Effect of transmission integration on prices of Congestion Revenue Rights:

Evidence from the Texas electricity market

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Effect of transmission integration on prices of Congestion Revenue Rights: Evidence from the Texas electricity market

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Abstract

Texas electricity market saw a recent integration of transmission as part of a large scale policy called Competitive Renewable Energy Zones (CREZ). Exploiting the commissioning date of integration of CREZ transmission as an exogenous treatment, this paper aims at analyzing the effect of transmission integration on market clearing prices of congestion revenue rights (CRR). Empirical estimates suggest that excess transmission led to a lowering of CRR prices for contracts at Peak Weekday, Peak Weekend, and Off Peak with the effect being largest in magnitude for CRRs at Peak Weekday and Peak Weekend. We find strong evidence of spatial, distributional, and firm type heterogeneity in the effect of transmission shock. Estimates show that CREZ transmission led to a lowering of auction revenue to the order of approximately $250 million over the period analyzed in this paper.

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1 Introduction

Texas electricity market is marked by a substantial wind energy penetration that accounted for about 17 percent of energy use in 2017[1], up from 9 percent in 2011, whereas wind generation capacity in 2017 was 22 percent (ERCOT, 2018a). This is in part credited to the recent integration of transmission built as a part of Competitive Renewable Energy Zones (CREZ) that seek to harness the wind energy in predominantly western part of Texas and add to the existing electricity transmission, thereby relieving the growing demand for electricity across the state. CREZ transmission project was an ambitious project both in terms of scale and cost (Lasher, 2014). The project, completed in January 2014, offers a unique setup to study the impact of additional transmission on the Texas electricity market.

The Independent System Operator (ISO) for the electricity market in Texas is the Electric Reliability Council of Texas (ERCOT). The regulatory body overlooking the operations of ERCOT is the Public Utility Commission of Texas (PUCT). With over 600 generating units and 46,500 miles of transmission lines, ERCOT is primarily responsible for maintaining the system reliability and managing the competitive wholesale and retail market. In this paper, we focus on the market of Financial Transmission Rights (FTR), commonly known as Congestion Revenue Rights (CRR) in the context of Texas electricity market and are a vital part of the competitive wholesale electricity market. CRRs are financial contracts that enable the holders (e.g., generating companies and retailers) to hedge the risk due to congestion costs in the day ahead market (DAM). The CRRs also serve as a financial instrument used for speculative purposes by various market players such as financial traders. These contracts are allocated via monthly and long term uniform price auctions conducted by ERCOT. We will return to the details of CRR and the allocation mechanism in the subsequent discussion.

In this paper, we study the impact of transmission integration as a part of CREZ on the monthly price of CRRs over December 2010 – May 2018. We use final commissioning date of all CREZ related transmission infrastructure in-service as an exogenous shock to the system. The construction of this transmission network began in 2010 and all the facilities started service by December 31, 2013. Hence, January 2014 serves as a credible exogenous change to the entire network and is used to analyze the effect of additional transmission on the market clearing price of CRR.

The present analysis falls into the part of literature that focuses on studying the efficiency of the market for FTRs. The efficiency of FTR market has been analyzed in a variety of ways for other competitive electricity markets like New York ISO (NYISO) and California ISO

[1] The Peak share of wind was 54 percent in October 27, 2017 at 4 AM.

(CAISO) in the US (Borenstein et al., 2002, 2008; Adamson et al., 2010; Deng et al., 2010; Mount and Ju, 2014; Leslie, 2018). A common theme in the literature to measure efficiency is to study the difference between market clearing prices and the DAM price (Borenstein et al., 2008; Adamson et al., 2010; Leslie, 2018). Inefficiency due to quantity constraints in these markets has also been found to create arbitrage opportunities that the market participants may exploit in order to profit from the FTR auction (Mount and Ju, 2014; Leslie, 2018). Another strand of literature looks at the incidence of market power in the generation side and the resulting inefficient allocation and pricing of FTR contracts (Bushnell, 1999; Joskow and Tirole, 2000; Borenstein et al., 2002, 2008). Inefficiency due to manipulative actions by market participants has been studied for the Midwest ISO (Birge et al., 2018). This paper is distinct from the existing literature in the sense that we do not focus on issues concerning the allocative efficiency of the market or incidence of market power or speculative behavior as a result of transmission integration. While these questions are interesting and hold policy relevance in their own right, we seek to address the gap in the literature on empirical relationship between transmission shock and CRRs.

The paper contributes to the contemporary literature in the following ways. Firstly, it presents a unique analysis of the CRR market post CREZ transmission project using monthly CRR auction data over December 2010 – May 2018. To the best of our knowledge, this is the only paper looking at the Texas electricity market pre and post CREZ. Secondly, this paper discerns the heterogeneous effect of the policy across different regions in Texas for different kinds of contracts. The paper also adds to the burgeoning literature on the effects of geographical integration in electricity markets. Recent empirical papers have looked at efficiency effects and competitiveness of electricity markets as a result of changes in transmission policy and infrastructure (Wolak, 2015; Davis and Hausman, 2016; Ryan, 2017). Efficiency in the context of this study is defined as a gradual convergence of prices of CRR contracts across different zones at different Time of Use (ToU).

The primary finding of this paper is that transmission integration as a result of CREZ led to a significant drop in market clearing prices of CRRs across all regions and ToUs. However, there is substantial heterogeneity in the effects of transmission shock on prices of contracts across West v.s. Other Zones. We find decrease in prices to be more pronounced for CRRs associated with West than for CRRs across other zones in Texas. This effect differs with respect to ToU of the CRR with the contracts at Peak Weekday and Peak Weekend displaying similar patterns. The impact of transmission integration is driven by contracts at the top 75 percent of the price distribution for Peak Weekday and Peak Weekend. Further, we find evidence regarding heterogeneity in bidding behavior of different firm types (generators, retailers, and traders) for CRRs at Peak Weekday and Peak Weekend. This heterogeneity is translated to a differential effect of transmission shock across different firm types at different ToUs.

We present estimates of change in auction revenues over January 2014 to May 2018 as a result of transmission integration. These revenue estimates are perhaps the first ones in literature that isolate the empirical effect of transmission integration on auction revenues in electricity market. We find an average drop of approximately \$960,000 per hour and an aggregate drop of \$250 million for the sample used in the analysis. Convergence in prices of CRRs linked with the West zone to the CRRs across other zones indicate a gain in efficiency of the overall CRR market.

The rest of this paper is organized as follows. Section 2 details the institutional background regarding CREZ transmission project, Texas electricity market and the CRR market. Section 3 describes the data, followed by the empirical model in Section 4. Results of the empirical model and further analysis of underlying heterogeneity is presented in Section 5. Section 6 presents revenue estimates and policy implications of the observed effects. Section 7 concludes.

2 Institutional details

2.1 CREZ transmission project

In 2005, Texas legislature passed the Texas Senate Bill 20 which mandated PUCT to identify 'Competitive Renewable Energy Zones' (CREZ) in consultation with ERCOT, in order to develop a transmission system to exploit the wind resources in West region of Texas and deliver renewable power to consumers in other parts of the state. In 2007, PUCT identified five CREZs based on preliminary transmission analysis and wind developer interests. After several rounds of analysis by ERCOT on various scenarios and plans, PUCT in 2008, selected the scenario that aimed to accommodate 18.5 GW of wind energy at a cost of \$6.8 billion. The goal was to build 3,600 circuit miles of 345 kV transmission over 2010 through 2013 and have all facilities in-service by December 31, 2013. Figure 1 shows various transmission lines built as a part of CREZ along with the dates of completion of individual links. As apparent from the figure, major parts of transmission across various regions of Texas were completed by the end of 2013, adding credibility to using January 2014 as an exogenous treatment to study the effect of transmission integration.

The CREZ transmission project has been deemed successful in terms of increasing the integration of wind generation along with elimination of various transmission bottleneck issues, higher reliability, and lowering of wholesale electricity prices (Lasher, 2014; Billo, 2017). This paper takes an alternative approach to study the effectiveness of transmission integration due to CREZ. Any change in market expectations about future congestion, in theory should be reflected as changes in the market clearing prices of CRR contracts purchased at auctions (Joskow and Tirole, 2000; Deng et al., 2010; Adamson et al., 2010). We look at how the addition of this transmission affected expectations of market players regarding future congestion at DAM by analyzing its effect on the prices of these contracts.

2.2 Electricity market restructuring and the Texas electricity market

The US electricity market underwent a wave of major regulatory reforms in many states over the period of late 1990s and early 2000s. This regulatory reform, commonly termed as restructuring was primarily aimed at reforms in generation, transmission, and retailing aspects of the market (Borenstein and Bushnell, 2015). Prior to the restructuring process, the US electricity market was primarily composed of vertically integrated investor owned utilities (IOU) that were responsible for generation, transmission, local distribution and retailing of electricity.

The restructuring process saw the deregulation of electricity generation in many states, in a sense that the electricity generation could now be pursued by unregulated plants called merchant generators or independent power producers (IPP). These merchant generators were responsible for the generation and selling of electricity to distributors and retailers. However, the transmission remained a monopoly and was still regulated to be not for profit entity. This restructuring took place at varied levels amongst the different markets of the US. Overall, the share of electricity generation from IPP grew from just 1.6 percent in 1997 to about 35 percent in 2005 and about 39 percent in 2016[2]. The deregulated electricity markets are managed by an ISO or Regional Transmission Organization that is a not-for profit entity responsible for smooth functioning of all aspects of the electricity market which includes (but not limited to) balancing demand and supply of electricity, allocation of CRRs, financial settlements between various market participants. This paper focuses on the Texas electricity market and the associated ISO ERCOT.

[2]Borenstein and Bushnell (2015) provide an excellent discussion on the electricity market restructuring, it's gains and losses.

The Texas electricity market is one of the deregulated or restructured electricity markets in the US. ERCOT is responsible for system reliability and managing the competitive wholesale and retail market of the Texas electricity market and is regulated by PUCT. As the ensuing discussion illustrates, it plays a vital role in the auction and subsequent allocation of CRR. In what follows, We will briefly describe the price formation of CRR in Texas electricity market followed by the determination of CRR payouts. This discussion on institutional details will be helpful to understand the research question this paper seeks to answer in a more precise manner.

2.3 CRR market

2.3.1 Determining market clearing price of CRR

The allocation of CRR in Texas electricity market takes place through uniform price auctions conducted by ERCOT prior to the realization of Day Ahead Market (DAM). These auctions are held monthly and semi-annually[3]. 90 percent of transmission capacity is available for allocation using monthly auctions. The objective of this auction for ERCOT is to maximize the auction revenue subject to transmission constraints and credit limits.

The timing of the auction is as follows:

1. ERCOT posts a CRR network model that basically represents transmission capacity available each month. The CRR network model is derived from network operations model by ERCOT that reflects characteristics of ERCOT transmission system that includes topology, equipment rating, and other operational limits in the system[4].

2. The network model is available to market participants on Market Information System (MIS), 10 business days before the monthly auction and 20 business days before the long term auction sequence.

3. ERCOT them collects bids to buy maximum quantity (in MW) of CRRs and offers to sell available quantity (in MW) of CRRs across different nodes[5] from the market participants.

[3]The long term auctions comprise of six successive auctions with six month windows with one window each month.

[4]CRR network model therefore reflects transmission facilities expected to be in-service for the specified month, significant outages, dynamic ratings, monitored elements, contingencies, and settlement points.

[5]A node in a network is simply combination of source i and sink j.

4. With total transmission capacity[6] and credit limits as constraints, ERCOT maximizes the net auction revenue which is essentially the difference between bid based value and offer based cost. The optimization problem can be written as:

$$\begin{aligned} \max_{q_b, q_o} \; & [(\textit{bid based value}) - (\textit{offer based cost})] \\ s.t. \; & \text{total transmission capacity} \qquad (1) \\ & \text{credit limits} \qquad (2) \end{aligned}$$

where,

$$\textit{bid based value} = \sum (\text{bid price} \times q_b),$$
$$\textit{offer based cost} = \sum (\text{offer price} \times q_o)$$

The optimization determines the optimal allocation of *cleared bid quantity*, q_b and *cleared offer quantity*, q_o of CRR contracts across various nodes in the network. The shadow value of transmission constraints (represented by (1) in the optimization problem) across a specific pair of nodes determines the market clearing price ($/MWh) of the CRR contract between those nodes. Shadow price, in this context simply refers to the marginal cost to make an additional increment of transmission capacity (i.e. 1 MW) available. Hence, the shadow price or in other words the market clearing price of CRR is dependent on bids and offers of CRR by various market participants.

Another layer of complexity in the monthly auction design of CRR is due to its treatment of contracts at different ToUs: Peak Weekday (Monday through Friday, 07:00 – 22:00), Peak Weekend (Saturday and Sunday, 07:00 – 22:00), and Off Peak (Monday through Sunday, 01:00 – 07:00 and 23:00 – 24:00). Market participants have an option to submit a single 24 hour bid for all three ToUs in a period t or submit bids for individual ToU[7]. Hence, a bid for an individual ToU is awarded if the bid price exceeds the market clearing price of the CRR at the corresponding ToU. However, a 24 hour bid is awarded if the bid price exceeds the weighted average (by hour) of all three ToU market clearing prices.

Consider a simple numerical example that illustrates this point:

Say a CRR account holder (market participant) enters a 24 hour bid of CRR from source i to sink j at a bid price of $10/MWh for the month of January 2019[8] in a monthly auction.

[6]Transmission constrains across a network are also referred as *simultaneous feasibility constraints* in various competitive electricity markets in the US. For more details refer: Leslie (2018).

[7]The occurrence of single 24 hour bids for all ToUs is extremely rare. In our data, single bids account for less than 3 percent of the data. This is confirmed by our correspondence with a CRR market expert.

[8]January 2019 had 23 weekdays and 8 weekends.

January 2019 had a total of 744 hours, including: 352 Peak Weekday hours, 144 Peak Weekend hours, and 248 Off Peak hours. Suppose the market clearing prices of CRR_{ij} for the three ToU are \$12/MWh, \$8/MWh, and \$4/MWh for Peak Weekday, Peak Weekend, and Off Peak respectively. The weighted average price for the three ToUs is calculated as: $\frac{352\times12+144\times8+248\times4}{744} = \$8.56/\text{MWh}$. Since, the bid price was \$10/MWh, the 24 hour bid is awarded.

Hence, if the account holder was awarded say 3 MW of CRR at the market clearing prices mentioned above for the month of January 2019, total auction revenue received by ERCOT for the month of January 2019 is: $3 \times ((352 \times 12) + (144 \times 8) + (248 \times 4)) = \$19,104$.

2.3.2 Determining CRR payout

In Texas electricity market, CRR payout is determined at the Day Ahead Market (DAM) which is realized one day prior to the real time market. CRR payout is essentially a payment or charge to the CRR holder when transmission grid is congested at DAM. These payouts are characterized by Locational Marginal Price (LMP), which as the name suggests is the cost to serve the next increment (hence, marginal) of Load at an electrical Bus[9]. Hence, in order to define the CRR payout, it is important to understand how LMP is determined at DAM:

1. ERCOT collects supply offers from various generators in the market. These offers consist of capacity commitments (in MW) at certain prices (\$/MWh) set by these generators.

2. Using the familiar CRR network model and MIS, ERCOT determines transmission constraints and other capacity constraints across the network.

3. With the supply offers and transmission constraints in place, ERCOT runs an optimization problem that minimizes the as-offered costs of supplying electricity subject to transmission constraints, supply meeting the demand, and generator constraints at

[9]An electrical Bus as defined by ERCOT is simply a physical transmission that connects one or more: loads, lines, transformers, capacitors, etc.

the DAM. The optimization problem can be written as:

$$\min_{Q_i} \sum_i Q_i \times C_i$$

$$s.t. \text{ Transmission constraints across the network} \quad (1)$$

$$\text{Supply} = \text{Demand} \quad (2)$$

$$\text{Generator capacity constraints} \quad (3)$$

The optimization determines the supply Q_i from each generator i in the market. The shadow value of the transmission constraints (1) determines the Locational Marginal Price (LMP) for each node in the network. The CRR payout at hour h for a market participant that holds the CRR between source i and sink j is given by:

$$\text{CRR payout (\$/MWh)} = \underbrace{LMP_{j,h} - LMP_{i,h}}_{\text{price swap}}$$

Hence, the total revenue (\$) if the market participant holds q_b units of CRR for total number of hours h is:

$$\text{Total Revenue} = q_b \times (LMP_{j,h} - LMP_{i,h}) \times h$$

CRR payout is zero if there is no congestion in the transmission between i and j[10]. However, if there is congestion, CRR payout would be non-zero and the magnitude is determined by the above expression. This difference of LMPs between sink j and source i is called a price swap because the CRR holder receives a payment if $LMP_{j,h} > LMP_{i,h}$ or faces a charge if $LMP_{j,h} < LMP_{i,h}$[11]. Hence, market participants have incentives to purchase CRRs in order to hedge against potential congestion costs at DAM. The following discussion illustrates this idea in detail.

2.3.3 What is the use of CRR?

From the previous sections, it is clear that CRR is essentially a forward contract wherein the forward price is set by the auction and the spot price is determined at the DAM. Hence, like any other forward contract, it can be used to hedge future risks which in this case happens to be congestion of transmission network.

[10]Congestion occurs when a transmission line operates at its capacity, for example when a 100MW transmission line carries 100MW of electricity. No congestion is another way of saying that the transmission constraints between two nodes are slack.

[11]In an ideal scenario, we would expect no congestion. However outages, transmission changes, or demand shocks may cause congestion and cost increases

During the settlement of DAM, ERCOT pays generator $i : Q_i \times C_i$ for its electricity and charges the retailer $j : Q'_j \times LMP_j$ where Q'_j is the amount of electricity demanded by the retailer. Due to congestion, there exists a price wedge and retailer might end up paying higher than what the generator receives for supplying electricity. In order to hedge potential risks of paying high amount of money at DAM, the retailer has incentives to purchase a CRR between source i and sink j at the auction[12].

Using the familiar example presented in Section 2.1, assume that the LMP at DAM between source i and sink j accrued hourly are as follows:

- Peak Weekday: $LMP_i^{pwd} =$ \$8/MWh, $LMP_j^{pwd} =$ \$20/MWh
- Peak Weekend: $LMP_i^{pwe} =$ \$4.6/MWh, $LMP_j^{pwe} =$ \$17/MWh
- Off Peak: $LMP_i^{off} =$ \$2.4/MWh, $LMP_j^{off} =$ \$2.4/MWh

Total revenue for January 2019 for the three ToUs at $q_b = 3$ MW is:

- Peak Weekday: $q_b \times (LMP_j^{pwd} - LMP_i^{pwd}) \times 352 = 3 \times (24 - 7.4) \times 352 = \$17,529.6$
- Peak Weekend: $q_b \times (LMP_j^{pwe} - LMP_i^{pwe}) \times 144 = 3 \times (17 - 4.6) \times 144 = \$5,356.8$
- Off Peak: $q_b \times (LMP_j^{off} - LMP_i^{off}) \times 248 = 3 \times (2.4 - 2.4) \times 248 = \$0$

$\implies$ Total CRR Revenue $= 17,529.6 + 5,356.8 + 0 = \$22,886.4$. Therefore, profits accrued to the CRR account holder over January 2019 $= \$22,886.4 - \$19,104 = \$3,782.4$.

As evident from the above discussion and the simplified example, CRR essentially acts as a hedging instrument for the contract holder because it prevents them against potential congestion risks at DAM. Having said that, various market participants may use CRR as a speculative device in order to profit from congestion between a pair of nodes in the network. Ideally, if the transmission feasibility constraints are not violated (or the set of contracts are simultaneously feasible) then the equilibrium allocation of contracts determined at the auction matches the realized flow of electricity in the market at DAM, hence the CRR payouts would equal to the auction revenue (Hogan, 1992). However, unforeseen transmission outages, supply shocks, arbitrage opportunities as a result of assymmetric information and quantity constraints might lead to CRR payouts being higher than the auction revenue. This

[12]This is a simplified scenario that is meant to show how CRR is useful as a hedging instrument. Retailer(s) may also purchase CRRs across points different than the ones it is purchasing electricity from. A similar argument holds for generators as well. They also have incentives to purchase CRRs in order to hedge potential risks.

is seen as a potential market inefficiency and has been a source of interest among researchers and a point of concern for policy makers (CAISO, 2016; Bushnell et al., 2018; Leslie, 2018).

3 Data

This paper uses market clearing data on monthly auctions of CRR over December 2010 – May 2018. The dataset is compiled from data on market clearing information of CRR contracts obtained from ERCOT. This data consists of auction data of individual CRR contracts awarded to various account holders for each of the monthly auctions.

The auction data comprises of market clearing price ($/MWh) determined by the ERCOT in a uniform price auction as described in the previous section. Along with prices, a CRR contract includes details on contract type (obligation/option), ToU (Peak Weekday, Peak Weekend and Off Peak), quantity of contracts expressed in MW and source (i) and sink (j). For the analysis in this paper, we focus on Obligation type CRRs between Hubs[13] and Load Zones[14] across West, North, South, and Houston.

In order to prepare the data for the analysis, we first separate the dataset for Obligation type CRRs with positive market clearing prices. The contracts with negative market clearing prices are called 'Counterflow CRRs'[15]. However, in case of ERCOT, counterflow CRRs can be treated as regular CRRs with positive price by flipping the Source and Sink and interpreting them as a Sell contract. This is greatly helpful as it doubles our sample size and provides more variation in the data to identify the effect of transmission shock. Next, we aggregate the quantities (MW) of identical CRR contracts wherein identical contracts are defined as the ones with the same source, sink, ToU, time period (month-year), and market clearing price. We then subset the dataset with the observations wherein the source and sink is either a Hub or a Load zone. Since, the effect of transmission shock might differ across ToUs because a variability in wind production at Peak v.s. Off Peak, we separate the

[13]ERCOT defines 'Hub' as a designated settlement point consisting of Hub Bus or group of Hub Buses. A Hub Bus in power engineering is an energized electrical Bus or a group of energized electrical Bus. Hence, the market clearing prices at Hubs is essentially a simple average of clearing prices at particular 345kV stations in a zone. The sample consists of following Hubs: North, West, South, Houston, ERCOT Hub Average, and ERCOT Bus Average.

[14]ERCOT defines 'Load Zone' as a group of electrical buses assigned to the same zone. Every electrical Bus in ERCOT with a Load must be assigned to a Load Zone for settlement purposes. Hence, Load Zones are Load distribution factor weighted averages of Load buses in a zone. The sample consists of following Load Zones: North, West, South, Houston, LCRA, RAYBN, AEN, and CPS.

[15]For a greater exposition on counterflow Financial Transmission Rights refer Adamson et al. (2010).

sample for Peak Weekday, Peak Weekend, and Off Peak. This leaves us with 3367, 3266, and 3268 monthly observations from December 2010 through May 2018 for Peak Weekday, Peak Weekend, and Off Peak CRRs respectively.

Table 1 presents summary statistics for CRR market clearing prices for the three samples before and after completion of CREZ in January 2014. There is a decrease in mean prices for Peak Weekday and Off Peak contracts and a slight increase in case of Peak Weekend.

In order to get a more clear picture of the underlying pattern, we plot the monthly price averages of CRR contracts at three ToUs in Figure 2. As evident, there is a clear drop in prices post January 2014, when the extra transmission built as a part of CREZ was brought in service. The drop in average prices is highest for contracts at Peak Weekday and Peak Weekend, followed by Off Peak. Hence, in the analysis that follows, we attempt to isolate the effect of the transmission shock in January 2014 on CRR prices.

4 Empirical Model

The empirical analysis in this paper aims at identifying the effect of transmission shock in January 2014 on the market clearing price of CRR contracts for the three times of use. We use fixed effects estimator to estimate the within variation in source and sink after controlling for a rich set of control variables. We estimate the following specification using a fixed effects model for the sample of Peak Weekday, Peak Weekend, and Off Peak CRR contracts.

$$CRR_{ij,t} = \beta_0 + \beta_1 D_{t \geq 01-2014} + \beta_2 (D_{t \geq 01-2014} \times trend) + t + q_{ij,t} + \delta_{2017} + z_{ij,t} + \epsilon_{ij,t} \quad (1)$$

where the dependent variable is the market clearing price (\$/MWh) of a CRR contract between source i and sink j for month-year t. The treatment effect variable is a binary indicator $D_{t \geq 01-2014}$ which equals 1 for time period post January 2014 and 0 for time period prior to January 2014. In order to capture the change in time trend as a result of the shock, we estimate the interaction of $D_{t \geq 01-2014}$ with the time trend t. Figure A.1 provides a graphical intuition for different signs of coefficient of interest $\hat{\beta}_1$ and $\hat{\beta}_2$ in Equation 1.

As discussed before, the completion or integration of CREZ transmission to the electricity network can be considered an exogenous shock to the network. In order to control for confounding factors, we use a rich set of fixed effects summarized by the variable $z_{ij,t}$. Concretely, $z_{ij,t} = \{\eta_i, \eta_j, m_t, \eta_i \times m_t, \eta_j \times m_t\}$, wherein, η_i and η_j are fixed effects for source i and sink j. To control for potential endogeneity due to seasonality, we use month fixed effects (m_t), source by month ($\eta_i \times m_t$) and sink by month ($\eta_j \times m_t$) fixed effects. Further, we control for a linear time trend t and quantity of CRR contracts ($q_{ij,t}$) across i, j in period t. The empirical specification also includes a fixed effect for 2017 (δ_{2017}) to control for the price spike as a result of massive floods in Texas due to hurricane Harvey in 2017 (Chokshi and Astor, 2017). Given the set of fixed effects and exogeneity of the treatment variable, the coefficient β_1 estimates the unbiased effect of treatment shock in January 2014 on the market clearing price of CRR.

5 Results

Table 2 presents the estimation results of Equation 1. As evident from Table 2, the addition of transmission led to a drop in CRR prices for the contracts across all the three times of use. This decrease in prices is largest in magnitude for Peak Weekday (\$0.9/MWh) and Peak Weekend (\$1/MWh) followed by Off Peak (\$0.3/MWh). We do not find a strong interaction effect of treatment and trend for contracts at Peak Weekday and Peak Weekend. However, this interaction effect is positive and statistically significant in case of Off Peak contracts. The magnitude of the coefficient $\hat{\beta}_2$ suggests that the on an average, off Peak prices rose by \$0.039/MWh each month post January 2014. The estimates of the transmission shock for the alternative specifications that do not control for seasonality and/or exclude time trend interaction are similar to the estimates of the baseline specification.

Due to spatial nature of CREZ, it is of interest to distinguish the effect amongst different regions of Texas. Because one of the primary goals of CREZ was to integrate the wind generation from West to other regions of the state, we might expect heterogeneity in the effect of the transmission integration to be different for contracts associated with West than contracts traded between other regions. For a better exposition, we plot the average CRR price for contracts with West Hub/Load Zone as source i and/or sink j against the contracts between other source i and/or sink j in Figure 3. Clear patterns emerge from this figure. Figure 3a shows that the contracts associated with the West Hub/Load Zone see a significant drop in average prices post transmission integration. CRR contracts across other regions do not exhibit this pattern, instead we see slight increase in average price across Peak Weekday, Peak Weekend, and Off Peak (Figure 3b). This significant lowering of prices can be interpreted as a sign of convergence of prices amongst contracts across different regions post transmission integration.

We estimate the baseline specification on the sample of CRR contracts associated with West and on the sample of contracts across other regions for Peak Weekday, Peak Weekend, and Off Peak. The results of this estimation are reported in Table 3. We see a large negative effect of transmission shock on CRR prices for contracts with source and/or sink as West Hub/Load Zone. This effect is similar in magnitude for Peak Weekday and Peak Weekend, approximately \$3.4/MWh, whereas it is about \$1.1/MWh for Off Peak contracts. Interestingly, we see a decrease in Peak Weekday and Weekend prices over time due to the transmission shock as reflected by the negative estimate of treatment and trend interaction variable. However, the Off Peak prices saw a modest increase over time. This drop in prices due to the transmission integration is only limited to contracts linked with West Hub/Load Zone. For contracts across other regions, we see a weakly negative estimate that is statistically indistinguishable from zero for all the three ToUs. Hence, in the analysis that follows, we restrict our attention to the sample of contracts with source and/or sink as West Hub/Load Zone.

5.1 Spatial heterogeneity in the effects of transmission integration

To further investigate the differential effect of transmission integration on CRR contracts with West source and/or sink, we estimate alternative specifications of Equation 1 by adding binary variables denoting different combinations of source i and sink j[16]. Table 4, Table 5, and Table 6 report the results of these specifications for Peak Weekday, Peak Weekend, and Off Peak respectively on the sample of CRR contracts associated with West Hub/Load Zone.

Column (1) Table 4 replicates the specification in Column (1) Table 3 for the ease of comparison. The results in Table 4 indicate an average decline of approximately \$3/MWh in prices of CRR for contracts with source in West and sink at North, South, West, and Houston. The coefficient of the interaction between $D_{t \geq 01-2014}$ and the binary variable $\mathbb{1}\{\text{Sink} = \text{j}\}$, where $j = \{\text{West, North, South, Houston}\}$ is found to be statistically insignificant in all the specifications. The magnitude of coefficient estimate of $D_{t \geq 01-2014}$ remains almost the same for all the specifications. This suggests that the average drop in prices due to transmission integration is similar across contracts whenever source is West Hub/Load Zone and Sink is West, North, South, and Houston at Peak Weekday. Further, the decreasing trend effect in prices due to transmission integration is similar in magnitude ($\sim$ \$0.15/MWh) across these contracts.

Table 5 reveals a similar pattern as that in Table 4. The parameter estimates suggest that the negative effect of transmission integration is driven by contracts with source at

[16] With the source as West Hub/Load Zone, we estimate specifications with dummy variables representing West, North, South, and Houston Hubs/Load Zones as Sinks.

West Hubs/Load Zone and is similar across contracts with Sink at West, North, South, and Houston Hub/Load Zone. The decreasing trend is also similar in magnitude across the specifications, with the prices decreasing by approximately \$0.099 – \$0.113/MWh each period. This is slightly lower in magnitude than the decrease in trend observed for Peak Weekday contracts.

The results for Off Peak contracts are somewhat different from Peak Weekday and Peak Weekend. As shown in Table 6, the contracts with the source in West are on an average \$2.36/MWh higher than other contracts. A similar effect is observed for contracts that had their sinks in West, i.e. they are on an average \$2.82/MWh higher than the other contracts. This suggests that contracts at Off Peak with source and sink in West saw an increase in prices as a result of transmission integration. This is in contrast with the results obtained for CRR at Peak Weekday and Peak Weekend, wherein CRRs with source and sink at West were associated with largest price drop. There is considerable heterogeneity in the effect across contracts with different sinks. The average drop in prices is highest for contracts with source at West and sink at South (Column (4) Table 6), followed by the contracts with sink at North and Houston. Hence the average decrease in prices across the contracts with sinks at North, South, and Houston offset the increase in prices observed for contracts traded within the West.

Another result that warrants attention is the estimate of interaction between trend and the treatment variable in Table 6. We observe that CRR clearing prices increased by \$0.09/MWh for contracts with West source and/or sink across all the specifications considered. A potential reason for this finding could be the attributed to the wind generation profile in Texas. Most of the wind production occurs during Off Peak hours or during periods of low demand (Potomac Economics, 2018). Wind penetration in overall electricity generation has seen an increasing trend over the years and is most significant at Off Peak (ERCOT, 2018a). Perhaps this increasing wind production at Off Peak is linked with higher market expectation for congestion, which in turn is reflected as increasing trend in CRR clearing prices post CREZ transmission integration.

5.2 Distributional heterogeneity in the effect of transmission integration

Thus far we have discussed spatial heterogeneity in the effect of transmission integration on contracts across different ToUs within the Texas electricity market. However, one might expect heterogeneity in the treatment effect at various parts of the price distribution as well. To explore this, we divide the sample into four equally sized quarters using quartiles of CRR market clearing price. Henceforth, we refer to these quarters as Q_τ where $\tau = 1, 2, 3, 4$ represents the respective quarter[17]. In order to isolate the effect of CREZ transmission on these quarters, we estimate Equation 1 for each of the four samples Q_1, Q_2, Q_3 and Q_4. The coefficients of interest, $\hat{\beta}_1$ and $\hat{\beta}_2$ for Peak Weekday, Peak Weekend, and Off Peak are reported in Table 7.

The parameter estimates for Peak Weekday show that CREZ transmission led to a \$4.65/MWh decrease in average prices for Q_4. This decrease is accompanied by a \$0.14/MWh drop per month as estimated by the interaction between the treatment and trend variable. However, the parameter estimates for other quarters of price distribution are economically small in magnitude and statistically insignificant. Similarly, in case of Peak Weekend, the strongest effect is observed for Q_4, wherein the decrease in mean prices is \$3.23/MWh followed by a slight increase of \$0.11/MWh in mean prices for Q_3. The estimates for other quarters and the trend effects are statistically indistinguishable from zero. For the Off Peak contracts, a modest decrease of \$0.02/MWh is observed for Q_2. Given relatively lower probability of congestion at Off Peak period as compared to Peak hours, the impact of CREZ transmission is found to be rather limited. Interestingly, we see that the positive trend effect estimated for Off Peak contracts in Table 3 and Table 6 due to growing wind penetration in Off Peak hours is primarily driven by Off Peak CRRs at Q_4.

5.3 Heterogeneity in the behavior of market participants post transmission integration

One of the major sources of heterogeneity in the Texas electricity market is the participation of different kinds of firms in CRR auction. As discussed in section 2.3.3, firms might have different incentives to own a CRR and hence we could expect heterogeneity in the behavior of various firm types in response to excess transmission. To explore this we classify each CRR account holder into three broad categories of firm types: Generating firms, Retailing firms, and Financial trading firms[18]. The CRR contracts are then aggregated based on market clearing price, source, sink, time period, and firm type. This leaves us with 4853, 4657, and 4670 observations for distinct CRR contracts for Peak Weekday, Peak Weekend, and Off

[17] It is important to note that Q_τ doesn't denote the quartile. Instead, it denotes one of four equal groups created by ordering the data and diving it in four equal parts using 25th quantile, median, and 75th quantile as the cut-points.

[18] Details on the classification and the firms in each category is summarized in Appendix.

Peak respectively.

As summarized in Table 8 we find a similar ownership pattern of CRRs for these three firm types across the three ToU. Traders hold nearly 50 percent of CRRs across various Hubs and Load Zones throughout the time period of the study. Interestingly, we find a dramatic rise in mean share of CRRs owned by generating firms, from approximately 23 percent to 40 percent post January 2014. This is primarily driven by a stark decrease in share of contracts owned by retailers. This drop is about 13 to 16 percent across different ToUs. Further, we observe a clear decline in market clearing price post transmission integration for all three firm types across Peak Weekday, Peak Weekend, and Off Peak. The decrease in clearing price could be driven by change in bidding behavior of different firms in response to the transmission shock post January 2014. In order to identify the differential effect of CREZ transmission integration on CRR clearing prices for different firm types, we estimate a specification similar to Equation 1.

$$\begin{aligned} CRR_{ij,t} = {} & \gamma_0 + \gamma_1 \cdot \mathbb{1}\{\text{Retailer}\} + \gamma_2 \cdot \mathbb{1}\{\text{Trader}\} + \delta_0 D_{t \geq 01-2014} + \\ & \delta_1 (D_{t \geq 01-2014} \times \mathbb{1}\{\text{Retailer}\}) + \delta_2 (D_{t \geq 01-2014} \times \mathbb{1}\{\text{Trader}\}) + t + q_{ij,t} + \delta_{2017} + z_{ij,t} + \epsilon_{ij,t} \end{aligned} \tag{2}$$

The coefficients in Equation 2 have a different interpretation than the parameter estimates in our baseline specification Equation 1. As mentioned earlier, we aggregate CRR contracts in terms of three broad firm types: Generators, Retailers, and Traders. The base category of firm type is Generator, therefore, the intercept γ_0 represents the conditional mean of market clearing price of CRR for a generating firm. γ_1 and γ_2 are the coefficients for the indicator variables specifying whether the firm type is a retailer or a trader respectively. In a similar vein, δ_1 and δ_2 capture the differential effect of transmission integration on clearing prices for retailers and traders with generating firms as the base case.

Table 9 reports the estimation result of Equation 2. The parameter estimates show a negative and statistically significant effect of transmission integration on market clearing prices for CRRs held by generating firms. This effect is \$1.5/MWh for Peak Weekend CRRs, followed by Peak Weekday and Off Peak where is the average decrease is approximately \$1.3/MWh and \$0.5/MWh respectively. Interestingly, the differential effect of transmission integration across different types of market players is statistically indistinguishable from zero in case of Off Peak CRRs. This result indicates that there isn't any significant difference in bidding strategy employed by different firm types for Off Peak contracts.

This is in contrast to what we find for Peak Weekday and Peak Weekend contracts. In this case, retailers and traders tend to employ a bidding strategy that is different than generating firms. Specifically, we estimate the conditional average treatment effect to be \$0.35/MWh and \$0.36/MWh higher than generating firms for retailers and traders respectively at Peak Weekend. Interestingly, the treatment effect for financial trading firms is approximately \$0.38/MWh higher than that of generating firms at Peak Weekday. However, the differential effect is statistically insignificant in case of retailers at Peak Weekday. This might indicate that financial trading firms took a more speculative position than generating firms and retailers post CREZ, and therefore bid across the nodes that had a higher probability of congestion at DAM. Retailers and generators on the other hand have an incentive to hedge congestion risk at DAM due to their physical interests in the market. Therefore, we can expect them switching to nodes wherein the probability of congestion is lower as a result of additional transmission and hence we see higher (magnitude) treatment effect at Peak Weekday.

The results obtained can be attributed to the fact that different market participants have different motives for holding CRRs which might incentivize them to bid in a manner that is unlike their competitors. Private information about the market and access to technology in order to predict future congestion is another aspect that might lead to such patterns. Firms may employ any such tools at their disposal so as to hedge risk against network congestion or bid in a speculative manner for higher profits. Even though we do not disentangle the effects due to various channels or mechanisms, the analysis in this section provides evidence of inherent heterogeneity amongst firm types using an exogenous shock to the network.

Figure 4a compares total expenditure (\$) by the three firm types pre and post CREZ transmission integration[19]. In order to maintain consistency in comparison we aggregate per hour expenditure over three years prior and post January 2014, the commissioning date for CREZ[20]. There is evidence of a clear drop in total expenditure across all the three ToUs post transmission integration for all the three firm types. Interestingly, we find total expenditure in Peak Weekday contracts to be highest for retailers, approximately \$80 million prior to 2014 and about \$52 million post 2014. The expenditure in CRRs at Peak Weekend is almost the same for both retailers and traders both Pre ($\sim$ \$19 million) and Post 2014 ($\sim$ \$13 million). With an approximate expenditure of \$27 million, financial trading firms lead the investment in Off-Peak CRRs by a wide margin prior to transmission integration, however this margin is much smaller post 2014.

[19]The discussion in this part is limited to expenditure in monthly CRR auctions of Obligation type contracts for the specific part of the network: Sources and Sinks that are Hubs and/or Load Zones.

[20]This implies that the Pre CREZ expenditure is an aggregate of expenditure over 2011 – 2013 whereas Post CREZ expenditure is an aggregate of expenditure over 2014 – 2016. Limiting calculation of Post CREZ expenditure to 2016 also circumvents the issue of CRR price hike due to flooding in Texas in 2017.

Aggregating expenditures for the three ToUs for the generators, retailers, and traders albeit for the short period of 6 years highlights the scale of the CRR market. Figure 4b shows that financial traders invested about \$112 million followed by retail firms ($\sim$ \$110 million) and generating firms ($\sim$ \$74 million) over 2011 – 2013. Interestingly the decrease in expenditure over 2014 – 2016 is also highest in case of traders, about \$48 million followed by retailers and generators with a decrease of approximately \$38 and \$25 million respectively. We return to this discussion on decrease in expenditure in Section 6, wherein we compute the average effect of CREZ on overall expenditure or equivalently auction revenues for the period January 2014 – May 2018.

5.4 Convergence of prices post CREZ transmission integration

A crucial aspect of the CRR market that is linked to lowering of prices is the effect of the transmission integration on the efficiency of this market. We define efficiency in this context as the gradual convergence of market clearing prices of CRR contracts across different spatial locations. Because we observe significant lowering of prices of contracts linked with the West zone post January 2014, we are interested in looking whether there is a convergence in prices of these contracts with the prices of contracts across zones other than the West. To motivate this discussion, we present the average prices of CRRs with West Source and/or Sink and CRRs with Source and/or Sink other than West at each period t for the three ToUs in Figure 5. We notice clear patterns of convergence amongst these contracts post January 2014 for all ToUs. The convergence in prices is perhaps most significant for CRRs at Peak-Weekend followed by Off Peak CRRs.

In order to formally test for the convergence we employ an empirical strategy that is similar in spirit to that of Borenstein et al. (2008). However, in their paper, Borenstein et al. (2008) test for convergence between forward and spot prices in the CAISO market. In order to test for convergence between prices in our context, we estimate the following specification:

$$\left(\mathrm{CRR}_t^{\mathrm{West}} - \mathrm{CRR}_t^{\mathrm{other}}\right) = \alpha_1 \cdot \mathbb{1}\{t < 01 - 2014\} + \alpha_2 \cdot \mathbb{1}\{t \geq 01 - 2014\} + \epsilon_t \qquad (3)$$

The dependent variable in Equation 3 is the difference between clearing price of CRR with Source and/or Sink at West ($\mathrm{CRR}_t^{\mathrm{West}}$), and CRR with Source and/or Sink other than West zone ($\mathrm{CRR}_t^{\mathrm{other}}$). Since, the number of contracts in the two cases are different in each period, we instead use the average price and different quantiles (25th, 50th, and 75th) of the price distribution in period t. Hence, total number of observations in each regression is 90. The parameters of interest are two binary variable that capture the average convergence of prices for the period prior and post transmission integration. Specifically, $\hat{\alpha}_1 > \hat{\alpha}_2$ implies that the price difference of contracts across the two sets of spatial locations was lower post transmission integration.

The results of this estimation are reported in Table 10. A general pattern evident from Table 10 is that of a decrease in the difference in prices of CRRs post transmission integration across the two classes of CRR for all the three ToUs. As seen from Panel A, the convergence in average prices is highest for CRRs at Peak Weekend followed by CRRs at Off Peak and Peak Weekday. This pattern is common across various quantiles as well, with the price difference being highest at Peak Weekday followed by Off Peak. The convergence in prices is strongest between Peak Weekend CRRs and that too for the 75th quantile, wherein $\hat{\alpha}_2$ is statistically indistinguishable from zero. These results point out to a gain in efficiency in CRR market post transmission integration in terms of significant convergence in prices with the contracts linked with West zone converging to the prices of contracts linked with other zones.

6 Change in auction revenue post CREZ transmission

The empirical analysis suggests that CREZ transmission integration led to a significant decline in prices for Peak Weekday, Peak Weekend, and Off Peak with considerable heterogeneity across ToU and regions. A major policy question, therefore, is the extent to which these estimates translate to a decrease in auction revenue per hour[21]. Recall that the market clearing prices of CRR contracts is determined via uniform price auction conducted by ERCOT. Lowering of prices due to an exogenous change in transmission would be reflected as a decrease in auction revenue. This is of policy relevance as the decrease in revenue reveals information about the change in expectations that market participants have for future congestion.

Alluding to the treatment effects literature, the conditional average treatment effect on the CRR price for a contract between i, j at period t as a result of transmission shock ($T = 1$) conditional on a set of control variables ($X_{ij,t}$) can be written as:

$$\begin{aligned} \Delta CRR_{ij,t} &= E[CRR_{ij,t}|T=1, X_{ij,t}] - E[CRR_{ij,t}|T=0, X_{ij,t}] \\ &= \hat{\beta}_1 + \hat{\beta}_2 \cdot trend \end{aligned} \tag{4}$$

[21] Because the market clearing prices are corresponding to an hour of Peak Weekday, Peak Weekend, and Off Peak, the revenue estimates are in \$/h.

The change in revenue ($/h) can then be expressed as:

$$
\begin{aligned}
\Delta\text{Revenue}_{ij,t} &= \Delta CRR_{ij,t} \times q_{ij,t} = (\hat{\beta}_1 + \hat{\beta}_2 \cdot trend) \times q_{ij,t} \\
\Delta R_T &= \sum_{t \geq 01-2014} \sum_{ij} \Delta\text{Revenue}_{ij,t} \\
&= \left[\left(\hat{\beta}_1 \cdot \sum_{t \geq 01-2014} \sum_{ij} q_{ij,t} \right) + \left(\hat{\beta}_2 \cdot \sum_{t \geq 01-2014} \sum_{ij} (trend \cdot q_{ij,t}) \right) \right] \qquad (5)
\end{aligned}
$$

Using the estimates of the baseline specification from Table 2 in Equation 5, we derive the change in revenue ($/h) for contracts at Peak Weekday, Peak Weekend, and Off Peak. The results of this exercise is summarized in Table 11. Several interesting observations are apparent. The magnitude of decrease in revenue for the sample in the analysis is highest for Peak Weekday ≈ $690,000/h followed by Peak Weekend ≈ $534,000/h. Although the treatment effect for Off Peak contacts is negative ($0.32/MWh), due to a positive time trend effect ($0.04/MWh), the change in revenue is found to be ≈ $262,000/h. Multiplying the quantity of contracts $q_{ij,t}$ with the total ToU hours for the particular month-year t, converts these numbers in dollar terms. This is a small modification in Equation 5 that can be written as:

$$
\Delta \text{R}_T(\$) = \left[\left(\hat{\beta}_1 \cdot \sum_{t \geq 01-2014} \sum_{ij} (q_{ij,t} \cdot \text{ToU}_t) \right) + \left(\hat{\beta}_2 \cdot \sum_{t \geq 01-2014} \sum_{ij} (trend \cdot q_{ij,t} \cdot \text{ToU}_t) \right) \right] \tag{6}
$$

where, ToU_t is the number of ToU hours for Peak Weekday, Peak Weekend, or Off Peak at period t[22]. The estimates of total revenue is presented in Column (2) Table 11. Since, Peak Weekday has the maximum number of ToU hours, we observe the drop in revenue to be highest for Peak Weekday CRRs, approximately $235 million which is about 3.45 percent of the total cost of CREZ ($6.8 billion). This is followed by contracts at Peak Weekend, wherein the decrease in revenue is approximately $78.3 million (∼ 1.15 percent of total cost of CREZ). Finally, the total increase in revenue for Off Peak contracts is approximately $63.8 million (∼ 0.94 percent of total cost of CREZ.). Hence, the total decrease in revenue is approximately $250 million (∼ 3.67% of total cost of CREZ) over the period January 2014 – May 2018 as a result of CREZ transmission integration.

Figure 6 presets the total annual change in revenue per month (in million $) post 2014 for contracts across the three ToU. Annual change in revenue per month is a better indicator for comparison as there are only 5 months for 2018 in the sample. The annual change is

[22] Data on ToU hours for the sample is compiled from ERCOT.

highest in magnitude for contracts at Peak Weekday, followed by Off Peak contracts whereas it is almost stable for contracts at Peak Weekend. The estimates of change in revenue imply that market participants on an average expect lower congestion at DAM for Peak Weekday and Peak Weekend. Hence, the expected risk premium for future congestion as reflected by the market clearing prices of CRR is much lower than that before integration of CREZ transmission[23].

An interesting observation in Figure 6 is with regard to the change in revenue for Off Peak CRRs. Even though the treatment effect is estimated to be negative, it is offset by the positive estimate of interaction between treatment variable and trend. This is translated to a gradual shift in estimate of change in revenue being negative in 2014 to positive post 2015. This provides an alternative interpretation of the positive trend effect as a result of higher expectation of congestion at Off Peak.

7 Conclusions

This paper finds evidence that transmission integration led to a significant lowering of market clearing prices of CRR across all ToU. The average decrease in prices is highest for Peak Weekday and Peak Weekend contracts with source and/or sink at West Hub/Load Zone, with a negative trend effect. Albeit the treatment effect for Off Peak contracts associated with West had a negative treatment effect, we estimate a positive time trend. The effect of this positive time trend is evident from the annual revenue estimates for Off Peak contracts wherein the change in revenue is positive post 2015. Substantial spatial heterogeneity is observed in the treatment effect in contracts at different zones in Texas across ToUs. This spatial heterogeneity is found to increase the efficiency of the CRR market due to convergence between prices of CRRs at West Zone and CRRs at North, South, and Houston.

One of the striking findings of this paper is the magnitude of change in revenue estimated for contracts across different ToUs. The cumulative effect is in the order of $250 million which is approximately 3.7% the cost of CREZ. A substantial decrease in revenue at Peak Weekday and Peak Weekend as a result of transmission integration is offset by an increase in revenue of Off Peak contracts. Exploring heterogeneity in the behavior of market participants, we find evidence of significant differences between generating firms, retailing firms, and financial trading firms at Peak Weekday and Peak Weekend.

[23]This assumes that market prices of CRR reveals information about the market expectations for future congestion. Another assumption embedded in this is minimal to no speculative behavior. Formally testing the presence or extent of speculative behavior is beyond the scope of this paper.

The estimates presented provide a compelling case of how a 'positive transmission shock' leads to lowering of prices for contracts that were earlier marked by higher probability of congestion at DAM and thereby a higher clearing price at the auction. However, a few caveats are in order. Note that we do not use data of the entire network, but only the data on CRRs with Source and/or Sink that are Hubs or Load Zones. The results obtained are specific to part of the network and therefore a lower bound to the actual effect of the policy. The choice of using part of the network is primarily due to concerns of endogeneity of the treatment due to addition of nodes within the network with the construction of transmission. Utilizing the complete dataset is certainly a worthwhile extension to the paper. Such an analysis would shed light on network spillover effects due to gradual integration of transmission in a major electricity market.

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Tables

Table 1: Summary Statistics of CRR market clearing price ($/MWh)

	Peak Weekday					
	Mean	Median	Std. Dev.	Min	Max	N
Pre January 2014	2.050	1.224	2.752	0.002	29.938	967
Post January 2014	1.841	1.060	2.300	0.001	29.037	2400
	Peak Weekend					
	Mean	Median	Std. Dev.	Min	Max	N
Pre January 2014	1.453	0.750	1.838	0.0005	10.500	942
Post January 2014	1.528	0.870	2.168	0.0004	25.390	2324
	Off Peak					
	Mean	Median	Std. Dev.	Min	Max	N
Pre January 2014	0.861	0.314	1.547	1×10^{-6}	12.452	944
Post January 2014	0.683	0.320	1.110	1×10^{-6}	16.188	2324

Table 2: Regression results for Peak Weekday, Peak Weekend, and off Peak CRR contracts

	CRR market clearing price								
	Peak Weekday			Peak Weekend			Off Peak		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$D_{t\geq 01-2014}$	-0.946^{***}	-0.771^{***}	-0.911^{***}	-1.173^{***}	-1.031^{***}	-1.039^{***}	-0.772^{***}	-0.719^{***}	-0.323^{***}
	(0.315)	(0.271)	(0.300)	(0.289)	(0.249)	(0.286)	(0.188)	(0.160)	(0.116)
$D_{t\geq 01-2014} \times trend$			-0.015			-0.008			0.039^{***}
			(0.012)			(0.011)			(0.006)
m_t		X	X		X	X		X	X
$\eta_i \times m_t$		X	X		X	X		X	X
$\eta_j \times m_t$		X	X		X	X		X	X
Observations	3367	3367	3367	3266	3266	3266	3268	3268	3268
R^2	0.238	0.367	0.368	0.238	0.322	0.362	0.217	0.341	0.341

Notes:

The dependent variable is CRR market clearing price for Peak Weekday (columns (1) to (3)), Peak Weekend (columns (4) to (6)), Off Peak (columns (7) to (9)) for the three model specifications. Robust standard errors, clustered at year-month level are presented in parenthesis. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression results for CRR contracts with source and/or sink West Hub/Load Zone, and CRR contracts excluding West Hub/Load Zone

	CRR market clearing price					
	Peak Weekday		Peak Weekend		Off Peak	
	West	Other	West	Other	West	Other
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{t\geq 01-2014}$	-3.491^{***}	-0.0489	-3.426^{***}	-0.172	-1.085^{**}	-0.074
	(1.105)	(0.188)	(1.062)	(0.165)	(0.440)	(0.068)
$D_{t\geq 01-2014} \times trend$	-0.153^{***}	0.027^{***}	-0.102^{**}	0.036^{***}	0.089^{***}	0.018^{***}
	(0.045)	(0.010)	(0.044)	(0.008)	(0.020)	(0.004)
Observations	884	2483	861	2405	823	2445
R^2	0.514	0.459	0.504	0.503	0.585	0.359

Notes:

The dependent variable is CRR market clearing price for Peak Weekday (columns (1) and (2)), Peak Weekend (columns (3) and (4)), Off Peak (columns (5) and (6)) for the three model specifications. Robust standard errors, clustered at year-month level are presented in parenthesis. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), source by month ($\eta_i \times m_t$), sink by month ($\eta_i \times m_t$) fixed effects, and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression results for CRR contracts with West source and/or sink

	CRR market clearing price				
	Peak Weekday				
	(1)	(2)	(3)	(4)	(5)
$D_{t \geq 01-2014}$	-3.491^{***}	-0.006	-3.478^{***}	-3.481^{***}	-3.489^{***}
	(1.105)	(1.759)	(1.140)	(1.105)	(1.104)
$D_{t \geq 01-2014} \times trend$	-0.153^{***}	-0.158^{***}	-0.153^{***}	-0.155^{***}	-0.148^{***}
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
$D_{t \geq 01-2014} \times \mathbb{1}\{\text{Source} = \text{West}\}$		-2.963^{**}			
		(1.350)			
$D_{t \geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{West}\}$		-2.186			
		(1.393)			
$D_{t \geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{North}\}$			-0.080		
			(0.712)		
$D_{t \geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{South}\}$				-1.500	
				(1.166)	
$D_{t \geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{Houston}\}$					1.674
					(1.033)
Observations	884	884	884	884	884
R^2	0.514	0.530	0.514	0.515	0.516

Notes:

The dependent variable is Peak Weekday CRR market clearing price for the model specifications. Robust standard errors, clustered at year-month level are presented in parenthesis. The variable of interest $D_{t \geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), source by month ($\eta_i \times m_t$), sink by month ($\eta_i \times m_t$) fixed effects, and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression results for CRR contracts with West source and/or sink

	CRR market clearing price				
	Peak Weekend				
	(1)	(2)	(3)	(4)	(5)
$D_{t\geq 01-2014}$	-3.426^{***}	-1.115	-3.431^{***}	-3.395^{***}	-3.446^{***}
	(1.062)	(1.478)	(1.099)	(1.033)	(1.063)
$D_{t\geq 01-2014} \times trend$	-0.102^{***}	-0.113^{**}	-0.102^{***}	-0.109^{***}	-0.099^{**}
	(0.044)	(0.045)	(0.043)	(0.046)	(0.044)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Source} = \text{West}\}$		-2.471^{*}			
		(1.357)			
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{West}\}$		-1.283			
		(1.141)			
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{North}\}$			-0.035		
			(0.626)		
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{South}\}$				-2.632	
				(1.879)	
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{Houston}\}$					1.273
					(0.990)
Observations	861	861	861	861	861
R^2	0.459	0.518	0.504	0.509	0.505

Notes:

The dependent variable is Peak Weekend CRR market clearing price for the model specifications. Robust standard errors, clustered at year-month level are presented in parenthesis. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), source by month ($\eta_i \times m_t$), sink by month ($\eta_i \times m_t$) fixed effects, and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression results for CRR contracts with West source and/or sink

	CRR market clearing price				
	Off Peak				
	(1)	(2)	(3)	(4)	(5)
$D_{t\geq 01-2014}$	-1.085^{**}	-4.441^{***}	-0.801^{*}	-1.050^{**}	-1.074^{**}
	(0.440)	(0.985)	(0.458)	(0.439)	(0.440)
$D_{t\geq 01-2014} \times trend$	0.089^{***}	0.092^{***}	0.086^{***}	0.087^{***}	0.086^{***}
	(0.020)	(0.023)	(0.021)	(0.020)	(0.021)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Source} = \text{West}\}$		2.356^{***}			
		(0.855)			
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{West}\}$		2.820^{***}			
		(0.736)			
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{North}\}$			-1.410^{***}		
			(0.395)		
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{South}\}$				-2.041^{*}	
				(1.128)	
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Sink} = \text{Houston}\}$					-1.014^{*}
					(0.565)
Observations	823	823	823	823	823
R^2	0.585	0.591	0.597	0.590	0.587

Notes:

The dependent variable is Off Peak CRR market clearing price for the model specifications. Robust standard errors, clustered at year-month level are presented in parenthesis. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), source by month ($\eta_i \times m_t$), sink by month ($\eta_i \times m_t$) fixed effects, and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression results for four quarters of CRR price distribution

	CRR market clearing price			
	Peak Weekday			
	$Q_{\tau=1}$	$Q_{\tau=2}$	$Q_{\tau=3}$	$Q_{\tau=4}$
	(1)	(2)	(3)	(4)
$D_{t\geq 01-2014}$	-0.035	0.007	0.0005	-4.652^{***}
	(0.023)	(0.046)	(0.077)	(1.460)
$D_{t\geq 01-2014} \times trend$	0.002	-0.0001	-0.005	-0.136^{**}
	(0.002)	(0.002)	(0.003)	(0.057)
Observations	842	842	842	841
R^2	0.409	0.455	0.409	0.514
	Peak Weekend			
	$Q_{\tau=1}$	$Q_{\tau=2}$	$Q_{\tau=3}$	$Q_{\tau=4}$
	(5)	(6)	(7)	(8)
$D_{t\geq 01-2014}$	0.020	-0.019	0.108^{**}	-3.230^{***}
	(0.017)	(0.044)	(0.053)	(1.137)
$D_{t\geq 01-2014} \times trend$	-0.0003	0.002	0.001	-0.052
	(0.001)	(0.002)	(0.003)	(0.046)
Observations	817	816	817	816
R^2	0.443	0.463	0.437	0.563
	Off Peak			
	$Q_{\tau=1}$	$Q_{\tau=2}$	$Q_{\tau=3}$	$Q_{\tau=4}$
	(9)	(10)	(11)	(12)
$D_{t\geq 01-2014}$	-0.005	-0.023^{**}	-0.021	-0.063
	(0.008)	(0.011)	(0.029)	(0.600)
$D_{t\geq 01-2014} \times trend$	-0.0004	-0.0009^{*}	0.001	0.089^{***}
	(0.0003)	(0.0005)	(0.001)	(0.026)
Observations	817	817	817	817
R^2	0.432	0.401	0.448	0.504

Notes:

The dependent variable is CRR market clearing price in all the three panels. Robust standard errors, clustered at year-month level are presented in parenthesis. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), source by month ($\eta_i \times m_t$), sink by month ($\eta_i \times m_t$) fixed effects, and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 8: Summary Statistics of CRR market clearing price ($/MWh) by firm type

	Peak Weekday					
	Generator		Retailer		Trader	
	Mean	Share (%)	Mean	Share (%)	Mean	Share (%)
Pre January 2014	2.540	23	2.101	27	2.143	50
Post January 2014	2.177	40	1.745	14	1.511	46
	Peak Weekend					
	Generator		Retailer		Trader	
	Mean	Share (%)	Mean	Share (%)	Mean	Share (%)
Pre January 2014	1.934	23	1.375	28	1.666	49
Post January 2014	1.796	39	1.288	13	1.131	48
	Off Peak					
	Generator		Retailer		Trader	
	Mean	Share (%)	Mean	Share (%)	Mean	Share (%)
Pre January 2014	1.005	21	0.727	29	1.143	50
Post January 2014	0.660	40	0.549	13	0.491	47

Notes:

The classification of CRR account holders as Generator, Retailer, and Trader is explained in Appendix. Total number of observations for Peak Weekday, Peak Weekend, and Off Peak CRRs is 4853, 4657, and 4670 respectively. Share (%) refers to the percentage of CRR contracts owned by a specific firm type for a particular ToU before and after January 2014.

Table 9: Regression results for firm heterogeneity in CREZ transmission

	CRR market clearing price		
	Peak Weekday	Peak Weekend	Off Peak
	(1)	(2)	(3)
Intercept	1.022**	0.910***	0.515**
	(0.458)	(0.302)	(0.238)
$\mathbb{1}\{\text{Retailer}\}$	−0.185	−0.396***	−0.189*
	(0.123)	(0.101)	(0.110)
$\mathbb{1}\{\text{Trader}\}$	−0.401***	−0.429***	0.066
	(0.153)	(0.151)	(0.012)
$D_{t\geq 01-2014}$	−1.332***	−1.459***	−0.530***
	(0.395)	(0.343)	(0.175)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Retailer}\}$	0.101	0.351***	0.116
	(0.145)	(0.132)	(0.115)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Trader}\}$	0.379**	0.362**	−0.174
	(0.187)	(0.175)	(0.120)
Observations	4853	4657	4670
R^2	0.366	0.344	0.297

Notes:

The dependent variable is CRR market clearing price for Peak Weekday, Peak Weekend, and Off Peak for the three model specifications. Robust standard errors, clustered at year-month level are presented in parenthesis. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. $\mathbb{1}\{\text{Retailer}\}$ equals one if the CRR is owned by a Retailer and $\mathbb{1}\{\text{Trader}\}$ equals one if the CRR is owned by a Trader. All specifications control for time trend t, quantity (MW), source fixed effects (η_i), sink fixed effects (η_j), source by month $(\eta_i \times m_t)$, sink by month $(\eta_i \times m_t)$ fixed effects, and fixed effect for the year 2017.

*p<0.1; **p<0.05; ***p<0.01

Table 10: Convergence of market clearing price post CREZ transmission integration

Panel	Statistic	Parameter	$\text{CRR}_t^{\text{West}}$ - $\text{CRR}_t^{\text{other}}$		
			Peak Weekday	Peak Weekend	Off Peak
			(1)	(2)	(3)
A	Mean	$\hat{\alpha}_1$	3.507***	2.949***	2.646***
			(0.295)	(0.261)	(0.176)
		$\hat{\alpha}_2$	0.794***	0.419*	0.487***
			(0.247)	(0.218)	(0.147)
B	25th Quantile	$\hat{\alpha}_1$	1.400***	1.317***	1.442***
			(0.175)	(0.141)	(0.128)
		$\hat{\alpha}_2$	0.441***	0.275**	0.432***
			(0.146)	(0.118)	(0.107)
C	Median	$\hat{\alpha}_1$	2.926***	2.359***	3.073***
			(0.345)	(0.247)	(0.250)
		$\hat{\alpha}_2$	0.696**	0.420**	0.527**
			(0.289)	(0.207)	(0.209)
D	75th Quantile	$\hat{\alpha}_1$	6.024***	4.799***	3.817***
			(0.620)	(0.601)	(0.317)
		$\hat{\alpha}_2$	1.315**	0.570	0.539**
			(0.518)	(0.502)	(0.265)

Notes:

The dependent variable is the difference between market clearing price of CRRs with West Source and/or Sink and CRRs with Other Source and/or Sink ($\text{CRR}_t^{\text{West}}$ - $\text{CRR}_t^{\text{other}}$) at the three ToUs. Different panels present OLS results of various statistics of the dependent variable at each period on the two binary variables $\mathbb{1}\{t < 01-2014\}$ and $\mathbb{1}\{t \geq 01-2014\}$ in Equation 3. Hence, each specification has 90 observations.

*p<0.1; **p<0.05; ***p<0.01

Table 11: Average change in revenue as a result of CREZ transmission

	Δ Revenue (\$/h)	Δ Revenue (\$)	% Δ Revenue
Peak Weekday	-\$689,544	- \$234,970,927	-3.45%
Peak Weekend	-\$534,512	- \$78,348,319	-1.15%
Off- Peak	\$261,670	\$63,788,939	0.94%
Total	-\$962,386	-\$249,530,307	-3.67%

Notes:

Δ Revenue (\$/h) is calculated using estimates from Table 2 in Equation 5. Δ Revenue (\$) is the total change revenue calculated using estimates from Table 2 in Equation 6. %Δ Revenue expresses the change in total revenue as a percentage of total cost of CREZ (\$6.8 billion).

Figures

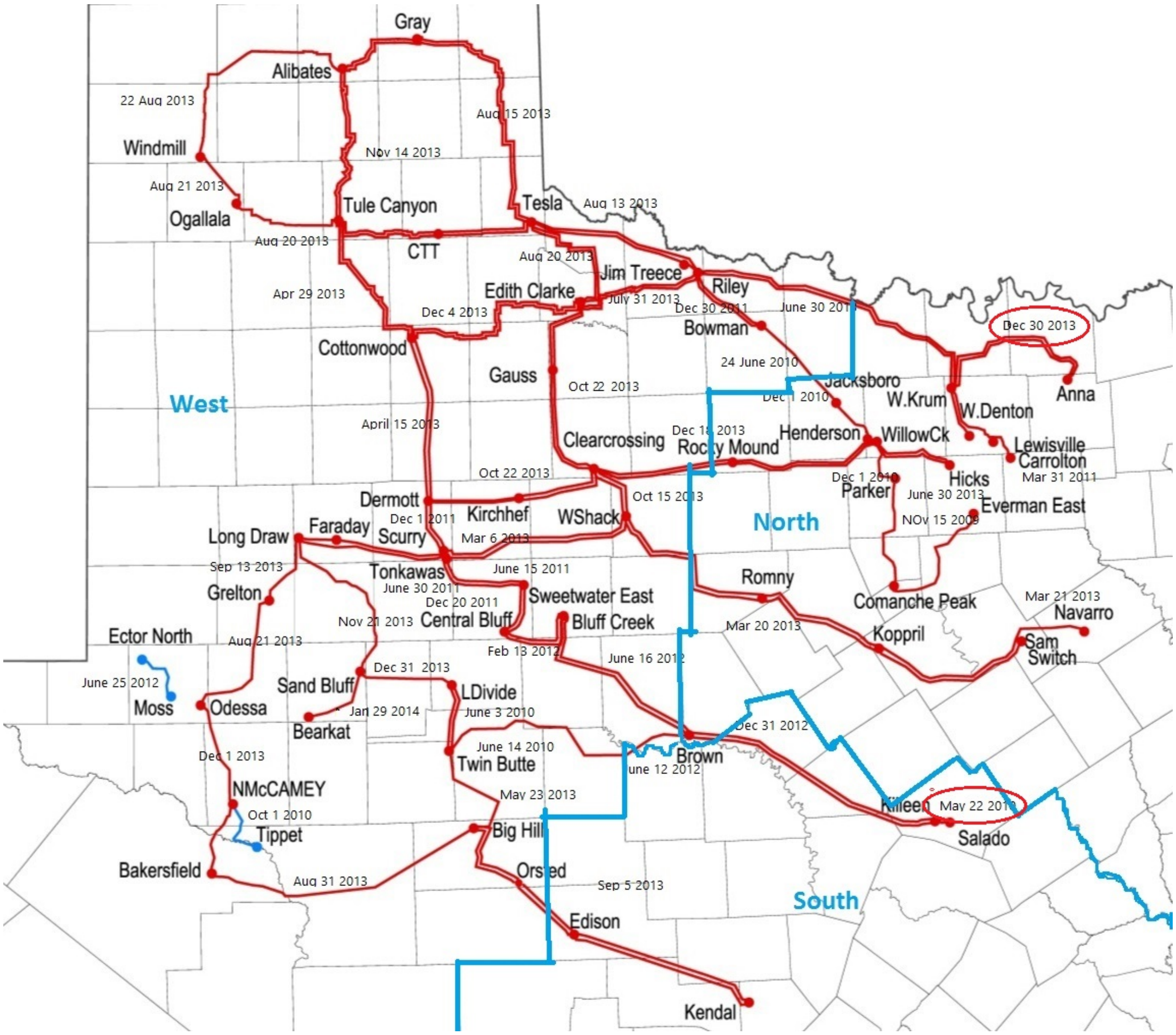


Figure 1: Timeline and spatial location of new transmission lines constructed as part of CREZ. The entire network was commissioned to be in service by January 2014. Source: Du et al. (2018).

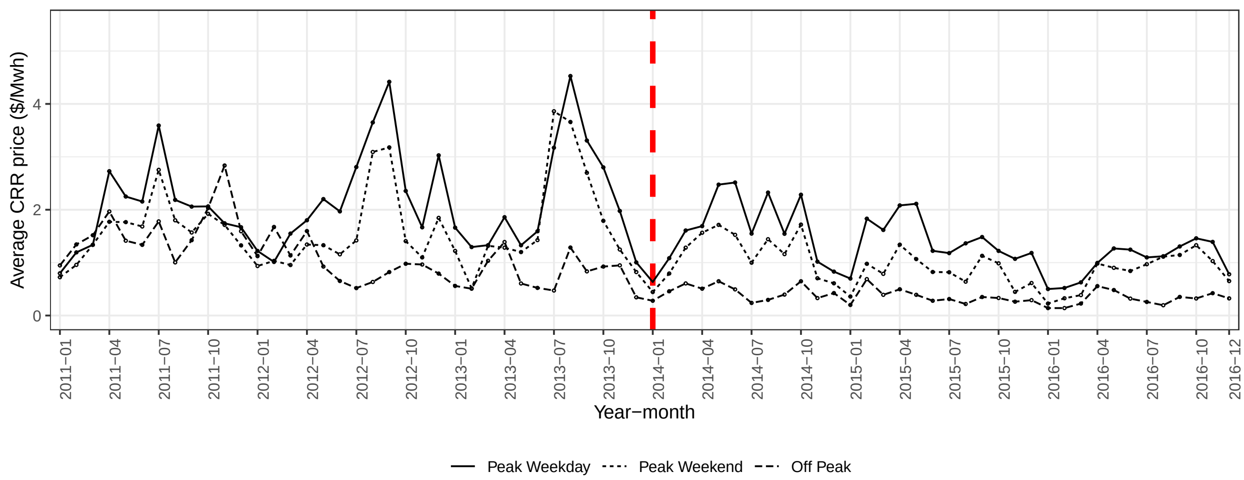
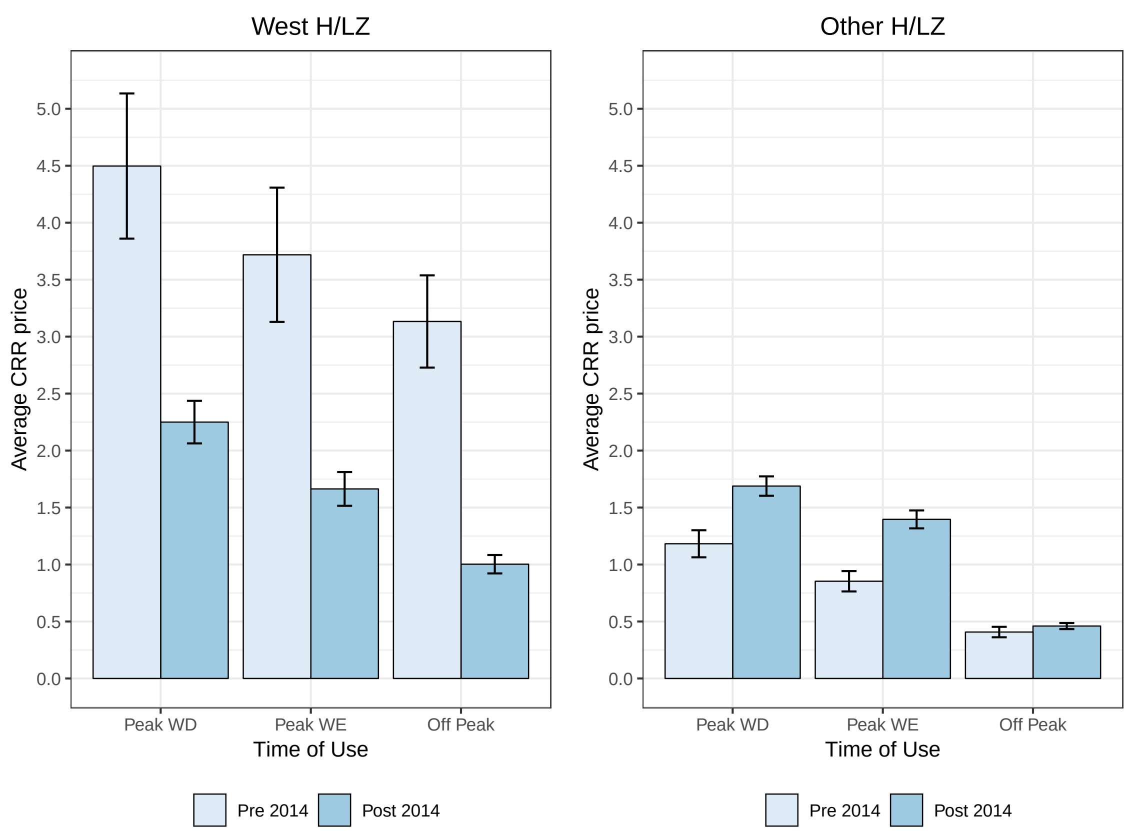
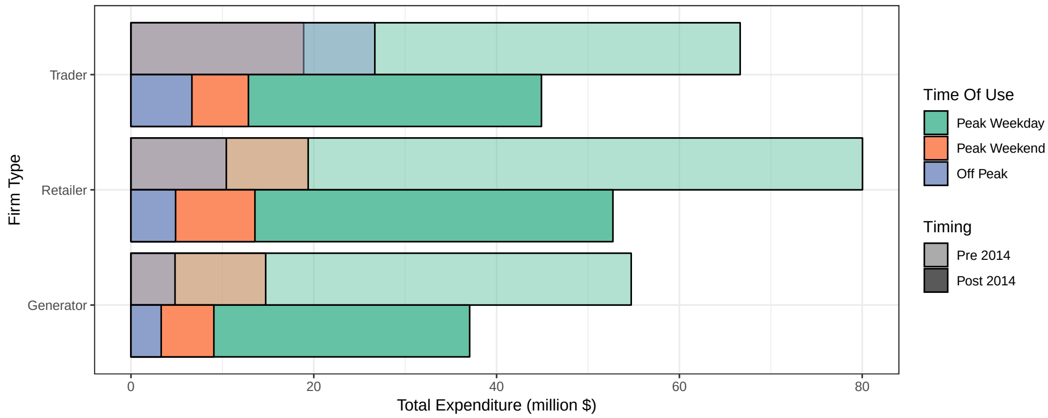


Figure 2: Monthly price averages of Peak Weekday, Peak Weekend, and Off Peak CRR contracts



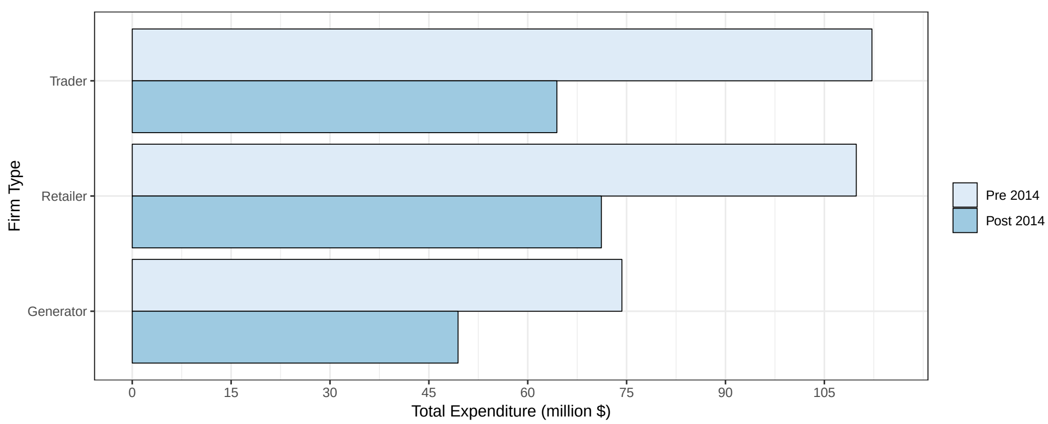
(a) CRR with West Source and/or Sink (b) CRR across other Source and/or Sink

Figure 3: Average CRR market clearing prices ($/MWh) Pre and Post CREZ completion



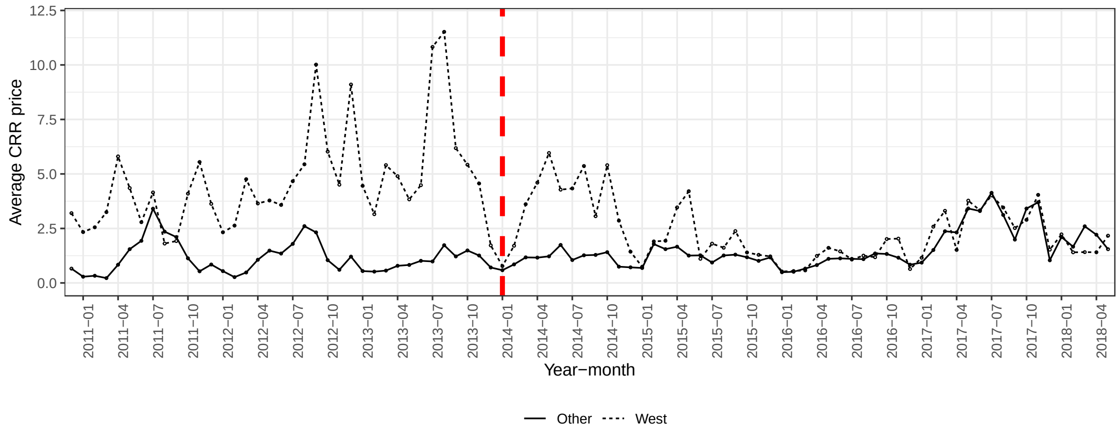
(a) Comparison of total expenditure (million $) by the three firm types Pre and Post CREZ completion at Peak Weekday, Peak Weekend, and Off-Peak[a]

[a]Note: The colors in the bars represent Time of Use whereas relative transparency represents the timing, i.e. Pre 2014 and Post 2014. For all the three firm types, top bar corresponds to Pre 2014 whereas bottom bar corresponds to Post 2014.

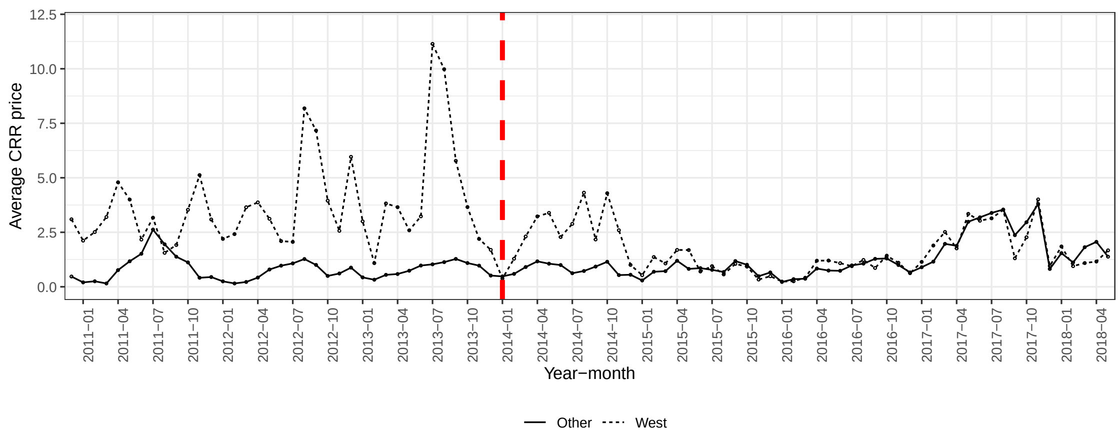


(b) Total expenditure (million $) over ToUs for the three firm types

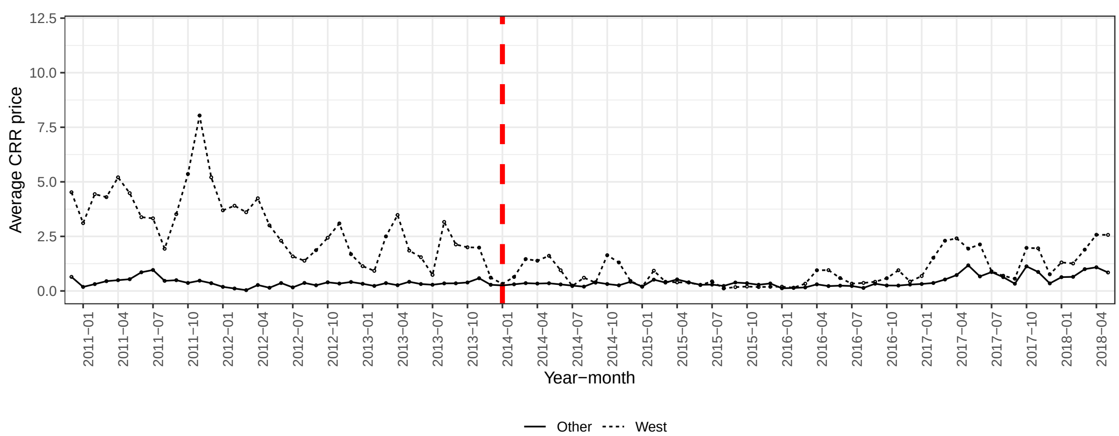
Figure 4: Total expenditure (million $) by various firm types in monthly CRR auctions. Pre 2014 bar aggregates expenditure over the years 2011 to 2013 whereas Post 2014 bar aggregates expenditure over the years 2014 to 2016



(a) Peak Weekday CRR



(b) Peak Weekend CRR



(c) Off Peak CRR

Figure 5: Convergence of average market clearing prices($/MWh) between CRRs with West Source/Sink and Other Source and/or Sink post CREZ transmission integration

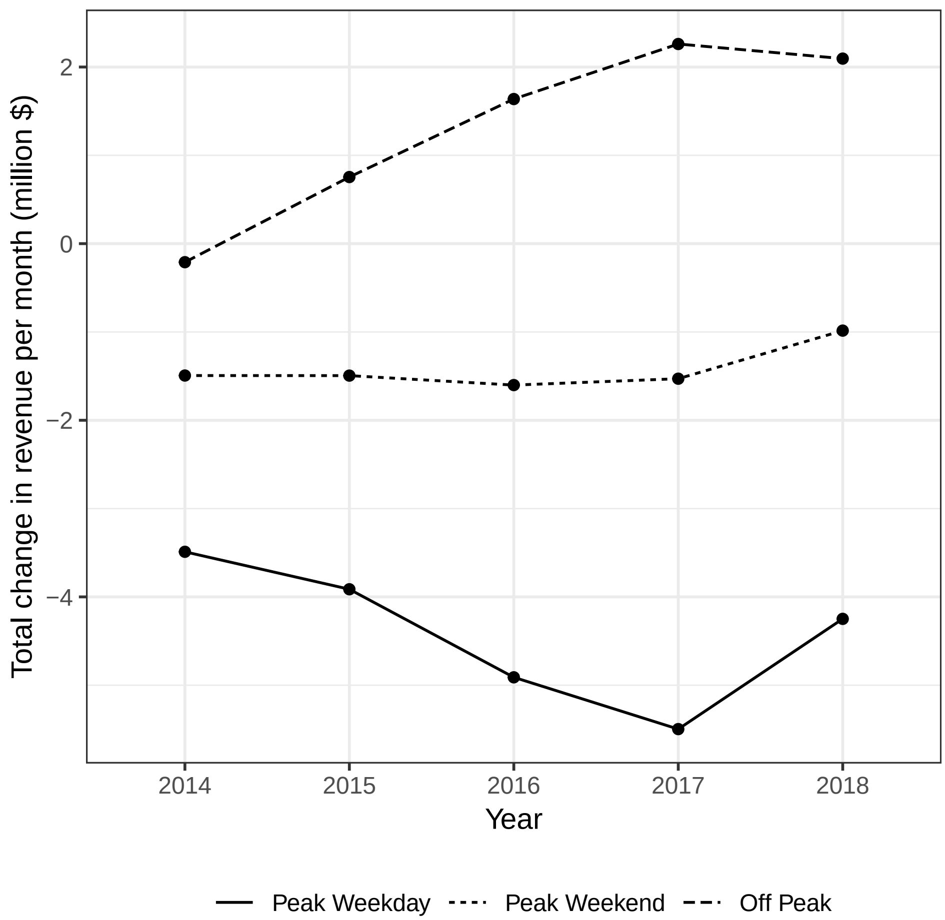


Figure 6: ΔRevenue per month (in million $) for Peak Weekday, Peak Weekend, and Off Peak CRR contracts post CREZ transmission integration

A Appendix

A.1 Acronyms

CAISO California ISO.

CREZ Competitive Renewable Energy Zones.

CRR Congestion Revenue Right.

DAM Day Ahead Market.

ERCOT Electric Reliability Council of Texas.

FTR Financial Transmission Right.

GW Gigawatt.

IOU Investor Owned Utility.

IPP Independent Power Producer.

ISO Independent System Operator.

LMP Locational Marginal Price.

MIS Market Information System.

MW Megawatt.

MWh Megawatt-hours.

NYISO New York ISO.

PUCT Public Utility Commission of Texas.

ToU Time of Use.

A.2 Classification of CRR account holders into firm types

Each account holder that appears in the data set and owns a CRR has been classified into three firm types: Generator, Retailer, and Trader. This categorization follows closely to the one used in Leslie (2018). We define Retailer as any firm that purchases wholesale electricity and provides electricity to residential and/or corporate consumers. Firms that own generation assets and participate in trading CRRs in Texas electricity market are classified as Generators. Finally, firms that neither have any physical (generation) assets nor serve residential and/or corporate consumers, but only participate in CRR trading are classified as Traders. Different firms or more broadly firm types might have different motives in the market, some might be interested in hedging their risks whereas some might have speculative interests and make profit. The classification is based on our judgement using information presented in the firm's website, company overview at www.bloomberg.com and account holder listing at ERCOT.

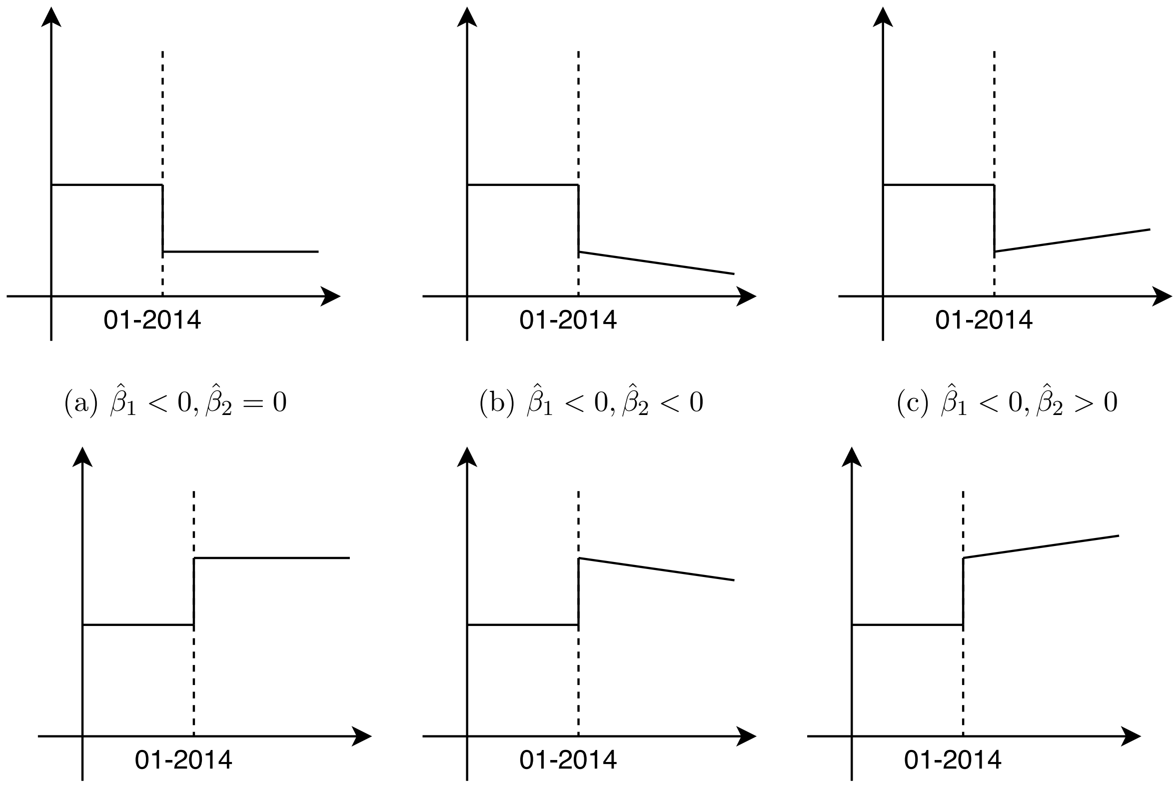
Generator: BJ Energy LLC; Brazos Electric Power Co Op Inc.; Calpine Power Management LLC; Cargill Power Markets LLC; City Of Georgetown; EDF Energy Services LLC; Exelon Generation Company LLC; Franklin Power LLC; Frontier Utilities LLC; Longhorn Energy LP; DBA Longhorn Electricity Marketing LP; Lower Colorado River Authority; MAG Energy Solutions Inc.; Midamerican Energy Company; NRG Texas Power LLC; NRG Texas Power LLC (GME); Optim Energy Marketing LLC; Pepco Energy Services Inc.; Shell Energy North America (US) LP; Source Operations Group LLC; Westar Energy Inc.

Retailer: BP Energy Company; Champion Energy Marketing LLC; Cirro Group INC; City Of Georgetown; Consolidated Edison Solutions INC; Denton Municipal Electric; EDF Energy Services LLC; First Choice Power LP; Frontier Utilities LLC; GDF Suez Energy Resources Na Inc.; Gexa Energy LP; Green Mountain Energy Company; Luminant Energy Company LLC REPS; Midamerican Energy Services LLC; New Braunfels Utilities; Noble Americas Energy Solutions LLC; Noble Americas Gas And Power Corp; Northern States Power Company; Spark Energy LP; Talen Energy Marketing LLC; Texas Energy Transfer Power Llc; Texas Power LP; Trieagle Energy LP; Yuma Electric LLC.

Trader: Appian Way Energy Partners Southcentral LP; Arcturus Power Trading LLC; Aspire Capital Management LLC; ATNV Energy LP; Barton Fund LLC; Biourja Power LLC; Boston Energy Trading And Marketing LLC; Citigroup Energy Inc.; Constellation Energy Commodities Group Inc.; Darby Energy LLLP; DB Energy Trading LLC; DC Energy Texas LLC; Denver Energy LLC DBA Denen LLC; Direct Energy LP; DTE Energy Trading Inc.; Dyon LLC; EDF Trading North America LLC; Edison Mission Marketing And Trading Inc.;

Endure Energy LLC; Engelhart CTP (US) LLC; Inertia Power III LP; J Aron And Company LLC; JP Morgan Ventures Energy Corporation; Keystone Energy Partners LP; Louis Dreyfus Energy Services LP; Luminant Energy Company LLC Trading; Macquarie Energy LLC; Merrill Lynch Commodities Inc.; Met Texas Trading LP; Met Texas Virtual LP; Midwest Energy Trading East LLC; Monterey TX LLC; Monterey TXF LLC; Morgan Stanley Capital Group Inc.; Nextera Energy Power Marketing LLC; North Maple Energy LLC; NPM Energy Llc; NRG Power Marketing LLC; Pacific Summit Energy LLC; Polaris Power Trading LLC; Raiden Commodities LP; Rainbow Energy Marketing Corporation; Rigby Energy Resources LP; PMH Energy LP; Sandalwood Power LLC; Saracen Energy West LP; SESCO Southwest Trading LLC; SESCO Southwest Trading LLC CAISO; SESCO Southwest Trading LLC KP; Shell Energy North America (US) LP; SIG Energy LLLP; Sunico LLC; SW Power Trading LLC; Trailstone Power LLC; Twin Eagle Resource Management LLC; TX Active Power Investments LLC; UNCIA Energy LP Series E; Uniper Global Commodities North America LLC; VBE Investments LLC; Vitol Inc; West Oaks Energy LP; Wolverine Trading LLC; XO Energy TX2 LP.

A.3 Figures



(a) $\hat{\beta}_1 < 0, \hat{\beta}_2 = 0$ (b) $\hat{\beta}_1 < 0, \hat{\beta}_2 < 0$ (c) $\hat{\beta}_1 < 0, \hat{\beta}_2 > 0$

(d) $\hat{\beta}_1 > 0, \hat{\beta}_2 = 0$ (e) $\hat{\beta}_1 > 0, \hat{\beta}_2 < 0$ (f) $\hat{\beta}_1 > 0, \hat{\beta}_2 > 0$

Figure A.1: Graphical interpretation of different cases of estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$