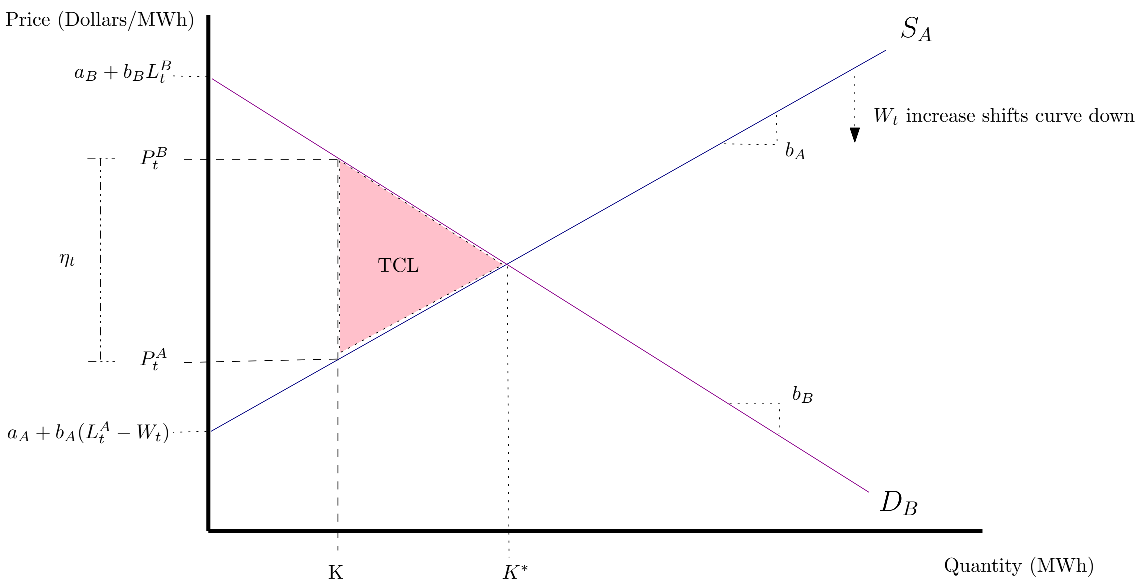

Figure 1: Impact of change in wind generation on shadow cost of transmission constraint.

Figure 1 shows that conditional on a given amount of transmission, η in any given time period is a function of wind generation conditional on load levels. More precisely, we constrain the quantity of traded electricity to be K and plug in the export supply and demand equations for Q_t:

$$\begin{aligned} \eta = P_B - P_A &= (a_B + b_B L_t^B - b_B K) - (a_A + b_A(L_t^A - W_t) + b_A K) \\ &= a_B - a_A + b_B L_t^B - b_A L_t^A + b_A W_t - (b_B + b_A)K \end{aligned} \tag{1}$$

Equation (1) explicitly shows the relationship between the shadow cost of the transmission constraint (e.g., η), model parameters and model dynamics. For example, the foregone benefits of "complete" trade due to transmission constraints varies as the net demand and supply curves shift up and down due to different net load and wind generation levels. An increase in wind generation shifts node A's supply function to the right: since wind is must take generation it will decrease the cost of meeting a given level of load in node A from fossil fuel generation. Figure 2 shows that when wind generation increases from W_0 to W_1, the net supply curve shift to the right. As a result, the price in node A decreases from p_0^A to p_1^A, thus increasing the price gap between A and B, with more wind generation and transmission constraint level K.[9] Put another way, the shadow cost of a transmission constraint increases with wind generation: $\frac{\partial \eta}{\partial W_t} = b_A > 0$. This makes intuitive sense: there is no change in node B but the price of electricity decreases in node A. Changes in load in node A and B affect η in a similarly straightforward manner.

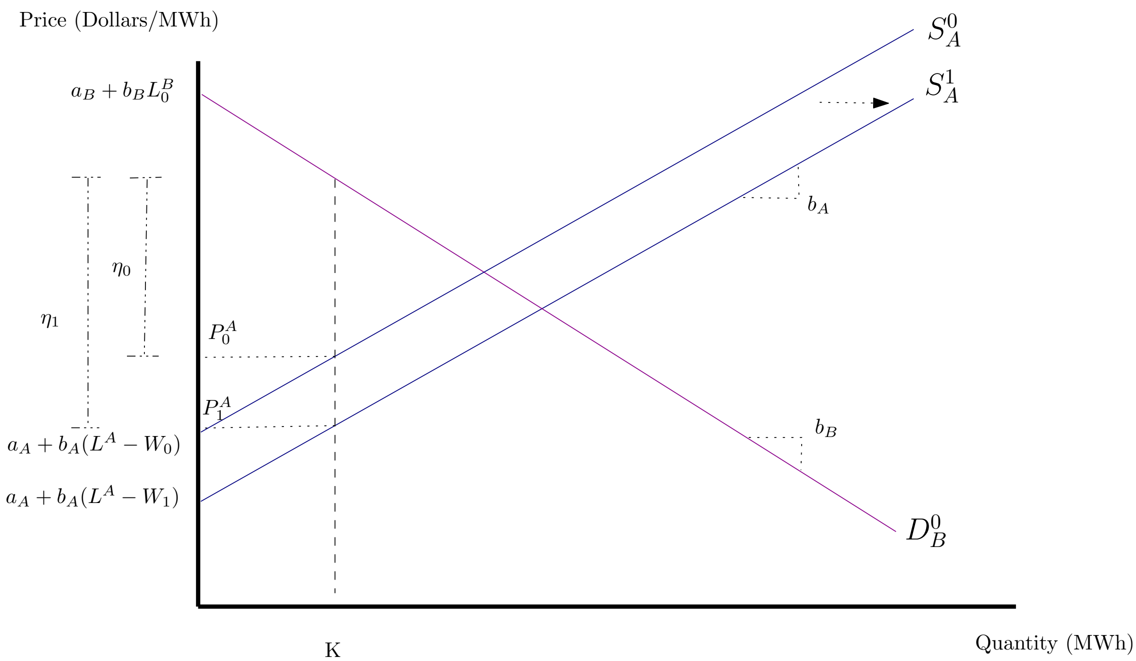

Figure 2: Net Supply Shock

This model also shows that the shadow price of constraint is decreasing in capacity: $\frac{\partial \eta}{\partial K} = -(b_B + b_A) < 0$. This is consistent with additional capacity allowing more trade and therefore a decrease in price discrepancies. In our subsequent empirical analysis, increases in K can be thought of as the increase in transmission capacity from the construction on

[9] This is only true when there are transmission constraints. So we will use data before the CREZ project to identify the slope. Same for the slope of net demand curve below.

CREZ power lines in Texas.

Figure 1 shows the price gap between exporting area and importing area (i.e. η) should be equal to the sum of the capacity gap (i.e. $K^* - K$) times the slope of net supply curve (i.e. b_B) and capacity gap times the slope of the net demand curve (i.e. b_A). To simplify notation, we denote $\triangle K = K^* - K | K^* > K$, which is the gap between the actual transmission capacity and the optimal transmission capacity. Note that $\triangle K$ is only positive when $K^* > K$ and otherwise takes the value of zero according to this definition. More precisely the price gap is:

$$b_B \triangle K + b_A \triangle K = \eta \tag{2}$$

Solving for $\triangle K$, we have:

$$\triangle K = \frac{\eta}{b_B + b_A} \tag{3}$$

The transmission constraint loss (TCL) can thus be calculated as the area of the shaded triangle in Figure 1:

$$TCL = \frac{1}{2}\eta \triangle K = \frac{\eta^2}{2(b_B + b_A)} \tag{4}$$

In any given time period, we can calculate a TCL for the market with observed η and estimated b_B and b_A. We use equation (4) to calculate the TCL associated with renewables when there are binding capacity constraints compared to when there are none.

From a welfare perspective, we can also write down the objective function of the regulator conditional on a particular level of installed wind capacity. This final step relates TCL to deadweight loss (DWL) from inefficient levels of transmission investment. To do so we introduce two additional functions. The first is a joint density of load in node B and wind generation in node A: $F(L_t^B, W_t)\ \forall\ t$. For simplicity, we ignore load in the exporting region. The second expression is a convex function governing the cost of transmission expansion: $c(K)$. The function $c(K)$ is a one time cost paid for K. Thus, optimal expected investment in transmission capacity is given by following maximization problem:

$$argmax_K \ -\Sigma_{t=1}^{T} \int\int \frac{1}{2}\eta_t \Delta K_t dF(L_t^B, W_t) - c(K). \tag{5}$$

Equation (5) is the negative of expected TCLs over some time period T. We subsume discount factors for simplicity. Recalling that η is a function of transmission constraints K, the key feature of equation (5) is the non-linearity of the product $\eta_t \Delta K_t$ in K. This creates the non-linearities in how TCLs relate to changes in K. Importantly, this model is made more complex due to the joint probability distribution $dF(L_t^B, W_t)$. The interaction of the function is the product $\eta_t \Delta K_t$ and $dF(L_t^B, W_t)$ is key innovation of our approach relative to other models of transmission constraints or wind generation.

Plugging in for the definition of ΔK, η and simplifying, the first order condition is:

$$\frac{1}{2}\Sigma_{t=1}^{T} \int\int \eta_t + (b_B + b_A)(K_t^* - K) dF(L_t^B, W_t) = \frac{\partial c(K)}{\partial K} \tag{6}$$

Equation (6) shows the well-known three components of supply decisions of a social planner. The first term η represents the benefits on the extensive margin from increasing transmission capacity by one unit. The second term $(b_B + b_A)(K_t^* - K) = (b_B + b_A)\Delta K_t$ represents the benefit on the intensive margin due to increased transmission capacity. Finally, the cost of additional capacity is given by $\frac{\partial c(K)}{\partial K}$ which is an engineering calculation.

The analysis to this point ignores all non-market gains from increased transmission capacity but the model can easily be extended to include them. Since renewables have zero emissions, there are additional gains from reducing TCLs proportional to the marginal damage of each unit of renewable generation exported to the importing region. For example, increase transmission of renewables decreases the need to burn fossil fuels which release CO2 and air pollutants which harm human health and indirect economic value to the ecosystem. If we assume that all generation in the importing region is due to fossil fuel generation with some non-market marginal cost of ψ, then expected additional gains from increasing K are $\Sigma_{t=1}^{T} \int\int \psi \Delta K dF(L_t^B, W_t)$. In calculating benefits from additional transmission capacity in the empirical section we include these benefits using estimates of

ψ taken from the literature. We let ψ vary by time of day and month of year to reflect changes in marginal emissions over time.

In the empirical section below we take the model to the data in five crucial ways. First, we estimate the impact of wind generation on ERCOT hub level prices. This provides validation of within node dynamics. Second, we estimate wind generated annual price dispersion across ERCOT by year and compare that to increased CREZ completion to verify across node model dynamics. Third, we estimate net supply and net demand slopes for each ERCOT zone pair. Fourth, we construct the implied transmission constraint (e.g., K_t) and TCL for each hour in the data. Fifth, we aggregate hourly TCLs and back of the envelope non-market costs to get annual estimates of benefits due to CREZ completion. In steps three through five we include a robustness check where we allow the net supply and net demand slopes to be non-linear.

Any model must make simplifying assumptions. We discuss in the empirical section the relationship between both market power and the production tax credit for the model.[10] We also don't model curtailment decisions of wind generators who might curtail generation during periods of wind due to negative prices induced by transmission constraints. The presence of curtailment implies that the market savings from the paper will be lower bounds. A lack of curtailment data available for ERCOT makes adding curtailment to the analysis implausible.

3 Background

In 2014 ERCOT finished construction of a multi-billion dollar expansion of the ERCOT transmission line network to connect remote windy regions in Texas to populations centers.[11] The expansion was long planned and understanding its evolution is useful for understanding our research design and the broader policy context for how Independent System Operators (ISOs) participate in transmission expansions.

In the U.S. Federal Energy Regulatory Commission (FERC) and Public Utility Com-

[10] At a high level, market power increases the within node marginal cost curve and thus increases the net demand curve for that region. The production tax credit changes none of the dynamics of the model since the model conditions on wind capacity.

[11] https://www.texastribune.org/2013/10/14/7-billion-crez-project-nears-finish-aiding-wind-po/.

missions (PUCs) typically jointly pay for transmission expansion through tariffs. FERC is self-funded and can levy fees to upstream market participants like electricity producers in order to act as an independent standard setter and regulator. PUCs can allow distributors to charge rates that will recover transmission investment costs thus increasing fees to rate payers. As a result, an ISO will often make the case for transmission line construction but actually assessing payments for the new construction involves negotiation between a variety of different agencies.

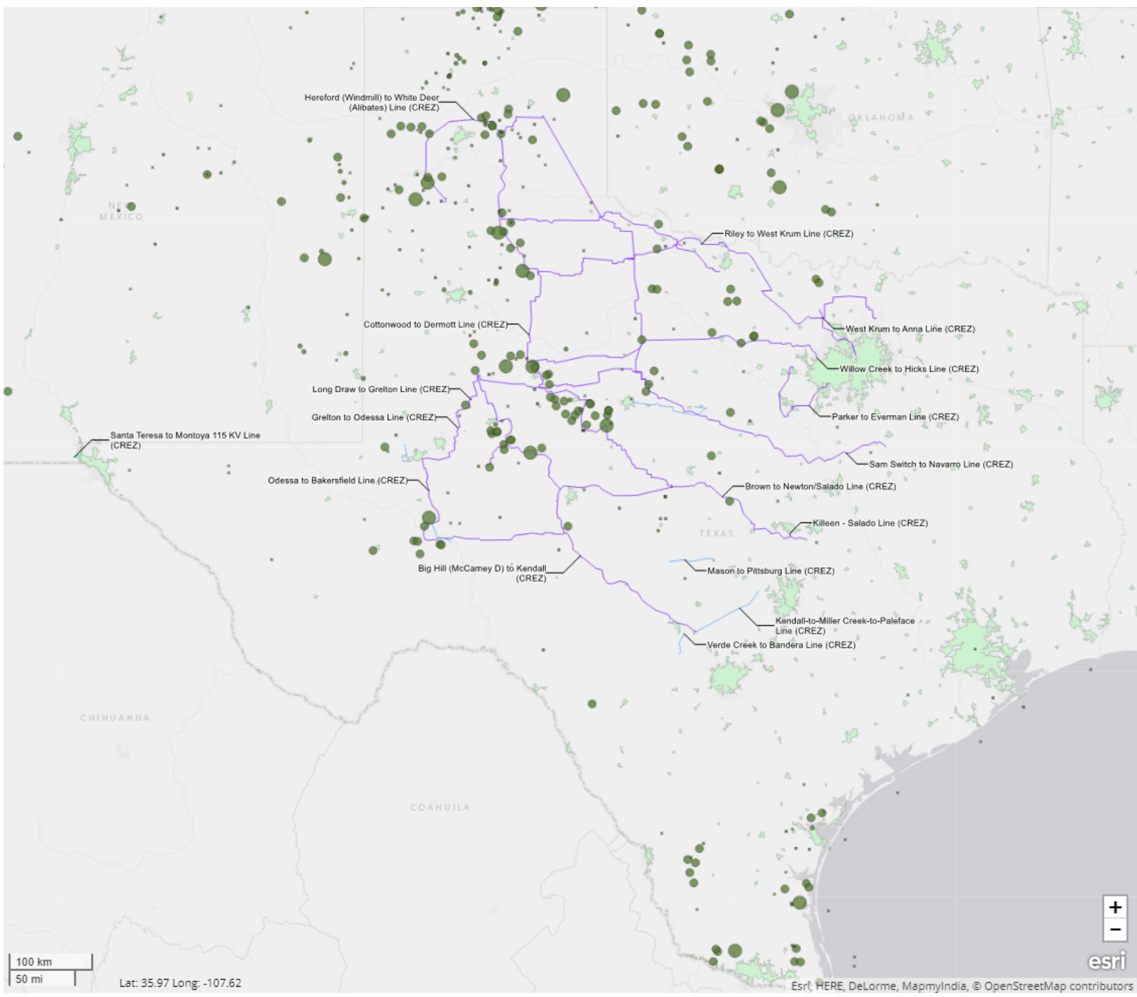

Figure 3: CREZ lines locations, wind capacity and urban centers in ERCOT

In 2008 ERCOT published a study which laid the groundwork for construction of new transmission lines which would connect remote but windy parts of northern and western Texas to load centers in the east and south.[12] The report followed the Public Utility Commission of Texas (PUCT) designation of five zones in northwest Texas as Competitive Renewable Energy Zones (CREZ) predisposed to high potential levels of wind generation. The report analyzed how to add transmission to the grid under four investment scenarios ranging from low to high wind capacity levels (12,000 MW to 24,400 MW of installed capacity). At the time, there were roughly 7,000 MW of installed capacity in ERCOT. The ISO's involvement (ERCOT in this case) in identifying the usefulness of expanded transmission is typical of how transmission expansions occur.

Table 1 Timing of CREZ's Construction

Year	Length (miles)	% Length	Spend ($ 1000s)	% Spend
2009	154.6	0.062	138,089	0.042
2010	478.7	0.253	137,759	0.084
2011	89.8	0.289	90,808	0.111
2012	136	0.344	159,226	0.159
2013	1290.3	0.859	2,427,627	0.895
2014	255.5	0.962	292,428	0.983
2015	39.1	0.977	13,871	0.987
2016	57	1	41,927	1

NOTE: CREZ line construction and spend by date.
All distances in miles and all dollar figures are in thousands of each years' dollars.

Figure 3 shows a snapshot of 2017 windfarm locations in ERCOT (circles of radius proportional to wind farm capacity), the location of CREZ transmission lines, and the location of population centers in Texas. The point of CREZ is clear from the Figure: connect windfarms in the west (node A in the theoretical model) to population centers in north, south and Houston hubs (node B in the theoretical model). There were three types of construction for the CREZ infrastructure: new construction, rebuilds and expansions of existing transmission capacity.

Table 1 shows the timing of CREZ's construction by year from 2009 to 2016 in two different ways: by total miles of construction and total spend of CREZ lines.[13] Each row

[12] `https://www.nrc.gov/docs/ML0914/ML091420467.pdf`.

[13] All data are taken from snl.com's database, which itself is a curated database from publicly available sources like ERCOT press releases.

describes the total miles and dollars for any CREZ project completed in that year in our data. By both metrics, 2013 stands out as the year in which CREZ construction peaks. As a percent of total CREZ construction mileage, 2013 saw an increase from 34% to 86% of total. The dollar spent analog is even more stark as 2013 saw an increase from 16% to 90%.

4 Data

We use hourly data from ERCOT to estimate transmission constraint loss (TCL) both before and after the construction of the CREZ lines. As shown in Figure 4, ERCOT is a power market which contains much of Texas. Moreover, ERCOT is its own interconnection meaning that trade of electricity between ERCOT and other FERC electric power markets is very small. For this reason, ERCOT is an ideal area of study because, unlike more integrated markets like CAISO which imports and exports to other regions, out of ERCOT are less of a concern (Borenstein, Bushnell, and Wolak (2002)).

The other reason we focus on ERCOT is its large capacity for wind generation over our 2011-2016 study window. Figure 5 shows total installed wind capacity in ERCOT over time. Wind capacity in ERCOT is increasing over our sample period with a sharp rise in capacity beginning in the second half of 2014. Figure 5 also shows that even before much CREZ expansion, there was a very significant wind capacity presence in ERCOT ($>$ 9,000 MW).

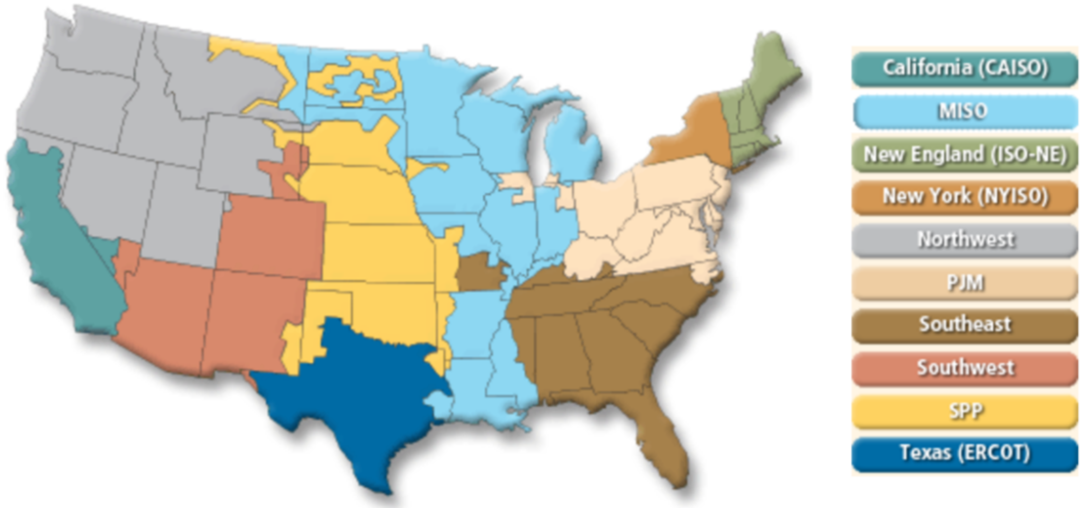

Figure 4: FERC Electric Power Markets

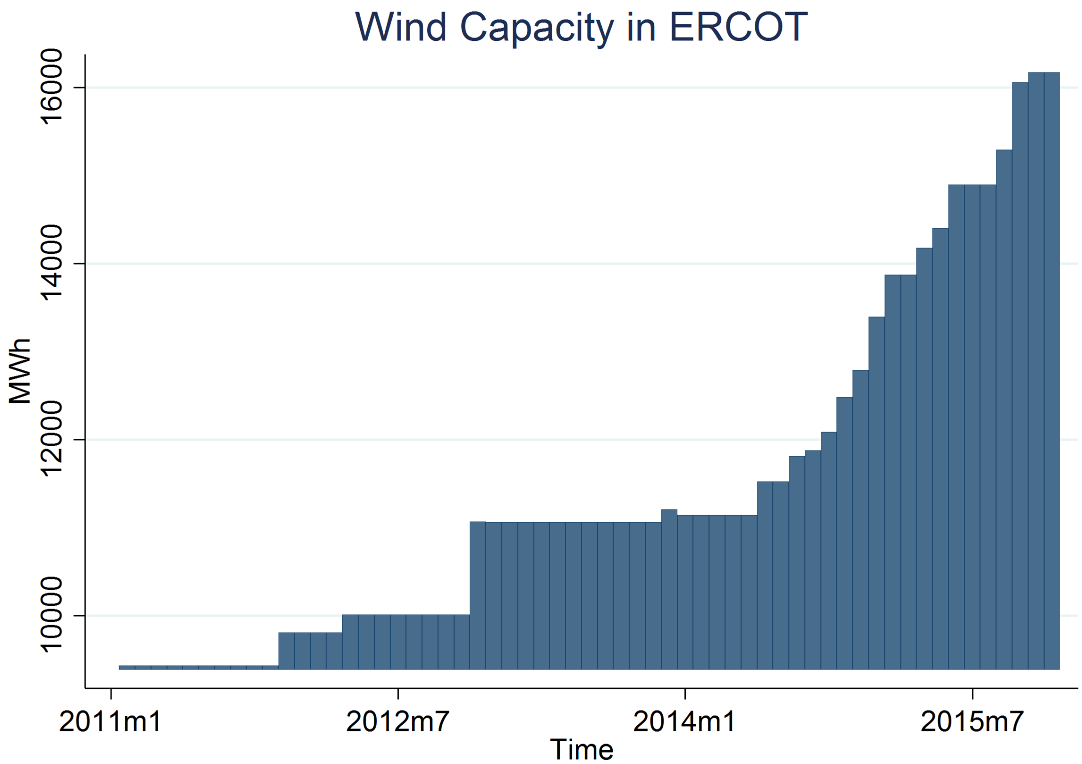

Figure 5: Wind Capacity in ERCOT by Month

We focus our analysis on price discrepancies across different electricity zones within ERCOT at different points in CREZ's construction timeline. ERCOT is divided into four electricity zones: West, North, South and Houston. ERCOT provides hourly zonal load levels (e.g., electricity demand), zonal day ahead prices of electricity, zonal real time prices of electricity, and wind generation. The day ahead price is the result of a disaggregated bidding process that clears over 90% of electricity the day before its needed. The real time price is another market which facilitates any additional electricity needed at the realized delivery time. These markets clear at more granular levels but we use hourly hub (zonal) prices in our study, as is common in the literature (Davis and Hausman, 2016).

Figures 6 and 7 shows how ERCOT zones are divided across Texas, wind capacity levels over space and county level populations. The figures show wind farms are located in the West zone (i.e. northwest of Texas) but there are no population centers. In the context of the theoretical model presented above, the West zone serves as the "node A" exporting electricity to the other zones when the wind blows. Each of other three zones contains at least one population center: the South includes Austin and San Antonio, the North includes Dallas, and Houston includes the Houston MSA.

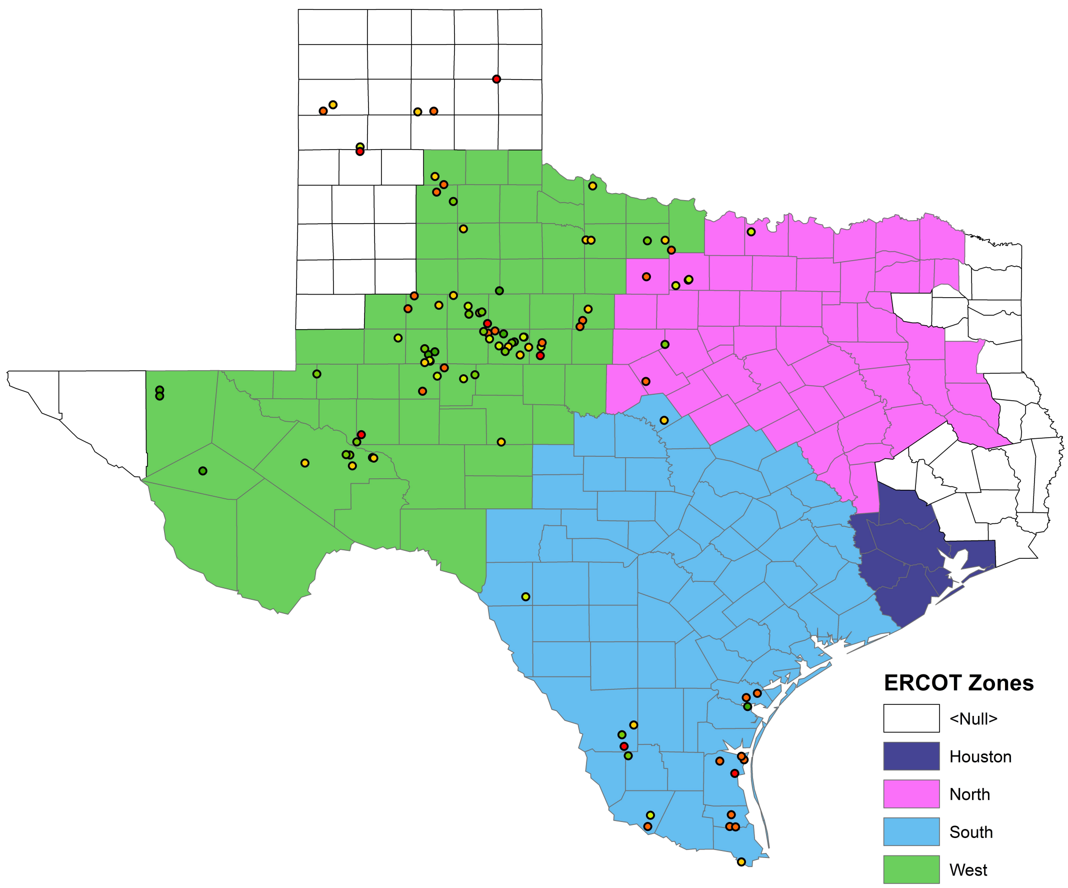

Figure 6: Load Zones in ERCOT. The color of the circles indicates capacity levels of the wind farms (red having more capacity and green less).

Figure 7 shows the spatial distribution of population and wind capacity. The color of the circles indicates capacity levels of the wind farms (red having more capacity and green less). Figure 7 shows population by county. The majority of wind capacity lies west and north of the population centers where load is concentrated.[14]

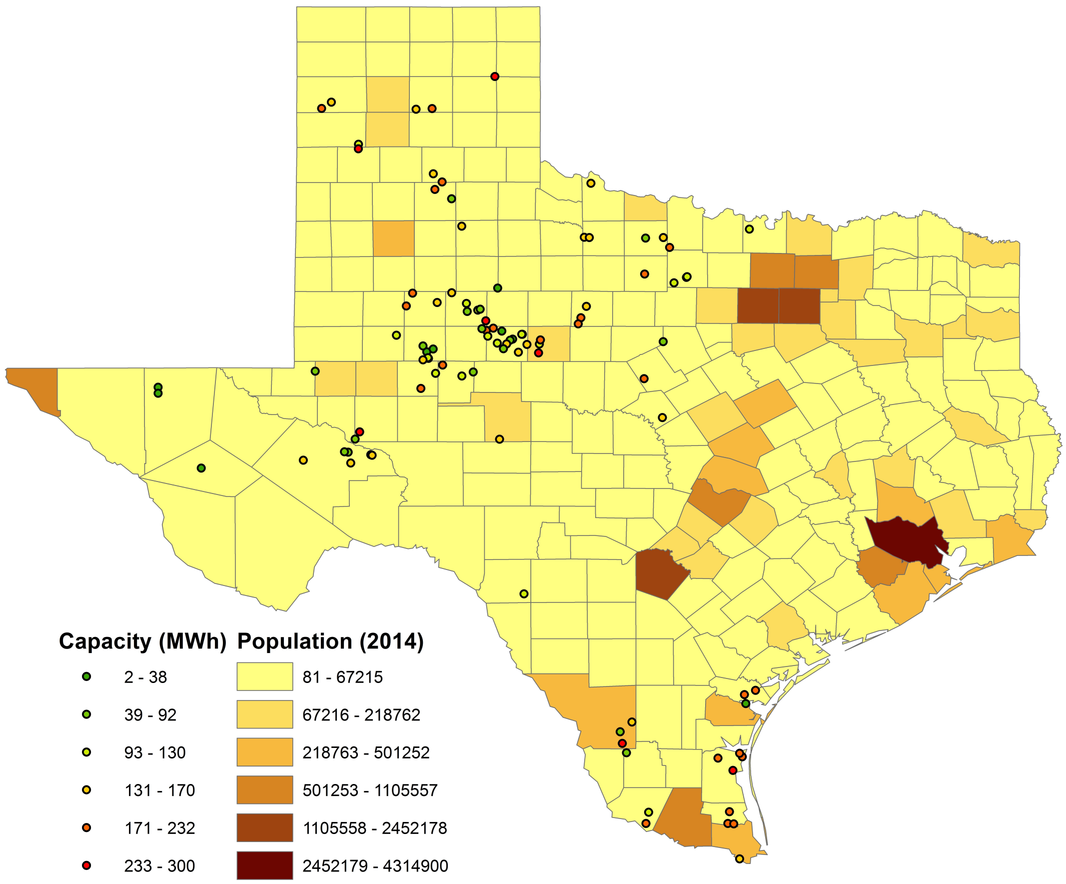

Figure 7: Wind Farms in ERCOT (Texas)

We merge several ERCOT datasets for the main analysis: 1) Hourly zone level prices, which are average nodal prices weighted by load for each electricity zone; 2) Hourly load

[14]The exception is the South where coastal wind generate electricity. Those coastal winds, though, have a different temporal generation pattern that the majority of capacity in the North and West. Since coastal wind are highly correlated with wind on land in west Texas, it creates measure error in our wind generation variable below and attenuates our estimates toward zero, but would not lead to bias, making our analysis on transmission constraint losses a lower bound.

at the zone level; 3) Total hourly wind generation data from ERCOT. We also use the CREZ completion data shown above disaggregated to the daily level. We merge these datasets by their respective time stamps.[15] All merging and analysis were performed with STATA and our code is available upon request.

We focus our analysis on year 2011-2016. There are other reasons for choosing this time period in addition to quasi-experimental variation in transmission capacity from incremental CREZ completion. First, natural gas prices were relatively flat and had been relatively low since 2009, mitigating their impact on wholesale electricity prices. Second, load levels in ERCOT were relatively flat, as they were in the rest of the US.

In order to identify the slopes of the net supply and the net demand curves, we take advantage of net supply shocks and net demand shocks and inelastic hourly demand characterizing electricity markets. According to the theoretical model, changes in either load or wind generation in one or both regions will shift the net supply and net demand curves. To identify the net demand curve we would ideally like to exogenously shift the net supply curve. Alternatively, to identify the net supply curve we would like to hold the net supply curve fixed and exogenously shift the net demand curve.

However, due to transmission constraints and not observing unconstrained equilibrium prices, that standard identification strategy will not work. In our case, though, we can leverage transmission constraints to identify the net supply and net demand curves. With binding transmission constraints, an increase in wind generation will only decrease the price of electricity in the west as the net supply curve shifts out. The reason is the inability to trade. It is as if demand is perfectly inelastic in the west when there is a transmission constraint with respect to wind driven price changes. The decrease in price with binding transmission constraints allows us to identify the slope of the net supply curve as shown in the theoretical section. Similar intuition holds for identifying net demand. We will discuss the identification strategy in details below.

Ideally, we would like hourly wind generation and load data from each zone. However, we do not observe wind generation in each zone but rather total wind generation for ERCOT for each hour as provided by ERCOT. Fortunately, we can rely on the spatial

[15]Prices and load data was provided by ERCOT but aggregated by SNL. Wind generation data was directly from ERCOT.

distribution of wind generation in ERCOT. Since the vast majority of ERCOT wind farms are located in the West zone (e.g., the net exporting region in the theoretical model), we use total wind generation in ERCOT to proxy wind generation in the West zone.[16] For the regions containing Dallas and Houston, we view this as a relatively innocuous assumption given the lack of windfarms in those zones, but in South ERCOT there does exist some wind capacity. In the empirical section this creates downward bias if hourly wind generation in different zones is positively correlated. Increasing wind generation in the exporting region is offset by increasing wind generation in the importing region. This amounts to contamination in the importing region biasing the effect of "treatment" (e.g., wind generation's impact on price discrepancies from transmission constraints) downward when comparing west Texas to south Texas. Since we estimate net supply and net demand curves at the region level, we feel this data aggregation issue does not invalidate the analysis.

Table 2 Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Real Time Price (West)	43,795	30.01	80.80	-367.6	4,493
Day Ahead Price (West)	43,795	32.25	64.66	-28.07	2,636
Real Time Price (South)	43,795	31.90	79.87	-169.9	4,351
Day Ahead Price (South)	43,795	33.89	63.55	5	2,634
Real Time Price (North)	43,795	31.67	79.52	-22.48	4,484
Day Ahead Price (North)	43,795	33.72	64.06	2	2,635
Real Time Price (Houston)	43,795	32.22	82.03	-55.94	4,374
Day Ahead Price (Houston)	43,795	34.19	63.60	5.010	2,634
Wind Generation	43,795	3,807	2,409	7	13,812
Load (West)	43,795	2,554	454.4	1,599	4,263
Load (South)	43,795	9,465	2,452	5,293	17,329
Load (North)	43,795	12,898	3,546	6,958	25,626
Load (Houston)	43,795	10,895	2,551	6,457	19,929

Table 2 shows the summary statistics of the wind generation, price and load at the

[16]In some specifications, we also assign wind generation to each zone according to their capacities.

zone level. There are several implications. First, load in the West zone is far lower than all other regions on average, which is consistent with our model assumption (Low load around exporting region). The max observed load in the west is less than the minimum observed load in any of the other zones. Load in the West zone is also lower than wind generation on average, which makes it possible to export electricity to other population centers with large load (even without accounting for Western zone fossil fuel generation). Second, the average prices for all the zones in the DA market range from \$32.25-34.13/MWh.[17] The average price in the West zone is lower than all other zones. In theory, without market power or transmission constraints these prices would be identical.[18] In this paper, the key input to the analysis is whether the discrepancies systematically vary with wind as predicted by the theoretical model and then are ameliorated with new line construction. Third, real time (RT) prices are systematically lower than DA prices for various institutional reasons which are beyond the scope of this paper. There is a growing literature attempting to solve the "DART spread puzzle". We do, though, estimate separate regressions for the DA and RT markets but focus on the DA market due to its volume relative to the RT market.

[17]This is higher than the nodal prices. Hub prices are average nodal prices weighted by load, and nodes around large load areas usually have high prices.

[18]Line loss is another possible explanation but it acts as a tax on far away transmission increasing all prices but theoretically preserving the equimarginal principle across zones.

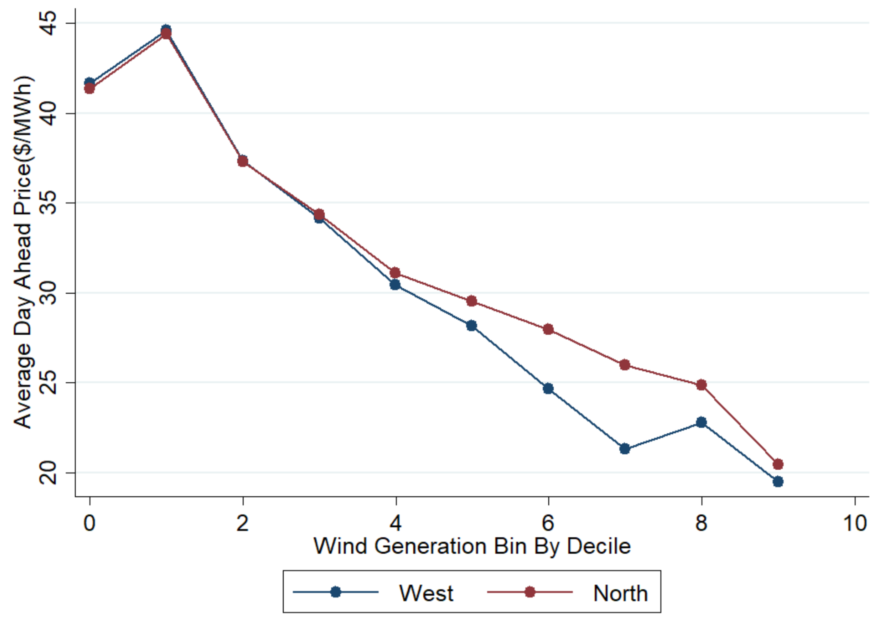

Figure 8: Average Day Ahead Electricity Prices by Wind Generation Levels

Figure 8 shows average electricity prices for West and North ERCOT in our sample broken out by wind generation deciles. The Figure is consistent with intuition that wind generation in ERCOT is negative correlation with load in ERCOT; prices are falling in wind generation. The Figure shows that during high wind days wholesale electricity prices are on average lower in the West than in the North. The Figure also shows that even though prices are roughly the same for low wind generation deciles, they are slightly higher in the North, although not in an economically significant way.

5 Reduced Form Results

We first investigate how wind generation affects wholesales electricity prices in levels. This serves to provide evidence of the first order effect that wind offsets higher marginal cost fuel. In the theoretical model the price impact is the shifting intercept of the net supply curve in the exporting region. We then investigate the impact of wind generation on price gaps across zones in ERCOT directly, which is the main contribution of this research.

5.1 Wind Generation and Prices

We first aggregate all ERCOT data and estimate the impact of wind on ERCOT wide average electricity prices controlling for load and many other fixed effects. Given the changes in transmission capacity over time we pick a single year, 2015, to increase internal validity. To account for possible nonlinear effects of wind generation and correlation between wind generation and load, we use a semi-parametric model to estimate the effects. For expositional clarity we divide hourly wind generation into 13 equal length (1000 MWh) bins ranging from 0-1000 MWh to 12,000-13,000 MWh, of which the first bin is served as baseline. Because wind generation is not uniform each bin doesn't have the same number of observations. We further divide load into 8 bins with an identical number of observations.[19] We then estimate the following equation:

$$P_t = \sum_{j=1}^{8} \sum_{i=1}^{13} \beta_{ij} 1\{Bin_i(W_t)\} 1\{Bin_j(L_t)\} + \delta_{hm} + \lambda_d + \varepsilon_t \tag{7}$$

where P_t is wholesale electricity price (real time or day ahead prices) at time t, W_t is wind generation at time t, L_t is load at time t, $1\{Bin_i(W_t)\}$ is an indicator for wind generation bin i, $1\{Bin_j(L_t)\}$ is an indicator for load bin j, δ_{hm} is the month-hour fixed effects, λ_d is the day fixed effects, ε_t is the error term. There are 13 wind generation bins. By adding month-hour fixed effects, identification comes from variation in load and wind within a month and across all identical hours (e.g., the 2pm hour in May, 2015). By further adding day of sample fixed effects, we further control for daily factors that could potentially affect prices. Standard errors are clustered by sample day to account for possible serial correlation within sample day.[20] β_{ij}'s are coefficients of interest, which indicates the price change by increasing wind generation from bin 1 (almost zero) to bin j conditional load level at bin i.

Figures 9 show estimation results from equation (7) for day ahead for ERCOT-wide

[19] Since we are focusing on the effects of wind generation, we divide wind generation into equal length bin for easy interpretation. To ensure certain amount of observations in each bin, we further divide load into bins with same number of observations. We could divide both into equal length bin or both into bins with same number of observations. The trend of the effects will not be affected much.

[20] We also cluster the standard errors by sample week in one of our robustness checks to account for serial correlation within a week.

prices (RT price results are larger and shown in the Appendix). Each subplot describes the size of a load bin and the y-axis shows the change in hourly DA prices. For all load levels electricity prices visually decrease as wind generation increases. The differences across wind generation levels are not always statistically significant but within a load bin the pattern is clear. We do not observe higher effects for large load bins. The pattern is more stark for real time than day ahead prices. There is an approximate \$0.5/MWh decrease in average day ahead time prices and \$0.7/MWh decrease in average real time prices per 1GWh increase in wind generation. The former is about 1.5% of the average electricity prices, while the latter is about 2.2% of the average electricity prices.

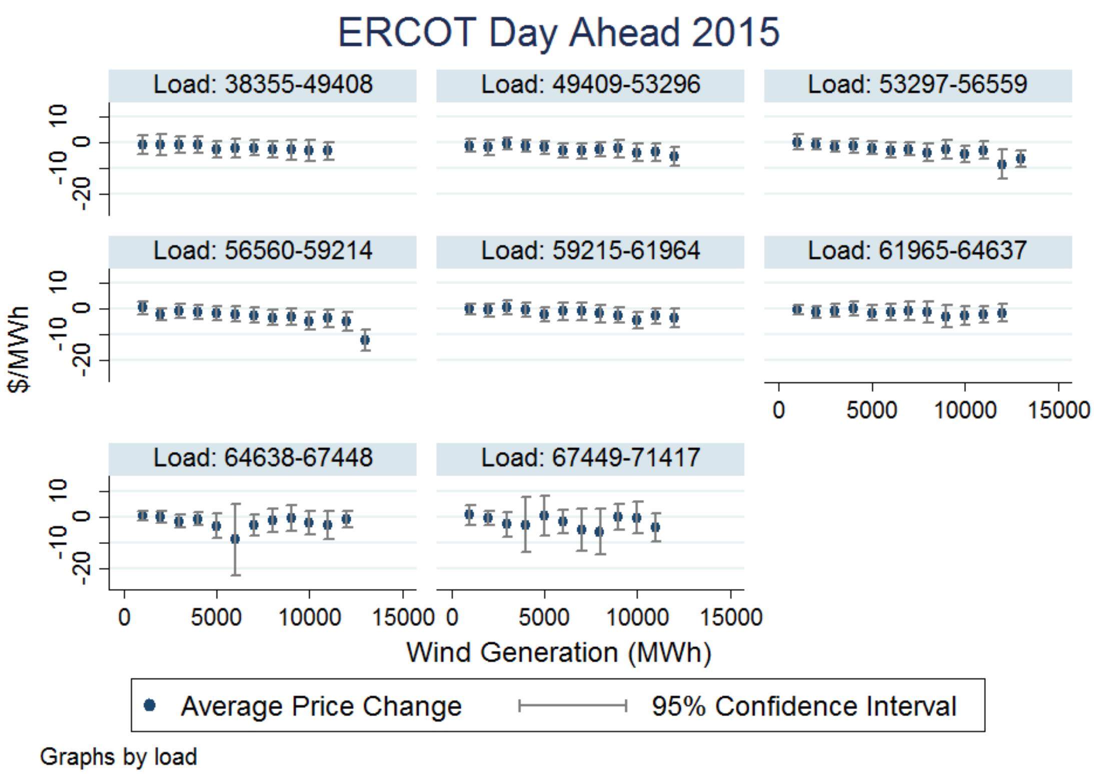

Figure 9: Effects of Wind Generation on Day Ahead Prices in ERCOT

There are several implications from the results: First, wind generation decreases electricity prices averaged at the hub level. We take this as evidence that short run variation in wind generation can shift the net supply curve as indicted by the model. Therefore the primitive extension of the Joskow and Tirole model appears valid: when wind generation increases, it offsets fossil fuel generation.[21]

Second, the effects of wind generation on prices appear linear conditional on all load levels (e.g., within subplot fixed effects seem roughly linear). We assume a linear net supply and net demand curves leveraged below as a result. If net supply and net demand curves are nonlinear, we would observe nonlinear effects of wind generation at different wind generation and load levels as well. Thus, we use linear specifications in our following analysis. We could straightforwardly extend the analysis to be non-parametric, however.

Third, there is no evidence that the price effects of wind generation on electricity prices vary systematically by load (e.g., across subplot effects). At the hub level, then, what the load level is on average when the wind blows may be a second order concern. We discuss this implication in more detail below.

5.2 Wind Generation, CREZ and Price Discrepancies

In this section, we test whether wind generation increases price discrepancies across regions, as posited in the model of renewables and transmission constraints presented above. We test whether the price discrepancies decrease after new CREZ transmission lines are completed. We later estimate the slopes of the net supply and net demand curves and TCLs for each hour with different wind generation and CREZ completion levels in the next section.

In order to show evidence of transmission constraints, we estimate the following equation:

$$\eta_t = \alpha_0 + \alpha_1 CREZ_t + \theta_1 (W_t - L_t^A) + L_t^B \theta_2 + \varepsilon_t \tag{8}$$

where η_t is the price gap between the west zone and one of the other zones at time t (Node B price minus Node A price in the theoretical model), W_t is the wind generation in the west Texas at time t, L_t^A is load in west Texas at time t, L_t^B is load in other ERCOT regions at time t, $CREZ_t$ is the percentage of CREZ completion (We denote %100 as 1) as a function of time. We thus estimate three unique regressions, one for each west/non-west zone pair.

[21] The results are even more stark when doing the same analysis for the west region only.

For example the average 2012 CREZ value is .344 and .859 in 2013. $W_t - L_t^A$ is net supply and L_t^B is net demand calculated from the hourly data, both of which serve as control variables. The error term ε_t is idiosyncratic. $\alpha_0 + \theta_1(W_t - L_t^A) + L_t^B\theta_2$ is the average price discrepancy before the CREZ program at different levels of net supply and net demand. In order to construct the average price discrepancy, we will take expectations of $E[\eta_t]$ to recover mean price discrepancies. The parameter of interest is α_1 which is the price discrepancy impact at full CREZ construction (i.e., % 100 completion when $CREZ_t = 1$). We expect $E[\eta_t]$to be positive in presence of transmission constraints. We expect α_1 to be negative since the model shows new transmission lines cause price discrepancies to decrease with lower transmission constraints. Standard errors are clustered by sample day to account for possible serial correlation within sample day. In the Appendix, we show robustness checks where standard errors are clustered by sample week to allow more possible serial correlation.

While the above regression examines the impacts of CREZ's completion on the price gap between regions, we also quantify the joint impacts of wind generation and CREZ on price discrepancies by estimating the following equation:

$$\eta_t = \alpha + \beta_0(W_t - L_t^A) + \gamma_0 L_t^B + \beta_1 CREZ_t \times (W_t - L_t^A) + \gamma_1 CREZ_t \times L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (9)$$

where δ_{hmy}'s are the year-month-hour fixed effects, η_d's are the day fixed effects, all else as above. The coefficients of interest are those on the variables representing the net supply and net demand curves. $(W_t - L_t^A)$ is net supply; it is increasing in wind generation and decreasing in load in west Texas (e.g. node A from the theory model). L_t^B is net demand; it is increasing in load in other ERCOT regions (e.g. node B in the theory model). β_0 and γ_0 are the impacts of decreases in net supply shock and increases in net demand shock on price discrepancies in the absence of CREZ lines. The model predicts them to be positive if transmission constraints bind. β_1 and γ_1 represent the marginal impact of CREZ construction on net supply changes and net demand changes. The theoretical model predicts them to be negative if CREZ relieves congestion allowing wind generation to be more easily traded with more transmission lines. Thus, we test the null hypothesis that $H_0 : \beta_1 = 0$ against the alternative that $H_0 : \beta_1 < 0$. Further, if the CREZ expansion completely eliminated the TCLs, we expect that $\beta_0 = -\beta_1$.

By adding year-month-hour fixed effects and day fixed effects, variation of identification mainly come from variation within a year-month across a specific hour (e.g., 2pm) as before. In using this short run variation for identification we are more confident that load and wind generation are exogenous to fossil fuel input prices which aren't likely to vary systematically within a year-month, let alone a year-month-hour. We thus rely on these fixed effects to control for variation in wholesale electricity prices due to longer run changes in fuel input prices.[22] In some regressions, we only add year-month-hour fixed effects (without sample day fixed effects) to allow more identifying variation.

5.3 Price Discrepancy Results

Table 3 Impacts of CREZ on Price Gap

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South DA	North RT	North DA	Houston RT	Houston DA
Percent Completion	-5.864***	-4.650***	-6.206***	-5.353***	-5.511***	-4.322***
	(0.632)	(0.334)	(0.462)	(0.290)	(0.654)	(0.322)
Net Supply (West)	0.817***	0.535***	0.779***	0.491***	0.960***	0.575***
	(0.0526)	(0.0259)	(0.0407)	(0.0241)	(0.0785)	(0.0264)
Net Demand (South)	0.105	-0.00994				
	(0.0714)	(0.0291)				
Net Demand (North)			0.0180	-0.0329**		
			(0.0268)	(0.0154)		
Net Demand (Houston)					0.247***	0.136***
					(0.0771)	(0.0290)
Constant	3.492***	3.975***	4.251***	4.578***	1.774*	2.492***
	(0.723)	(0.334)	(0.621)	(0.313)	(1.010)	(0.374)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.022	0.107	0.056	0.193	0.013	0.111

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Standard errors clustered by sample day are reported in parentheses.

Table 3 shows results from Equation (8) where we don't allow CREZ completion to interact with the net supply nor net demand curve for both DA and RT prices. This table

[22] Residents usually sign up relatively long contracts with utility and the retail price is also different from the wholesales price, so demand (load) will not be endogenously affected by wholesales prices in short run. Wind generation has almost zero marginal cost, hence wind farm owners will always want to bid zero to sell their electricity, so they will not be affected by wholesales prices in short run either.

shows CREZ completion impacts on price differences over space conditional on net supply and net demand. Column (1) (2) show results between the West zone and the South zone, Column (3) (4) show results between the West zone and the North zone, and Column (5) (6) show results between the West zone and the Houston zone. Column (1) (3) (5) are results for real time markets, and Column (2) (4) (6) are results for day ahead markets. In this table and all tables below, net supply and net demand are in units of 1,000MWh (or 1 GWh).

We can use Table 3 to get high level impacts of the CREZ line construction. From Table 2, average wind generation is 3.8 GWh, average load in the West is 2.6 GWh, and average load in the South is 9.5 GWh. Column (2) shows that the average DA (RT) price gap between the West zone and the South zone is $3.8 + 0.54 \times (3.8 - 2.6) - 0.01 \times 9.5 = \$4.35/MWh$ ($\$5.5/MWh$). After the CREZ construction, the price gap drops by $\$4.65/MWh$ ($\$5.8/MWh$). Results in other regions can be interpreted similarly. The impacts of CREZ are large in all regions and don't qualitatively change in size (e.g., the value of the $CREZ$ coefficient is roughly the size of the average price gap). These finds are consistent with CREZ relieving congestion.

Figures 10 shows results by replacing CREZ percentage completion in (8) by a set of year dummies. This highlights the evolution of how the wind weighted price gap changes over time. In Figure 10, price gap decreases each year as CREZ lines are completed. The biggest drop in the price gap is in 2011 and 2012 despite only 15.9% of CREZ being completed at that time. The large drop is consistent with building transmissions lines that are likely to have the biggest impact in prices first. This makes sense: a regulator constructing a large infrastructure project should build in places that have the highest marginal benefit first. Also, the price gap increases slightly in 2016. One possible explanation is that wind capacity in 2015 increases while CREZ construction is effectively fixed. Lastly, we take this as evidence that the first order effects of CREZ can be inferred using a model which doesn't recreate the entire ERCOT transmission network.

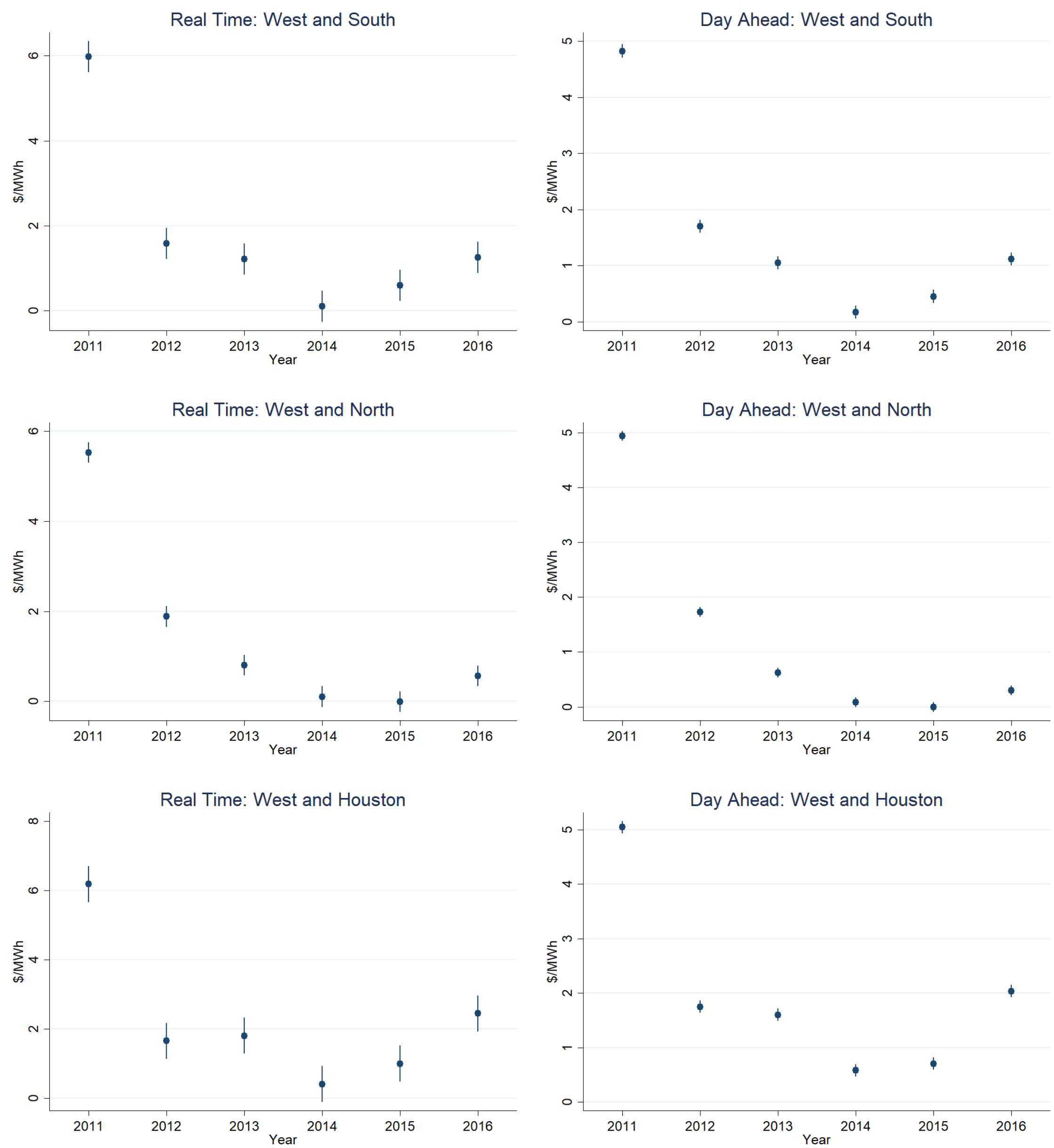

Figure 10: Price Gap By Year

Table 4 Impacts of CREZ and Wind Generation on Day Ahead Price Gap

VARIABLES	(1) South DA	(2) South DA	(3) North DA	(4) North DA	(5) Houston DA	(6) Houston DA
Net Supply (West)	2.066***	1.662***	2.154***	1.665***	2.200***	1.725***
	(0.119)	(0.104)	(0.103)	(0.0948)	(0.108)	(0.0990)
Net Demand (South)	-0.0923	0.000750				
	(0.446)	(0.203)				
Net Supply (West)*Percent	-1.980***	-1.625***	-2.158***	-1.662***	-2.044***	-1.662***
	(0.127)	(0.111)	(0.108)	(0.100)	(0.115)	(0.108)
Net Demand (South)*Percent	0.0582	0.0958				
	(0.473)	(0.224)				
Net Demand (North)			-0.0984	0.00351		
			(0.0802)	(0.127)		
Net Demand (North)*Percent			0.110	0.0584		
			(0.0866)	(0.139)		
Net Demand (Houston)					-0.396**	-0.260
					(0.185)	(0.171)
Net Demand (Houston)*Percent					0.669***	0.609***
					(0.209)	(0.204)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.415	0.652	0.526	0.784	0.470	0.710
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Standard errors clustered by sample day are reported in parentheses.

Table 4 reports the results from Equation (9) for day ahead markets when we allow $CREZ$ to interact with the net supply and net demand curves. Real time market results are in the Appendix. Column (1) (2) show results between the West zone and the South zone, Column (3) (4) show results between the West zone and the North zone, and Column (5) (6) show results between the West zone and the Houston zone. For all columns, year-month-hour fixed effects are added, which controls for hourly pattern of prices within sample month. Column (2) (4) and (6) further control for sample day fixed effects, then the identifying variation only comes from variation across a given hour in a month not common to hours in the same day. Column (2) (4) and (6) are our preferred specification.

The primary coefficients of interest are the interactions of $CREZ$ with the net supply and net demand curves. Before CREZ, an increase in the net supply ($W_t - L_t$) in the West zone of $1GWh$ increased the price gap between the West zone and the South zone increases by \$2.154/MWh in day ahead markets. The increased price discrepancy when wind generation increases is consistent with transmission constraints. Comparing full completion of CREZ to no CREZ project (e.g., $CREZ$ goes from 0 to 1), the impact of a net supply increase on price dispersion drops by \$2.158/MWh in day ahead markets. We take this as evidence that the strategic behavior studied in previous work is not a primary factor in the price spreads across zones in ERCOT due to wind generation although we discuss extensions in the discussion section (Hortacsu and Puller (2008) and Hortacsu, Luco, Puller, and Zhu (2017)).

Taken together, an increase in net supply led to no increase in price dispersion after CREZ completion. The relative magnitudes of wind generation and load in the west shown in Table 2 are consistent with wind generation being the reason. As before, Figure 11 show the impacts of net supply increases on price dispersion by year. The marginal impact of net supply increases on price dispersion clearly falls over time as before.

These results are consistent with transmission constraints in the theoretical model. After the full completion of the CREZ project, wind generation has almost no statistically significant effect on price dispersion indicating that post-CREZ there is enough free transmission capacity to trade wind generation across space. The effects of net demand is almost zero in most of the specifications, indicating relatively flat net demand curves. Results in other regions can be interpreted similarly. Figure 11 shows the marginal impacts of net supply by year as we did with average price gaps visually showing identical intuition.

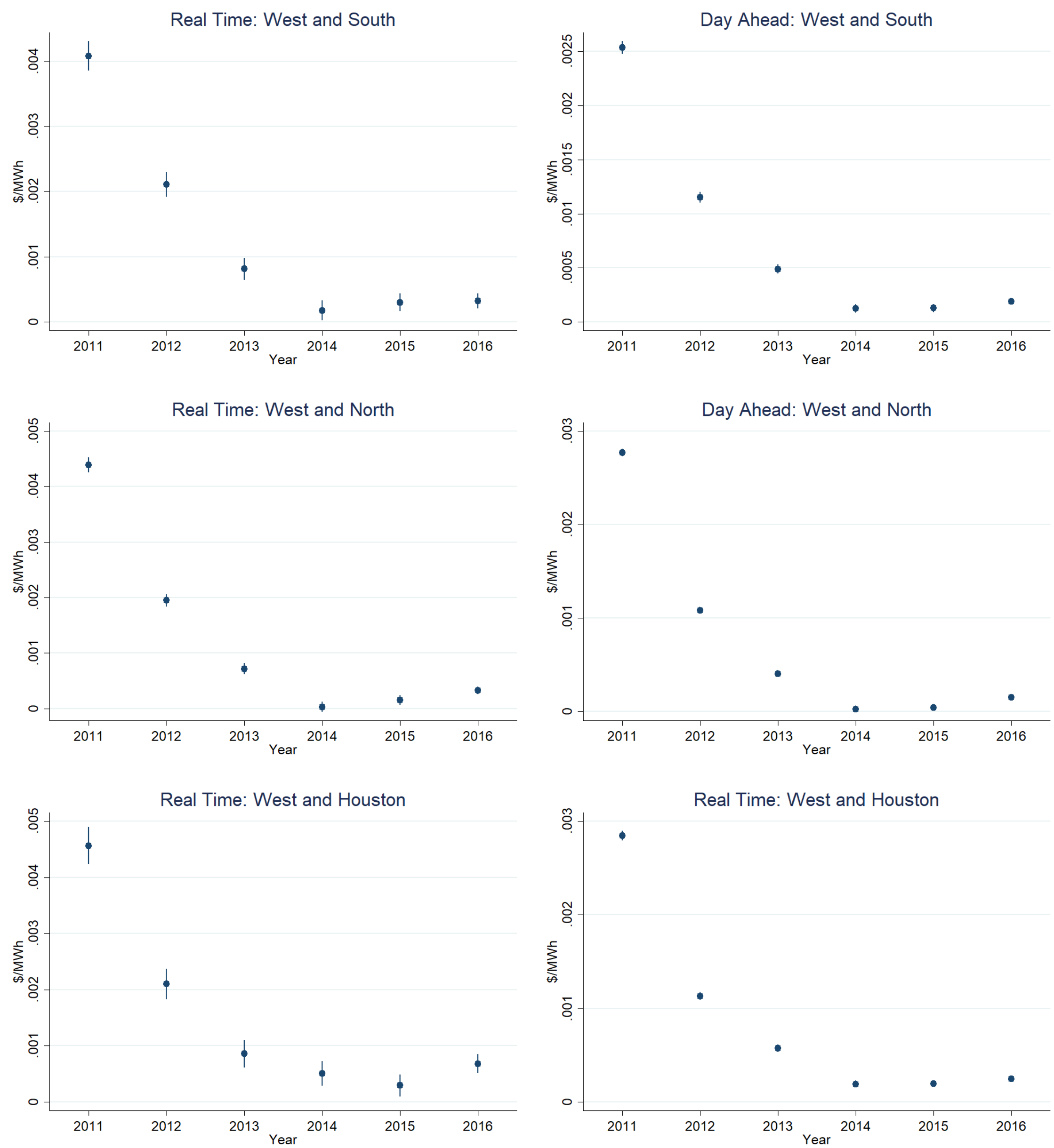

Figure 11: Effects of Net Supply on Price Gap By Year

6 Transmission Constraint Losses and Incidence of CREZ

6.1 Transmission Constraint Losses

The theoretical model gives us a framework to quantify foregone gains from increased trade between exporting and importing regions (i.e. TCLs). In order to do so, we first estimate the slopes of the net supply and net demand curves directly. Whereas in the regression specifications above we estimated the impact of wind generation on the price gap between two zones to test for evidence of transmission constraints, we now estimate the slope of the net demand and net supply curves directly using price levels.

To identify net demand and net supply slope coefficients, we would like to take advantage of exogenous net demand shocks to estimate the slope of net supply curve and an exogenous net supply shock to identify net demand. However, there are endogeneity issues with that simple identification strategy in our context share by estimating supply and demand curves for a standard consumer good. When we estimate the slope of net demand curve, it needs to be held unchanged when net supply shock occurs. Hence, we need to control for net demand when we are looking at how net supply change affect prices. Similarly, we need to control for net supply when we look at how net demand change affect prices. As a result, we would have to include both net demand and net supply in the same regression and they serve as each others' control.[23]

Our identification strategy for both curves relies on inelastic demand, the must take nature of wind generation and the presence of transmission constraints. First, assume that there are capacity constraints such that there is a price gap between the exporting region (node A) and importing region (node B). In practice, we can trim our estimating sample to hours where there is a price gap between west ERCOT and other zones. As shown in Figure 2, when there is a positive net supply shock, which shifts the net supply curve to the right (or downwards), the price in the West will drop.[24] Using only net supply shocks from wind generation and price change in the exporting region (node A in the theory model, West Texas in ERCOT), we can identify the slope of the net supply curve (e.g., b_A in the theoretical model) conditional on existence of transmission constraints. Put another way, during periods in which the transmission constraint binds, variations in load and wind generation in the exporting region trace out the export region net supply

[23] There is non-trivial correlation between net demand and net supply stemming from correlation between load and wind generation, and correlation between load across zones. This correlation would contaminate both estimates without adequate controls and we are not convinced that two-way fixed effects would control for all correlation of net supply and net demand. The normal instruments for wind generation and load (e.g. wind speed and weather variables like temperature) cannot solve the potential correlation issue either since they don't satisfy the exclusion restriction. Therefore, we propose a unique method in our context taking advantage of the constrained prices in importing and exporting regions to estimate the slopes.

[24] The exception is if there is no capacity constraint and the net demand curve is fully flat.

curve, and variations in load in the import region trace out the import region net demand curve.[25] Specifically, the slope term is given by:

$$b_A = \frac{p_1^A - p_0^A}{W_1 - W_0} \tag{10}$$

Similarly, as shown in Figure 12, we use demand shock from load in Node B to identify the slope of the net demand curve under transmission constraints. When load in Node B increases from L_0 to L_1, the net demand curve shift to the right. As a result, the price in Node B increases from p_0^B to p_1^B. Therefore, the slope of the net demand curve (e.g., b_B in the theoretical model) is given by:

$$b_B = \frac{p_1^B - p_0^B}{L_1 - L_0} \tag{11}$$

[25]Without binding transmission constraints, this identification strategy does not work and the normal supply and demand endogeneity woul persist.

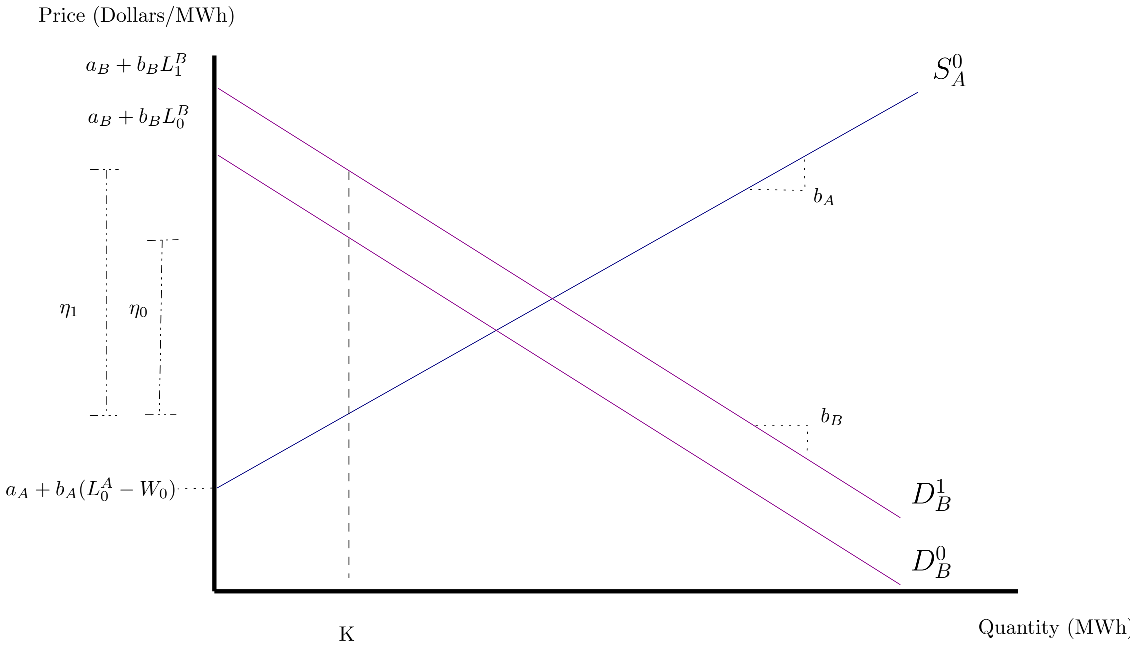

Figure 12: Net Demand Shock

Since the formula for slopes of net supply and net demand curves from Equation (10) and (11) are conditional on existence of transmission constraints, we use the response of prices on net supply shock and net demand shock under transmission constraints to identify the slopes. In our analysis below, we restrict the estimating sample to time periods with a price gap between the West and any other zone of at least $2/MWh. Qualitative results are identical when we trimmed the estimating sample to include time periods to include only 2011-2013 before CREZ completion, which we show in the Appendix. Thus, we condition on there being evidence of transmission constraints consistent with the theoretical model to identify net supply and net demand parameters.

On the trimmed sample, we estimate the slopes of the net supply and net demand curves by the following equations:

$$p_t^A = \alpha + \beta(W_t - L_t^A) + \gamma_2 L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \tag{12}$$

$$p_t^B = \alpha + \beta_2(W_t - L_t^A) + \gamma L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (13)$$

where p_t^A is the price in the West, p_t^B is the price in any other zones, all else are the same as above. The absolute value of β in Equation (12) gives us the slope of the net supply curve, which is identified from net supply shock from either increasing wind generation or/and decreasing load in Node A under transmission constraints as Equation (10). Similarly, γ in Equation (13) gives us the slope of the net demand curve, which is identified from net demand shock from increasing load in Node B under transmission constraints as Equation (11).

By adding year-month-hour fixed effects and day fixed effects, variation of identification mainly come from variation within a year-month across a specific hour (e.g., 2pm) as before. Identifying the parameters with short run variation means load and wind generation are exogenous to fossil fuel input prices which aren't likely to vary systematically within a year-month, let alone a year-month-hour. We thus rely on these fixed effects to control for variation in wholesale electricity prices due to longer run changes in fuel input prices. Note that β estimated above is expected to be negative, so we take the absolute value for the slope and calculation below.

Table 5 Identification of Net Supply and Net Demand Curves West and North DA

	(1)	(2)	(3)	(4)	(5)	(6)
	P(North)	P(West)	P(North)	P(West)	P(North)	P(West)
VARIABLES	P(Gap)> 1	P(Gap)> 1	P(Gap)> 2	P(Gap)> 2	P(Gap)> 5	P(Gap)> 5
Net Demand (North)	0.705***	1.030***	0.543**	1.024***	0.609**	1.013***
	(0.225)	(0.298)	(0.237)	(0.333)	(0.269)	(0.325)
Net Supply (West)	-0.804***	-2.226***	-0.766***	-2.438***	-0.724***	-2.272***
	(0.156)	(0.194)	(0.192)	(0.248)	(0.223)	(0.311)
Observations	10,371	10,371	7,326	7,326	4,421	4,421
R-squared	0.748	0.762	0.861	0.855	0.920	0.900
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table 5 shows parameter estimates from equations (12) and (13) on the 2011-2016 data for the West Zone and the North Zone. Estimates from the South and Houston zones are available upon request, but we don't provide them here in the interest of brevity. We trim sample where the price difference between the west and other zones is at least \$2/MWh for all analysis. We also show how point estimates remain very stable as we change the strength of the price dispersion in the estimating sample to be more aggressive (gap of \$1 or more) to more conservative (gap of \$5 or more). Results for the subset of hours pre-CREZ completion in 2014 is shown in the Appendix and offer very similar point estimates with larger standard errors, as expected given the smaller sample.[26]

Our main specification is when the price gap is at least \$2/MWh in Table 5 columns (3) and (4). Due to us leveraging price dispersion which we attribute to a binding transmission constraint as our identification strategy, the slope coefficients on net demand from the North and net supply from the West are .543 an -2.438 respectively. The table shows the coefficients are consistent across specifications. Both coefficients are statistically significant. The estimated signs are reversed relative to the theoretical model since increases in the net supply curve decrease prices in ERCOT West, whereas the opposite is true in ERCOT North for net demand. The Appendix describes a semi-parametric technique we use to infer if there are non-linearities in the net demand and net supply curves between the west and the North. We find no significant evidence of non-linearity in the net demand curve and modest increasing net supply slope for high levels of net supply (14% increase significant at the 10% level).

Robustness Checks

Given the importance of the point estimates for subsequent calculation of transmission constraint loss, we include several robustness checks in the Appendix. First, we allow error terms to be autocorrelated within sample week rather than sample day to be more conservative. Table A1-A3 show that the standard errors increase slightly but the significance levels do not change. Second, the CREZ project was almost finished before April 2014, but wind capacity levels rose rapidly afterward, which may bias our point estimates on the

[26] We've also estimated this model on the entire sample. In those specifications the magnitude of the slope coefficients falls slightly, which is consistent with changing net supply and net demand curves having less of an effect on local prices when electricity can be traded freely.

interaction term downward since any transmission constraints would be exacerbated. We report the results in Table A4-A6 by only including data before April 2014. The results become slightly larger in general as expected. Third, we control for loads from all regions to allow potential interactions among those markets in Table A7-A9. The results do not change significantly. Finally, we've run all specifications without controls to be more directly in line with the theoretical model (e.g., no controls for load in the other zone) and all point estimates are very similar. Those results are available upon request. In sum, all robustness checks show consistent results with our main specification.

Market Power

There is a large literature which shows that market power in electricity markets significantly influences prices, including in ERCOT (Hortacsu and Puller (2008) and Hortacsu, Luco, Puller, and Zhu (2017)). Market power occurs when a single electricity supplier is able to influence market price. In the theoretical model, prices increases from load increases can be from either increasing marginal costs of electricity or increasingly exercised market power. Transmission constraints preventing trade in electricity markets preventing trade across nodes and hubs could certainly contribute to market power in ERCOT.

Transmission constraints can cause price increases due to both lack of trade and increased market power due to inability to trade. There is a distinction between price increases due to lack of trade and market power induced price increases. Price increases due to lack of trade imply that the lowest cost producers to service an entire market are not producing. Price increases due to market power imply that the lowest costs producers can produce, but that market clearing prices are above costs. From a welfare perspective, then, the precise mechanism through which prices increase in the presence of transmission constraints, lack of trade or market power from lack of trade, doesn't matter. If increased trade reduces prices then it reduces transmission constraint loss.

While our research design doesn't allow us to fully parse between sources for transmission constraint induced price increases (e.g., lack of trade versus market power), we can determine if some of our results are consistent with market power. Previous research highlights that market power is likely to be largest during highest demand hours when a single firm can impact market prices (Borenstein, Bushnell, and Wolak (2002)). In order to determine if market power affects the net supply and net demand curve estimates, we run our main empirical specification trimming the sample to exclude the top 10% of load hours for the west and north ERCOT regressions and report them in the Appendix. These high load hours would be serviced by the steepest part of the MC curve in north ERCOT, which would be even steeper if market power were exercised. Their inclusion would thus make the net demand curve steeper and excluding them should make the net demand curve flatter. There should be no effect on the net supply curve estimate. Thus, if we find a flatter estimated net demand curve it is consistent with high load hours being serviced by a steeper part of the north's marginal cost curve where market power is likely to be exercised.

We estimate net demand and net supply curve slope coefficients of .385 and -2.465 with the trimmed sample (see Table A11), compared to point estimates of .543 and -2.438 reported in the main specification in this section. The change in the point estimate is 29% which we view as moderate. Consistent with economic intuition, there is no impact on the net supply curve. The point estimate for the slope of net demand curve is slightly lower, though, meaning that the curve is estimated to be slightly flatter. This is consistent with the theoretical model: by trimming the highest load hours which are serviced by the steepest part of the North's marginal cost curve, the estimated net demand curve is flatter. While far from parsing between transmission constraint loss attributable to lack of trade versus market power from lack of trade, we view this as at least consistent with the possibility of reductions in market power being attributable to the CREZ expansion.

It is beyond the scope of this paper and would require a different research design to precisely disentangle the impacts of lack of trade versus market power from lack of trade. Most importantly, benefits from reduced market power attributable to more transmission capacity are benefits that matter for welfare. Even if all benefits from increased transmission capacity were to accrue due to market power there would still be welfare gains from the policy, although incidence from the policy would be different.[27]

The Production Tax Credit

Wind investment was subsidized through the Production Tax Credit (PTC) over the course of our study. The PTC served to increase the level of wind investment relative to a

[27] To do a full welfare analysis in that case, the reduced producer surplus from market power would be partially offset through increased consumer surplus. Our discussion of incidence below has flavors of this.

baseline of no PTC. Wind generation is must take so that there is no strategic component to deploy wind generation: when the wind blow wind farms generate. In the model, this is the shifting of the net supply curve in the exporting node. Thus, the existence of the PTC doesn't impact our theoretical nor empirical model for any given level of installed wind capacity.[28]

6.2 Calculating TCLs

The main contribution of the paper is leveraging the estimated slope coefficients to determine what the increase in equilibrium electricity trade would have been without transmission constraints. We focus the exposition here on hourly TCLs, the distribution of those TCLs, and what drives them in the model. As shown in the theory section, we can use the estimated net supply and new demand coefficients and the theoretical model's structure to calculate the spending saved by the CREZ project due to increased trade. In any hour where we observe price differences between west Texas and other ERCOT zones, we can use the estimated slopes to determine what equilibrium prices and total traded electricity would be without transmission constraints. By summing across all hours we do a simple cost-benefit analysis for the project. Transmission capacity was desired because the wholesale price of electricity was too high in load centers (North, South, and Houston) and too low near the majority of windfarms (e.g., West) and there was insufficient capacity to facilitate renewable electricity trade. Put another way, estimating the slopes of the net supply and net demand curve combined with the theoretical model provides us the opportunity to back out the transmission capacity shortfall, ΔK_t, for each hour when there is a price gap as shown in equation (3). Equation (4) then shows how the imputed ΔK_t maps to a particular hour's TCL.

We start by showing the imputed hourly ΔK_t as a function of ERCOT wind generation. These values are a function of the estimated net supply and net demand slope coefficients between the West Zone and the North Zone by year as show in equation (3)

[28] Insofar as the PTC did increase installed wind capacity over our sample there are two implications. First, it makes all of our subsequent transmission constraint loss calculations below lower bounds since wind capacity increased over the sample but we perform the TCL calculations assuming 2011 levels of capacity. Insofar as increased capacity biases our coefficients, our pre-April 2014 robustness check addressed this issue.

and observed price discrepancies. We focus on these two Zones due to how well they map to the theoretical model.

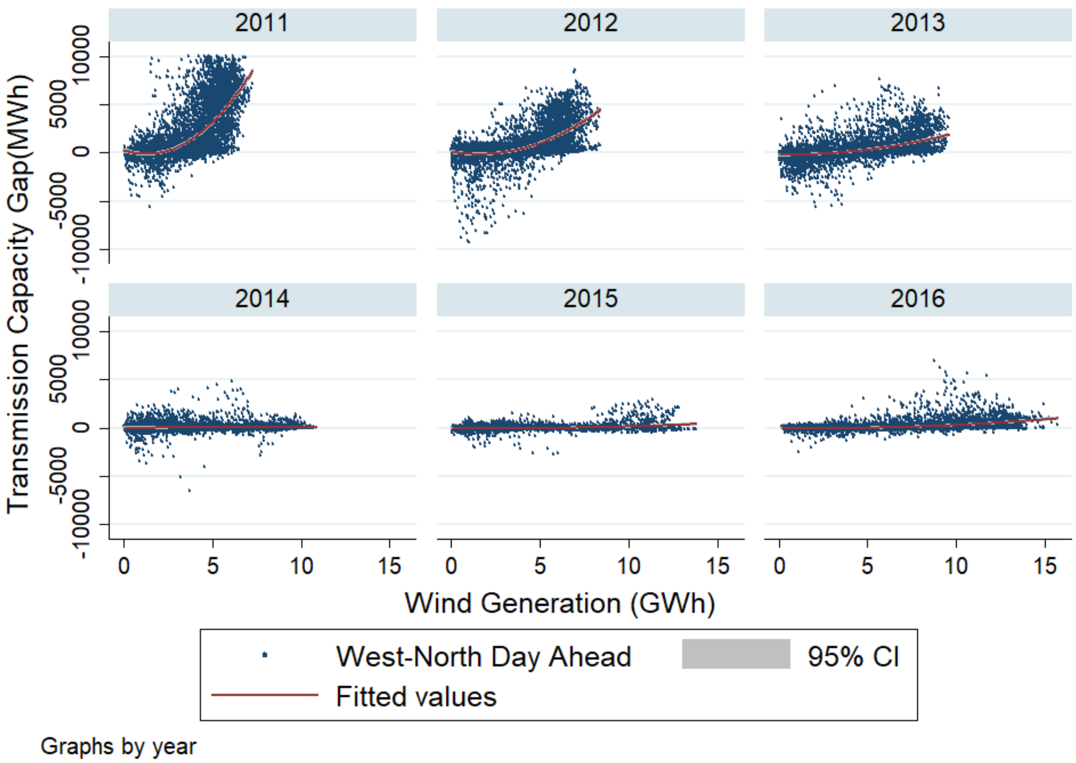

Figure 13: Implied transmissions shortfall by year.

Figure 13 shows the yearly imputed transmission capacity gap.[29] Each point represents a single imputed hourly ΔK_t using the formula derived in the theoretical section. In 2011, when CREZ is still in its early stages, we observe a strong positive relationship between wind generation on the transmission gap. Recalling equation (3), the non-linearity in Figure 13 reflects how wind generation correlates with the net supply and demand curve. The 2011 subplot highlights how, in the context of transmissions constraints, correlation between wind generation, load and the slope of the net supply and demand curves jointly determine the implied level of transmission congestion (e.g., a congestion analog of Call-

[29]In this Figure we've dropped the highest observed 20 hours of DA wholesale electricity prices. Those types of price spikes often occur due to unexpected outages. This trimming procedure narrows the focus to transmission constraint related price differences.

away, Fowlie, and McCormick (2018)). There is an increasing convex relationship between wind generation and implied transmission constraints. The positive relationship still exists in 2012 and 2013 albeit less intensely. By 2014, the positive relationship no longer exists. In 2016, there is a mild rebound consistent with continued increases in wind capacity but stagnant transmission capacity. This is evident in the Figure 13 by observing the support of observed hourly wind generation levels increasing above 2014 and 2015 levels.

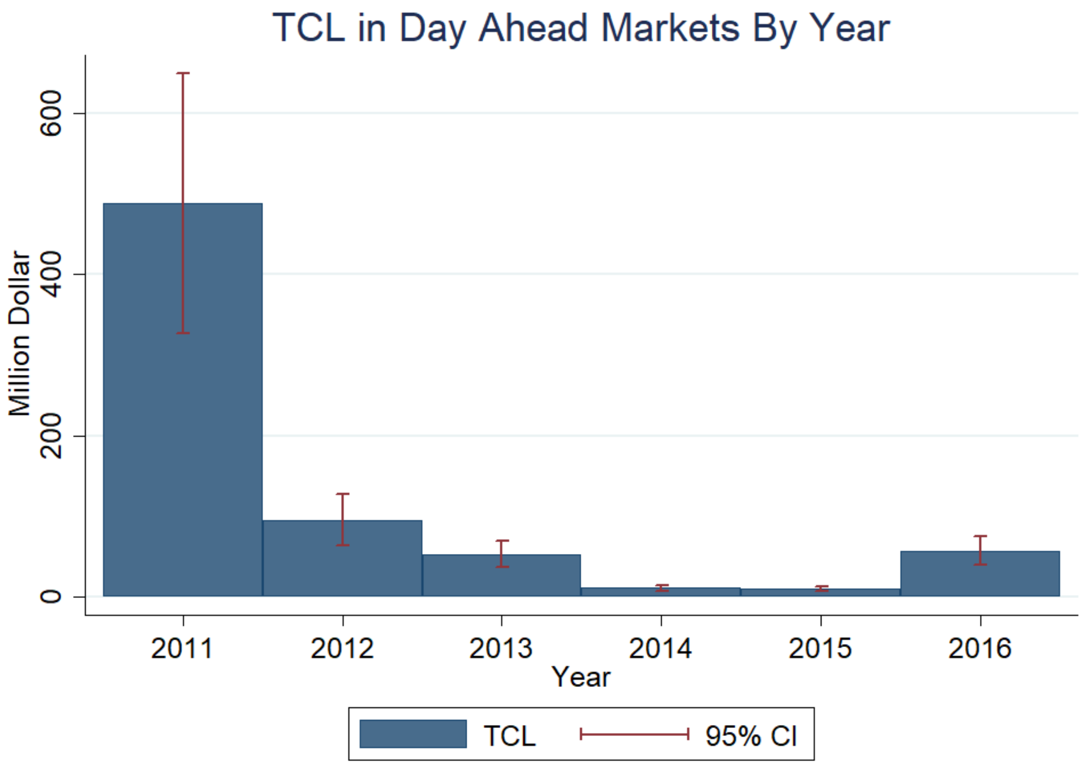

Figure 14: Yearly sum transmission constraint losses for all regions.

The transmission capacity gaps shown in Figure 13 map to hourly TCLs. Figure 14 aggregates these hourly observations to show the annual TCL aggregated across all of these hours and across all zones and includes 95% confidence intervals are calculated by delta method. Figure 14 shows TCLs when the transmission gap between the West and the North is positive and there is positive wind generation. The Figure shows annual Pre-CREZ losses on the order of $500M/year dropping to nearly zero in 2014 and 2015.

Losses then rise again in 2016. These estimates are likely lower bounds since total wind capacity in 2011 was roughly 10,000 MWs and 11,000 MWs or more starting in 2013. As a result, the TCLs mitigated by CREZ would have been higher had the additional wind capacity been present in 2011. We don't make a claim about CREZ's impact beyond the $500M/year level post 2013 because that would require us to determine how CREZ interacted with windfarm development decisions. Thus, we conclude that annual TCLs mitigated by CREZ were at least roughly $500M/year.

In addition to market impacts, there are also non-market impacts of CREZ. With trading possible, wind generation offsets fossil fuel generation in non-west ERCOT. We use hourly marginal emissions estimates for CO2 using the technique developed in Zivin, Kotchen, and Mansur (2014) and updated in Holladay and LaRiviere (2017). To map the implied transmission shortfalls to tons of CO2, we use hourly marginal emissions estimates from Holladay and LaRiviere (2017) across all hours and all zones. Using $\$37/ton$, a standard carbon price measure, the CO2 costs mitigated by CREZ are on the order of $31,000,000 * \$37 = \$1.15B$ per year in 2011 if the entire transmission capacity gap were curtailed or lost on lines, roughly double the market impacts. That is not what actually occurs, though, and curtailment rates are difficult to know given the lack of data. The U.S. Department of Energy's market report[30] shows suggestive evidence that curtailment decreased rapidly as CREZ was constructed from a height of 17% in 2009 to roughly .3% in 2014. We assume 10% curtailment attribute to congestion to give CO2 benefits of roughly $115M/year. This is in addition to the roughly $200M in non-market benefits from CREZ estimated by Fell, Kaffine, and Novan (2017) due to reshuffling of dispatch and changes in local pollutants.

Summing across market and non-market impacts, the benefits from CREZ conditional on installed wind capacity are on the order of $\$800M/year$. Critically, roughly 38% of the benefit are due to non-market externalities. The Appendix shows that allowing non-linearity in the net demand and supply curve impact the market and non-market TCL calculations. We find almost identical losses so we conclude the linear approximation captures the important quantitative and qualitative findings.

[30]See `https://www.energy.gov/eere/wind/downloads/2016-wind-technologies-market-report`.

The cost of CREZ ERCOT ratepayers face is roughly between \$7B according to the U.S. Energy Information Administration.[31] According to our estimates, then, the payback period is roughly 8.75 years when accounting for non-market externalities. That payback period- in addition to the stream of future gains- is more than adequate. Excluding the non-market benefits, the payback period is 14 years. Given relatively low bonds rates over this period, this is not completely unreasonable even completely ignoring CO2 mitigation for public projects. Certainly, though, a payback period on the order of nine years makes this transmission expansion a good investment from a social welfare perspective.

6.3 Incidence of CREZ

While the price gap and transmission gap might have decreased between the West and other zones due to CREZ, in order to calculate the incidence of CREZ we must determine price increases in the west attributable to CREZ and price decreases in other parts of ERCOT attributable to CREZ. The beneficiaries of CREZ are wholesale ratepayers in load centers (e.g., the demand side of the market) and bidders into the electricity market in the West during windy hours (e.g., windfarms). This analysis focuses on wholesale electricity market price impacts in the North, South, and Houston ERCOT zones and discusses the incidence of those impacts.

We denote price gap before CREZ project as η_0 and that after the project as η_1. Disaggregated further, denote the price difference for people in the population center and the West before and after the CREZ project as η_0^B, η_0^A, η_1^B and η_1^A respectively (using B superscripts for load centers and A for the exporting zone west Texas in line with the theoretical model). From the theoretical model, we can calculate them as:

$$\triangle\eta_0^B = \gamma\triangle K = \frac{\gamma\eta_0}{(\beta+\gamma)} \tag{14}$$

[31] See `https://www.eia.gov/todayinenergy/detail.php?id=16831` although other outlets report as high as \$8B.

$$\triangle\eta_0^A = \beta\triangle K = \frac{\beta\eta_0}{(\beta+\gamma)} \tag{15}$$

$$\triangle\eta_1^B = \gamma\triangle K = \frac{\gamma\eta_1}{(\beta+\gamma)} \tag{16}$$

$$\triangle\eta_1^A = \beta\triangle K = \frac{\beta\eta_1}{(\beta+\gamma)} \tag{17}$$

Noting that a negative number indicates spending decreases, the spending change for market participants in load centers (again denoted with the B superscript in line with the theoretical model) and market participants in the West (again denoted with the A superscript in line with the theoretical model) is:

$$\triangle Spend_B = (\triangle\eta_1^B - \triangle\eta_0^B) \times L^B = \frac{\gamma(\eta_1 - \eta_0)}{(\beta+\gamma)} \times L^B = \frac{\gamma\triangle\eta}{(\beta+\gamma)} \times L^B \tag{18}$$

$$\triangle Spend_A = (\triangle\eta_1^A - \triangle\eta_0^A) \times L^A = \frac{\beta(\eta_1 - \eta_0)}{(\beta+\gamma)} \times L^A = \frac{\beta\triangle\eta}{(\beta+\gamma)} \times L^A \tag{19}$$

where L^B and L^A are average load in population center and the West respectively. $\triangle\eta$ is the impact of CREZ on price gap estimated by Equation (8). The the total spending change for all people is given by:

$$\triangle Spend = \triangle Spend_B + \triangle Spend_A \tag{20}$$

Table 6 Incidence Analysis of CREZ Project

	Real Time			Day Ahead		
	South	North	Houston	South	North	Houston
Net Supply Slope ($/MWh per GWh)	3.637	4.8173	3.5317	1.9856	2.4383	1.6002
Net Demand Slope ($/MWh per GWh)	-0.0067	-0.8065	-0.1845	-0.756	-0.543	-1.1681
Load West (GWh)	2.6228	2.6228	2.6228	2.6228	2.6228	2.6228
Price Change West ($/MWh)	5.8537	5.316	5.2378	3.3676	4.3783	2.4982
Spending Change West ($/h)	15353	13943	13738	8833	11483	6552
Average Spending Change West ($/h)		14345			8956	
Load Pop Center (GWh)	9.534	12.9072	11.0282	9.534	12.9072	11.0282
Price Change Pop Center ($/MWh)	-0.0108	-0.89	-0.2736	-1.2822	-0.975	-1.8237
Spending Change Pop Center ($/h)	-103	-11487	-3017	-12224	-12585	-20112
Total Spending Change Pop Center ($/h)		-14607			-44921	
Net Spending Change ($/h)		-262			-35965	

Table 6 report the results for all the three pairs of regions using a back of the envelope calculation which only looks at market averages. Using this simple calculation, the annual saving outside of the west in the day ahead market ranges from $12,224/hour to $20,112/hour. Since prices in West ERCOT increase, there is a price increase in West ERCOT on average. We can take this number and then aggregate up to the annual level. West is calculated repeatedly so we use an average for the West when we calculate the total spending saving in the whole ERCOT. The total spending change per hour across ERCOT is -$315M in terms of lower wholesale rates. This is an intuitive finding: the increased transmission of wind generation to greater ERCOT means more zero marginal cost electricity supplied to the market.

The $315M calculation masks the fact that ratepayers will be passed through the cost of CREZ construction. ERCOT market participants had to pay for CREZ through market participation fees. This ultimately impacts rate payers. Thus the TCL sums calculated in the paper, rather than incidence of changes in wholesale market prices, are the appropriate metrics for calculating the benefits from lower TLCs attributable to CREZ.

However, while ratepayers and windfarms gained from hourly wholesale electricity prices, generators not in the west are harmed by lower prices. Benefits to ratepayers and windfarms in the west are costs to generators not in the west (in addition to ratepayers in the west). Thus CREZ led to a very large negative impact on non-west generators. To this end, 4,000 MWs of coal capacity was recently approved from retirement.[32] However, this is a joint function of lower natural gas prices and increased wind capacity (Fell and Kaffine (2018)). We don't make the claim that CREZ caused these closures but to a first order approximation CREZ does not appear to be a good thing for non-west ERCOT generators.

As with any paper, there are some drawbacks to our approach. First, while we allow for non-linearities in the net supply and net demand curve and found mild non-linearities in the net supply curve, further identification of precisely how the non-linearity arises could be important for understanding trading in the wholesale electricity market broadly. Second, we have no theory explaining differing results between the real time and day ahead markets. Third, we don't perform a cost benefit analysis of how the additional costs of transmission lines relate to the economic gains from additional trade enabled by them. Fourth, transmission line loss is one factor that will result in price discrepancy that we have not accounted for explicitly. More transmission lines imply more line loss, but we observe little wind generation induced price gaps post CREZ so for our sample period and our study, line loss is a second order impact. Fifth, we haven't accounted explicitly for plant start up costs which are important for coal fired generation (Reguant (2014)). We view the interaction of wind generation and the value of quick dispatchable electricity to be its own important economic question. Sixth, our results highlight how implementing yet to be identified better mechanisms to resolve federal versus regional discrepancies in energy, environmental and transmission policy making could lead to higher welfare.

7 Discussion and Conclusion

This paper extends the electricity transmission framework from Joskow and Tirole (2005) to characterize how policy encouraging intermittent renewable investment can interact with extant transmission grid constraints to create transmission constraint loss. Consistent with the model, we find evidence in ERCOT that increased wind generation of windfarms decreases wholesale electricity prices at market settlement points near wind-

[32] See goo.gl/X6vLCB/.

farms. Consistent with transmission constraints which prevent trade of low cost electricity regions to high cost regions, increased wind generation also creates a wedge between wholesale electricity prices near windfarms relative to nearby nodes, such as population centers. A large expansion in transmission capacity decreased the price wedge caused by wind generation between generation and load centers. The benefit cost analysis for the project ride very much on the value of mitigated carbon for our analysis. Based purely on market gains through more trade the payback period is roughly 14 years while including non-market CO2 reductions the payback period falls to less than 9 years.

The principle policy implication of these findings are for complementary policies which encourage new renewable capacity. One feature of wind subsidies in the US is that relative to other policies, Production Tax Credits can exacerbate transmission constraints. PTCs encourage locating windfarms in areas with high capacity factors instead of locations with a high wholesale price of electricity. While it is beyond the scope of this paper to investigate, an investment tax credit (ITC) might preserve marginal incentives compared to a PTC since the PTC encourages investment in higher volume locations, regardless of price, on the margin.[33]

The major contribution of this analysis is for transmission capacity expansion. While there was no federal subsidy for transmission construction as part of the PTC, we show that ERCOT made investments to facilitate the increased level of electricity trade and increase overall welfare. As a result, ERCOT's current wholesale electricity market outcomes are a function of both its electricity generation portfolio (including wind capacity receiving PTC payments) and transmission investments from CREZ. Compared to a counterfactual world in which case there was no PTC and no CREZ, is ERCOT better off? The PTC is funded at the national level but ERCOT farms receive annual subsidies of roughly \$600M/year or 12% of the PTC.[34] This \$600M/year is a transfer from federal taxpayers to windfarm developers. If those developers live in ERCOT then citizens living in ERCOT are no bet-

[33]In the Appendix, we sketch a theoretical model which shows the comparative decrease in incentives to invest near high wholesale price areas due to the PTC and the ITC. Combined with the findings here, there is some evidence that policy makers should evaluate the merits of policies which don't have this incentive or the merits of complementary policies encouraging either transmission grid construction or storage technology. We don't claim that PTCs are always the least desirable second best policies for renewables but rather highlight a cost of this policy which hasn't yet received adequate attention in either the economics literature nor from policy makers.

[34]See `goo.gl/T3y8mu`.

ter or worse off when considering the PTC except insofar as they benefit from receiving a disproportionate amount of the PTC. According to the Census, Texas' population is roughly 28M people or 8.7% of the population.[35] However, windfarm developers and their financing partners receive a very large benefit: the CREZ combined with the PTC served to both subsidize windfarm development and then increases the revenue received by the windfarms. Reduced wholesale electricity prices in ERCOT induced by CREZ are both transfers from electricity producers in ERCOT to citizens. However, the cost of CREZ expansion is passed through to ratepayers in ERCOT leading to increased costs overall. Thus, the true welfare gains of CREZ conditional on the PTC depend on the impacts of local air pollutants and non-local air pollutants. Finally, since there are also non-market benefits to global citizens (reduced CO2), those global benefits must be internalized by regional decision makers for efficient global policies. These complexities highlight the challenge efficient policy given the current mechanism for investing in transmission capacity in the U.S.

Lastly, increased renewable penetration combined with low natural gas prices in the electricity sector is driving down prices in wholesale electricity markets and decreasing fossil fuel and nuclear generators viability to service debt. The question of revenue adequacy, capacity markets and "missing money" in which market signals (e.g., price caps, unpriced option value of generation capcity, etc.) don't provide sufficient incentives for the grid is back at the forefront of electricity policy circles (Joskow and Tirole (2007), Joskow (2008), Joskow (2013), and Cramton, Ockenfels, and Stoft (2013)). We hope this paper highlights how developing a functional market solution to ensure low cost and reliable electricity should account for efficient investment in the transmission system.

[35] See `https://www.census.gov/quickfacts/TX`.

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8 Appendix

8.1 Wind Capacity Figures

Figure 15 [36] shows the increasing trend of total wind capacity in the United States. We can see that wind capacity has increased dramatically since 2007. Figure 16 shows wind capacity distribution across the United States by state by the second quarter of 2015. Among all the states, Texas has the largest wind capacity, much more than California that follows.

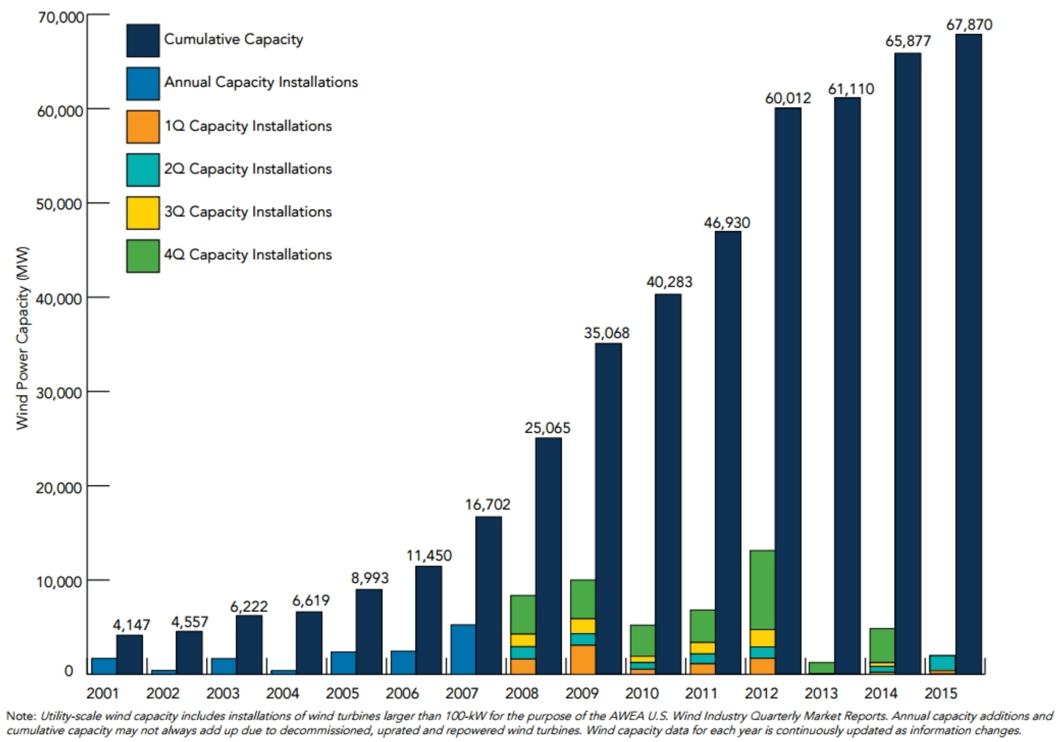

Figure 15: Wind Capacity by Year

[36] Source: https://cleantechnica.com/2015/08/06/us-installs-record-wind-capacity-q215-texas-reigns-supreme. Same for Figure 16.

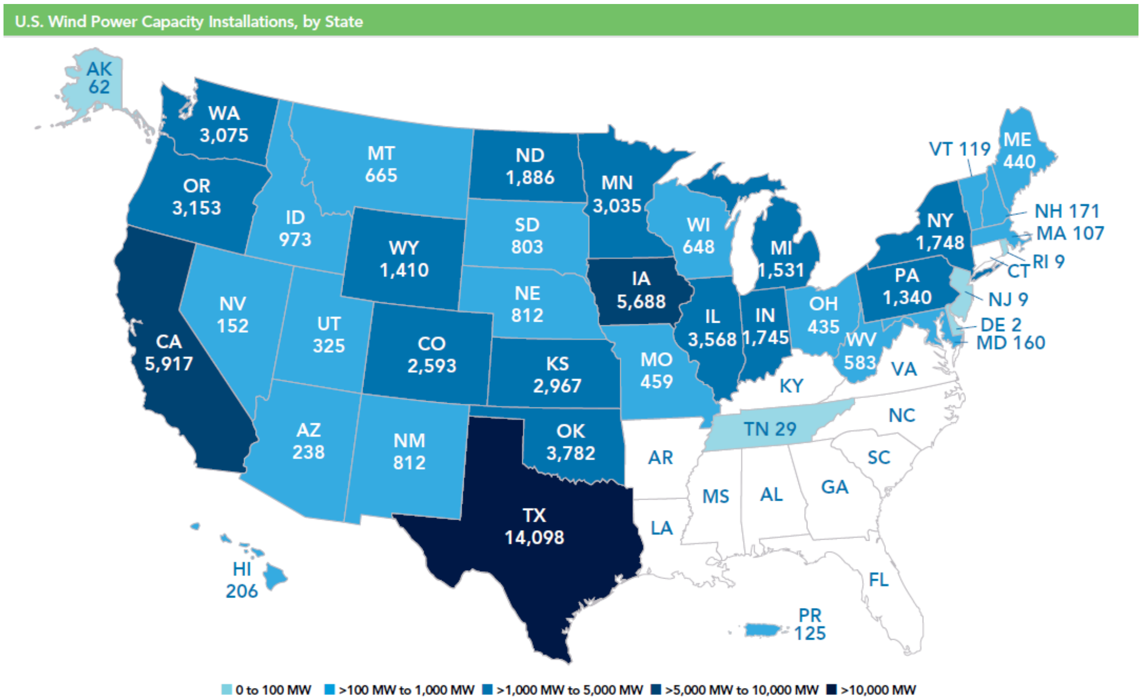

Figure 16: Wind Capacity by State by Q2 2015

8.2 Results For Real Time Markets and Other Zones

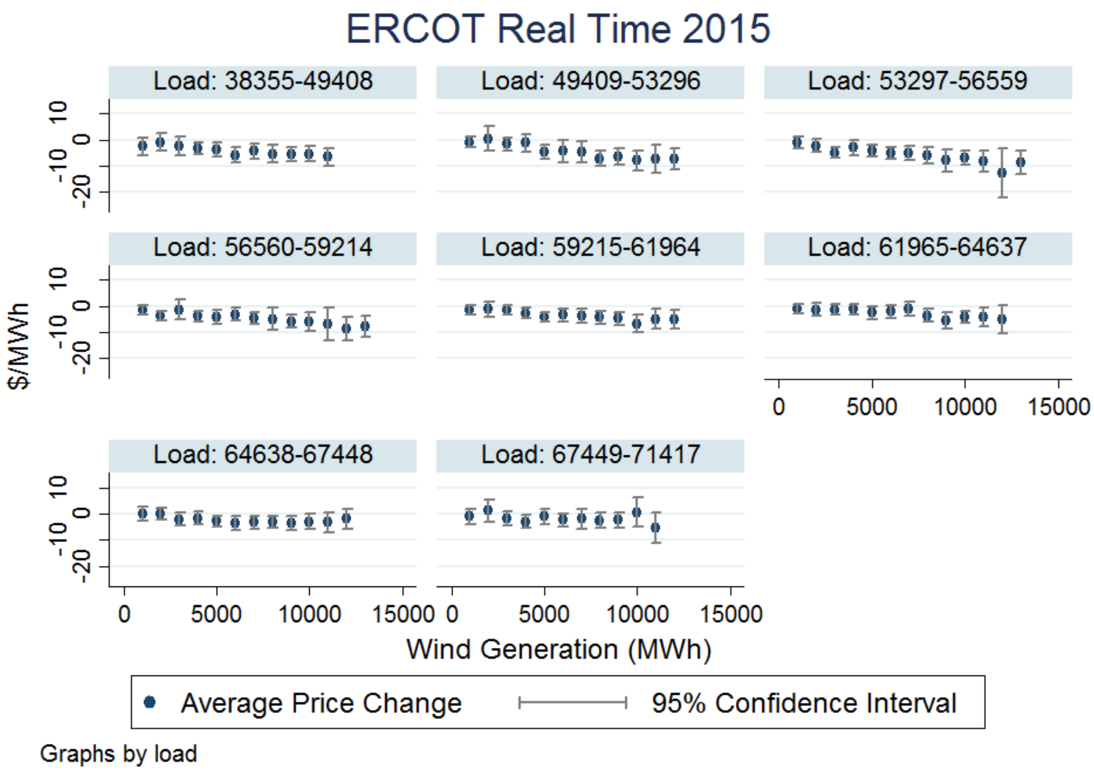

Figure 17: Effects of Wind Generation on Real Time Prices in ERCOT

Table A0 Impacts of CREZ and Wind Generation on Real Time Price Gap

VARIABLES	(1) South RT	(2) South RT	(3) North RT	(4) North RT	(5) Houston RT	(6) Houston RT
Net Supply (West)	3.458***	4.116***	3.526***	4.017***	3.588***	4.072***
	(0.237)	(0.393)	(0.193)	(0.341)	(0.218)	(0.389)
Net Demand (South)	1.658	0.309				
	(1.327)	(0.618)				
Net Supply (West)*Percent	-3.298***	-3.937***	-3.456***	-3.964***	-3.183***	-3.707***
	(0.261)	(0.426)	(0.206)	(0.361)	(0.284)	(0.451)
Net Demand (South)*Percent	-1.765	-0.231				
	(1.410)	(0.740)				
Net Demand (North)			0.115	0.529		
			(0.161)	(0.422)		
Net Demand (North)*Percent			-0.0994	-0.442		
			(0.174)	(0.463)		
Net Demand (Houston)					-0.271	-0.536
					(0.433)	(0.724)
Net Demand (Houston)*Percent					0.742	0.731
					(0.529)	(1.091)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.098	0.260	0.173	0.352	0.068	0.198
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

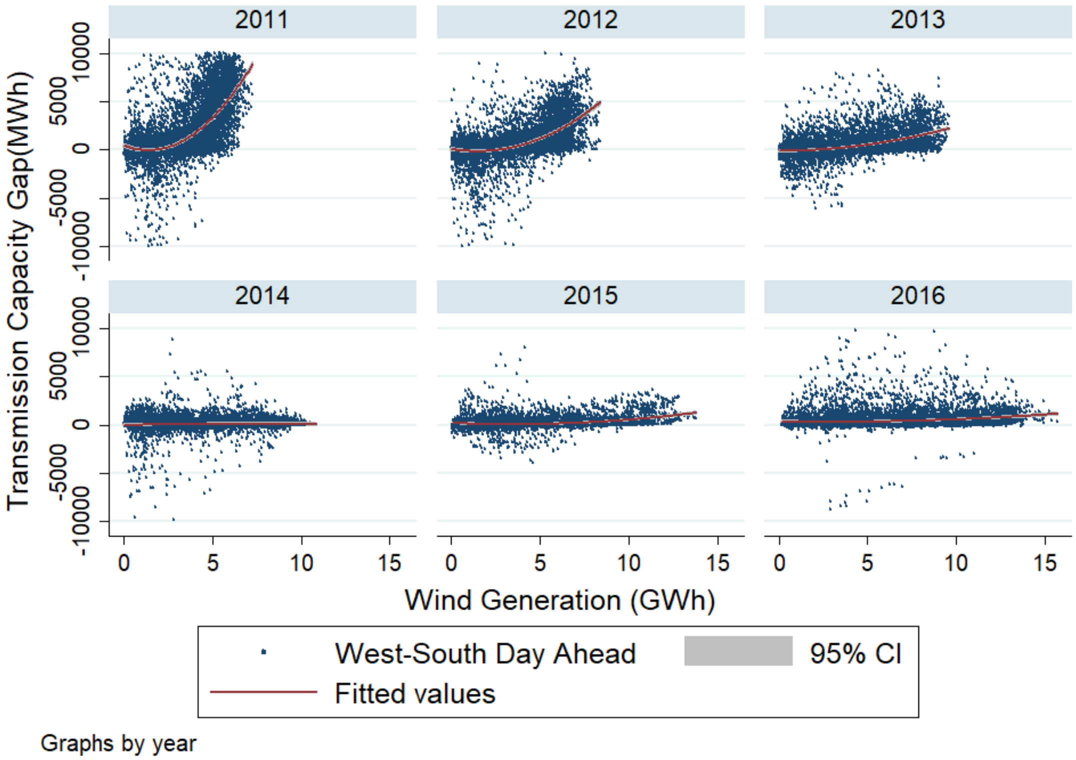

Figure 18: Implied transmissions shortfall by year: West-South DA.

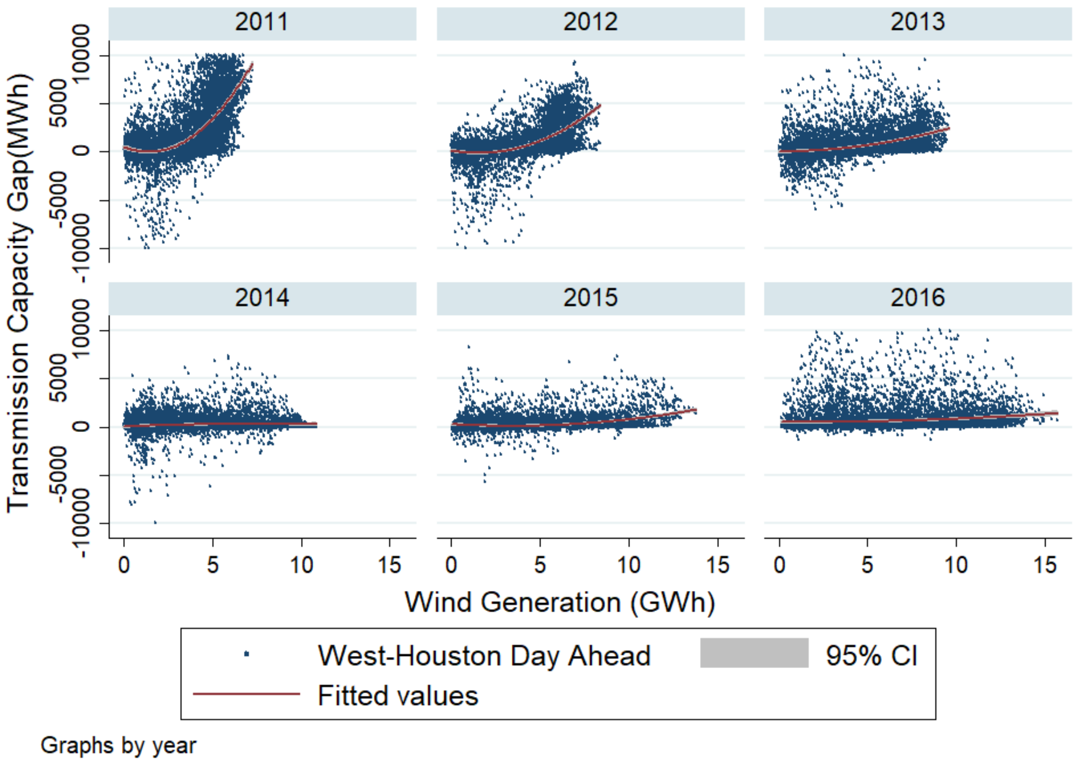

Figure 19: Implied transmissions shortfall by year: West-Houston DA.

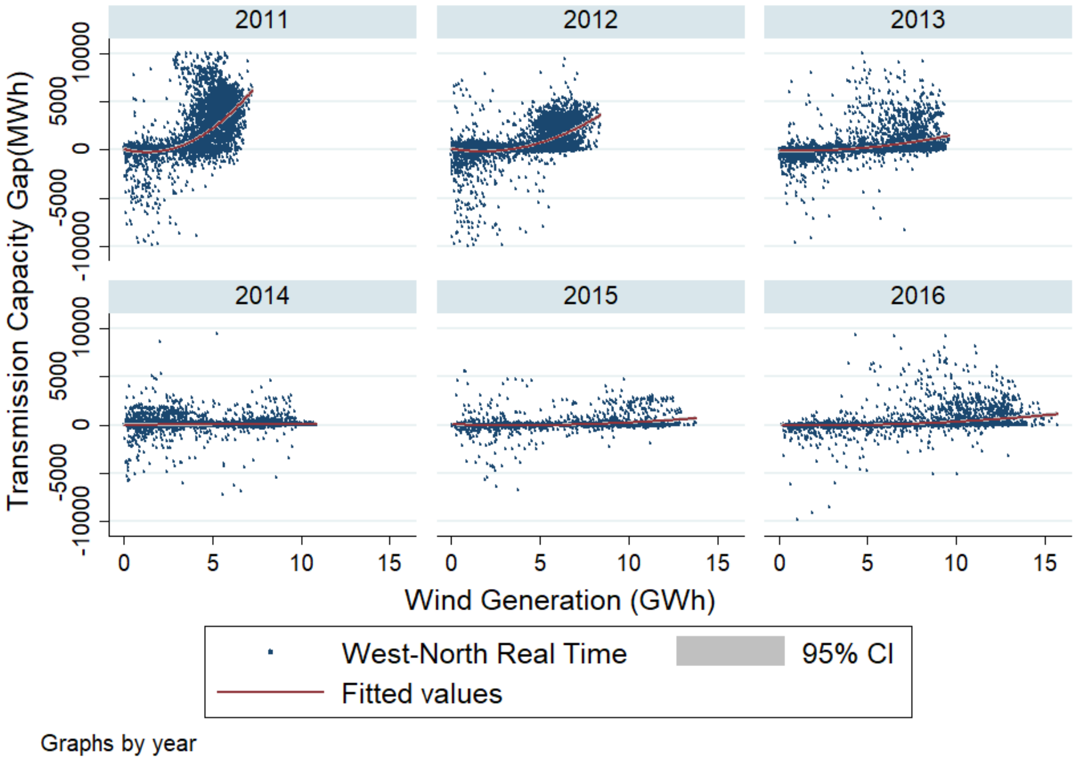

Figure 20: Implied transmissions shortfall by year: West-North RT.

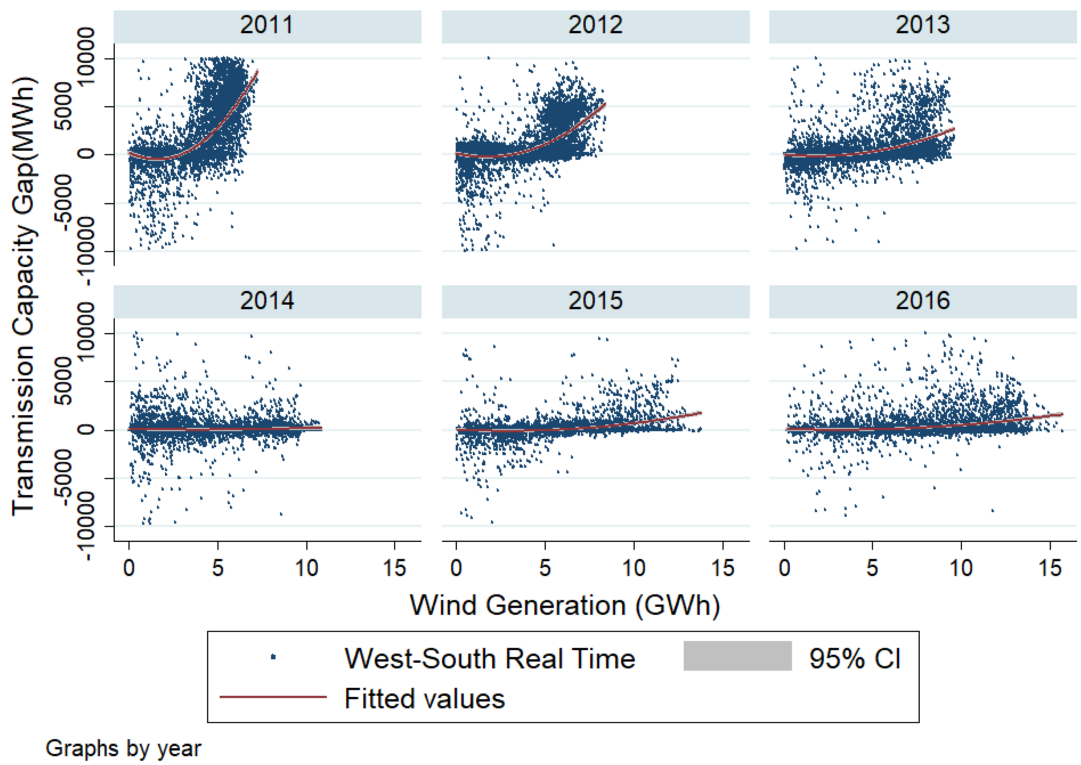

Figure 21: Implied transmissions shortfall by year: West-South RT.

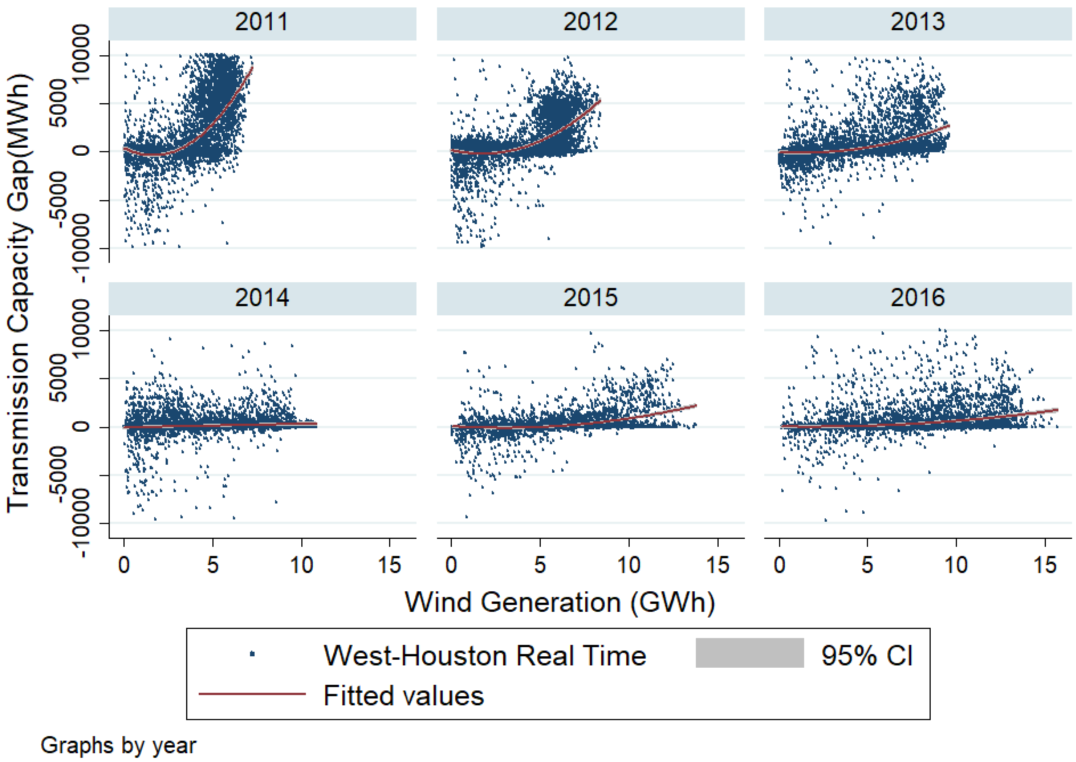

Figure 22: Implied transmissions shortfall by year: West-Houston RT.

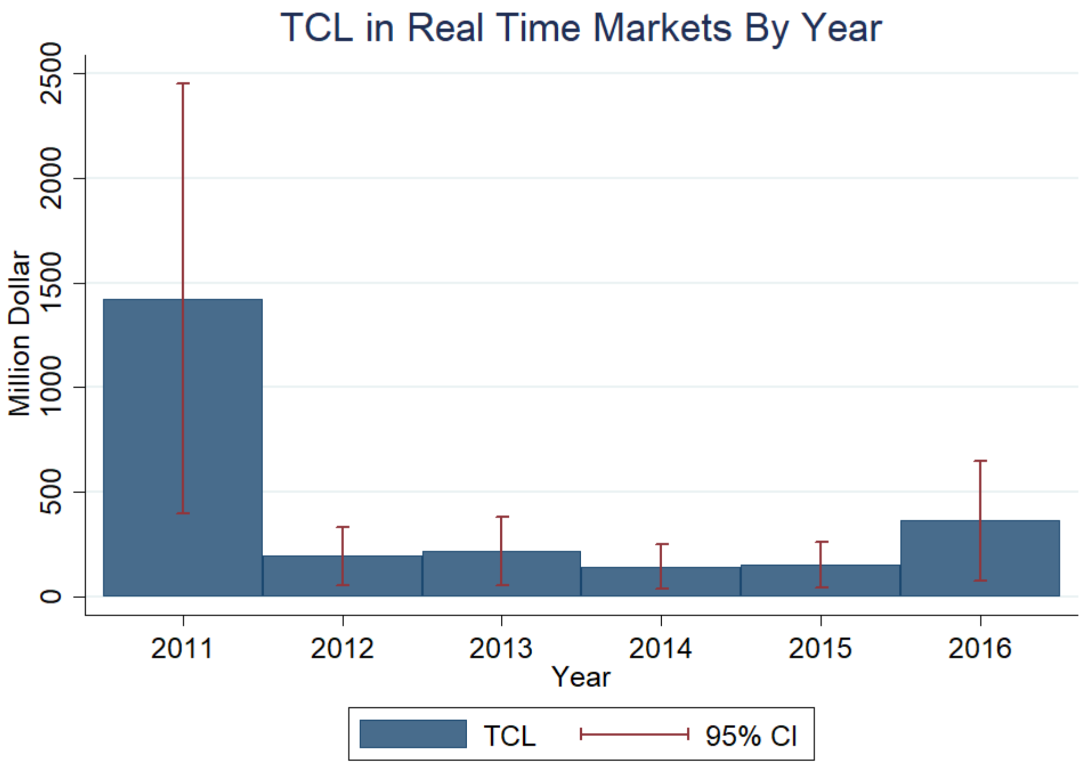

Figure 23: Yearly sum transmission constraint losses for all regions RT.

8.3 Robustness Checks

Table A1 Impacts of CREZ on Price Gap: Cluster By Week

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South DA	North RT	North DA	Houston RT	Houston DA
Percent Completion	-5.864***	-4.650***	-6.206***	-5.353***	-5.511***	-4.322***
	(0.812)	(0.618)	(0.678)	(0.513)	(0.854)	(0.610)
Net Supply (West)	0.817***	0.535***	0.779***	0.491***	0.960***	0.575***
	(0.0769)	(0.0470)	(0.0721)	(0.0461)	(0.0963)	(0.0487)
Net Demand (South)	0.105	-0.00994				
	(0.0866)	(0.0485)				
Net Demand (North)			0.0180	-0.0329		
			(0.0379)	(0.0300)		
Net Demand (Houston)					0.247**	0.136**
					(0.0981)	(0.0605)
Constant	3.492***	3.975***	4.251***	4.578***	1.774	2.492***
	(0.917)	(0.590)	(0.798)	(0.529)	(1.249)	(0.688)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.022	0.107	0.056	0.193	0.013	0.111

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A2 Impacts of CREZ and Wind Generation on Real Time Price Gap: Cluster By Week

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South RT	North RT	North RT	Houston RT	Houston RT
Net Supply (West)	3.458***	4.116***	3.526***	4.017***	3.588***	4.072***
	(0.320)	(0.506)	(0.296)	(0.453)	(0.311)	(0.503)
Net Demand (South)	1.658	0.309				
	(1.226)	(0.681)				
Net Supply (West)*Percent	-3.298***	-3.937***	-3.456***	-3.964***	-3.183***	-3.707***
	(0.344)	(0.541)	(0.314)	(0.480)	(0.363)	(0.563)
Net Demand (South)*Percent	-1.765	-0.231				
	(1.303)	(0.804)				
Net Demand (North)			0.115	0.529		
			(0.160)	(0.477)		
Net Demand (North)*Percent			-0.0994	-0.442		
			(0.175)	(0.525)		
Net Demand (Houston)					-0.271	-0.536
					(0.425)	(0.665)
Net Demand (Houston)*Percent					0.742	0.731
					(0.530)	(1.046)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.098	0.260	0.173	0.352	0.068	0.198
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A3 Impacts of CREZ and Wind Generation on Day Ahead Price Gap: Cluster By Week

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South DA	South DA	North DA	North DA	Houston DA	Houston DA
Net Supply (West)	2.066***	1.662***	2.154***	1.665***	2.200***	1.725***
	(0.160)	(0.136)	(0.168)	(0.132)	(0.170)	(0.134)
Net Demand (South)	-0.0923	0.000750				
	(0.220)	(0.201)				
Net Supply (West)*Percent	-1.980***	-1.625***	-2.158***	-1.662***	-2.044***	-1.662***
	(0.170)	(0.145)	(0.178)	(0.140)	(0.181)	(0.147)
Net Demand (South)*Percent	0.0582	0.0958				
	(0.250)	(0.227)				
Net Demand (North)			-0.0984	0.00351		
			(0.0887)	(0.115)		
Net Demand (North)*Percent			0.110	0.0584		
			(0.0962)	(0.127)		
Net Demand (Houston)					-0.396	-0.260
					(0.244)	(0.173)
Net Demand (Houston)*Percent					0.669**	0.609***
					(0.282)	(0.228)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.415	0.652	0.526	0.784	0.470	0.710
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A4 Impacts of CREZ on Price Gap: Trim Data

VARIABLES	(1) South RT	(2) South DA	(3) North RT	(4) North DA	(5) Houston RT	(6) Houston DA
Percent Completion	-8.333***	-6.739***	-8.095***	-7.151***	-8.203***	-6.317***
	(1.221)	(0.497)	(0.684)	(0.427)	(1.229)	(0.503)
Net Supply (West)	1.777***	1.235***	1.782***	1.167***	1.825***	1.258***
	(0.114)	(0.0605)	(0.0935)	(0.0564)	(0.131)	(0.0587)
Net Demand (South)	0.176	-0.111**				
	(0.126)	(0.0484)				
Net Demand (North)			0.0820*	-0.0143		
			(0.0457)	(0.0257)		
Net Demand (Houston)					0.152**	-0.0421
					(0.0736)	(0.0401)
Constant	2.609**	4.849***	2.959***	4.197***	2.743**	4.311***
	(1.195)	(0.450)	(0.871)	(0.399)	(1.131)	(0.478)
Observations	28,460	28,460	28,460	28,460	28,460	28,460
R-squared	0.037	0.174	0.084	0.255	0.029	0.203

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors clustered by sample day are reported in parentheses.

Table A5 Impacts of CREZ and Wind Generation on Real Time Price Gap: Trim Data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South RT	North RT	North RT	Houston RT	Houston RT
Net Supply (West)	3.828***	4.228***	3.915***	4.369***	3.970***	4.430***
	(0.277)	(0.448)	(0.220)	(0.382)	(0.247)	(0.430)
Net Demand (South)	2.064	0.229				
	(1.371)	(0.721)				
Net Supply (West)*Percent	-4.316***	-4.266***	-4.525***	-4.944***	-4.199***	-4.730***
	(0.433)	(0.653)	(0.301)	(0.490)	(0.408)	(0.582)
Net Demand (South)*Percent	-3.084*	0.0651				
	(1.645)	(1.202)				
Net Demand (North)			0.243	0.760		
			(0.169)	(0.479)		
Net Demand (North)*Percent			-0.498**	-1.118*		
			(0.215)	(0.646)		
Net Demand (Houston)					0.193	-0.924
					(0.448)	(0.814)
Net Demand (Houston)*Percent					-0.789	2.034
					(0.677)	(1.251)
Observations	28,460	28,460	28,460	28,460	28,460	28,460
R-squared	0.106	0.270	0.171	0.347	0.089	0.213
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A6 Impacts of CREZ and Wind Generation on Day Ahead Price Gap: Trim Data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South DA	South DA	North DA	North DA	Houston DA	Houston DA
Net Supply (West)	2.269***	1.750***	2.429***	1.805***	2.398***	1.851***
	(0.136)	(0.116)	(0.117)	(0.104)	(0.123)	(0.109)
Net Demand (South)	0.172	0.105				
	(0.458)	(0.224)				
Net Supply (West)*Percent	-2.534***	-1.869***	-2.919***	-2.051***	-2.576***	-2.021***
	(0.184)	(0.161)	(0.158)	(0.130)	(0.179)	(0.150)
Net Demand (South)*Percent	-0.805	-0.193				
	(0.527)	(0.303)				
Net Demand (North)			-0.00296	0.0264		
			(0.0840)	(0.141)		
Net Demand (North)*Percent			-0.189*	-0.00680		
			(0.109)	(0.184)		
Net Demand (Houston)					-0.119	-0.138
					(0.187)	(0.199)
Net Demand (Houston)*Percent					-0.249	0.297
					(0.266)	(0.301)
Observations	28,460	28,460	28,460	28,460	28,460	28,460
R-squared	0.417	0.653	0.513	0.778	0.469	0.723
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A7 Impacts of CREZ on Price Gap: Control For All Load

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South DA	North RT	North DA	Houston RT	Houston DA
Percent Completion	-6.097***	-4.926***	-6.261***	-5.380***	-6.188***	-4.765***
	(0.566)	(0.321)	(0.468)	(0.295)	(0.642)	(0.314)
Net Supply (West)	0.772***	0.499***	0.774***	0.488***	0.883***	0.522***
	(0.0516)	(0.0250)	(0.0407)	(0.0240)	(0.0789)	(0.0253)
Net Demand (South)	1.362**	0.620***	0.426***	0.433***	-0.139	0.169
	(0.610)	(0.195)	(0.145)	(0.0816)	(0.338)	(0.153)
Net Demand (North)	-0.754***	-0.524***	-0.169**	-0.202***	-0.680***	-0.544***
	(0.117)	(0.0543)	(0.0766)	(0.0434)	(0.132)	(0.0549)
Net Demand (Houston)	-0.250	0.0705	-0.140	-0.175***	1.203***	0.645***
	(0.509)	(0.154)	(0.0972)	(0.0539)	(0.312)	(0.120)
Constant	4.232***	4.197***	4.195***	4.588***	1.909*	2.683***
	(0.803)	(0.373)	(0.636)	(0.326)	(1.054)	(0.389)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.025	0.120	0.057	0.196	0.015	0.133

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A8 Impacts of CREZ and Wind Generation on Real Time Price Gap: Control For All Load

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South RT	North RT	North RT	Houston RT	Houston RT
Net Supply (West)	3.521***	4.130***	3.547***	4.017***	3.588***	4.086***
	(0.218)	(0.394)	(0.195)	(0.342)	(0.217)	(0.391)
Net Demand (South)	4.572	1.233	-0.0258	-0.215	-0.235	0.705
	(3.293)	(1.324)	(0.603)	(0.940)	(0.816)	(1.501)
Net Demand (North)	-0.121	0.212	0.370	0.707	0.207	0.424
	(0.408)	(0.597)	(0.289)	(0.454)	(0.383)	(0.735)
Net Demand (Houston)	-3.179	-1.426	-0.547	-0.181	-0.328	-1.424
	(2.104)	(1.065)	(0.510)	(0.853)	(0.700)	(1.099)
Net Supply (West)*Percent	-3.402***	-3.968***	-3.476***	-3.965***	-3.234***	-3.728***
	(0.240)	(0.427)	(0.208)	(0.362)	(0.281)	(0.453)
Net Demand (South)*Percent	-4.528	-0.704	-0.0386	0.408	-0.0409	-1.605
	(3.565)	(1.512)	(0.659)	(1.017)	(0.967)	(1.824)
Net Demand (North)*Percent	-0.653	-0.822	-0.324	-0.709	-0.936*	-0.432
	(0.512)	(0.724)	(0.322)	(0.504)	(0.523)	(0.909)
Net Demand (Houston)*Percent	4.209*	1.683	0.537	0.168	1.910**	2.266
	(2.304)	(1.223)	(0.548)	(0.932)	(0.863)	(1.414)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.101	0.261	0.173	0.352	0.069	0.198
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A9 Impacts of CREZ and Wind Generation on Day Ahead Price Gap: Control For All Load

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South DA	South DA	North DA	North DA	Houston DA	Houston DA
Net Supply (West)	2.061***	1.664***	2.163***	1.667***	2.172***	1.728***
	(0.114)	(0.104)	(0.103)	(0.0947)	(0.104)	(0.0988)
Net Demand (South)	0.414	0.216	-0.432	0.182	-0.692	0.327
	(1.090)	(0.350)	(0.276)	(0.271)	(0.719)	(0.298)
Net Demand (North)	-0.236	0.0624	0.168	0.0492	-0.146	0.0475
	(0.168)	(0.177)	(0.132)	(0.154)	(0.150)	(0.174)
Net Demand (Houston)	-0.228	-0.358	-0.101	-0.321	0.355	-0.541**
	(0.702)	(0.317)	(0.215)	(0.220)	(0.489)	(0.261)
Net Supply (West)*Percent	-1.990***	-1.629***	-2.167***	-1.664***	-2.031***	-1.667***
	(0.121)	(0.111)	(0.108)	(0.1000)	(0.111)	(0.108)
Net Demand (South)*Percent	-0.559	-0.236	0.402	-0.175	0.598	-0.637*
	(1.181)	(0.390)	(0.298)	(0.292)	(0.787)	(0.338)
Net Demand (North)*Percent	0.0758	-0.137	-0.133	-0.000763	-0.0460	-0.00623
	(0.189)	(0.202)	(0.145)	(0.169)	(0.177)	(0.208)
Net Demand (Houston)*Percent	0.626	0.614*	0.0753	0.346	0.231	1.074***
	(0.768)	(0.359)	(0.233)	(0.238)	(0.544)	(0.305)
Observations	52,575	52,575	52,575	52,575	52,575	52,575
R-squared	0.417	0.653	0.528	0.784	0.474	0.710
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A10 Identification of Net Supply and Net Demand Curves West and North DA

VARIABLES	(1) P(North) P(Gap)> 1 Year <= 2013	(2) P(West) P(Gap)> 1 Year <= 2013	(3) P(North) P(Gap)> 2 Year <= 2013	(4) P(West) P(Gap)> 2 Year <= 2013	(5) P(North) P(Gap)> 5 Year <= 2013	(6) P(West) P(Gap)> 5 Year <= 2013
Net Demand (North)	0.477**	0.870***	0.379	0.917***	0.604**	1.027***
	(0.241)	(0.321)	(0.240)	(0.342)	(0.269)	(0.323)
Net Supply (West)	-0.899***	-2.505***	-0.916***	-2.730***	-0.816***	-2.406***
	(0.154)	(0.202)	(0.147)	(0.225)	(0.213)	(0.310)
Observations	8,699	8,699	6,478	6,478	4,262	4,262
R-squared	0.725	0.743	0.918	0.893	0.934	0.894
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

Table A11 Net Supply and Net Demand Curves North: Top 10% load hours trimmed

VARIABLES	(1) P(North) P(Gap)> 1	(2) P(West) P(Gap)> 1	(3) P(North) P(Gap)> 2	(4) P(West) P(Gap)> 2	(5) P(North) P(Gap)> 5	(6) P(West) P(Gap)> 5
Net Demand (North)	0.464**	0.727***	0.385*	0.801***	0.291*	0.609**
	(0.192)	(0.256)	(0.204)	(0.286)	(0.168)	(0.309)
Net Supply (West)	-0.787***	-2.228***	-0.781***	-2.465***	-0.828***	-2.404***
	(0.145)	(0.189)	(0.183)	(0.245)	(0.216)	(0.324)
Observations	9,698	9,698	6,903	6,903	4,173	4,173
R-squared	0.838	0.838	0.847	0.841	0.962	0.934
Year-Month-Hour FE	YES	YES	YES	YES	YES	YES
Sample Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

8.4 Production Tax Credits and Location Incentives

Consider how a production tax credit (PTC) can interact with congestion constraints described in the theoretical model above and lead to decreased incentives to invest in high value areas where electricity fetches a high price. The goal of this subsection is to show how a PTC creates an incentive to invest in areas with high levels of wind generation, regardless of wholesale electricity price, relative to other policies. We then describe how high initial PTC levels could lead to investment in wind generation capacity even when severe congestion constraints exist. This motivates the subsequent research design as it highlights how wind construction decisions might be somewhat exogenous with respect to the precise timing of CREZ completion.

As a first step, consider the equilibrium quantity of electricity trading if there were no transmission constraints. This would mean prices in the exporting node A and importing Node B equalize. This implicitly defines the unconstrained amount of traded electricity Q as a function of wind generation and market characteristics:

$$\begin{aligned} a_B + b_B L_t^B - b_B Q^* &= a_A + b_A(L_t^A - W_t) + b_A Q^* \\ Q^*(W) &= \frac{a_B - a_A + b_B L_t^B - b_A(L_t^A - W_t)}{b_A + b_B} \end{aligned} \tag{21}$$

This convenient expression lets us determine how the volume of traded electricity changes with wind generation: $\frac{\partial Q^*}{\partial W} = \frac{b_A}{b_A + b_B} < 1$. This is the familiar expression that the rate of change in Q is a function of the relative slopes of the supply and demand curve when there are no capacity constraints: $Q^* < K$. Alternatively, if there are capacity constraints, the total change in traded quantity is zero, by definition: $\frac{\partial Q^*}{\partial W} = 0$ if $Q^* \geq K$.

Plugging in equilibrium Q^* in the price equation for node A provides insights on how additional wind generation would impact equilibrium price in node A (e.g., the wind generation hub) with and without capacity constraints. Specifically, if $Q^* < K$ then $\frac{\partial P_A^*}{\partial W} = b_A(\frac{b_A}{b_A+b_B} - 1) < 0$. Note that $-1 < (\frac{b_A}{b_A+b_B} - 1) < 0$. Alternatively, if $Q^* \geq K$ then $\frac{\partial P_A^*}{\partial W} = -b_A$. As a result, we have the simple result that in equilibrium, $abs(\frac{\partial P_A^*}{\partial W})|Q^* < K| < abs(\frac{\partial P_A^*}{\partial W})|Q^* \geq K$, where $abs()$ is the absolute value operator. In words, this means that the price impact on increased wind generation in the exporting region is larger (e.g., more negative) if there are capacity constraints. At a high level, the barrier to trade due to transmission constraints harms wind generators in node A relative to when there is no transmission constraint.

Now consider the firms investment decision with and without a PTC subsidy. In this simple model, we ignore investment costs to focus solely on how different subsidy schemes interact with transmission constraints. Note that W is the quantity of wind generation sold, hence $P * W$ is revenue to a representative wind farm in node A. In equilibrium, total revenue for wind farms is $TR = P(Q(W)) * W$ in the absence of a PTC and $TR = (P(Q(W)) + s) * W$ with a production tax credit of s.

One way to see the interaction of the PTC with capacity constraints is to evaluate the marginal impact of wind generation on total revenue to the total revenue of a wind farm in the presence of capacity constraints both with and without the PTC. We can then compare the PTC to other policy instruments. For example, consider a subsidy on the wholesale price of electricity, $\tau > 0$: $TR = P(Q(W)) * (1 + \tau) * W$. The marginal revenue to a wind farm for a marginal increase in wind generation when $Q_t^* > K$ is:

$$\begin{aligned}
w/\ PTC \quad \frac{\partial TR}{\partial W} &= \frac{\partial P^*(W)}{\partial W} W + P^*(W) + s \\
&= -b_A W + P^*(W) + s \qquad (22) \\
w/\ price\ subsidy: \quad \frac{\partial TR}{\partial W} &= \frac{\partial P^*(W)}{\partial W}(1+\tau)W + P^*(W)(1+\tau) \\
&= -b_A W(1+\tau) + P^*(W)(1+\tau) \qquad (23)
\end{aligned}$$

The first first term in both equations (22) and (23) is the indirect price impact of additional wind generation and the second term is the quantity impact. Because $\tau > 0$ the price decrease of additional wind is internalized more with a price instrument (τ) relative to a quantity instrument with the PTC (s) conditional on W: $-b_A W(1 + \tau) < -b_A W$. The quantity impact of the policy instrument (e.g., the second terms) are not directly comparable. More importantly, there is no interaction of the PTC and market signals to windfarms: $\frac{\partial^2 TR}{\partial W \partial s} = 1$. For a price based subsidy, there is an interaction: $\frac{\partial^2 TR}{\partial W \partial \tau} = -b_A W + P^*(W)$. Note that an investment tax credit would not impact marginal incentives whatsoever since there is no impact price nor quantity interaction from a cost based policy.[37]

In sum, this framework shows that with transmission constraints, there is no feedback link between the policy instrument and price. Intuitively, a PTC creates an incentive to invest in areas with high levels of wind generation, regardless of price. A price subsidy or investment tax credit leverages, or at least preserves, price signals to the investor. As a result, we would expect the nature of a PTC to impact the location of wind farms on the margin to areas with high levels of wind generation, even in the presence of transmission constraints.

[37] In particular if $TR = P(Q(W)) * W + t$ then $\frac{\partial^2 TR}{\partial W \partial t} = 0$.

8.5 Net Supply and Demand Non-linearities and TCLs

Introducing non-linearity into the net supply and net demand models requires care in augmenting equations (12) and (13) used to estimate the net supply and net demand slope parameters. Adding polynomials in net supply/demand is not feasible because we need to perform functions on the slope coefficients to subsequently calculate the transmission capacity gap. Polynomials don't easily allow that because the slope is a function of the net supply/demand levels which are themselves changing over time.

We perform the following procedure to allow for non-linearity: first we trim the sample to include the sample we use to estimate equations (12) and (13) (e.g., only hours where we observe a price gap of \$2/MWh or more). Second, we create a dummy variable equal to one when the price gap is above the median price gap in the sample. Third, we interact that indicator variable with net supply and net demand, to test for a change in the net supply and net demand elasticities for large or small level of net demand or net supply:

$$p_t^A = \alpha + \beta(W_t - L_t^A) + \beta^h 1\{W_t - L_t^A \geq P_{50|\eta>\$2}\} * (W_t - L_t^A) + \gamma_2 L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (24)$$

$$p_t^B = \alpha + \beta_2(W_t - L_t^A) + \beta_2^h 1\{W_t - L_t^A \geq P_{50|\eta>\$2}\} * (W_t - L_t^A) + \gamma L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (25)$$

The coefficients of interest in these regressions are β^h and β_2^h respectively. A estimated coefficient which is significantly different from zero means elasticities change for net supply gaps above the median conditional on price differences great than \$2/MWh.

Table A12 Identification of Slopes North DA: Nonlinear Checks

VARIABLES	(1) P(North) P(Gap)> 2	(2) P(West) P(Gap)> 2
Net Demand (North)	0.630**	1.012***
	(0.268)	(0.333)
Net Supply (West)	-0.767***	-2.121***
	(0.192)	(0.364)
1(Net Demand Above Median)*Net Demand	-0.0356	
	(0.0317)	
1(Net Supply Above Median)*Net Supply		-0.304*
		(0.180)
Observations	7,326	7,326
R-squared	0.861	0.856
Year-Month-Hour FE	YES	YES
Sample Day FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Standard errors clustered by sample day are reported in parentheses.

Table A13 Identification of Slopes South DA: Nonliear Checks

VARIABLES	(1) P(South) P(Gap)> 2	(2) P(West) P(Gap)> 2
Net Demand (South)	0.619	1.071
	(0.743)	(0.653)
Net Supply (West)	-0.940***	-1.643***
	(0.228)	(0.388)
1(Net Demand Above Median)*Net Demand	0.0547	
	(0.0878)	
1(Net Supply Above Median)*Net Supply		-0.352
		(0.240)
Observations	10,895	10,895
R-squared	0.806	0.810
Year-Month-Hour FE	YES	YES
Sample Day FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Standard errors clustered by sample day are reported in parentheses.

Table A14 Identification of Slopes Houston DA: Nonliear Checks

VARIABLES	(1) P(Houston) P(Gap)> 2	(2) P(West) P(Gap)> 2
Net Demand (Houston)	1.199***	1.061***
	(0.363)	(0.349)
Net Supply (West)	-0.592***	-1.459***
	(0.166)	(0.345)
1(Net Demand Above Median)*Net Demand	-0.0132	
	(0.0497)	
1(Net Supply Above Median)*Net Supply		-0.143
		(0.226)
Observations	12,689	12,689
R-squared	0.838	0.839
Year-Month-Hour FE	YES	YES
Sample Day FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered by sample day are reported in parentheses.

The Tables show the results of the regressions for day-ahead elasticities for the North, South and Houston all relative to the West. The general result is that there doesn't appear to be any strong evidence of non-linearity in the net demand nor net supply curves with non-linearity defined in this way. Only between the West and the North is there mild evidence of a non-linearity increasing net supply elasticity for high levels of net supply: -.304 versus -2.121 or a 14% increase significant at the 10% level.

Focusing on the West to North relationship we use the estimated non-linear net supply and net demand slope coefficients to construct transmission shortfalls. By inspection, the findings are very similar to the linear counterparts shown in them main text. Figure 24 shows the same flattening over time. Figures 25 shows TCLs for market impacts and Figure 26 shows TCLs for non-market impacts using the non-linear results for each region. We again observe no qualitative nor quantitative difference between these findings and those from the main text.

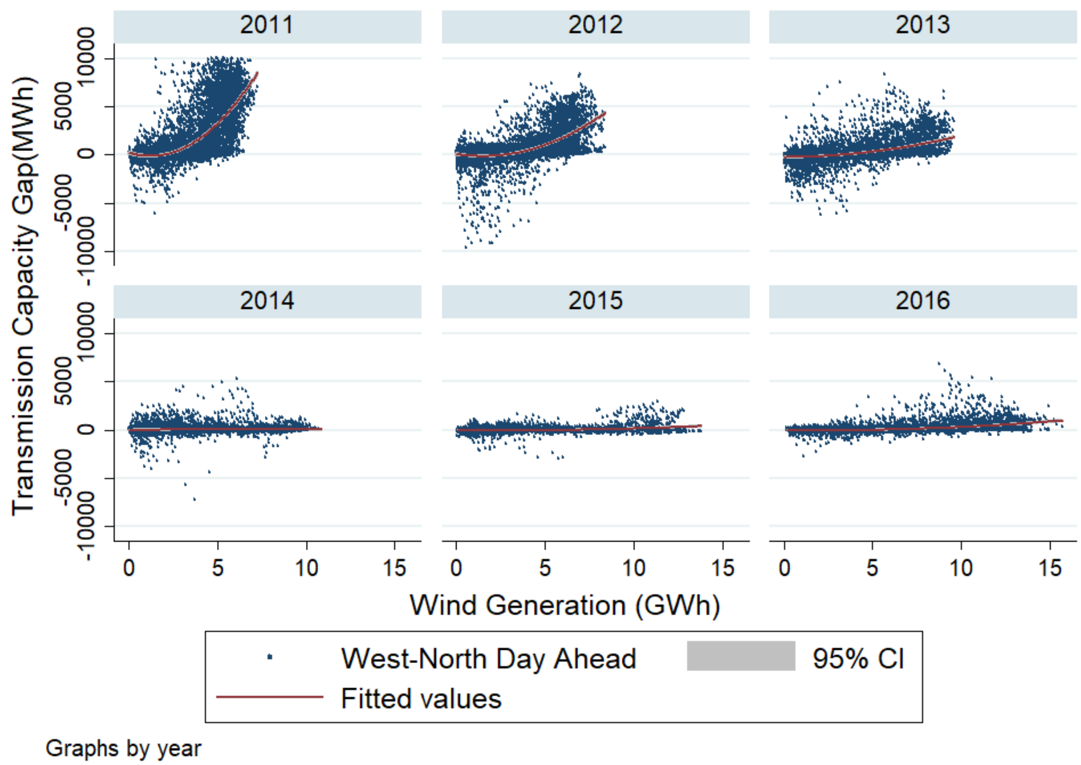

Figure 24: Implied transmissions shortfall by year with Non-linear model: West-North DA.

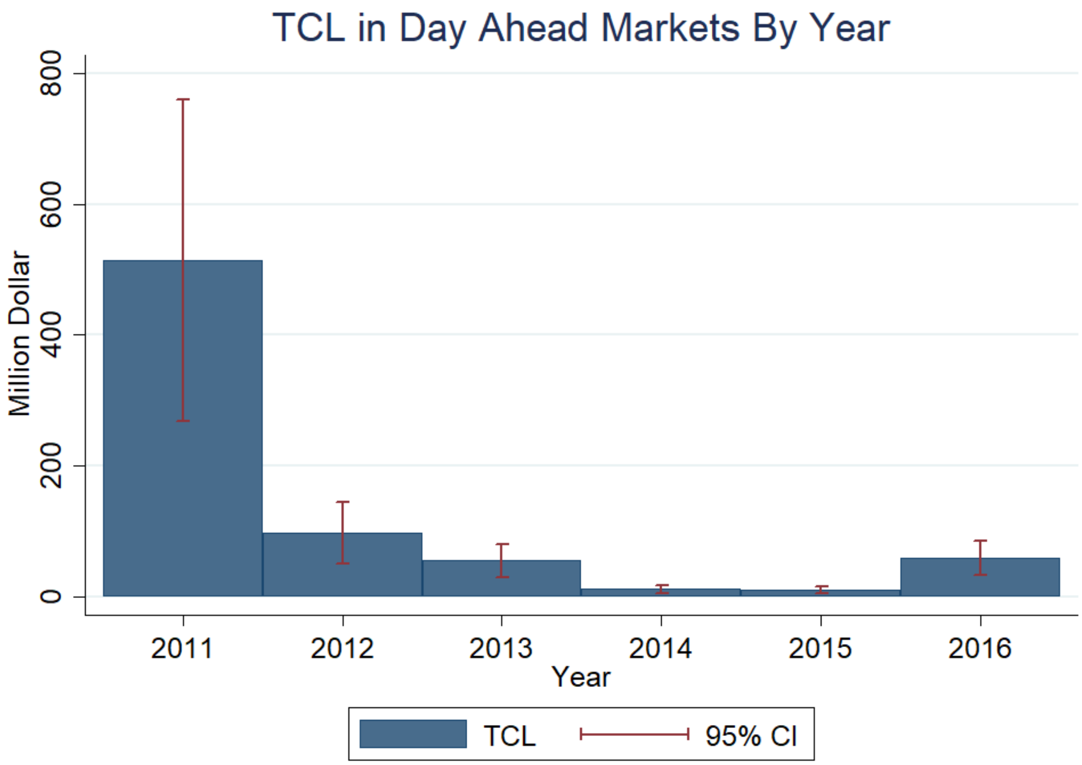

Figure 25: Market TCL for ERCOT with non-linear DA model

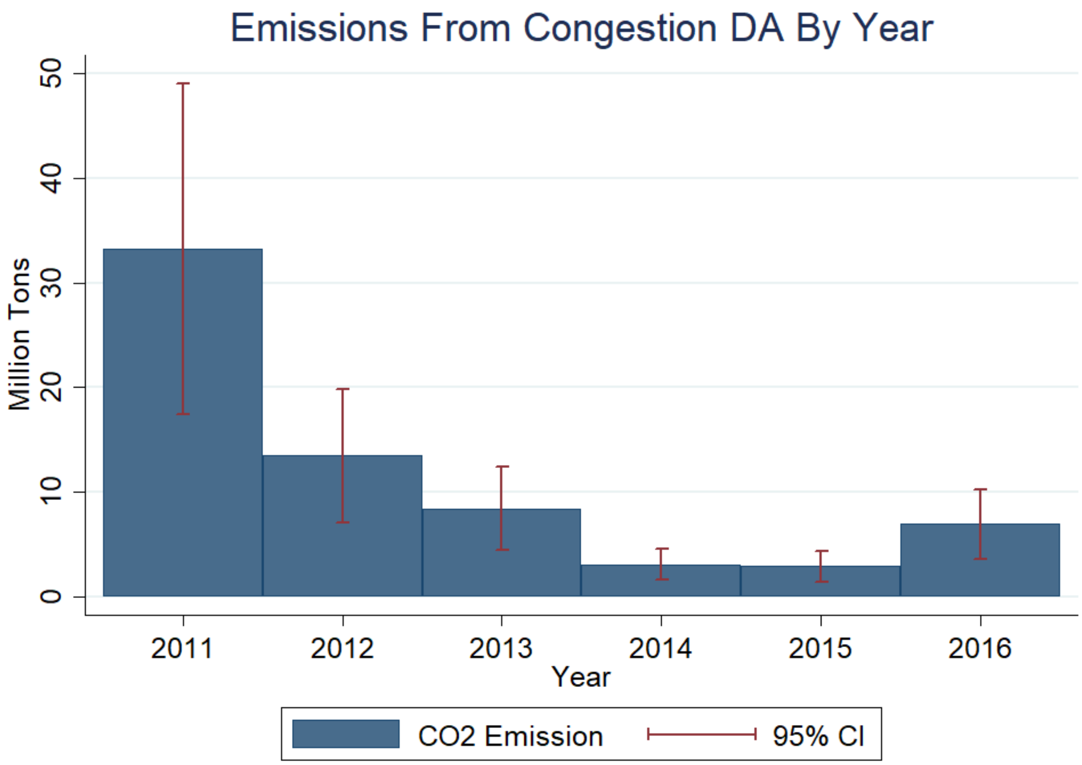

Figure 26: Non-market TCL for ERCOT with non-linear DA model