Transmission Constraints, Intermittent Renewables and Welfare

Jacob LaRiviere[a] and Xueying Lyu[b]

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. The value of transmission expansion varies greatly with how it impacts new renewable investment with payback periods ranging from 40 years (no impact) to 21 years (observed capacity increase attributed to transmission expansion). Welfare improvements also depend critically on how global pollutants like carbon and regional pollutants like PM 2.5 are internalized by regional policy makers reducing the payback period further to as little as 11 years.

JEL Codes: D03; Q58

Keywords: Electricity; Industrial Organization; Policy instruments.

[a]Microsoft, jlariv@microsoft.com. Theoretical Model, Research Design, Manuscript. Declarations of interest: none.

[b]Corresponding author. Nankai University, School of Economics, 94 Weijin Road, Nankai District, Tianjin, China, 300071. Email: xueying@nankai.edu.cn. Empirical Work, Research Design, Manuscript. Declarations of interest: none. Seminar participants at UCSD, UCLA, Penn State, Vanderbilt, and Yale provided feedback which improved this research. Judson Boomhower, Ken Davies, Brian Janous, Brian Marrs, and Vanessa Miller provided very useful feedback.

1 Introduction

Because electricity is non-storable, electricity produced at one location must be moved via transmission lines to locations where it is immediately 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 generation capacity are straining the grid and advocates argue that wind farms require more transmission to fully benefit investors, ratepayers, and federal taxpayers subsidizing pollutant free wind.[1]

There is reason to believe that transmission line construction cannot be provided efficiently 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.

Regional electricity entities that plan transmission construction must respond to federal energy policies thereby creating a regulatory federalism issue. One sharp example is the federal Production Tax Credit (PTC) designed to spur investment in wind generation. 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. Windfarm investors have used the PTC extensively to increase the profitability of windfarms: federal payments of the PTC in 2015 were roughly $4.4 billion.[2]

The interaction between large increases in wind generation and a transmission grid built before wind capacity build out is likely very important because wind patterns are spatially concentrated. For example, in the U.S. wind capacity is greatest in the mostly rural plains far away from urban demand centers. However, the U.S. federal govern-

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

[2]The PTC for the U.S. was $0.023/kWh of generation through 2016 declining to $0.0184/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`).

ment's PTC didn't include a complementary federal policy which explicitly optimized the electricity transmission grid in response to new wind capacity. As a result, the federal government relied on regional grid transmission planners to appropriately plan and invest in transmission capacity to complement isolated and spatially clustered new windfarms. Federal Energy Regulatory Commission (FERC) order number 1000, issued in 2016, 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".[3]

We present evidence in this paper that in order to understand the welfare and incidence of federal electricity policies, it is vital to also understand the transmission implications of those policies. To do so, we estimate the economic benefits of building new large scale transmission capacity conditional on large increases in wind capacity. 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. CREZ construction occurred mainly between 2011 and 2014. We use hourly wind gener-

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

ation, hourly wholesale 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.

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.[4] 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.[5] Our approach is 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 might capture some complexities like network loop flows, we provide evidence that our more parsimonious approach is sufficient for evaluating impacts of new transmission construction.

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 ∼\$0.50/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

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

[5]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.

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 before CREZ began is roughly \$170M/year due to reduced transmission constraint loss from increased trade. We also measure benefits from CREZ assuming that all increased capacity over the sample would have occurred even in the absence of CREZ in which case transmission constraint losses increase to \$330M/year. Hence, the \$170M/year estimate eliminates any potential endogeneity in wind investment and is a lower bound whereas the \$330M/year estimate is an an upper bound. Hence we find that accounting for investment impacts of transmission expansions on renewables is material for measuring gains.

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. 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.[6] That number ignores other unpriced pollutants like PM 2.5, making it a lower bound. Non-market benefits due to production reshuffling from increased trade of roughly \$200M/year from Fell, Kaffine, and Novan (2021) implies annual non-market benefits of roughly \$315M/year. In sum, we estimate annual benefits of CREZ conditional on installed wind capacity at a lower bound of roughly \$370M/year (short run, no curtailment) to \$645M/year (long run, 10% curtailment) over our sample. Recalling the project was \$7 billion, we estimate a payback period between roughly 11 and 19 years accounting for non-market externalities.

There are 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 modestly. Similarly, generators in west ERCOT received higher wholesale prices while generators in the rest of

[6]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 (2021) to size the non-market impacts of CREZ's construction through increased trade of wind generation.

ERCOT earned modestly lower 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 since it lowered wholesale prices where the coal fired plants were located. Importantly, these incidence measures are transfers from one set of stakeholders to another so they don't factor in our benefit cost analysis.

In addition to payback periods, transmission costs also matter for assessing the incidence of benefits and costs of the renewable policy more broadly. We focus on measuring the payback period for transmission lines conditional on wind investment having already overextended the existing transmission grid. However, the annual cost of the PTC, which almost certainly led to incremental windfarm development, cost U.S. taxpayers $4.4 billion in 2015 alone. Transmission investment, which we find matters for region welfare and incidence, is born by regional authorities. Our findings are consistent with a regulatory federalism issue that federal policy leads to changes in optimal regional policy.

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 20-40 years when not accounting for pollution and carbon. The payback period drops to 10-20 years when valuing pollution and carbon mitigation. 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 with demand meaning that transmission capacity might be less important. Finally, we don't address any potential benefits from increased security of the transmission grid due to additional transmission capacity, hence benefits could be modestly larger accounting for those benefits.

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 (2021) 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. 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. Hence, our work addresses the benefits of market integration in electricity markets and trade supporting investments generally.

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)) and shows that market participants leverage market power in ERCOT. Our research design doesn't allow us to disentangle welfare gains from increased transmission capacity attributable to increased trade directly (e.g., selling wind into higher priced regions) versus indirectly from decreased market power of market participants (e.g., fossil fuel generators strategically bidding in electricity at lower prices due to increased competition from renewables). Both effects of increased transmission capacity work in the same direction however so that our approach still allows us to aggregate measure welfare and incidence impacts. We do discuss implications of market power in detail and also perform robustness checks by trimming our sample to periods where market power is the least likely to occur, but we don't disentangle the relative impact of increased trade versus reductions in market power from increased trade.

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 calculates transmission constraint loss associated with wind generation and discusses incidence of the CREZ project. Section 6 concludes. We also include an extensive Appendix which documents reduced form results consistent with the theoretical model.

2 Theoretical Model

2.1 Theoretical Framework

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. Since renewable electricity has zero marginal cost, 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

[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.

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 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 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:

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

Equation (1) explicitly shows the relationship between the shadow cost of the transmission constraint (e.g., η) and model parameters. 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.

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 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:

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

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

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 in 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 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 comparative statics. Second, we estimate wind generated annual price dispersion across ERCOT by year and compare that to increased CREZ completion to verify across node model comparative statics. 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. First, with respect to market power, we assume that the slope coefficient b_A on marginal cost of electricity in the node with no wind generation includes both cost information and exercised market power. This implicitly assumes that market power is exercised as a constant percentage mark-up over marginal costs. This is directionally consistent with the broader literature: higher absolute markups occur when aggregate electricity demand is higher. However, due to this assumption we can not decompose welfare or incidence impacts of expanded transmission capacity into the direct trade component and the indirect competition increasing component.

Second, we don't model investment decisions as this is a static framework hence we don't directly address how transmission impacts investment in this paper. However, it is useful to disaggregate how new transmission capacity could differentially impact short run (SR) prices versus long run (LR) prices in wholesale electricity markets. In the Appendix, we relax the fixed renewable capacity assumption and discuss how LR aggregate wholesale electricity price could decrease further due to increased wind generation capacity. We only briefly sketch the intuition since more capacity for trade leading to increased prices to electricity exporters is likely to be intuitive for many economists. The distinction is important for us, though, since observed installed capacity increases significantly when transmission capacity increases both in our sample and after our sample thereby impacting the economics of transmission investment. We do address this issue by disaggregating TCLs to be those from previously installed capacity versus new capacity. We view the SR TCL as a lower bound for welfare impacts of transmission and the SR plus LR TCLs as an upper bound since it is unclear how much investment might have occurred absent the transmission expansion.

Third, we 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.

Finally, wind will displace different generators in different hours and the benefits from transmission will depend on this. By assuming a linear slope this paper is not able to capture some of these nuances when, for example, a gas plant generates to temporarily cover a lower cost coal plant that can't quickly ramp. Because the vast majority of electricity is traded on the day ahead market in ERCOT based upon forecasted wind generation, we view any impacts of this linearity assumption to be second order to the first order transmission constraint losses we estimate in this paper.

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 population centers.[10] 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 Commissions (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.

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.[11] 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.

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

[10] https://www.texastribune.org/2013/10/14/7-billion-crez-project-nears-finish-aiding-wind-po/.
[11] https://www.nrc.gov/docs/ML0914/ML091420467.pdf.

different ways: by total miles of construction and total spend of CREZ lines.[12] Each row 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. 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 4 shows total installed wind capacity in ERCOT over time. It shows three things. First, even before much CREZ expansion, there was a very significant wind capacity presence in ERCOT (nearly 10,000 MW). Second, wind capacity in ERCOT is increasing over our sample period with a sharp rise in capacity beginning in the second half of 2014. Further, installed wind capacity has continued to increase in ERCOT with installed capacity at roughly 22,000 MW as of early 2019.[13]

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

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

[13]See `http://www.ercot.com/content/wcm/lists/172484/ERCOT_Quick_Facts_02.4.19.pdf`.

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).

Figure 5 shows how ERCOT zones are divided across Texas along with wind capacity levels over space. Wind farms are located in the West zone (i.e. northwest of Texas) but there are no population centers and hence little demand in west ERCOT (see Figure 3). 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.

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 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.[14] All merging and analysis were performed with STATA and our code is available upon request.

We focus our main analysis on years 2011-2016.[15] 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 in their post-fracking 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.[16] Third, these are the years with the largest changes in transmission capacity (2012-2014) with one or two additional year on each side providing a narrow bandwidth.

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.

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

[15] Our reduced form analysis is based on years 2011-2016, while our structural analysis is based on years 2011-2015 due to availability of the fossil fuel generation data.

[16] See `https://www.eia.gov/todayinenergy/detail.php?id=38572`.

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 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.[17] 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.

[17] In some specifications, we also assign wind generation to each zone according to their capacities. Available upon request.

Table 2 shows the summary statistics of the wind generation, price and load at the 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.[18] 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.[19] 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.

Figure 6 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.

[18] 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.

[19] 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.

5 Reduced Form Results

In this section we present reduced form evidence that prices respond as predicted in the theoretical model using data from 2011-2016. The main result is that as CREZ construction progressed, the price gap between west Texas and other regions decreased significantly. The Appendix presents evidence that conditional on load, increased wind generation only very modestly depresses wholesales electricity prices in ERCOT after CREZ was completed. Hence wind generation in western ERCOT appears to have small and diffuse impacts on prices in the rest of ERCOT.

5.1 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:

$$\eta_t = \alpha_0 + \alpha_1 CREZ_t + \theta_1(W_t - L_t^A) + L_t^B \theta_2 + \varepsilon_t \tag{7}$$

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. For example the average 2012 CREZ value is 0.344 and 0.859 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:

$$\eta_t = \alpha + \beta_0(W_t - L_t^A) + \gamma_0 L_t^B + \beta_1 CREZ_t \times (W_t - L_t^A) + \gamma_1 CREZ_t \times L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (8)$$

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.[20] In some regressions, we only add year-month-hour fixed effects (without sample day fixed effects) to allow more identifying variation.

5.2 Price Discrepancy Results

Table 3 shows results from Equation (7) 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 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 7 shows results by replacing CREZ percentage completion in (7) by a set of year dummies. This highlights the evolution of how the wind weighted price gap changes over time. In Figure 7, 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

[20] 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.

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.

Table 4 reports the results from Equation (8) 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)).

Robustness Checks

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 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.

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 8 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 8 shows the marginal impacts of net supply by year as we did with average price gaps visually showing identical intuition.

6 Transmission Constraint Losses and Incidence of CREZ

6.1 Estimating Elasticities

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.[21]

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 restrict 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.[22] 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 exporting region net supply curve, and variations in load in the importing region trace out the importing region net demand curve.[23] Specifically, the slope term is given by:

[21] 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.

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

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

$$b_A = \frac{p_1^A - p_0^A}{W_1 - W_0} \tag{9}$$

Similarly, as shown in Figure 9, 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:

$$b_B = \frac{p_1^B - p_0^B}{L_1 - L_0} \tag{10}$$

Since the formula for slopes of net supply and net demand curves from Equation (9) and (10) 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.

Since we use net supply shocks and net demand shocks conditional on there being transmission constraints, defining criteria in which transmission constraints are present is important. We define a transmission constraint in two ways, one ad hoc and one data driven. Our ad hoc assumption is that transmission between two regions is constrained if the price difference is greater than \$5MWhs. \$5MWhs is roughly 15% of the average prices over our sample and is also roughly the average price difference in 2011, when transmission constraints are most severe. The second approach is assuming transmission is constrained when price differences are over 1 standard deviation from their observed difference when wind generation is less than 1,000 MWhs. 1000 MWhs is roughly a 10% capacity factor for wind in 2011. Further, the average price difference between the west and all other regions is a statistical zero when wind generation is 1,000 or less (regression output available upon request). Observing a price difference outside of 1 standard deviation above the mean price difference thus indicates non-standard transmission by definition. In practice both definitions give similar estimates and lead to similar Transmission Constraint Loss calculations. Finally, in our analysis below we estimate net supply and demand elasticities using years 2011-2015. We include results with hours from only 2011-2013 in the Appendix which show similar results.

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

$$p_t^A = \alpha + \beta(W_t - L_t^A) + \gamma_2 L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \tag{11}$$

$$p_t^B = \alpha + \beta_2(W_t - L_t^A) + \gamma L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \tag{12}$$

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 (11) 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 (9). Similarly, γ in Equation (12) 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 (10).

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 shows parameter estimates from equations (11) and (12) on the 2011-2015 data for the West Zone and the North Zone for \$5/MWh and standard deviation price gap (\$2.5/Mwh) calipers. Estimates from the South and Houston zones are available upon request, but we don't provide them here in the interest of brevity.[24] The slope

[24] One standard deviation price gaps for Houston and South are both in the \$4-\$5MWh range.

coefficients on net demand from the North and net supply from the West are 0.60 and -2.29 respectively for the $5 caliper, and 0.48 and -2.35 for the one standard deviation caliper. We've estimated the same model for the 2011-2013 sample and results are all similar. All coefficients are statistically significant at a minimum of the 10% level. 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 two techniques 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 both the net demand and net supply curves in the North, and only modest increasing net supply slope (in absolute value) for high levels of net supply in the South and modest increasing net demand slope (in absolute value) for high levels of net demand in the Houston zone. These are evidence that non-linearity is not a first order concern in terms of estimating the slopes.

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 prices. In the theoretical model we assume that the slope coefficient b_A on marginal cost of electricity in the node with no wind generation includes both cost information and exercised market power. Put another way, increased costs of supplying electricity can be from either increasing marginal costs of electricity or market power increasing as a constant share of costs.

Transmission constraints can cause price increases due to both lack of trade and increased market power due to inability to trade. Our research design does allow for price decreases due to decreased market power since there are no limits to how trade of electricity changes prices at the node level. However, it doesn't allow us to decompose 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. Hence the model allows for reduced market power from additional transmission capacity to reduce prices but does so in a reduced form way.

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)) providing a natural and simple way to assess if TCLs are attributable to market power, lack of trade or both. 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 0.287 (0.276) and -2.422 (-2.406) with the trimmed sample (see Table A11), compared to point estimates of 0.600 (0.483) and -2.289 (-2.353) reported in the main specification in this section. 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.[25]

[25] 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.

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 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.[26]

Additional Considerations

As with any paper, there are some limitations to our approach. First, when we investigated them, we found some mild non-linearities in the net supply or net demand curve in some regions, further identification of precisely how the non-linearity arises could be important for understanding trading in the wholesale electricity market broadly. Put another way, it would be possible to make additional structural assumptions to improve model fit. Second, we focus on the day ahead market since the vast majority of electricity is traded on the DA market and prices are a bit less volatile. Third, 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. Fourth, we don't account 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.

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

[26]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.

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 make two assumptions in constructing transmission shortfalls, ΔK. First, we don't impose that prices in different regions exactly equal to each other but rather they only need to be "close". This assumption is based upon the observation that even in periods with little to no wind variation there are often differences in regional prices despite the mean difference being close to zero. Hence we make the conservative assumption that in equilibrium occurs when prices in two regions are within one standard deviation of observed price differences in hours with little to no wind generation ($\sim$ \$4.85). This creates a lower ΔK for each hour by effectively trimming off the right tip of the TCL triangle in Figure 1.

Second, we impose that the maximum possible transmission shortfall in any given hour is the minimum of ΔK and excess generation capacity up and above that observed in the west region (e.g., $W + G - L_{west}$). This assumption ensures that our TCL calculations from 2011-2015 are internally consistent. It also is conservative since it assumes fossil fuel generation would not increase if transmission constrained hours were no longer constrained. This second assumption does not bind very much, however: 4% between west and north, 4.9% between south and north and 6.2% between Houston and north.

Two additional comments before proceeding: first, equation (4) shows that TCLs are proportional to the square of price differences. This implies that TCLs are disproportionately driven by hours with very large price differences. Both of the assumptions above mitigate this issue. We show in the Appendix TCLs estimated when we impose neither constraint and they roughly double. Hence we feel the order of magnitude of the effect we estimate is robust even to these clearly conservative assumptions.

Second, there are some hours in which the price in the west is above the price in other regions. These are hours when wind generation is very low and are often hours of extreme price spikes when day ahead or real time prices are well above $1000/MWh. We drop these hours from our analysis. However transmission constraints might impact these outlier hours is well beyond the scope of our study but we do want to highlight it could be material for assessing welfare impacts from transmission expansions.

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

Figure 10 shows the yearly imputed transmission capacity gap.[27] 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 10 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 Callaway, 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 and in 2015 the relationship is flat to slightly rebounding as wind investment rises.

[27] 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.

The transmission capacity gaps shown in Figure 10 map to hourly TCLs. Figure 11 aggregates these hourly observations to show the annual TCL aggregated across all of these hours and across all zones and 95% confidence intervals are calculated by delta method. Figure 11 shows 2011 pre-CREZ losses on the order of $170M/year dropping to nearly zero in 2014 and 2015 as CREZ was completed. Hence we conclude that if 2011 wind generation capacity levels would have stayed unchanged, we would have expects TCLs on the order of $170M/year.

Wind capacity did change between 2011 and 2015, however, but we can't assess how much of that increased investment would have occurred in the absence of the CREZ project. As a result we estimate the TCLs leveraging hourly capacity factors from each hour in the observed data but with an installed wind generation capacity in West Texas equal to the 2015 capacity. This exercise provides an upper bound of LR TCL. This approach yields modestly higher TCLs in all years including roughly $330M in 2011. As mentioned above, assessing the causal impact of CREZ on actual investment decisions would require layering in another structural model to the approach we have here. Rather than take a firm stand on a specific number we offer bounds of $170M-$330M per year. We consider these both to be conservative given our assumptions on equilibrium prices and trading limits mentioned above. If we impose neither restriction, 2011 TCL is roughly $500M per year.

Finally, the $170M-$330M range fully ignores any curtailment from wind generators due to negative wholesale electricity prices. Curtailment decreases observed price gaps between west ERCOT and other regions. Hence the existence of curtailment leads this to understate TCLs. However, as we discuss below, disaggregate data on curtailment largely doesn't exist for ERCOT over our sample. As a result the $170M-$330M range is an underestimate precisely in the hours when price discrepencies are the largest between western ERCOT and other regions. Hence we are confident in $170M as being an floor for market impacts.

6.3 Non-market impacts

In addition to market impacts, there are also non-market impacts of CREZ on CO2 and other pollutants. With trading possible, wind generation offsets high cost fossil fuel generation in non-west ERCOT. Without free trade enabled by CREZ, wind still offsets fossil fuel generation but instead of high cost fossil fuel generation in non-west ERCOT it offsets more efficient fossil fuel in the west. In order to estimate emission impacts we would need to calculate the differential emission rates of more efficient western fossil fuel generators and less efficient non-west fossil fuel generators. That would be a complicated process meriting its own paper in the spirit of Fell, Kaffine, and Novan (2021). As a result we instead perform a back of the envelope calculation on how transmission constraints lead to curtailment and how curtailment impacts emissions.

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 calculate hourly marginal emissions in ERCOT. 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, materially more than market impacts.[28] That is not what actually occurs with lack of trade. Lack of trade means that wind offsets more efficient generation in the west instead of less efficient generation in the non-west. However, transmission constraints do lead to curtailment when prices in the west get sufficiently low and wind farms choose not to generate.

Curtailment means that wind generators choose not to generate when the wind is blowing, often because the wholesale price of electricity is too low. One MWh of wind curtailment means that one MWh of fossil fuel generation must occur. Curtailment rates are difficult to know given the lack of data. The U.S. Department of Energy's market report[29] shows suggestive evidence that curtailment decreased rapidly as CREZ was constructed from a height of 17% in 2009 to roughly 0.3% in 2014. We assume 10% curtailment attribute to congestion to give CO2 benefits of roughly \$115M/year (e.g., \$115M/year = $.10 * \$1.15B$). This is in addition to the roughly \$200M non-market benefits from CREZ

[28]Estimates range from 21 millions tons to 39 million tons depending primarily if we use the 2011 installed capacity base or the 2015 installed capacity base to measure marginal emissions. We choose 31 million to split the difference but the estimate can be adjusted proportionally. Detailed results for non-market impacts are available upon request.

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

estimated by Fell, Kaffine, and Novan (2021) 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 \$600$M/year$. Critically, roughly half of the benefit is due to non-market externalities. The Appendix shows that allowing non-linearity in the net demand and supply curves does not materially impact elasticity estimates and thus lead to similar TCL losses.

The cost of CREZ ERCOT ratepayers face is roughly \$7B according to the U.S. Energy Information Administration.[30] Using an annual benefit of \$600M the payback period is roughly 11 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 21 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 11 years makes this transmission expansion a good investment from a social welfare perspective.

6.4 Incidence of CREZ

While the price gap decreased between the West and other zones due to CREZ, in order to calculate the incidence of CREZ we must determine how much of the price gap decrease was due to rising prices in west ERCOT versus decreasing prices in other parts of ERCOT. For example, if price discrepancies going to zero were driven by price decreases in ERCOT load centers then ratepayers in load centers benefit from CREZ. Alternatively if CREZ drove price increases in western ERCOT then windfarm owners and developers benefit. We therefore focus 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

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

theoretical model). From the theoretical model, we can calculate them as:

$$\triangle\eta_0^B = \gamma\triangle K = \frac{\gamma\eta_0}{(\beta+\gamma)} \tag{13}$$

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

$$\triangle\eta_1^B = \gamma\triangle K = \frac{\gamma\eta_1}{(\beta+\gamma)} \tag{15}$$

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

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:

$$\triangle Spend_B = (\triangle\eta_1^B - \triangle\eta_0^B) \times L^B = \frac{\gamma(\eta_1-\eta_0)}{(\beta+\gamma)} \times L^B = \frac{\gamma\triangle\eta}{(\beta+\gamma)} \times L^B \tag{17}$$

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

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 (7). The the total spending change for all people is given by:

$$\triangle Spend = \triangle Spend_B + \triangle Spend_A \quad (19)$$

Table 6 report the results for all the three pairs of regions using a back of the envelope calculation which evaluates market averages. We use elasticities estimated from using both the \$5/MWh and the \$2.50/Mwh calipers. Using the main estimates (caliper of \$5/Mwh) the annual saving outside of the west in the day ahead market ranges from -\$8,557/hour in Houston to \$14,517/hour in North ERCOT. Prices in West ERCOT increase by \$9,975/hour on average.

Aggregating up to the annual level, we find that prices in West ERCOT increased by roughly \$87 million per year and prices in the North (Houston) decreased by roughly \$127 million per year (\$74M). As expected, we find that ratepayers in western ERCOT and generators in other parts of ERCOT paid more and earned less respectively. Conversely, ratepayers in outside of West ERCOT and both generators and windfarm owners benefited from CREZ construction.

We recover that net spending changes were small on net so that aggregate prices did not fall by much if at all. For example, using the \$2.5 caliper elasticity point estimates imply that net spending changes were actually positive. We don't report standard errors for these average spending change estimates but they include zero. Rather, we highlight that aggregate rate impacts were small. This is consisent with the reduced form wind price impacts results shown in the Appendix. This is also consistent with us estimating a relatively flat net demand curve. That said, 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.

While non-Western ERCOT ratepayers and windfarms gained from hourly wholesale electricity prices, generators not in the west were 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 decreased revenues for non-west generators. To this end, 4,000 MWs of coal capacity was recently approved from retirement.[31] However,

[31] See goo.gl/X6vLCB/.

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.

There is an additional important consideration of building new transmission lines for incidence very much related to retirement: new windfarm investment. Just as more competition can drive firms out of the market, permitting more trade through increased transmission lines encourages investment in windfarms. As of early 2019, installed ERCOT wind capacity was 22,000 MWs. It is hard to imagine this is not due partially to CREZ.

Assessing the impact of new transmission on investment is hard and requires dedicated analysis. It must be dynamic to account for expected changes in market conditions in addition to extant market conditions. Over our study, for example, the price of natural gas varied between \$2.50 and \$6.00. A full long run assessment of incidence must assess transfers from changing investment decisions.

7 Discussion and Conclusion

This paper characterizes 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 windfarms. 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 windfarms and load centers. The cost benefit analysis for the project ride very much on the value of mitigated carbon for our analysis. We estimate annual benefits of CREZ conditional on installed wind capacity at a lower bound of roughly \$370M/year (short run, no wind curtailment) to \$645M/year (long run, 10% wind curtailment) over our sample. The value of transmission expansion varies greatly with how it impacts new renewable investment with payback periods ranging from 40 years (no impact) to 21 years (observed capacity increase attributed to transmission expansion). Welfare improvements also depend critically on how global pollutants like carbon and regional pollutants like PM 2.5 are internalized by regional policy makers reducing the payback period further to as little as 11 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.

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.[32] 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 better 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.[33] However, windfarm developers and their financing partners receive a very large benefit: the CREZ combined with the PTC served to both subsidizes 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.

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

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

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 of efficient policy given the current mechanism for investing in transmission capacity in the U.S.

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.

There are two shortfalls in our research design that merit further work. First, we do not decompose welfare or incidence impacts of expanded transmission capacity into the direct trade component and the indirect competition increasing component. More trade leads to reduced market power. A different structural model could directly account for changes in bidding above marginal costs due to market power enjoyed by fossil fuel generators before CREZ in addition to benefits from market clearing prices being driven by lower costs of the marginal plant when more renewable electricity is available across ERCOT broadly. Second, the economic benefits of greater grid safety and resiliency is an important consideration for grid operators as well. A different approach including an objective function of the grid operator would be required to assess that question.

References

Borenstein, S., J. B. Bushnell, and F. A. Wolak (2002): "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, 92(5), 1376–1405.

Bushnell, J. B., E. T. Mansur, and C. Saravia (2008): "Vertical arrangements, market structure, and competition: An analysis of restructured US electricity markets," *American Economic Review*, 98(1), 237–66.

Callaway, D. S., M. Fowlie, and G. McCormick (2018): "Location, location, location: The variable value of renewable energy and demand-side efficiency resources," *Journal of the Association of Environmental and Resource Economists*, 5(1), 39–75.

Cramton, P., A. Ockenfels, and S. Stoft (2013): "Capacity market fundamentals," *Economics of Energy & Environmental Policy*, 2(2), 27–46.

Cullen, J. (2013): "Measuring the environmental benefits of wind-generated electricity," *American Economic Journal: Economic Policy*, 5(4), 107–133.

Cullen, J., and S. Reynolds (2017): "Dynamic Competitive Equilibrium with Persistent Firms," *University of Arizona Working Paper.*

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

Fell, H., and D. Kaffine (2018): "The Fall of Coal: Joint impacts of fuel prices and renewables on generation and emissions," *American Economic Journal: Economic Policy*, forthcoming.

Fell, H., D. Kaffine, and K. Novan (2021): "Emissions, transmission, and the environmental value of renewable energy," *American Economic Journal: Economic Policy.*

Fowlie, M. L. (2009): "Incomplete environmental regulation, imperfect competition, and emissions leakage," *American Economic Journal: Economic Policy*, 1(2), 72–112.

Gowrisankaran, G., S. S. Reynolds, and M. Samano (2016): "Intermittency and the value of renewable energy," *Journal of Political Economy*, 124(4), 1187–1234.

Holladay, S., and J. LaRiviere (2017): "The Impact of Cheap Natural Gas on Marginal Emissions from Electricity Generation and Implications for Energy Policy," *Journal of Environmental Economics and Management*, 85(5), 205–227.

Hortacsu, A., F. Luco, S. L. Puller, and D. Zhu (2017): "Does Strategic Ability Affect Efficiency? Evidence from Electricity Markets," *National Bureau of Economic Research No. 23526.*

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

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

Joskow, P. (2008): "Capacity payments in imperfect electricity markets: Need and design," *Utilities Policy*, 16(3), 159–170.

——— (2013): "Symposium on capacity markets," *Economics of Energy & Environmental Policy*, 2(2), V–VI.

Joskow, P., and J. Tirole (2005): "Merchant transmission investment," *The Journal of Industrial Economics*, 53(2), 233–264.

——— (2007): "Reliability and competitive electricity markets," *The Rand Journal of Economics*, 38(1), 60–84.

Mansur, E. T. (2008): "Measuring welfare in restructured electricity markets," *The Review of Economics and Statistics*, 90(2), 369–386.

Mercadal, I. (2018): "Dynamic Competition and Arbitrage in Electricity Markets: The Role of Financial Players," *Columbia University Working Paper.*

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

Puller, S. L. (2007): "Pricing and firm conduct in California's deregulated electricity market," *The Review of Economics and Statistics*, 89(1), 75–87.

Reguant, M. (2014): "Complementary bidding mechanisms and startup costs in electricity markets," *The Review of Economic Studies*, 81(4), 1708–1742.

Zivin, J. S. G., M. J. Kotchen, and E. T. Mansur (2014): "Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies," *Journal of Economic Behavior & Organization*, 107, 248–268.

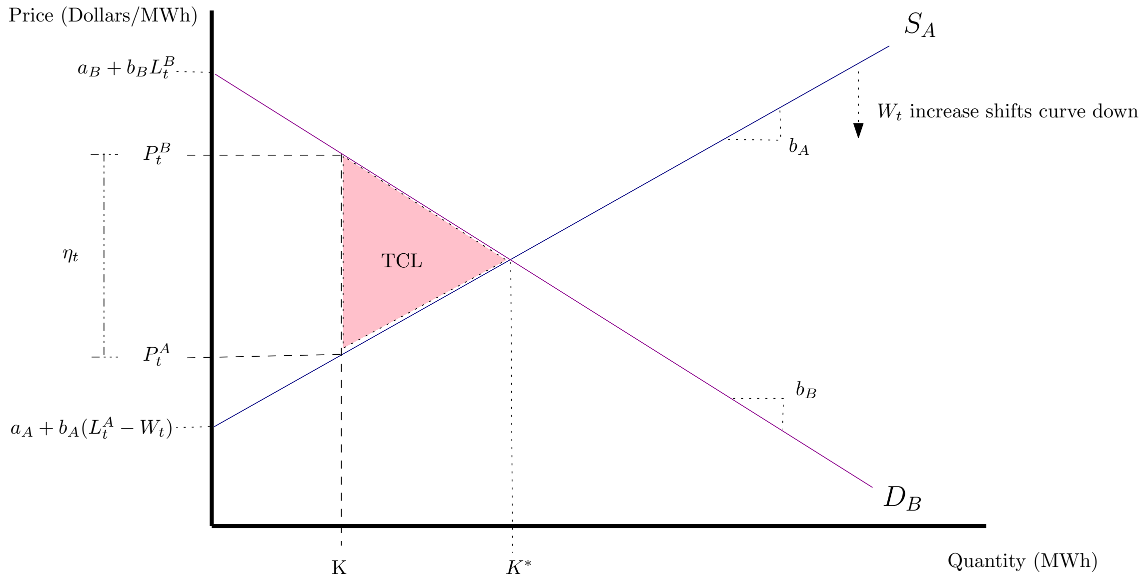

Figure 1: Impact of change in wind generation on shadow cost of transmission constraint.

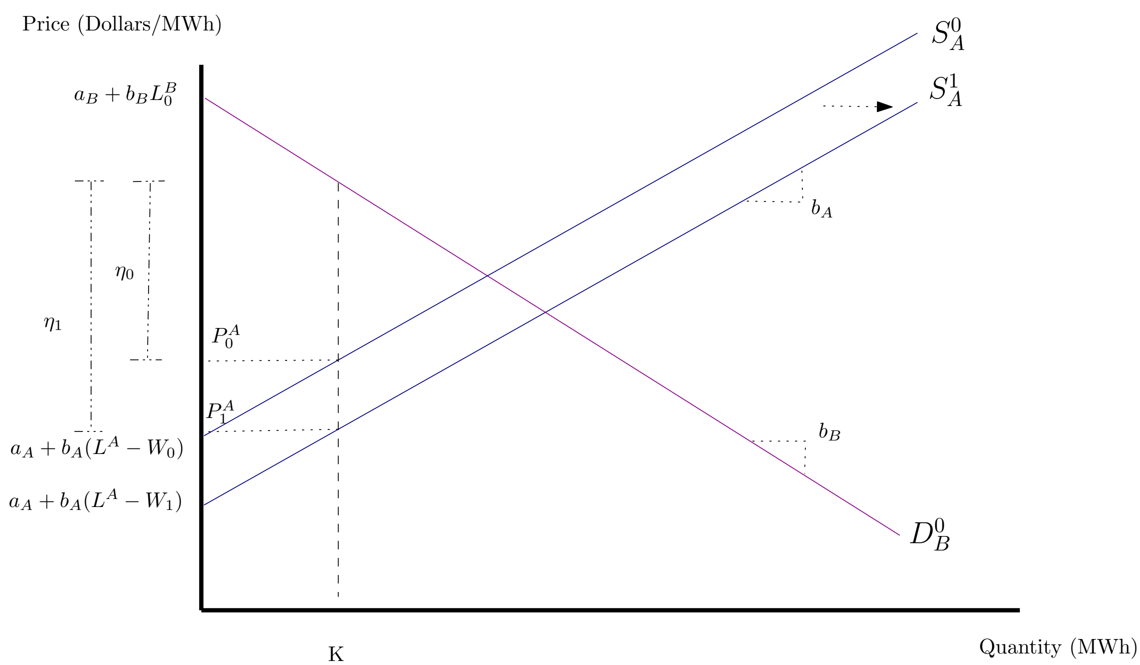

Figure 2: Net Supply Shock

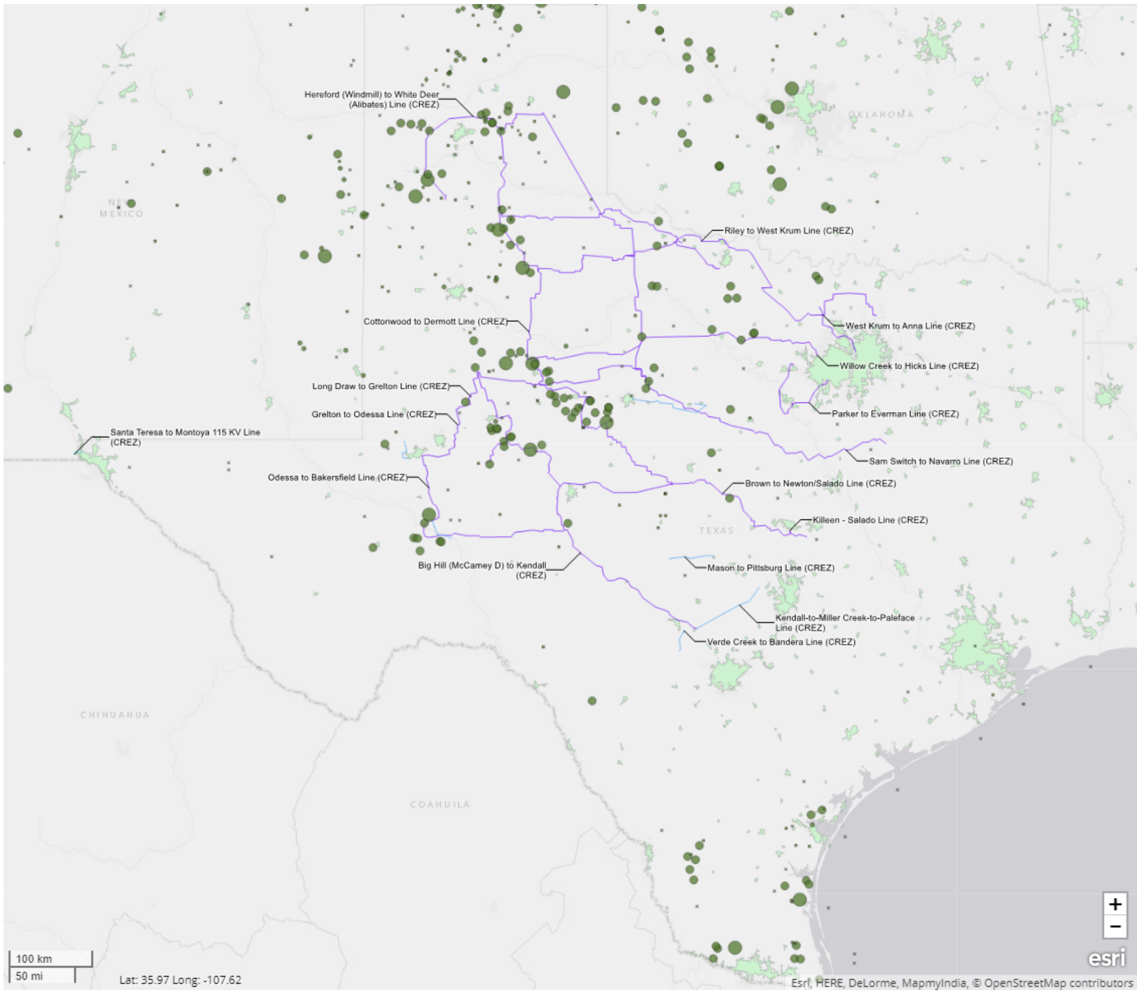

Figure 3: CREZ lines locations, wind capacity and urban centers in ERCOT

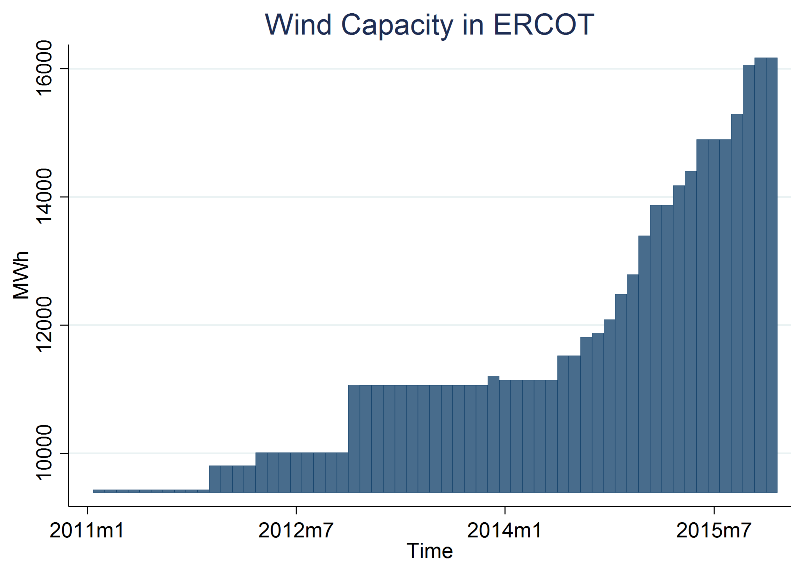

Figure 4: Wind Capacity in ERCOT by Month

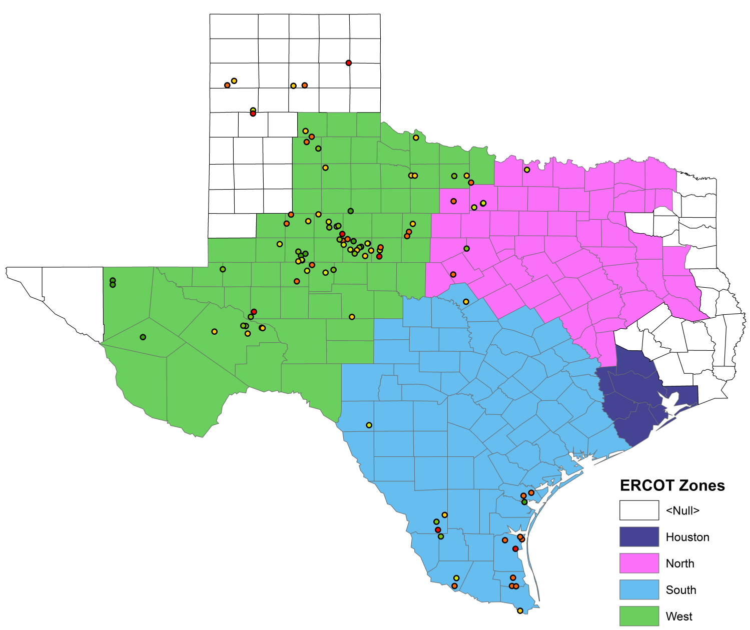

Figure 5: Load Zones in ERCOT. The color of the circles indicates capacity levels of the wind farms (red having more capacity and green less).

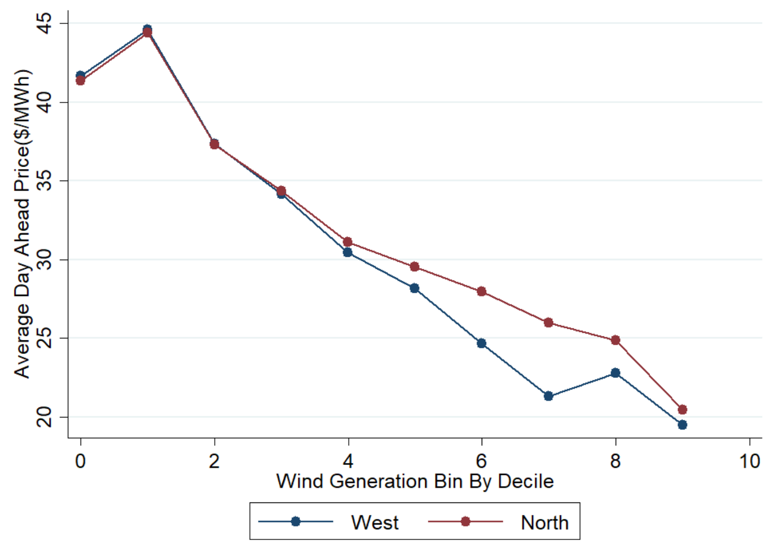

Figure 6: Average Day Ahead Electricity Prices by Wind Generation Levels

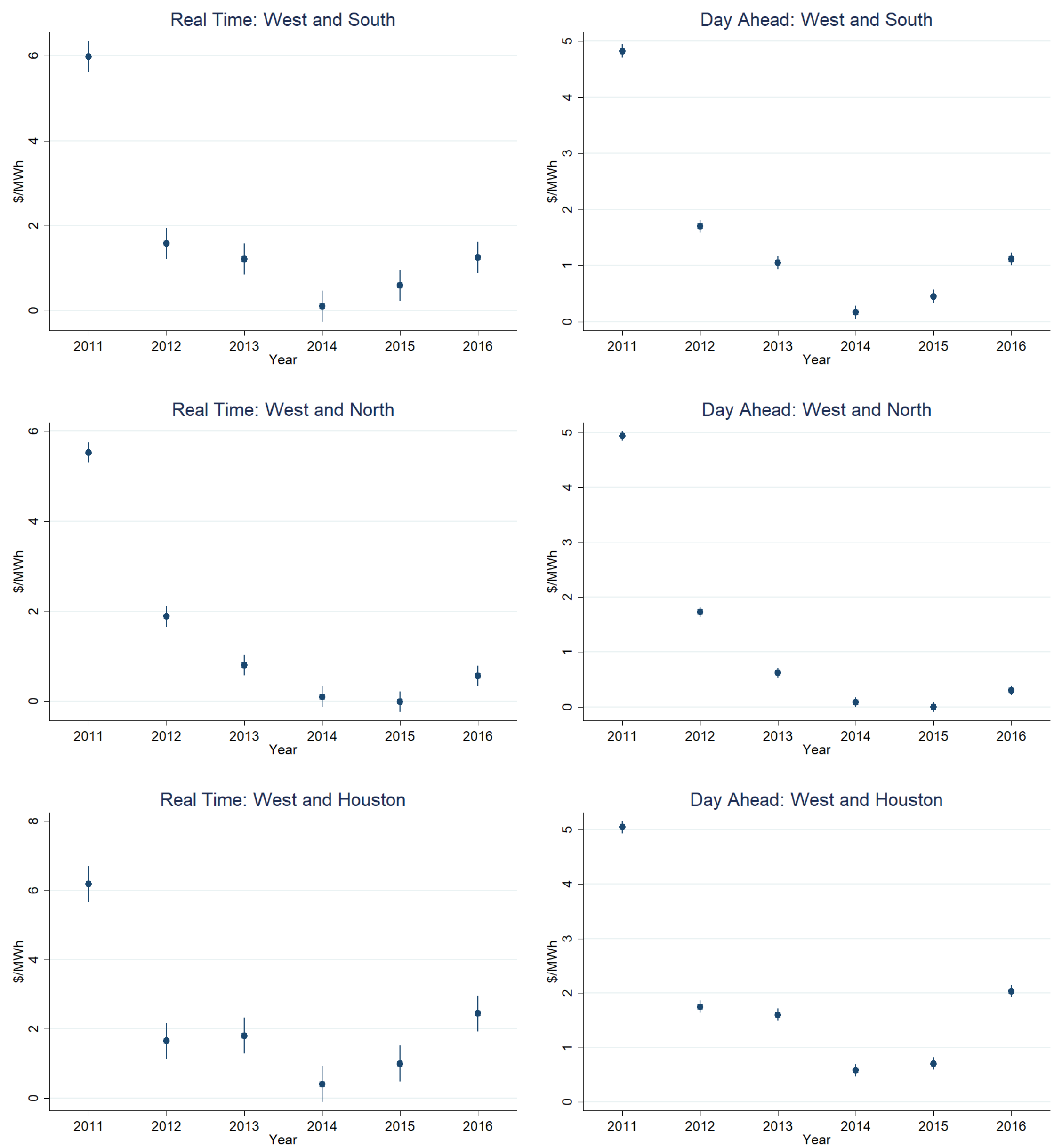

Figure 7: Price Gap By Year

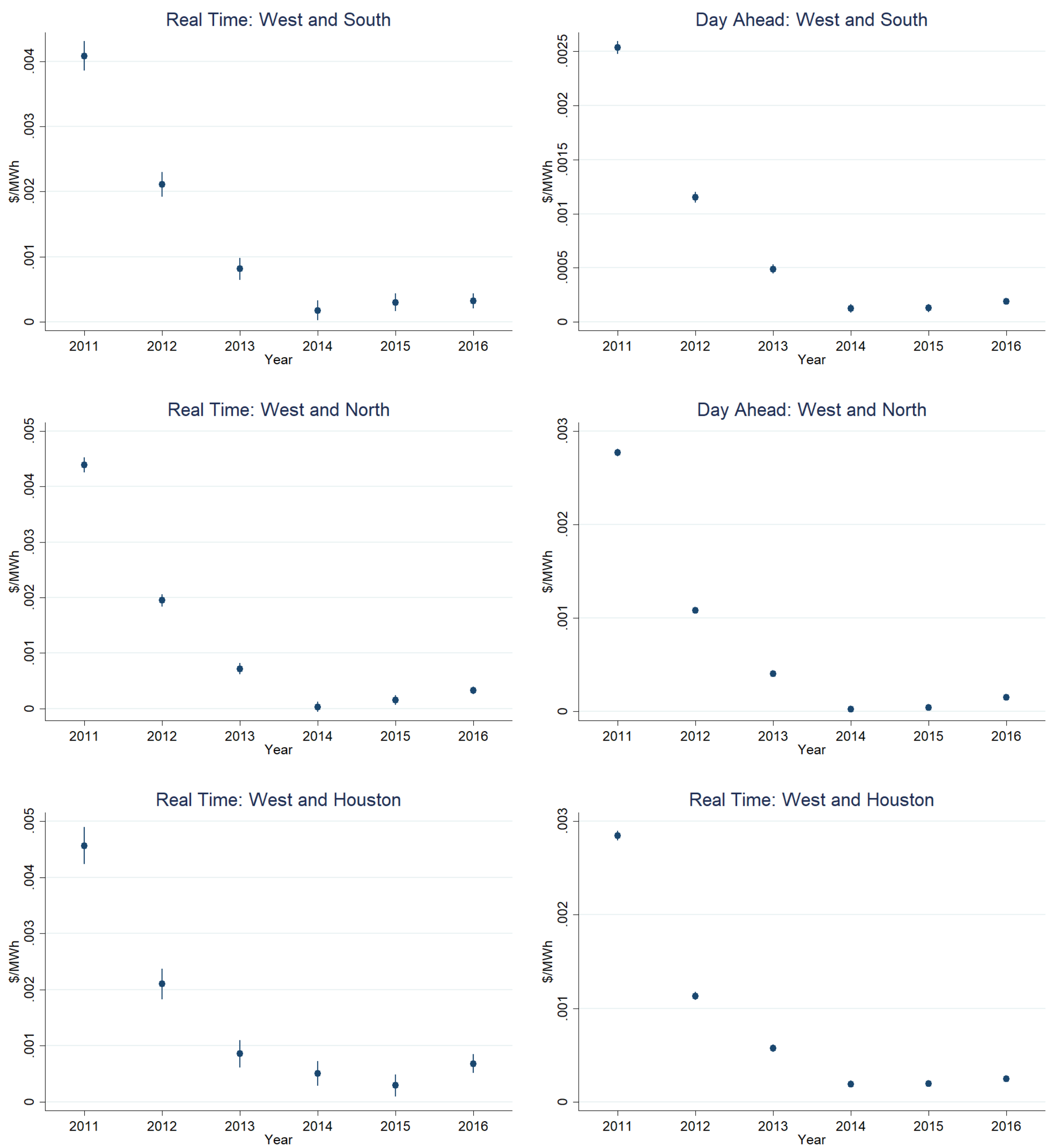

Figure 8: Effects of Net Supply on Price Gap By Year

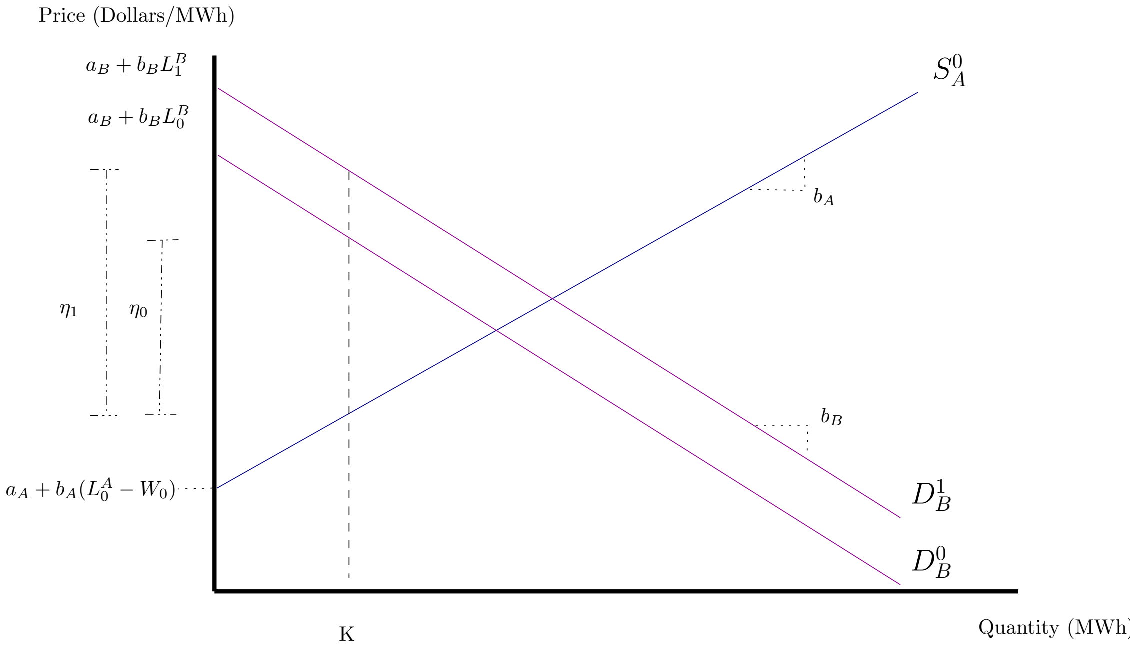

Figure 9: Net Demand Shock

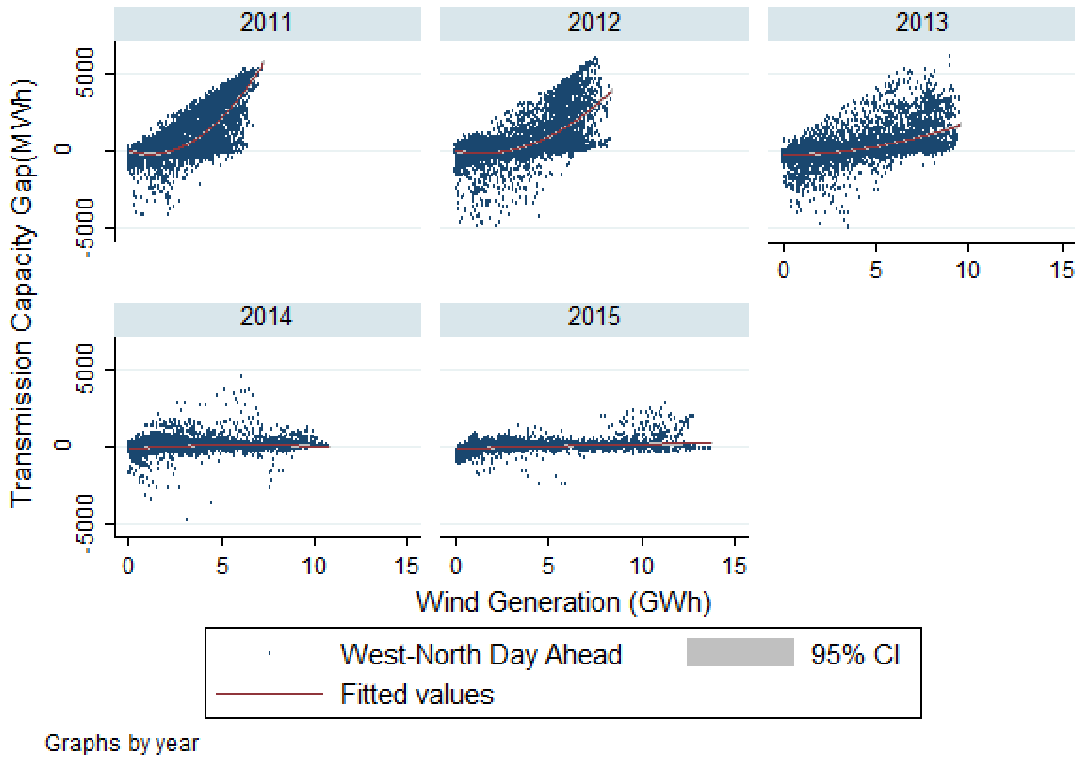

Figure 10: Implied transmissions shortfall by year between West and North. Elasticities with caliper of $5Mwh estimated on 2011-2015 sample.

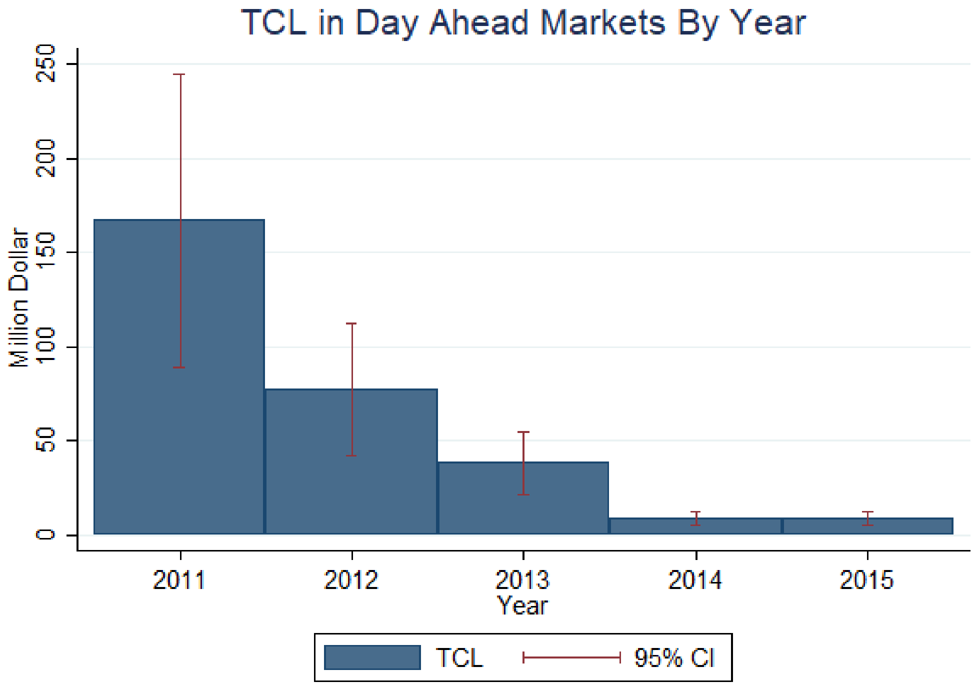

Figure 11: Yearly sum transmission constraint losses for all regions using observed generation levels (lower bound). Elasticities with caliper of $5Mwh estimated on 2011-2015 sample.

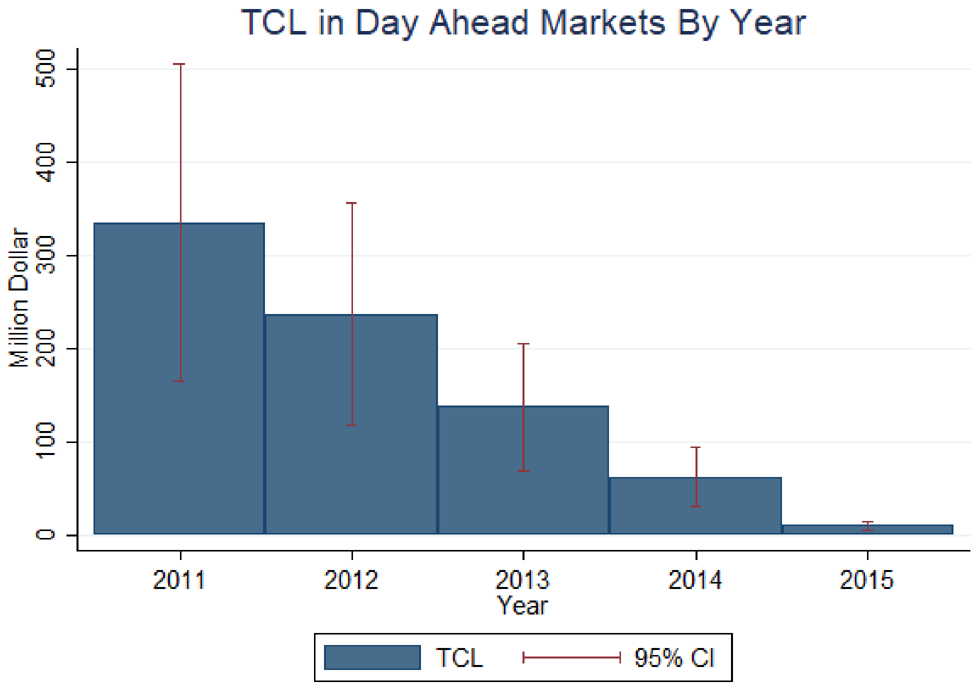

Figure 12: Yearly sum transmission constraint losses for all regions projecting 2015 capacity onto 2011-2014 capacity factors (upper bound).

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.

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 3 Impacts of CREZ on Price Gap

VARIABLES	(1) South RT	(2) South DA	(3) North RT	(4) North DA	(5) Houston RT	(6) 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 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 5 Identification of Net Supply and Net Demand Curves

VARIABLES	(1) P(North) P(Gap)> 5	(2) P(West) P(Gap)> 5	(3) P(North) P(Gap)> 2.5	(4) P(West) P(Gap)> 2.5
Net Demand (North)	0.600**	1.024***	0.483*	0.974***
	(0.271)	(0.325)	(0.266)	(0.342)
Net Supply (West)	-0.706***	-2.289***	-0.590***	-2.353***
	(0.226)	(0.316)	(0.222)	(0.278)
Constant	22.90***	9.265**	24.43***	13.21***
	(3.370)	(4.199)	(3.281)	(4.227)
Observations	4,316	4,316	6,162	6,162
R-squared	0.921	0.900	0.864	0.859
Year-Month-Hour FE	YES	YES	YES	YES
Sample Day FE	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 6 Incidence Analysis of CREZ Project DA

	Caliper = 5			Caliper = 2.5		
	South	North	Houston	South	North	Houston
Net Supply Slope ($/MWh per GWh)	2.6773	2.2893	1.8781	2.2161	2.3528	1.7193
Net Demand Slope ($/MWh per GWh)	0.9648	0.6002	0.3839	0.3401	0.4828	0.4976
Load West (GWh)	2.554	2.554	2.554	2.554	2.554	2.554
Price Change West ($/MWh)	3.5812	4.2931	3.8425	4.2235	4.496	3.5891
Spending Change West ($/h)	9146	10965	9814	10787	11483	9167
Average Spending Change West ($/h)		9975			10482	
Load Pop Center (GWh)	9.4648	12.8979	10.8947	9.4648	12.8979	10.8947
Price Change Pop Center ($/MWh)	-1.2905	-1.1255	-0.7854	-0.6482	-0.9226	-1.0388
Spending Change Pop Center ($/h)	-12214	-14517	-8557	-6135	-11900	-11317
Total Spending Change Pop Center ($/h)		-11763			-9784	
Net Spending Change ($/h)		-1788			698	

A Appendix

A.1 Transmission and Investment

It is useful to disaggregate how new transmission capacity could differentially impact short run (SR) prices versus long run (LR) prices in wholesale electricity markets. In the the theory model, we've assumed a fixed capacity of wind generation. Here, we relax that assumption with a discussion of how LR aggregate wholesale electricity price could decrease further due to increased wind generation capacity. We only briefly sketch the intuition since more capacity for trade leading to increased prices to electricity exporters is likely to be intuitive for many economists. The distinction is important for us, though, since observed installed capacity increases significantly when transmission capacity increases both in our sample and after our sample thereby impacting the economics of transmission investment.

When transmission capacity increases there will be fewer hours with a price difference across regions. As shown above, this will increase prices in regions exporting electricity. For wind generating nodes the impact is a boon for wind generators. When transmission is constrained windy hours often see depressed prices precisely when generation is highest. Conversely, without transmission constraints prices are higher exactly when total megawatts hours produced are the largest. Hence the expected revenue from developing a windfarm increases when transmission constraints are relaxed via new transmission construction in an renewable exporting region.

Hence there are two effects of increased transmission capacity: first, TCLs like those described above decrease as existing generators are now able to export their electricity. Second, new windfarms attributable to increased expected revenue from more transmission capacity could impact market prices. The new windfarms likely would not have existed but for the new transmission lines. Larger new equilibrium installed capacity levels lead to more generated electricity being traded for any given level of prevailing wind. Hence LR welfare impacts should be calculated based on marginal windfarm construction attributable to new transmission capacity whereas SR impacts are calculated from installed windfarm capacity pre-transmission expansion.

Consider the following simple example to highlight the difference between SR and

LR TCLs. Assume that initially there are 10,000MWs of installed wind capacity with an observed capacity factor of 33% and (quantity weighted) average price in the wind generating region of \$30/MWh. Given prevailing transmission capacity assume annual TCLs of \$200M annually. Now assume a large transmission expansion eliminates all TCLs and leads to average prices increasing to \$35/MWh in the wind generating region.

Upon observing the increased revenue, wind investors invest in an additional 5,000 MWs increasing capacity to 15,000MWs. For simplicity assume the capacity factor stays identical at 33%. In equilibrium, additional investment would stop when average price in the wind generating region decreases back to \$30/MWh.[34] At the new level of installed capacity (e.g., 15,000MWs with a capacity factor of 33%) but at the initial level of transmission capacity would have a TCL of something more than \$200M/year. Perhaps \$300M/year is the right order of magnitude, but one needs precise net supply and net demand slope coefficients to know. In this case, we call \$200M/year the SR TCL. We call the \$300M/year the LR TCL because it is calculated ex post at higher levels of observed wind generation capacity.

To be clear, in this paper we do not carefully examine the causal effect of new transmission lines on renewable investment. Rather, we disaggregated TCLs to be those from previously installed capacity versus new capacity. We view the SR TCL as a lower bound for welfare impacts of transmission and the SR plus LR TCLs as an upper bound since it is unclear how much investment might have occurred absent the transmission expansion. Since theory predicts the private market will compete away economic rents for windfarm investment and we consider gains to investors and instead focus on the incidence impacts of wholesale price effects for market participants. Investment induced from increased transmission capacity is likely a first order concern but is beyond the scope of this paper.

A.2 Wind Generation and Prices

We 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

[34] Note that the importing region would also have equilibrium price of \$30MWh if there were no transmission constraints with the additional installed capacity. Previously the price would have had to be at least \$35/MWh if not more.

transmission capacity over time we pick a single year, 2015, after the majority of CREZ was completed to measure how ERCOT prices respond to increases in wind generation.

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.[35] We estimate the following equation:

$$P_t = \sum_{j=1}^{8} \sum_{i=1}^{13} \beta_{ij} 1\{Bin_i(W_t)\} 1\{Bin_j(L_t)\} + \delta_{hm} + \lambda_d + \varepsilon_t \tag{20}$$

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.[36] 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 13 show estimation results from equation (20) for day ahead for ERCOT-wide prices. Figure 14 shows real time prices but because over 90% of electricity is traded on the DA market we focus our discussion on those results. Each subplot describes the size of a

[35] 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.

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

load bin and the y-axis shows the change in hourly DA prices. For all load levels electricity prices show a slight decrease as wind generation increases. The differences across wind generation levels are often not statistically significant but within a load bin the pattern is clear. We also do not observe higher effects for large load bins as we would expect with a convex marginal cost curve.

For real time price impacts there is a larger effect but that is both small in economic impact since over 90% of electricity is sold on the DA market. Further, bidding rules often force a mechanically lower real time prices since windfarms often are required to be conservative with their forecasted generation into the DA market since reducing scheduled fossil fuel generation is thought to be easier than ramping on the RT market.

Overall we take this as evidence there is some modest impact of increased wind generation on day ahead prices in ERCOT but the impacts seem small in magnitude. Using point estimates and averaging across load levels, there is roughly a \$0.2/MWh decrease in average day ahead time prices per 1000MWh increase in wind generation, or far less than a 1% of the average electricity prices.

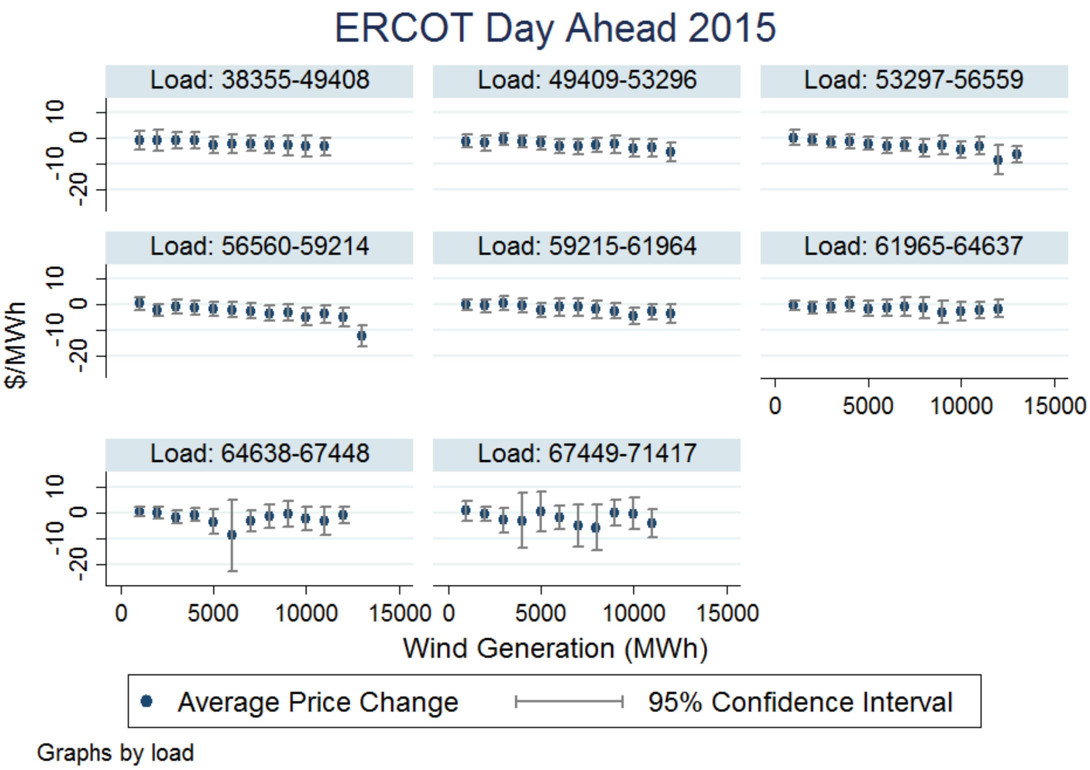

Figure 13: Effects of Wind Generation on Day Ahead Prices in ERCOT

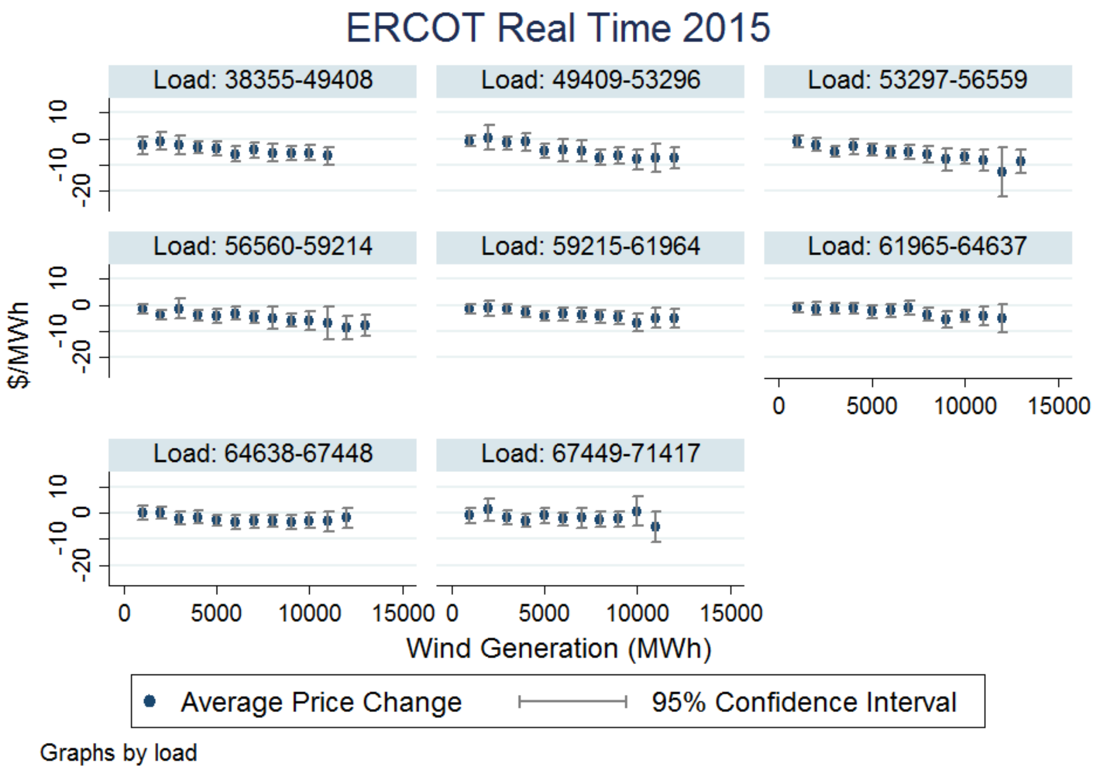

Figure 14: Effects of Wind Generation on Real Time Prices in ERCOT

There are several implications from the results: First, wind generation seems to decrease electricity prices averaged at the hub level but only very modestly. We take this as evidence that short run variation in wind generation can shift the net supply curve as indicted by the model. Therefore our extension of the Joskow and Tirole model appears valid: when wind generation increases, it offsets fossil fuel generation.

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.

Fourth, these very modest effects are very consistent with the relatively flat net demand curve we estimate and use in our structural model. Increased wind generation supplied to the rest of the ERCOT from the west seems to have modest diffuse impacts on prices for ERCOT broadly. We recover that final result with our structural model.

A.3 Reduced Form Robustness Checks

This section shows different specifications of reduced form models estimated in the main section to highlight how CREZ completion impacts average price gaps between western ERCOT and other ERCOT regions to ensure robustness. The first set of results, Tables A1-A3, clusters standard errors by week instead of day for the reduced form results on CREZ completion on average day ahead and real time price gaps across ERCOT regions. The second set, Tables A4-A6, trims the data when estimating price gaps to include only observations from 2011-2013. The third set of robustness checks, Tables A7-A9, explicitly controls for load. The coefficients of interest throughout are consistently negative and significant.

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 week 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 week 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 week are reported in parentheses.

Table A4 Impacts of CREZ on Price Gap: Trim Data

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	South RT	South DA	North RT	North DA	Houston RT	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.

A.4 Elasticity Robustness

These robustness checks serve to provide additional evidence for our net supply and net demand slope coefficient estimates. We proceed in two ways. First, we trim the sample to include years 2011-2013. Second, we estimate models in which we trim the top 10% of hours measured by load. This second model serves as a robustness check for whether extremely high load hours are driving identification of our slope coefficients. Both approaches find elasticity estimates largely in line with our main results.

Table A10 Identification of Net Supply and Net Demand Curves (Year<=2013)

	(1)	(2)	(3)	(4)
	P(North)	P(West)	P(North)	P(West)
	P(Gap)> 5	P(Gap)> 5	P(Gap)> 2.5	P(Gap)> 2.5
VARIABLES	Year <= 2013	Year <= 2013	Year <= 2013	Year <= 2013
Net Demand (North)	0.604**	1.027***	0.412	0.911***
	(0.269)	(0.323)	(0.254)	(0.334)
Net Supply (West)	-0.816***	-2.406***	-0.764***	-2.547***
	(0.213)	(0.310)	(0.149)	(0.229)
Constant	22.78***	9.091**	25.12***	13.65***
	(3.333)	(4.175)	(3.091)	(4.094)
Observations	4,262	4,262	5,915	5,915
R-squared	0.934	0.894	0.926	0.900
Year-Month-Hour FE	YES	YES	YES	YES
Sample Day FE	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 Identification of Net Supply and Net Demand Curves (Top 10% Load Trimmed)

	(1)	(2)	(3)	(4)
	P(North)	P(West)	P(North)	P(West)
	P(Gap)> 5	P(Gap)> 5	P(Gap)> 2.5	P(Gap)> 2.5
VARIABLES	Load < 18.4	Load < 18.4	Load < 18.4	Load < 18.4
Net Demand (North)	0.287*	0.652**	0.276	0.753**
	(0.168)	(0.310)	(0.205)	(0.303)
Net Supply (West)	-0.809***	-2.422***	-0.611***	-2.406***
	(0.219)	(0.328)	(0.204)	(0.271)
Constant	26.60***	14.07***	26.51***	15.93***
	(2.199)	(3.953)	(2.644)	(3.781)
Observations	4,070	4,070	5,825	5,825
R-squared	0.963	0.935	0.855	0.849
Year-Month-Hour FE	YES	YES	YES	YES
Sample Day FE	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.

We also introduce non-linearity into the net supply and net demand models directly. To do so requires care in augmenting equations (11) and (12) 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 (11) and (12) (e.g., only hours where we observe a price gap of \$5/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:

$$p_t^A = \alpha + \beta(W_t - L_t^A) + \beta^h 1\{W_t - L_t^A \geq P_{50|\eta > \$5}\} * (W_t - L_t^A) + \gamma_2 L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (21)$$

$$p_t^B = \alpha + \beta_2(W_t - L_t^A) + \beta_2^h 1\{W_t - L_t^A \geq P_{50|\eta > \$5}\} * (W_t - L_t^A) + \gamma L_t^B + \delta_{hmy} + \lambda_d + \varepsilon_t \quad (22)$$

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 \$5/MWh (or \$2.5/MWh).

Table A12 Identification of Slopes North DA: Nonlinear Checks

VARIABLES	(1) P(North) P(Gap)> 5	(2) P(West) P(Gap)> 5	(3) P(North) P(Gap)> 2.5	(4) P(West) P(Gap)> 2.5
Net Demand (North)	0.561*	1.004***	0.538*	0.961***
	(0.321)	(0.325)	(0.303)	(0.341)
Net Supply (West)	-0.703***	-2.035***	-0.592***	-2.042***
	(0.224)	(0.411)	(0.222)	(0.423)
1(Net Demand Above Median)*Net Demand	0.0162		-0.0224	
	(0.0367)		(0.0323)	
1(Net Supply Above Median)*Net Supply		-0.230		-0.288
		(0.157)		(0.196)
Constant	23.24***	9.173**	23.93***	13.04***
	(3.811)	(4.197)	(3.596)	(4.228)
Observations	4,316	4,316	6,162	6,162
R-squared	0.921	0.900	0.864	0.859
Year-Month-Hour FE	YES	YES	YES	YES
Sample Day FE	YES	YES	YES	YES

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

Table A13 Identification of Slopes South DA: Nonliear Checks

VARIABLES	(1) P(South) P(Gap)> 5	(2) P(West) P(Gap)> 5	(3) P(South) P(Gap)> 2.5	(4) P(West) P(Gap)> 2.5
Net Demand (South)	0.602	1.388	-0.00760	0.766
	(1.475)	(1.268)	(0.895)	(0.801)
Net Supply (West)	-1.427***	-2.491***	-0.941***	-1.768***
	(0.495)	(0.666)	(0.281)	(0.457)
1(Net Demand Above Median)*Net Demand	0.153		0.139	
	(0.116)		(0.0901)	
1(Net Supply Above Median)*Net Supply		-0.181		-0.456*
		(0.267)		(0.262)
Constant	31.89**	16.12	35.87***	23.18***
	(12.99)	(11.47)	(7.894)	(7.280)
Observations	5,116	5,116	8,170	8,170
R-squared	0.861	0.866	0.810	0.816
Year-Month-Hour FE	YES	YES	YES	YES
Sample Day FE	YES	YES	YES	YES

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

Table A14 Identification of Slopes Houston DA: Nonliear Checks

VARIABLES	(1) P(Houston) P(Gap)> 5	(2) P(West) P(Gap)> 5	(3) P(Houston) P(Gap)> 2.5	(4) P(West) P(Gap)> 2.5
Net Demand (Houston)	0.1000	0.608	0.302	0.615
	(0.407)	(0.453)	(0.425)	(0.427)
Net Supply (West)	-0.601**	-1.620***	-0.499**	-1.371***
	(0.281)	(0.472)	(0.222)	(0.408)
1(Net Demand Above Median)*Net Demand	0.106*		0.0765	
	(0.0566)		(0.0486)	
1(Net Supply Above Median)*Net Supply		-0.249		-0.350
		(0.207)		(0.231)
Constant	33.91***	20.08***	32.54***	23.40***
	(4.360)	(4.934)	(4.533)	(4.657)
Observations	5,793	5,793	9,272	9,272
R-squared	0.852	0.854	0.855	0.857
Year-Month-Hour FE	YES	YES	YES	YES
Sample Day FE	YES	YES	YES	YES

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

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 South (Houston) is there mild evidence of a non-linearity increasing net supply (demand) elasticity for high levels of net supply (demand) significant at the 10% level in one specification. We have used these estimates to construct TCLs and find similar orders of magnitude for the TCLs as those presented in our main text.

A.5 Unconstrained TCL Construction

We made two conservative assumptions when constructing TCLs in this paper. First, we assumed that equilibrium in an unconstrained transmission world doesn't occur when prices are exactly equal but rather when prices are within one standard deviation. Second, we imposed that the maximum observed transmission traded in any hour must be less than total wind generation plus total fossil fuel generation in the west less load in the west in any given hour (e.g., $W + G - L_{west}$). This section relaxes both of those assumptions and reports transmission shortfalls and TCLs.

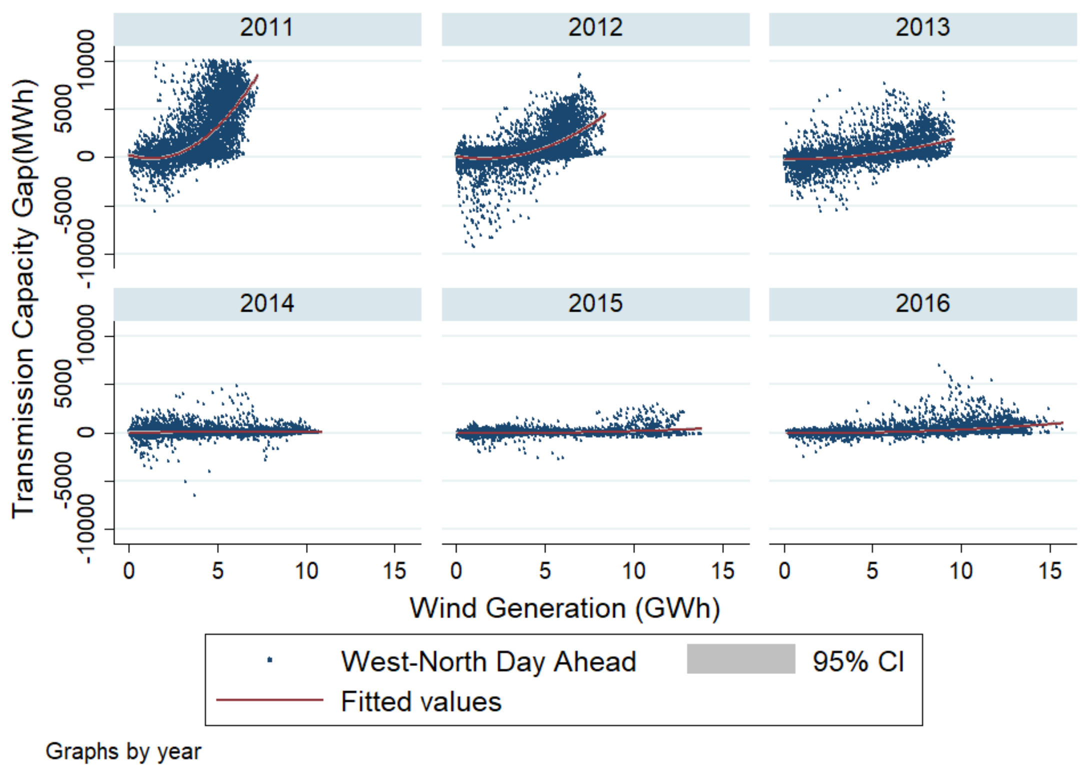

Figure 15: Implied transmissions shortfall by year, unconstrained.

Figure 15 shows the yearly imputed transmission capacity gap.[37] Each point represents

[37] 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.

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 16 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 Callaway, 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 16 by observing the support of observed hourly wind generation levels increasing above 2014 and 2015 levels.

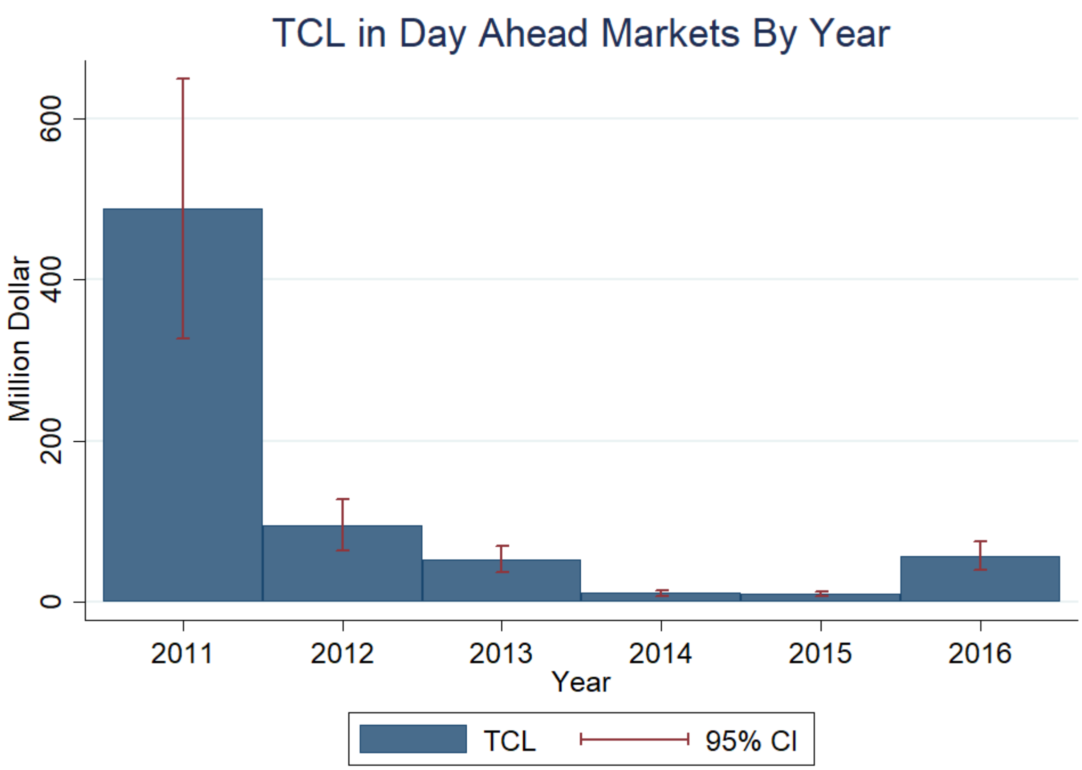

Figure 16: Yearly sum transmission constraint losses for all regions, unconstrained.

The transmission capacity gaps shown in Figure 15 map to hourly TCLs. Figure 16 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 16 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 using the fully unconstrained TCL construction. We take this as an extreme upper bound for likely TCL impact.

A.6 Results For Other Zones

This section reports some main findings for the other zones. TCL calculations using RT price data are available upon request.

Table A15 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.

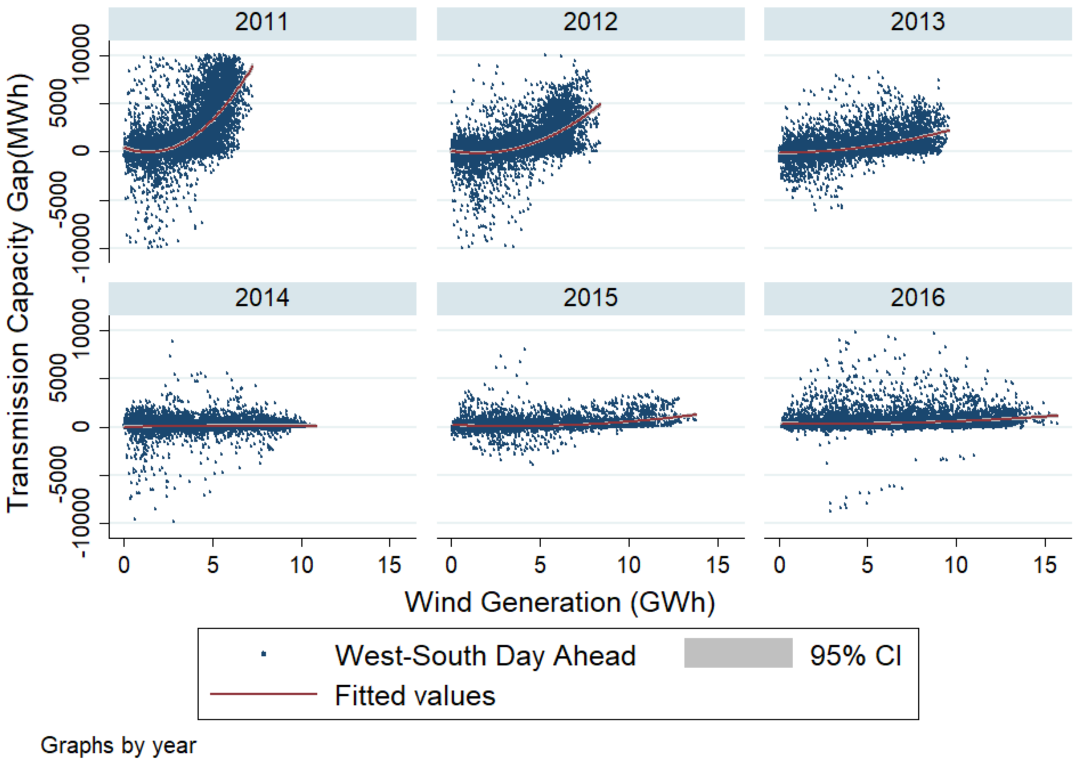

Figure 17: Implied transmissions shortfall by year: West-South DA.

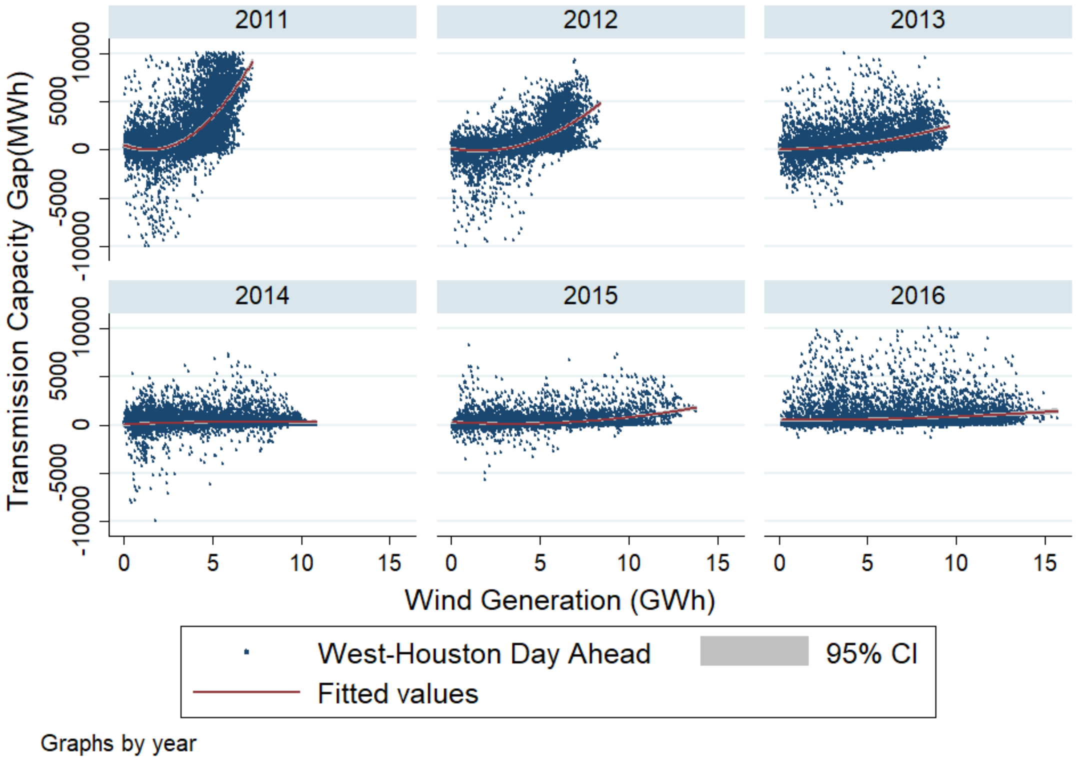

Figure 18: Implied transmissions shortfall by year: West-Houston DA.