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Does Locational Marginal Pricing Impact Generation Investment Location Decisions? An Analysis of Texas's Wholesale Electricity Market

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Abstract

Using data from Texas's wholesale electricity market, we investigate if there is a relationship between nodal prices and investment location decisions of utility-scale generation. We find some evidence that new investment arises in areas with recently elevated nodal prices. However, we find no evidence that new generation resources receive a nodal price premium post-entry as projected by the expectation of higher nodal prices. Further, we employ a regression analysis to test the relationship between expected nodal prices and the probability of entry at a given node. While this analysis finds a positive relationship between expected nodal prices and investment for natural-gas-fueled peaking assets, this relationship is sensitive to model specification. Our findings suggest that factors other than nodal prices are more likely drivers of utility-scale generation capacity investment location decisions in Texas.

Keywords: Electricity, Regulation, Entry, Locational Marginal Pricing

JEL Codes: L11, L51, L94, Q41, Q48

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1. Introduction

A fundamental component of restructured electricity markets is the establishment of competitive prices to determine equilibrium supply and demand. Price formation is especially important in power markets because of the inability to store electricity at low-cost, the need to instantaneously balance supply and demand, and the high outage costs associated with supply shortfalls. Allowing electricity to be transacted at prices reflective of its time and location-varying value has been a long-standing foundation of competitive electricity markets (Schweppe et al., 1988). A central component of achieving this objective is locational marginal prices (LMPs) based on marginal costs of generation that account for the network's physical and operational constraints.

LMPs are utilized in all restructured markets in the United States (FERC, 2014). Absent transmission congestion, LMPs converge across all nodes within a jurisdiction. When there is congestion, low-cost energy is unable to flow to high-cost nodes, thus elevating the LMPs at these nodes.

The theoretical benefits of LMPs are well-established (Schweppe et al., 1988; Baughman et al., 1997). In addition, there are numerous empirical studies that evaluate the benefits of transitioning from postage or zonal pricing to the more granular nodal pricing. For example, these studies have focused on Texas (CRA, 2008; Zarnikau et al., 2014), England and Wales (Green, 2007), Pennsylvania-Jersey-Maryland (PJM) Interconnection (Synapse Energy Economics, 2006), and New York (Tierney and Kahn, 2007).[1] These studies primarily focus on the benefits of reduced congestion, improved dispatch of resources, reduced operation reserve requirement, and improved competition.

Another often cited benefit of nodal pricing is its price signals for generation investment location decisions (Schweppe et al., 1988; Green, 2007). While this idea has been widely accepted, there is limited empirical evidence that tests the hypothesis that generators tend to locate in electric network pockets with high nodal prices.[2] We test this hypothesis using detailed LMP data and recent generation investment decisions in Texas's wholesale electricity market. Texas is an ideal testing ground as it has an energy-only market design under which power plant investment incentives are mainly energy-price-based *sans* centralized capacity markets that now exist in PJM, New York, and New England (Spees et al., 2013) or procurement auctions that occur under California's resource adequacy requirement (Woo et al., 2016).

[1] For a summary of the studies performed in several U.S. markets, see Neuhoff and Boyd (2011). For a broader summary of the trade-offs associated with nodal pricing, see Weibelzahl (2017).

[2] Synapse Energy Economics (2006) compares generation investment in PJM to lagged LMPs and finds no evidence that generation investment occurred in regions with higher lagged LMPs. Brown and O'Sullivan (2019) document the spatial and temporal variation in the value of solar power across the U.S. using nodal price data. However, unlike our analysis which focuses on observed investment, the authors consider simulated solar PV investment.

Our analysis is made possible by the 15-minute real-time market (RTM) nodal price data from the Electric Reliability Council of Texas (ERCOT) for the period 2011 – 2019 and data from the Energy Information Administration (EIA) on all constructed and planned generation capacity investments in ERCOT since 2011. It focuses on investment in wind, natural gas, and solar technologies which make up the vast majority of observed investments.

We carry out three empirical tests to evaluate the relationship between LMPs and generation investment location decisions. First, we decompose observed generation investment into various pricing tiers based on lagged nodal prices to evaluate whether new investments arise in regions that have experienced higher LMPs prior to entry. This allows us to evaluate if there is empirical evidence that LMPs signal investment location decisions.

Second, we compare LMPs at nodes with and without recent nearby entry to investigate if new generation resources receive an LMP-premium post-entry. If generators locate in a region due to the expectation of higher LMPs, we might expect to find nodes with nearby entry to have higher RTM prices post-entry than nodes without recent nearby entry.

Third, we establish an illustrative two-stage investment model and regression analysis to empirically test if firms are more likely to locate in a region with higher expected RTM nodal price levels and variance. Starting in the second stage, we establish a forward-looking model to forecast each node's RTM price level and variance. This serves as a proxy for a generator's expectation of future LMPs that impact expected operating profits. In the first stage, firms decide where to locate their generation capacity investment. Among other factors, firms' investment location decisions depend on the expected nodal price levels and variance. To evaluate if this relationship is empirically significant, we utilize a discrete (binary logit) model to estimate the probability of generation capacity investment at a particular node as a function of expected forward-looking nodal price levels and variance.

Our three key findings are as follows. First, while RTM nodal prices have been declining, we observe substantial investment in wind (20,000+ MWs) and natural gas (14,000+ MWs) capacity over our sample period. Further, we document increased dispersion in LMPs across nodes starting in 2014, suggesting potential opportunities for LMP-driven investment location decisions. Using descriptive statistics, we find some evidence that generation resources tend to locate near nodes with higher average LMPs in recent years. This is consistent with the theory that nodal prices send location-based investment signals. However, looking across nodal price quartiles, we find that the lowest two price quartiles have more new capacity (in MWs) compared to the highest two price quartiles.

Second, nodes which have experienced recent nearby entry do not have a RTM nodal price premium post-entry compared to nodes that have not observed recent nearby entry. In fact, nodes with recent nearby entry often have statistically significantly lower average RTM nodal prices. This effect is largest for nodes that have experienced nearby entry of combined cycle gas turbines (CCGTs) fueled by natural gas, consistent with the intuition of suppressed nodal prices as the result of entry.

Finally, our formal statistical results find limited evidence of a relationship between average forecasted LMP levels and variance and location-specific investment decisions. We find some evidence that location decisions for combustion turbines (CTs) fueled by natural gas are related to higher average LMPs in the evening hours. However, these results are sensitive to the model specification.

Our analysis presents limited evidence that expected LMPs drive investment location decisions of large-scale generation assets. Investment decisions are complex long-run decisions. Nodal price signals are likely overwhelmed by other factors such as site availability, transmission access, interconnection costs, fuel availability or renewable resource potential, etc. Further, nodal prices are volatile and likely to decline after the entry of a large power plant. Consequently, it is unlikely that a new power plant is able to establish long-term financing based primarily on the expectation of higher nodal prices.

Our analysis proceeds as follows. Section 2 describes Texas's wholesale electricity market. Section 3 presents the data utilized in our analysis. The empirical methodology is detailed in Section 4. Section 5 presents our empirical findings. Section 6 concludes and identifies directions for future research.

2. Texas's Wholesale Electricity Market

Over our sample period, electricity needs increased by roughly 2% per year in ERCOT, resulting in considerable need for new generation investment (EIA, 2019c). Serving over 85% of the electrical needs of the largest electricity-consuming state in the U.S., ERCOT is an ideal market to explore how LMPs affect power plant investment decisions. This intra-state electricity market has had an LMP structure since December 2010 (Zarnikau et al., 2014). A real-time security-constrained economic dispatch (SCED) model is used to simultaneously manage energy, system power balance, and network congestion. This system yields updated nodal prices every 5 minutes, at most. ERCOT deploys operating reserves, procured on the prior day, to control frequency and resolve potential reliability issues. While the LMPs calculated every 5 minutes (or less) are used to compensate generators, time- and load-weighted 15-minute zonal prices are used to settle the demand side of the market.[3] Although an operating reserve demand curve (ORDC) has been introduced to raise prices across the market equally when operating reserves approach low levels, the ORDC adder had a very limited impact on LMPs during the period of our study (Zarnikau et al., 2019a).

[3] We utilize 15-minute LMPs in our analysis because of computational tractability and 5-minute prices are nearly identical within a 15-minute interval.

ERCOT is the only restructured competitive wholesale electricity market in the U.S. that relies substantially on an energy-only market design, allowing LMPs to rise as high as $9,000 per MWh. Power plant investment decisions are not complicated by the capacity markets or resource adequacy requirements that have been introduced in other U.S. markets.

The cost of interconnecting power plant additions in ERCOT is largely borne by the market. The generator pays for the “spur” and the “point of interconnection,” while bulk transmission costs are borne by the demand side of the market,[4] in contrast to the Eastern Interconnection where generators additionally pay for some of the bulk transmission costs (Andrade and Baldick, 2017). Postage stamp transmission rates are paid by load-serving entities. Lines losses are ignored in system dispatch decisions.[5] Thus, the state’s transmission configuration may not be a major factor in power plant siting decisions, notwithstanding that transmission congestion raises LMPs.

In recent years, the majority of the generation additions have been renewable energy projects. Texas leads the U.S. in wind generation development, with an installed capacity of roughly 26 GW in 2019 and an expected addition of 9 GW by 2022. While Texas’s solar generation lags California’s, it is expected to grow rapidly from its present level of 3 GW to over 11 GW by 2021 (ERCOT, 2019).

Texas’s energy-only market relies on market forces to induce the generation investments necessary to support a reliable system. No resource adequacy requirements are placed upon load-serving entities, although failing to hedge may have its consequences. Market forces alone may yield an “economically optimal” reserve margin of 9% (Brattle Group, 2018), below the 17.6% level under the traditional loss-of-load expectation standard of 1-day-in-10-years (Northbridge, 2017). Hence, ERCOT’s adopted reserve margin target of 13.75% is more the result of judgement and compromise than any strict economic or engineering criteria.

3. Data

We employ several data sets that span the years of 2011 – 2019. First, we utilize 5-minute real-time market (RTM) LMP data at the resource node level made available by ERCOT for the period January 1, 2011 to June 12, 2019. We aggregate the LMP nodal data up to the 15-minute interval by taking the time-weighted average of the 5-minute LMPs. Our analysis focuses on 160 of the current 252 resource nodes that existed in January 2011. Because our objective is to understand the relationship between spatial entry decisions and LMPs, we

[4] See PUCT Subst. R. 25.195(c): http://www.puc.texas.gov/agency/rulesnlaws/subrules/electric/25.195/25.195.pdf
[5] Potential market changes to implement the recognition of marginal losses in dispatch decisions were debated and ultimately rejected in PUCT Project No. 47199: Project to Assess Price-Formation Rules in ERCOT’s Energy-Only Market, https://interchange.puc.texas.gov/Search/Filings?ControlNumber=47199.

eliminate resource nodes that were created during our sample period as the result of entry, thereby avoiding endogenous selection into our sample.[6] Figure A1 in the Appendix demonstrates that our analysis captures a broad spatial distribution of ERCOT's market.

Second, we utilize market-level data made available by ERCOT that include information on market demand, Henry Hub gas prices, and observed generation installations by technology. Third, we gather location information (longitude and latitude) of all nodes in ERCOT. This will be utilized to map the distance from each new generation resource to the existing nodes.

Fourth, we use data from the Energy Information Administration (EIA) to gather information on all generation units in ERCOT. We use the 2018 EIA Form 860 data that includes all existing power plants with nameplate capacities that are 1 MW or greater (EIA, 2019a). In addition, we use the EIA's Planned Generation Unit Addition data from the EIA's Electric Power Monthly dataset to gather information on planned capacity additions (EIA, 2019b).

From these data sets, we have detailed information on generation unit characteristics, locations, and operating month and year. Our primary analysis will focus on generation units built on or after January 2011 that operate under ERCOT's jurisdiction. This yields a sample of 319 generation assets where 226 (71%) were constructed and operating by June 2019. The remaining 93 assets are planned to begin operating between July 2019 and December 2022.

4. Empirical Methodology

We take a multi-pronged approach to analyze whether LMPs drive entry location decisions. First, we evaluate the dispersion in observed LMPs between 2011 and 2019 to assess the degree to which LMP-driven investment could have arisen. We utilize several measures of price dispersion, including the difference between the 75th and 25th percentile LMPs within a 15-minute interval, variance, the coefficient of variation, and a Gini coefficient.

Second, we decompose generation capacity investments into various price-tiers based on lagged LMPs. This presents illustrative evidence of whether generation investment location decisions are concentrated at locations that have observed systematically higher LMPs prior to their entry. This provides descriptive evidence of whether LMPs send signals for investment location decisions.

Third, we use descriptive statistics to investigate if newly constructed power plants receive an LMP premium post-entry. More specifically, we compare LMPs at nodes with and

[6] In addition, resource nodes that were created as the result of entry during our sample do not have historical LMP data that we can utilize to understand how lagged LMPs relate to entry decisions near a given node.

without nearby entry in prior periods. If power plant investments decisions are driven by the expectation of higher LMPs, one might expect new entry to receive a higher average LMP than the average LMP observed at a non-entry node.

Fourth, we establish a two-stage regression analysis to investigate if firms locate at a specific node based on the expectation of higher operating profits due to higher expected LMPs. Our regression analysis is motivated by an illustrative two-period model of investment location decisions.

a. Two-Period Investment Model

This section presents a simple two-period model of an independent power producer (IPP) deciding to invest in technology with fuel type k. Our analysis focuses on four technologies: (1) natural gas combustion turbine (CT), (2) natural gas combined-cycle gas turbine (CCGT), (3) solar, and (4) wind. In period 1, an IPP decides whether to invest in a plant using technology k at node $j = 1, \dots, J$. In period 2, the IPP profitably sells the new plant's output in the real-time market. We analyze the IPP's decision made in each period recursively.

i. Operating Decision in Period 2

Consider a plant located at node j that uses technology k. For ease of exposition and without any loss of generality, we suppress the subscripts j and k when defining the plant's per MWh operating profit under the assumption of the plant being available:[7]

$$\pi_t = \max(P_t - C_t, 0), \tag{1}$$

where P_t is the real-time nodal price and C_t equals the per MWh variable cost of the new plant in time interval $t = 1, 2, \dots, T$.

Suppose the plant has a fossil-fuel heat rate HR in MMBtu/MWh (= 0 for solar and wind), faces fuel price F_t (= 0 for solar and wind), and incurs per MWh variable operating and maintenance (O&M) cost M that is typically small and hence assumed to be invariant with t. The plant's per MWh cost is:

$$C_t = HR \times F_t + M. \tag{2}$$

Equation (1) shows that the expected per MWh operating profit $E(\pi_t)$ increases with $E(P_t)$ but decreases with $E(C_t)$. Further, we anticipate that $E(\pi_t)$ increases with the price variance $var(P_t)$ because rising electricity price volatility implies a higher likelihood of high price hours (Woo et al., 2016).

[7] Accounting for a plant's random availability vastly complicates the subsequent discussion without the benefit of additional insights, see Woo et al. (2019) for the effect of a plant's availability on a generation plant's profitability.

ii. Investment Decision in Period 1

Now, we consider the first period in which an IPP decides on its investment location decisions. Define ω_j to equal the present discounted value of the expected operating profit ($E(\pi_{jt})$) of a technology-specific plant to be located at node j. An IPP's investment is profitable if:

$$\Delta_j = \omega_j - K_j > 0, \tag{3}$$

where K_j is the plant's capacity cost (Zarnikau et al., 2019a). An IPP selects node j^* when $\Delta_{j^*} = \max\left(\Delta_1, \Delta_2, \dots, \Delta_J\right)$. As the expected profitability of entry at node j depends on the expected level and variance of nodal prices and fuel prices, node j is more likely to be selected than node j' if it is expected to have higher and more volatile RTM nodal prices but lower capacity and fuel cost.

Capacity cost K_j in equation (3) can be decomposed into two parts: (i) K_{j1} reflects the installed physical capital cost plus the present value of fixed O&M costs and (ii) K_{j2} represents the present value of location-specific costs for land, water, regulatory compliance, transmission charge, interconnection, etc. K_{j1} is largely location-invariant and will only impact the decision of whether or not to invest in a given technology rather than its precise location. In contrast, K_{j2} can vary greatly by location. In the subsequent empirical analysis, we control for regional fixed effects to proxy for location-specific fixed costs. We utilize the intuition established from this simple illustrative model to empirically test if entry location decisions are being driven by expected nodal price levels and variance.

b. Regression Model Specification

We employ a two-step empirical strategy to test the hypotheses established by the illustrative model above. First, we utilize a regression approach to estimate 15-minute RTM nodal prices. We use the results of this estimation procedure to compute each node's price forecasts and their variances that serve as a firm's expectations of the average nodal price expectation and variance when an IPP decides its investment location. Second, we estimate a binary logit regression model to determine the probability of entry by generation technology k at a specific node j in a given year. This regression analysis helps evaluate how the average forecasts of nodal price level and variance impact the likelihood of entry at a specific node.

i. Real-Time Market Nodal Price Regressions

We estimate the following 15-minute RTM price regression with random error ϵ_{jt}, intercept α_j, and coefficient vectors $\boldsymbol{\beta}_j$ and $\boldsymbol{\delta}_j$ for each node j:

$$P_{jt} = \alpha_j + \boldsymbol{X_{jt}\beta}_j + \boldsymbol{D_t\delta_j} + \epsilon_{jt} \tag{4}$$

where $\boldsymbol{D}_t$ is a vector of dummy variables for indicating t's hour, day of week, and month, and $\boldsymbol{X_{jt}}$ is market-level controls including Henry Hub natural gas prices and net market demand which equals market demand minus observed solar, wind, and nuclear generation.[8] ϵ_{jt} is estimated via Newey-West robust standard errors with 24 lags.

We employ this nodal price regression to forecast future LMP levels and variances at each node. More specifically, we start by estimating equation (4) using data for the 2011 – 2012 period. For each node, we utilize the fitted model to forecast LMP levels and variances out-of-sample for the period 2013 – June 2019. This is utilized to represent a firm's expectations over the future LMPs it will face upon entry if it chooses to enter in 2013.[9] As discussed in detail below, these forecasted average LMP levels and variances enter the binary logit regressions to model entry decisions in the year 2013.

We then estimate equation (4) using data for the 2011 – 2013 period to forecast LMP levels and variances out-of-sample for the 2014 – June 2019 period. The forecasted average LMP levels and variances help explain entry decisions for the year 2014. We continue this process to establish average forward-looking LMP level and variance forecasts to model node-specific entry decisions for the years 2013 – 2018.

For the logit regressions described below, we estimate node-specific forward-looking average LMP levels and variances across all hours and broken down by five time-of-day (TOD) periods: (i) 12 AM – 6 AM and 10 PM – 12 AM; (ii) 6 AM – 10 AM; (iii) 10 AM – 2 PM; (iv) 2 PM – 6 PM; and (v) 6 PM – 10 PM.[10] It is important to note that the forecast period shortens as we approach the end of our logit estimation sample. Consequently, we consider several robustness checks where we exclude entry decisions in the later years of our sample (e.g., 2017 and 2018).

ii. Discrete Nodal Entry Analysis

Define $Y_{jht} = 1$ if node j has attracted a new plant using technology h in year t, and 0 otherwise. The probability that entry of technology h occurred near node j in year t is:

[8] Our empirical results throughout the paper are robust to decomposing the net demand variable into the individual demand and observed generation by technology variables.

[9] Because our analysis is reduced-form in nature, we are unable to explicitly model the impact of generation capacity additions on expected LMPs post-entry. In the conclusion, we stress the importance of future research that establishes a structural model that permits such counterfactual simulations.

[10] Similar TOD measures are utilized in Woo et al. (2017).

$$P(Y_{jht} = 1) = \frac{\exp(U_{jht})}{[1 + \exp(U_{jht})]}. \tag{5}$$

We define U_{jht} as follows:

$$U_{jht} = \theta_{0h} + \theta_{1h}\, \mu_{jt} + \theta_{2h}\, \sigma_{jt}^2 + \boldsymbol{Year_t}\, \boldsymbol{\gamma_h} + \boldsymbol{Zone_j}\, \boldsymbol{\omega_h} + \eta_{jht} \tag{6}$$

where μ_{jt} and σ_{jt}^2 are the forward-looking estimated average RTM nodal price level and variance, $\boldsymbol{Year_t}$ is a vector of year controls, and $\boldsymbol{Zone_j}$ is a zone fixed-effect representing ERCOT's 8 weather zones.[11] The year covariates capture changes in market trends over our sample period, while the zonal fixed effects capture non-price factors that may impact entry.[12] We utilize cluster-robust standard errors on η_{jht} where the clustering is at the node-level. As discussed above in our illustrative model, if LMP levels and volatility impact an IPP's locational investment decision, we expect $\theta_{1h} > 0$ and $\theta_{2h} > 0$.

Our data includes entry of a diverse array of technologies including natural gas, solar, wind, biomass, storage, and coal. While we discuss the entry of each of these technologies in detail below, our primary focus is entry of natural gas, solar, and wind generation facilities. We decompose natural gas generation into two technologies: combined cycle gas turbines (CCGTs) and combustion turbines (CTs). CTs are smaller gas plants that typically operate as peaking units that can quickly reach full power but often only operate during high demand hours. CTs have lower capital cost than CCGTs, but also operate at higher marginal cost of generation. Unlike CTs, CCGTs operate in non-peak demand hours because of their lower marginal costs.

The empirical approaches outlined above require us to spatially map the distance between each new generation unit and the nodes in our sample. We use QGIS to create a spatial matrix that computes the distance of all generation units to each node in our sample. This allows us to match each facility with nearby nodes that existed before the asset entered. We employ several definitions to spatially define when a node is "nearby" a new generation unit. First, we match each asset with the first, second, and third closest node by distance. We establish 3 entry indicators where each equals 1 at node j if it is within the first $k = 1, 2,$ and 3 closest nodes. Second, we draw a circle around each node ranging from 10 and

[11] In Section 4(a), we noted that a firm's expected operating profits will depend on expected fuel input prices. However, in our annual discrete entry regressions, we are identifying off of the variation across nodes within a weather-zone and year. Consequently, we do not include Henry Hub gas prices as a regressor as there is limited-to-no variation in expected natural gas prices faced by generators across nodes within a weather-zone and year.

[12] We are unable to include node fixed effects because this would limit the variation we are identifying off of to the node-by-year level. This often results in multi-collinearity as there is limited variation in entry of a specific technology within a node-year. ERCOT's weather zones segment Texas into 8 regions, for details see http://www.ercot.com/news/mediakit/maps.

25 miles. Entry is said to occur at node j if a new unit falls within the specified distance. Both approaches allow us to establish a node-by-year data set that matches new entry to existing nodes with varying definitions of spatial distance.[13]

As our baseline specification, we employ the spatial measure that matches each new generation unit with its nearest node by distance. This allows us to proxy for the most relevant LMP that the new generation unit will face upon entry. Throughout our analysis, we employ numerous robustness checks utilizing the alternative spatial measures.

5. Results

a. LMP Dispersion

We investigate changes to LMPs over our sample period to assess the degree to which LMP-driven investment could have arisen. Figure 1 presents the average LMPs by quarter across all nodes in our sample. Besides two periods of higher prices in 2011 and 2014, average LMPs have decreased. This price reduction occurred over a time period which observed a sizable decrease in natural gas prices and growth in wind resources. Despite the overall decline in average LMPs, we will show the dispersion in LMPs have increased in latter part of our sample period.

We use four measures to illustrate LMP dispersion across nodes within each 15-minute interval: (i) the difference between the 75th and 25th percentile LMPs; (ii) LMP variance; (iii) the coefficient of variation; and (iv) a Gini Coefficient. The coefficient of variation reflects the ratio of the standard deviation to the mean LMP and the Gini coefficient is defined by:

$$G_t = \frac{\sum_{j=1}^{n} \sum_{i=1}^{n} |LMP_{it} - LMP_{jt}|}{2n^2\, \overline{LMP_t}}. \tag{7}$$

Equation (7) represents the sum of the average absolute differences in LMPs of all pairs of $i, j = 1, 2, \ldots, n$ nodes in our sample, normalized by the average LMP ($\overline{LMP_t}$) for scale (Sen, 1973).

[13] We also considered broader spatial distance measures. However, we find that these broader spatial measures begin to allocate new resources to multiple "nearby" nodes resulting in double, triple, or quadruple counting.

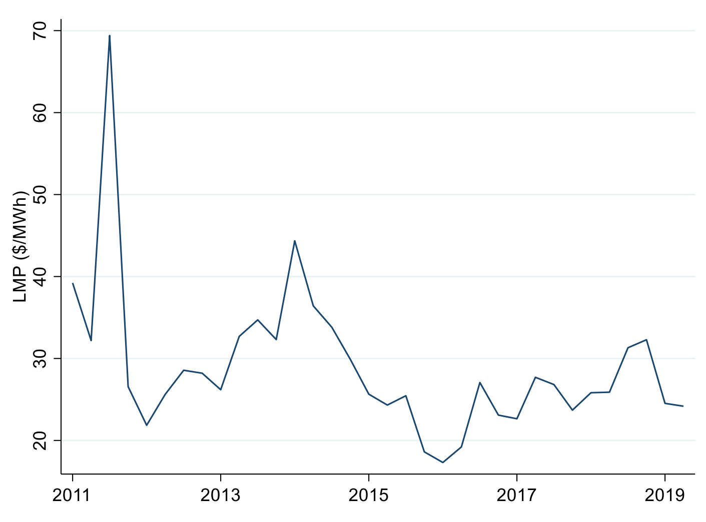


***Figure 1**. Average LMPs by Quarter*

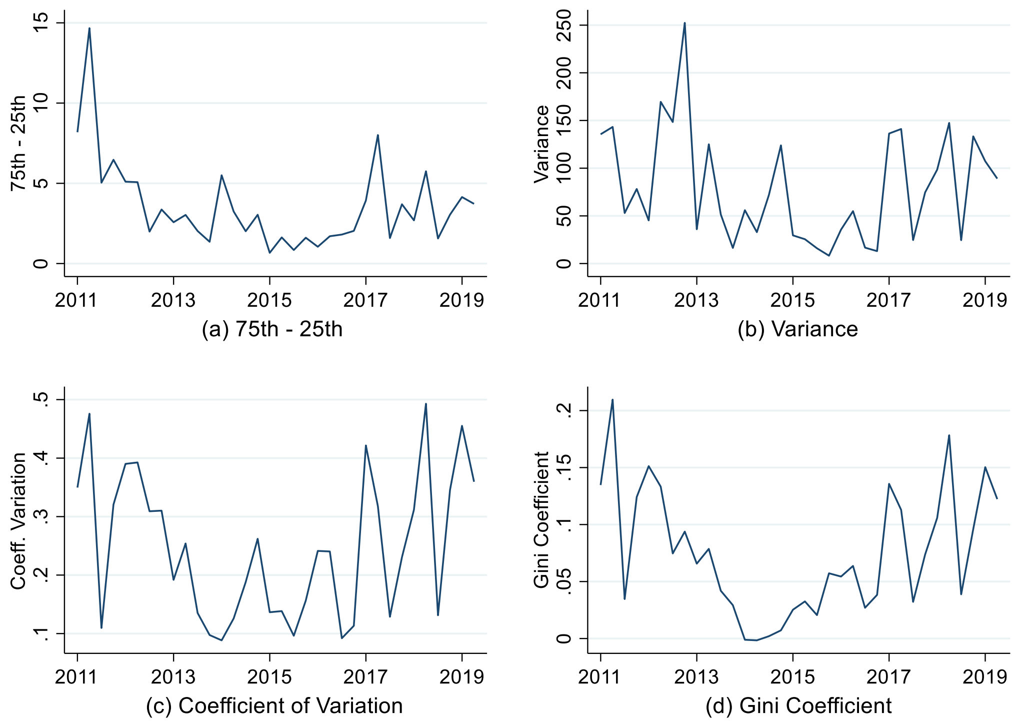
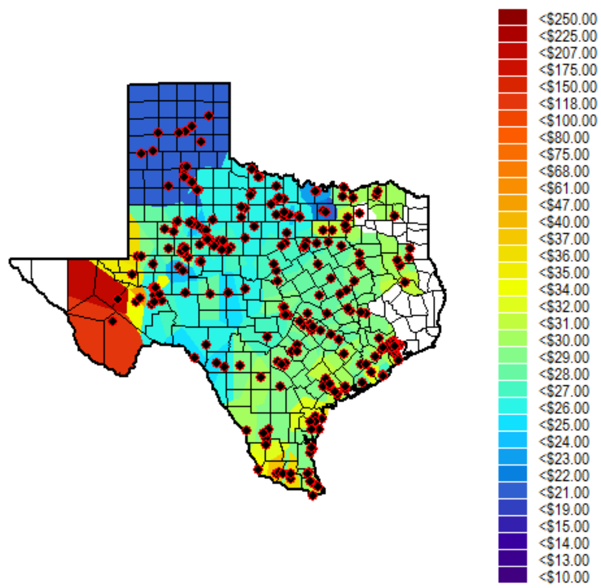


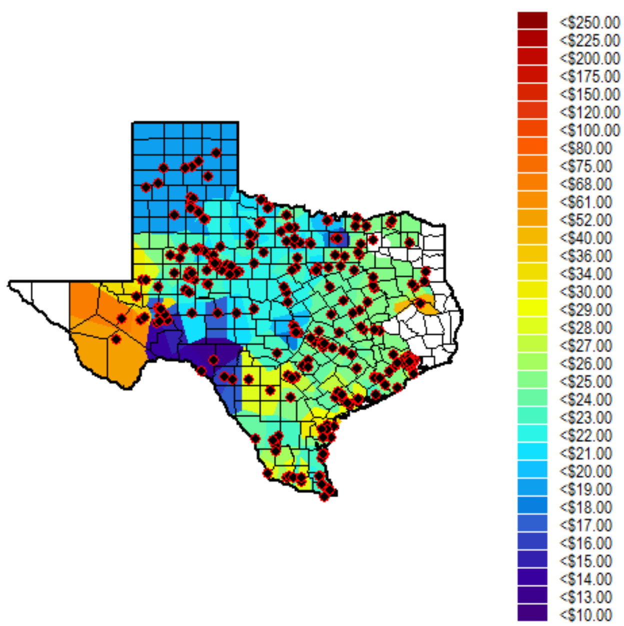
***Figure 2**. Measures of LMP Dispersion by Quarter*

Figure 2 presents the four LMP dispersion measures over our sample period. While each measure differs in scale and variability overtime, all four measures show a distinct pattern. LMP dispersion was higher at the beginning of our sample, declined until 2014-2015, and has increased in the latter years. This is most clearly represented by the increase in the Gini Coefficient in Figure 2(d) which measures the inequality of LMPs across all nodes within a given 15-minute interval.

Spatial differences in LMPs arise because of transmission congestion that prevents a least-cost dispatch of generation units based on their merit order of marginal costs. Consistent with the findings in Figure 2, real-time transmission congestion cost has increased considerably in ERCOT since 2015 (Potomac Economics, 2017, 2019).



(a) 2018



(b) 2019

Figure 3*. LMP Contour Map – Average Nodal LMPs*[14]

Figure 3 provides a contour plot of ERCOT's average LMPs by node in 2018 and 2019 to illustrate the type of geographical price dispersion that arise in our data. In this figure, we

[14] The LMP contour plots in Figure 3 were created using code in Elhabr (2018).

observe suppressed LMPs in certain regions (e.g., the panhandle with high penetrations of wind resources) and elevated LMPs in the far western region of ERCOT. Figures 1 - 3 illustrate that while average LMPs have decreased, LMP dispersion has increased since 2014 – 2015 back towards the elevated levels observed in 2011-2012. These figures provide evidence that there are potential opportunities for resources to locate in geographical regions with elevated LMPs. In the remainder of our analysis, we will investigate if there is evidence of LMP-driven investment based on the documented increase in LMP dispersion.

b. Observed Entry

In this section, we document the amount of new capacity investment by year and generation technology. We summarize investment based on 5 technology categories: (i) wind, (ii) CT, (iii) CCGT, (iv) solar, and (v) other.[15] Despite the relatively low LMP levels over our sample period, we observe 42,552 MWs of operational or planned capacity investments since 2011.

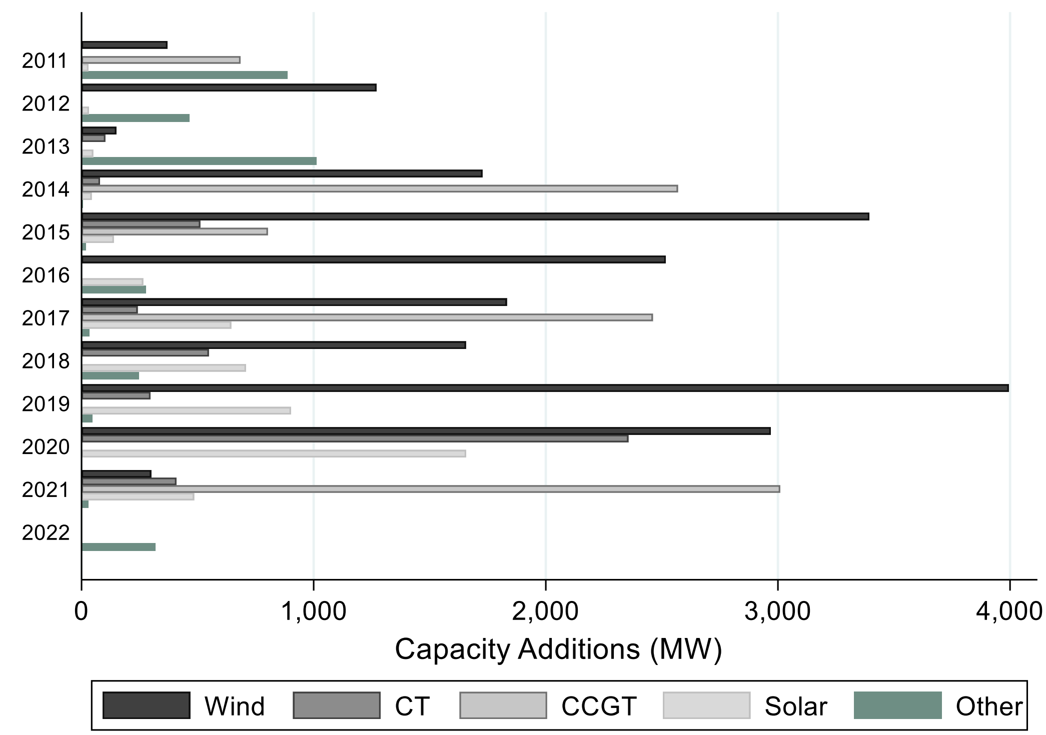


***Figure 4**. Capacity Additions (MW) by Year and Technology (Count: 319)*

Figure 4 presents capacity additions by year and technology. New generation units in 2020 – 2022 (60 facilities) represent planned investments. By technology, the new capacity additions in MWs are wind (20,181, 47%), CCGT (9,530, 22%), CT (4,548, 11%), solar (4,961,

[15] The other category includes batteries/flywheel storage (11), hydro (1), biomass (1), coal (2), and other natural gas (54). The coal units are additions to existing facilities. Other gas represents small assets (< 20 MWs) with technologies such as landfill gas, steam turbines, and one large facility with natural gas compressed air storage.

12%), and other (3,332, 8%).[16] These statistics illustrate the large growth in wind capacity since 2011, followed by CTs and CCGTs and more recently solar capacity.

Table 1 decomposes the number of new generation facilities by year and technology. It shows wind investment arises throughout our sample. Investment in natural-gas based CT and CCGT investments arise periodically throughout our sample, with a large number of CTs and CCGTs planned to begin operating in 2020 – 2021. Since 2017, there has been a sizable increase in the number of solar facilities operating in ERCOT.

***Table 1**. New Generation Facilities by Year and Technology (Count)*

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
Wind	2	10	1	9	19	12	11	8	18	11	1	0	102
CT	0	0	1	1	4	0	4	7	5	17	2	0	41
CCGT	5	0	0	11	3	0	6	0	0	0	12	0	37
Solar	1	5	2	2	5	4	17	14	7	11	2	0	70
Other	7	6	5	4	3	19	3	15	3	0	2	2	69
Total	15	21	9	27	34	35	41	44	33	39	19	2	319

Notes. Other represents storage (11), hydro (1), biomass (1), coal (2), and other gas (54).

Figure 5 provides a map of all new generation assets by technology. The majority of CT assets are located between Houston and San Antonio. CCGTs are often located throughout eastern and central Texas. Wind generation units are concentrated in the panhandle region, southern coast, and western Texas where wind potential is highest. Except for southern Texas, solar assets are dispersed across all regions of ERCOT. Lastly, the other technologies are often located near Houston, Austin, San Antonio, and Dallas. These facilities are often linked with industrial processes (i.e., representing cogeneration facilities).

By comparing Figures 3 and 5, it is difficult to discern any clear location patterns between the entry of new generation units and regions that have experienced higher LMPs. Hence, we carry out several empirical strategies to investigate the degree to which LMPs are related to generation unit location decisions.

[16] See Table A1 in the Appendix for a detailed summary of capacity additions by year and technology in MWs.

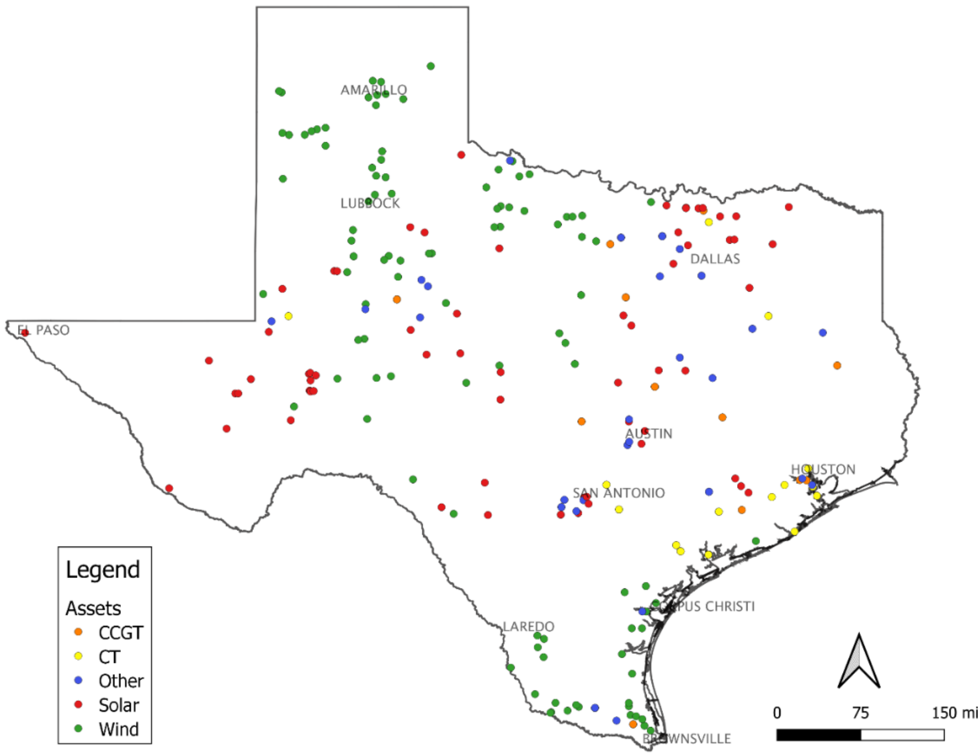


***Figure 5**. New Generation Units by Location and Technology (2011 – 2022)*

c. New Capacity by Lagged Pricing Tiers

We first evaluate whether generation investment location decisions are concentrated near nodes that have observed systematically higher LMPs prior to their entry. This allows us to investigate the claims that LMPs send location-specific investment signals for new potential investments.

We decompose generation capacity investments that occurred during our sample period into various price-tiers based on lagged LMPs. Using the distribution of the RTM nodal prices from the previous three years, we categorize each node into one of four pricing tiers: (1) 0 - 25th, (2) 25th – 50th, (3) 50th – 75th, and (4) 75th – 100th percentile.[17] The higher the pricing tier, the higher the average annual lagged LMP at a specific node. For each year, we summarize the annual capacity additions (in MWs) by pricing tier where MWs are attributed to the geographically closest node.

We consider new capacity investments for the period 2012 – 2021. It is important to note that for the years 2012 and 2013, we use all data available on a rolling basis back to January

[17] We also considered alternative lagged structures such as one and two years to categorize the pricing tiers and find that our results are robust.

1, 2011. For planned investments arising after our sample period ending June 12, 2019, we utilize the most recently available three years of LMP data to categorize the price tiers.[18]

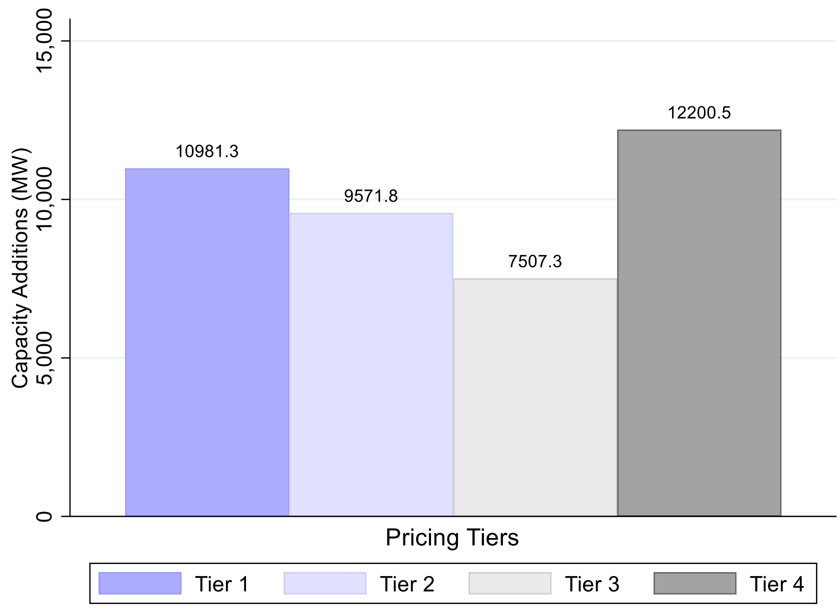


***Figure 6**. Capacity Additions (MWs) by Lagged Pricing Tiers – Nearest Node (2012 – 2021)*

Figure 6 provides capacity investments in MWs by three-year lagged pricing tier between the years 2012 – 2021. The largest quantity of MWs of capacity were added in the highest pricing tier, thus providing evidence that generators are motivated to locate in regions with recently elevated LMPs. This is consistent with the principle that LMPs send location-specific investment signals for new capacity investments. That said, the capacity additions in MWs in the lowest two price tiers (20,553.10 MWs) were slightly higher than those added in the highest two pricing tiers (19,707.80 MWs).

Figure 7 decomposes capacity additions by year and pricing tier. For certain years, capacity additions were dominated in the highest pricing tier (2012, 2015, 2016) over the bottom two pricing tiers. However, for other years, capacity additions systematically arose at nodes that were in the bottom two pricing tiers (2018, 2020, 2021). These descriptive statistics provide mixed evidence on the role of recent LMPs in motivating location decisions.

The findings presented in Figures 6 and 7 persist when we utilize our alternative spatial definitions. For example, Figure A2 and Figure A3 present analogous figures for the 10-mile radius measure.[19] These figures continue to find the largest amount of capacity additions (in MWs) arising in the highest pricing tier.

[18] Similar results arise if we focus only on investments between the period 2014 – 2019.
[19] It is important to note that the other spatial measures can result in assets being counted more than once or not counted at all. For example, for 25-mile distance measure, a single asset can fall in multiple nodes' 25-mile radius.

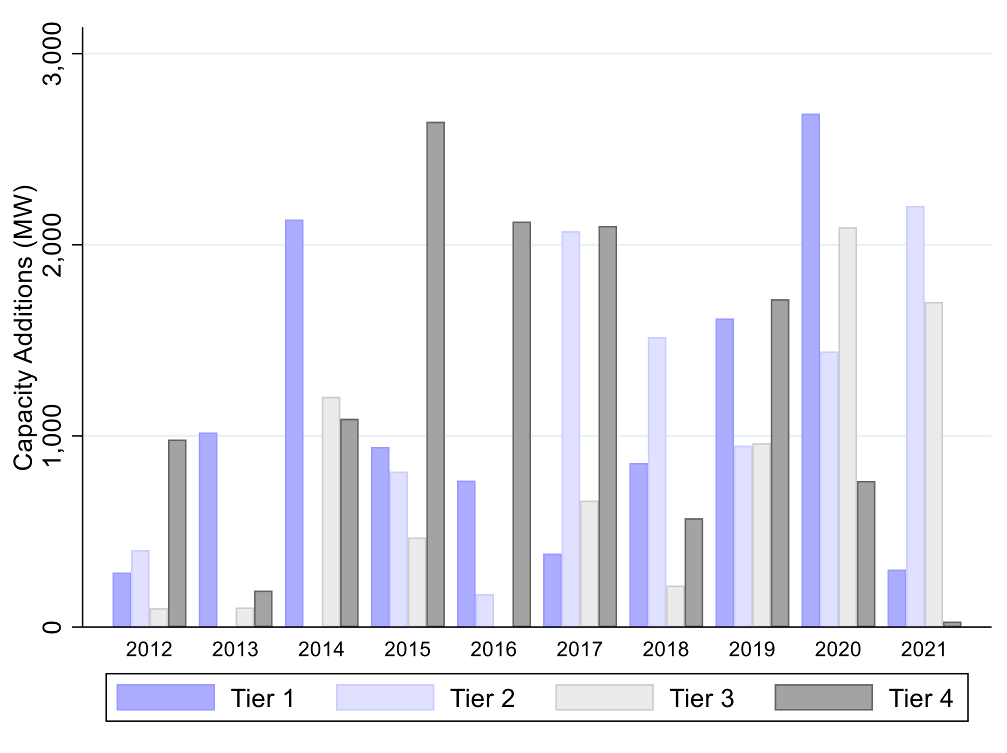


Figure 7*. Capacity Additions (MWs) by Pricing Tiers and Year – Nearest Node*

d. LMP Post-Entry Premium

We now investigate if new generation resources receive an LMP-premium post-entry compared to nodes where recent nearby entry did not occur. If generation resource locations decisions are driven by higher expected LMPs (post-entry), then we might expect the post-entry nodes to have elevated LMPs compared to nodes that have not experienced recent nearby entry, an intuition based on the illustrative model in Section 4.

To investigate this question, we compare the average LMPs at nodes with and without recent nearby entry. As noted above, we utilize our primary spatial measure that matches each new generation resource that began operating in period t with its nearest node j. We consider three lagged structures to define recent entry. We focus on nodes where nearby entry has occurred in the last 1, 2, and 3 years. We decompose recent entry by fuel type CT, CCGT, Wind, Solar, and Other to investigate if the results vary by generation technology.

Table 2 presents the average LMP comparisons for the 3-year lag structure. More specifically, this table compares average LMPs at nodes where entry occurred in the last 3 years to nodes that have not observed entry during this time period. Table 2 illustrates that

Alternatively, for the 10 mile radius, a handful of isolated assets are not linked to nodes. Consequently, the number of MWs of new capacity can deviate from the actual number of capacity additions (MWs). It is for these reasons that our preferred specification focuses on the nearest node spatial measure.

nodes with recent nearby entry have systematically lower average LMPs than nodes without recent nearby entry. This result persists across all technologies and when we decompose the nodes with recent nearby entry by technology.

We employ a difference in means test to compare the average LMPs in non-entry nodes and recent nearby entry nodes across all technologies and by technology. For all technologies, except CT and other, the differences in average LMPs are all positive and statistically significant. The largest difference in average LMPs arise at nodes which have observed recent nearby entry of CCGT units. It is important to note that CCGT (CT and other) units are often the largest (smallest) new capacity additions observed in our sample. Consequently, these results are consistent with the fact that entry of these assets is more (less) likely to result in a suppression of local RTM nodal prices post-entry.

Table 2. *Average LMPs at Nodes with and without Recent Entry – Nearest Node (3 Year Lag)*

	Non-Entry	Entry					
		All Tech.	CT	CCGT	Wind	Solar	Other
Mean	29.13	26.77	27.22	25.72	26.44	25.96	28.24
Std. Dev.	7.36	5.73	4.47	4.30	5.97	5.03	6.57
Difference in Means		2.36***	1.92	3.41***	2.70***	3.17***	0.90
		(0.42)	(1.14)	(0.87)	(0.63)	(0.63)	(0.87)

Notes. Difference in means performs a t-test on the equality of means with unequal variances. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Tables A2 and A3 in the Appendix consider a 1- and 2-year lagged structure to define recent entry at a given node j. In addition, we considered our alternative spatial measures to define recent nearby entry. The results for these alternative cases are consistent with those presented in Table 2. We find no evidence that resources receive an LMP-premium post-entry compared to nodes that have not experience recent nearby entry. In fact, across all spatial measures and lag structures we considered, nodes with recent nearby entry often have statistically significantly lower average LMPs compared to nodes that have not experienced recent nearby entry. This could be driven by the fact that the entry of the resources under consideration put downward pressure on LMPs post-entry. However, our two-stage model in Section 4 suggests that if investment location decisions are motivated by the expectation of higher LMPs post-entry, we expect new capacity additions to receive an LMP-premium compared to LMP levels at non-entry nodes.

e. Regression Analysis

In this section, we employ the two-period investment model in Section 4(a) and the associated empirical strategy in Section 4(b). This allows us to evaluate whether expected nodal price levels and variances are related to a generator's location investment decision.

i. Real-Time Market Nodal Price Regressions

We carry out the RTM nodal price regressions in equation (4). More specifically, starting with the period 2011 – 2012, we use pre-entry data to forecast RTM nodal price levels and variances on a forward-looking basis out-of-sample. This results in estimating 160 regressions (one for each node) for 6 different time horizons.[20] We focus on aggregate level statistics that represent the voluminous results of these RTM nodal price regressions.

***Table 3**. Summary Statistics - Observed and Estimated*

		Mean	Std Dev	Min	Median	Max
Observed	$Net\ Demand$	7,387.02	2,497.65	2,211.10	6,964.83	15,947.49
	$Henry\ Hub$	3.23	0.79	1.49	3.03	8.15
	LMP	28.98	82.77	-8,122.96	22.58	9,050.08
Estimated	σ^2_{LMP}	640.78	417.59	144.47	520.46	4,755.51
	$\overline{LMP}$	27.71	3.65	21.75	26.83	56.09
	$\overline{LMP}_{TOD1}$	16.86	2.75	7.93	17.16	27.75
	$\overline{LMP}_{TOD2}$	27.22	2.71	22.01	26.85	47.63
	$\overline{LMP}_{TOD3}$	29.29	5.45	23.21	28.00	82.32
	$\overline{LMP}_{TOD4}$	49.32	10.32	32.28	46.05	125.71
	$\overline{LMP}_{TOD5}$	26.72	2.68	21.01	26.67	51.63

Table 3 presents summary statistics of the key regressors in our sample. Net Demand (in MWh) and LMPs (in $/MWh) represent 15-minute level observed data. Henry Hub prices (in $/MMBTU) represents daily-level henry hub natural gas prices. There is considerable variation in these measures over our sample period.

Table 3 also presents summary statistics of our model estimated average nodal RTM price levels ($\overline{LMP}$) and variances (σ^2_{LMP}). It is important to note that this data represents annual forward-looking averages at the node-level, whereas the observed data represents higher frequency observations (e.g., daily or 15-minute data). The model estimated nodal price levels are also broken down by our 5 TOD periods. The high correlation (> 0.96) across TOD periods in the nodal price variance measure limits our ability to include TOD-specific variance measures in our analysis due to multi-collinearity issues.

Table 3 reports considerable variation in the estimated LMP levels and variances across the nodes in our sample. The empirically estimated average LMP falls within approximately $1

[20] Recall, we utilize 2011 – 2012 data to forecast forward for the period 2013 – 2019, 2011 -2013 data to forecast the period 2014 – 2019, and so on until we are utilizing 2011 – 2017 data to forecast RTM nodal prices for the period 2018 and 2019.

of the observed average LMP. As expected, the average forecasted LMPs vary considerably by TOD with the highest average nodal prices arising in the mid-day (TOD3) and afternoon (TOD4) periods.

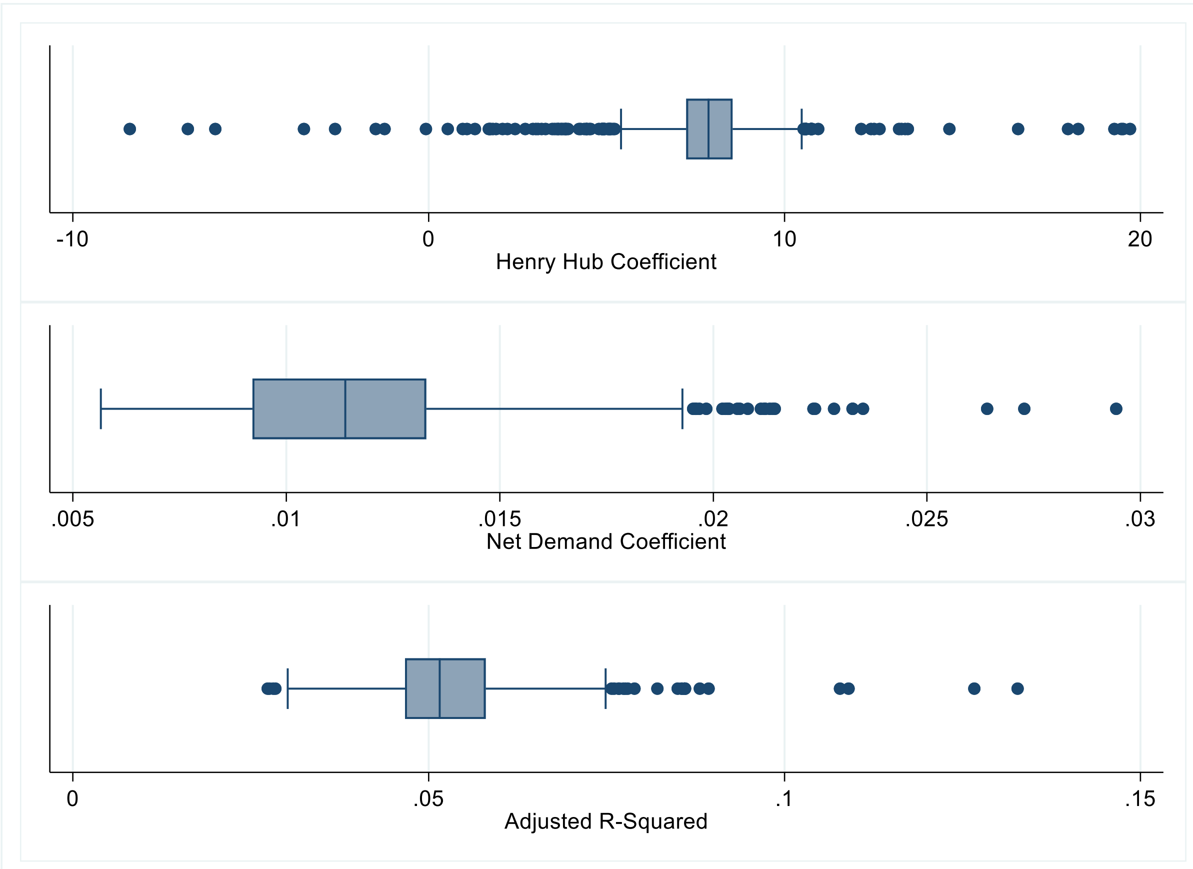


***Figure 8**. RTM Nodal Price Regression Results Box and Whisker Plot*

Figure 8 presents a box and whisker plot summary of the results of our RTM nodal price regressions detailed in equation (4). The "whiskers" above and below reflect the locations of the 10^{th} and 90^{th} percentiles and the center line corresponds to the median. The Henry Hub coefficients systematically vary between 6 and 10 and are statistically significant, which is a reasonable range reflecting the heat rates of CTs and CCGTs that normally operate on-the-margin in ERCOT.[21] The net demand coefficients are positive, statistically significant, and systematically between 0.008 and 0.08 with a median value of 0.052. Consequently, at the median net demand coefficient value, a one standard deviation change in Net Demand would result in a $129.88 increase in the RTM nodal price, holding all else constant.[22]

[21] Liu et al. (2016) and Zarnikau et al. (2019b) find similar henry hub coefficients in the range of 7 to 9. While there are a handful of negative henry hub coefficients, they are not statistically significant and often arise at nodes in industrial regions where idiosyncratic local consumption behavior is more likely to drive nodal price patterns.
[22] From Table 3, $\sigma_{NetDemand} = 2497.65$ such that a one standard deviation change in net demand equals $2497.65 \times 0.052 \approx 129.88$.

Figure 8 demonstrates that the adjusted R-squared of our RTM nodal price regressions varies between 0.044 and 0.065 in the inner-quartile range, owing to the widely dispersed 15-minute nodal prices. However, the estimated annual average LMPs closely match the observed values in-sample, the key statistic in our discrete entry analysis in the next subsection.

ii. Discrete Nodal Entry Analysis

Corresponding to the first period of our investment model, we estimate the logit regression specified in equations (5) and (6) to evaluate the relationship between the likelihood of entry at a specific node j in year t and average forecasted (forward-looking) nodal price levels and variances. We focus on our primary specification that considers the spatial measure that matches capacity additions to the nearest existing node.

Table 4 presents the results of our nodal entry regressions across all technologies and decomposed by technology. These results come from two model specifications, one with average nodal price levels across all hours and another where average nodal price levels by TOD period.[23]

Looking across all technologies, the LMP coefficient in column (1) is positive and statistically significant, suggesting entry is more likely to arise at a specific node when its forecasted average LMP level increases. The variance coefficient is negative but statistically insignificant. Column (2) provides a more flexible specification that allows the impact of average forecasted LMPs to vary by TOD. This specification only finds a statistically significant and positive average forecasted LMP level coefficient in the evening hours (i.e., TOD5). However, these regressions mask important heterogeneity across generation technologies.

Columns (3) and (4) present the results for natural gas CT, indicating a positive and significant relationship between average forecasted nodal LMPs and the likelihood of investment. When decomposed by TOD, all coefficients are statistically insignificant except for the coefficient on the average forecasted LMP levels in the evening (TOD5) period. This coefficient is positive and significant at the 5% level. These results suggest that a CT unit's location decisions are partly motivated by average forecasted LMP levels in the evening hours.

[23] The variability in the number of observations across technologies arises from the fact that we have weather zone and year fixed effects to control for important regional and time-varying factors that drive investment decisions. Consequently, our analysis identifies off of variation in entry decisions within a year and weather zone. If there is a year or weather zone with no investment in a certain generation technology, then the nodes in this zone-year are dropped from our sample due to multi-collinearity.

***Table 4**. Nodal Entry Logit Regression by Technology - Nearest Node*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All	All	CT	CT	CCGT	CCGT	Solar	Solar	Wind	Wind
$\overline{LMP}$	0.180**		0.227**		0.750		0.145		0.0595	
	(0.0743)		(0.0777)		(0.476)		(0.113)		(0.103)	
σ^2_{LMP}	-0.0013	-0.0024*	-0.0002	-0.0089	-0.0091**	-0.0091	-0.0017	-0.0077	0.0007	-0.0025**
	(0.0010)	(0.0015)	(0.0005)	(0.0057)	(0.0043)	(0.0240)	(0.0013)	(0.0059)	(0.0012)	(0.0012)
$\overline{LMP}_{TOD1}$		-0.3150		-1.553		-1.244		-0.404		-0.419
		(0.211)		(0.961)		(1.137)		(0.273)		(0.272)
$\overline{LMP}_{TOD2}$		0.0124		-0.336		-0.133		0.159		0.205
		(0.176)		(0.754)		(1.348)		(0.370)		(0.174)
$\overline{LMP}_{TOD3}$		-0.176		-0.302		-1.285*		-0.749**		0.110
		(0.136)		(0.413)		(0.661)		(0.254)		(0.232)
$\overline{LMP}_{TOD4}$		0.0839		0.525		0.296		0.478**		0.0542
		(0.111)		(0.432)		(0.869)		(0.203)		(0.227)
$\overline{LMP}_{TOD5}$		0.513**		1.766**		3.764		0.754*		-0.0167
		(0.248)		(0.634)		(2.338)		(0.404)		(0.361)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	48.65***	69.34***	115.3***	42.62***	126.9***	718.3***	29.51***	73.84***	19.81***	37.27***
N	888	888	270	270	264	264	888	888	558	558

Notes. Cluster-robust standard errors are in parentheses. $***p < 0.01$, $**p < 0.05$, and $*p < 0.10$.

Results for CCGTs in columns (5) and (6) suggest no positive and significant relationship between average forecasted LMPs and CCGT location decisions. In fact, column (6) finds a negative and marginally significant coefficient on average forecasted LMPs in the mid-day hours (TOD3). The negative and statistically significant coefficient on the expected LMP variance measure in column (5) suggest that CCGT units locate near nodes with a lower average forecasted LMP variance. [24] This result contradicts our *ex-ante* expectations because a CCGT investment's profitability tends to be enhanced by high price level and volatility (Woo et al., 2016). However, the statistical significance vanishes when we control for average nodal price levels by TOD in column (6).

Columns (7) and (8) present the results for solar investment. Focusing on the statistically significant coefficients, these results demonstrate that solar resources are more likely to locate near nodes with lower average forecasted LMPs in mid-day hours (TOD3) and higher average forecasted LMPs in the afternoon and evening hours (TOD4 and TOD5). These relationships are consistent with the fact that solar units are observed to co-locate (e.g., due to high solar irradiance and low siting costs), suppressing mid-day prices when the sun

[24] The negative forecasted LMP variance and TOD5 coefficients in columns (5) and (6) could be capturing factors such as the fact that CCGT often locate on land that includes other existing base-load facilities (e.g., other CCGT units) that suppress forecasted mid-day nodal price levels and variance. Regardless, these results are inconsistent with the hypothesis that investment location decisions are positively related to expected nodal prices.

is shining and raising evening price as the sunsets.[25] Consequently, the results presented in columns (7) and (8) are consistent with other drivers of investment location decisions (such as siting cost and solar irradiance potential) rather than solar resources being motivated by the expectation of higher average forecasted LMPs in mid-day hours when the sun is shining and solar output is positive.

Columns (9) and (10) illustrate the results for wind generation. These results find no statistically significant relationship between average forecasted LMP levels and investment location decisions. In column (10), there is a negative and marginally significant coefficient on forecasted LMP variance suggesting that wind resources are more likely to locate near nodes with lower expected LMP variance. While seemingly odd, this coefficient could reflect the incentive for a new wind resource, which is a non-dispatchable unit, to locate near a node with relatively stable prices (e.g., with fewer nearby existing wind resources).[26]

While our primary focus is on the sign and significance of the logit regression coefficients, Table 5 provides the average marginal effects (AME) in order to illustrate the magnitude of the effects we have identified in Table 4.[27] For brevity, we will focus on the statistically significant coefficients in the CT regressions whose findings described above are consistent with a positive and significant relationship between nodal prices and investment location decisions. It is useful to note that 41 CT units entered during our period of interest and there are 160 nodes in our sample. Consequently, to establish a scale for reference, if CT units were randomly allocated across nodes, there would be an approximate 25.6% probability that a CT unit would be constructed at any given node during our sample period. In column (3), the AME of a one standard deviation increase in the average forecasted LMP ($\overline{LMP}$) increases the likelihood of a CT unit being constructed at a node j by 2.19 percentage points.[28] From column (4), the AME of a one standard deviation increase in $\overline{LMP}_{TOD5}$ results in an 11.55 percentage point increase in the likelihood of a CT unit being constructed at a given node j.[29] These results demonstrate that the significant LMP coefficients in columns (3) and (4) represent economically significant effects.

[25] See Bushnell and Novan (2018) for an analysis of the impact of solar PV on wholesale prices in California.

[26] We also decomposed the wind assets by coastal and non-coastal wind. While the precise quantitative results vary, the overall lack of statistically significance and qualitative conclusions are unaffected.

[27] The average marginal effects are calculated by taking a marginal change in the variable of interest, while holding all other variables at their observed values. An alternative approach would be to calculate the marginal effects at the mean which holds all other variables at the sample average values. While this changes the precise quantitative results in Table 5, the qualitative conclusions and statistical significance are unchanged.

[28] From Table 3, a one-standard deviation change in $\overline{LMP}$ equals 3.65 such that $3.65 \times 0.0060 = 0.0219$.

[29] From Table 3, a one-standard deviation change in $\overline{LMP}_{TOD5}$ equals 2.68 such that $2.68 \times 0.0431 = 0.1155$.

Table 5. *Average Marginal Effects – Nodal Entry Logit Regression – Nearest Node*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All	All	CT	CT	CCGT	CCGT	Solar	Solar	Wind	Wind
$\overline{LMP}$	0.0151**		0.0060**		0.0192		0.0045		0.0029	
	(0.0062)		(0.0028)		(0.0126)		(0.0036)		(0.0050)	
σ^2_{LMP}	-0.0001	-0.0002	-0.00001	-0.0002	-0.0002*	-0.0002	-0.00005	-0.0002	0.00003	-0.0001*
	(0.0001)	(0.0001)	(0.00001)	(0.0002)	(0.0001)	(0.0004)	(0.00004)	(0.0002)	(0.0001)	(0.00006)
$\overline{LMP}_{TOD1}$		-0.0260		-0.0379		-0.0295		-0.0122		-0.0204
		(0.0175)		(0.0254)		(3.1297)		(0.0084)		(0.0135)
$\overline{LMP}_{TOD2}$		0.0010		-0.0082		-0.0032		0.0048		0.0100
		(0.0145)		(0.0186)		(0.0376)		(0.0111)		(0.0084)
$\overline{LMP}_{TOD3}$		-0.0145		-0.0074		-0.0305		-0.0226***		0.0053
		(0.0111)		(0.0100)		(0.5173)		(0.0081)		(0.0114)
$\overline{LMP}_{TOD4}$		0.0069		0.0128		0.0070		0.0144**		0.0026
		(0.0091)		(0.0108)		(0.3014)		(0.0065)		(0.0110)
$\overline{LMP}_{TOD5}$		0.0423**		0.0431**		0.0892		0.0227*		-0.0008
		(0.0203)		(0.0182)		(0.2840)		(0.0124)		(0.0176)

Notes. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

To ensure the robustness of our results, we consider various other model specifications. Tables A4 and A5 in the appendix present the alternative spatial measures that links entry that occurs within a 10-mile radius of a given node and entry to the nearest two nodes, respectively. Consistent our baseline analysis, when looking at column (3) of both tables, we continue to find a positive relationship between average expected LMP levels and the likelihood of entry for CT units, although this effect is only marginally significant in both specifications. When decomposing this effect by TOD in column (4), we only find a positive and significant relationship in the average expected LMPs in the evening hours for the 10-mile radius regression.

Columns (5) and (6) continue to show no positive and significant relationship between CCGT location decisions and average expected LMP prices. The solar results discussed above persist, though weaker and/or insignificant. For wind generation facilities, columns (9) and (10) continue to find a limited positive and significant relationship between average expected LMP levels and the likelihood of entry of wind at a specific node.

Table A6 presents the results for our primary model specification with the nearest node distance measure, excluding the years 2017 and 2018. There may be concerns that the forward-looking RTM nodal price regressions has insufficient data to accurately model how expected nodal price levels and variances impact entry decisions near the end of our sample period. Table A6 demonstrates that our key findings persist, with the exception that we no longer find a positive and significant coefficient in column (4) for the CT specification when average expected LMPs are broken down by TOD.

In summary, these results present limited evidence of a relationship between average forecasted LMPs and location-specific investment decisions. For CT assets, the likelihood of investment at a given node increases as the average expected RTM nodal price increases. However, this result is sensitive to model specification. Taken together, these results suggest that other market and location-specific factors are likely more important drivers of investment location decisions.

6. Conclusion

We investigate the role of ERCOT's nodal pricing in motivating location-based generation capacity investment decisions. We document increased dispersion of LMPs across nodes and substantial investment in wind and natural gas capacity. We find limited evidence that nodes with recent nearby entry experience an LMP-premium post-entry compared to nodes where nearby entry has not occurred. In particular, we find that nodes with recent nearby entry have systematically lower average nodal price levels, consistent with suppressed LMPs as the result of entry.

We find that the largest number of capacity additions (in MWs) arise in the top quartile of the nodal price distribution when focusing on lagged LMPs. This provides some evidence that recent LMPs send price signals for location-based investment. However, when looking across the full nodal price distribution, over 50% of new capacity additions (in MWs) arise in the lowest two LMP quartiles. Our statistical analysis finds limited evidence that expected average LMP levels and variance drive location-based investment decisions. We find some evidence that smaller peaker natural gas (CT) assets have a positive and significant relationship between the likelihood of investment near a node and that node's expected average nodal price level. However, this relationship is sensitive to the regression model specification.

Overall, our analysis presents limited evidence that LMPs drive location-based investment decisions in Texas during our sample period. Investments in power plants are complex long-run decisions that entail many factors. There are important reasons why higher nodal prices may not be a primary driver of power plant location decisions:

- Plant location decisions are also driven by other factors such as site availability, transmission access, interconnection costs, access to fuel or renewable resources, and local regulation and approvals.
- Nodal prices are volatile, resulting in a highly uncertain stream of revenues that may hinder a power plant developer's ability to obtain project financing based on higher expected LMPs (Stern, 1998).
- A load pocket's high nodal prices may collapse as the result of a plant's lumpy capacity investment, thus discouraging investments in large facilities.

- A load pocket's nodal price spikes tend to be concentrated in a relatively few critical hours of the year (e.g., extremely hot summer afternoons). This makes demand response (DR) and demand-side management (DSM) likely more cost-effective investments due to their low capital expenditure requirements.[30] As a result of growing distributed generation, DR, DSM, and entry of small to medium-sized battery storage, an IPP's planned construction based on high nodal prices may become unprofitable.
- A regulator may choose to build more transmission to reduce a load pocket's high LMPs and reliability concerns. This threat of transmission investment can elevate the risk of LMP-driven generation investment.[31]

Our analysis suggests several directions for future research. First, our analysis is reduced-form and aims to evaluate relationships between location-based investment and LMPs. A caveat with this approach is that we are unable to fully unentangle the relationship entry location decisions and post-entry expected LMPs because we do not simulate post-entry LMPs under various location-based entry scenarios. A structural analysis that permits counterfactual simulations can provide additional important insights into the drivers of investment location decisions. A related analysis that employs techniques in the structural industrial organization literature is needed. Second, we focus on investment in utility-scale generation assets. However, LMPs may be more likely to motivate investment in smaller-scale distributed generation, battery storage, and DR. An analysis of the location-based decisions of these technologies and how it relates to RTM nodal prices is warranted.

Third, our analysis focused on investment location decisions, conditional on observed investment in a given technology. Future research should explicitly model the decision to invest in a technology prior to the investment location decision. Fourth, a similar analysis of other jurisdictions with nodal pricing is needed to evaluate the robustness of our findings to other market and regulatory environments.

[30] Utilities like Pacific Gas and Electric (PG&E) and Bonneville Power Administration (BPA) have been seeking non-wire solutions based on DR and DSM (Sreedharan et al., 2002; Woo et al., 2014; E4 The Future, 2018).
[31] For example, in 2014, ERCOT approved a transmission line to alleviate local congestion in Houston, a move that was opposed by several generation companies (Tiernan, 2015).

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Appendix

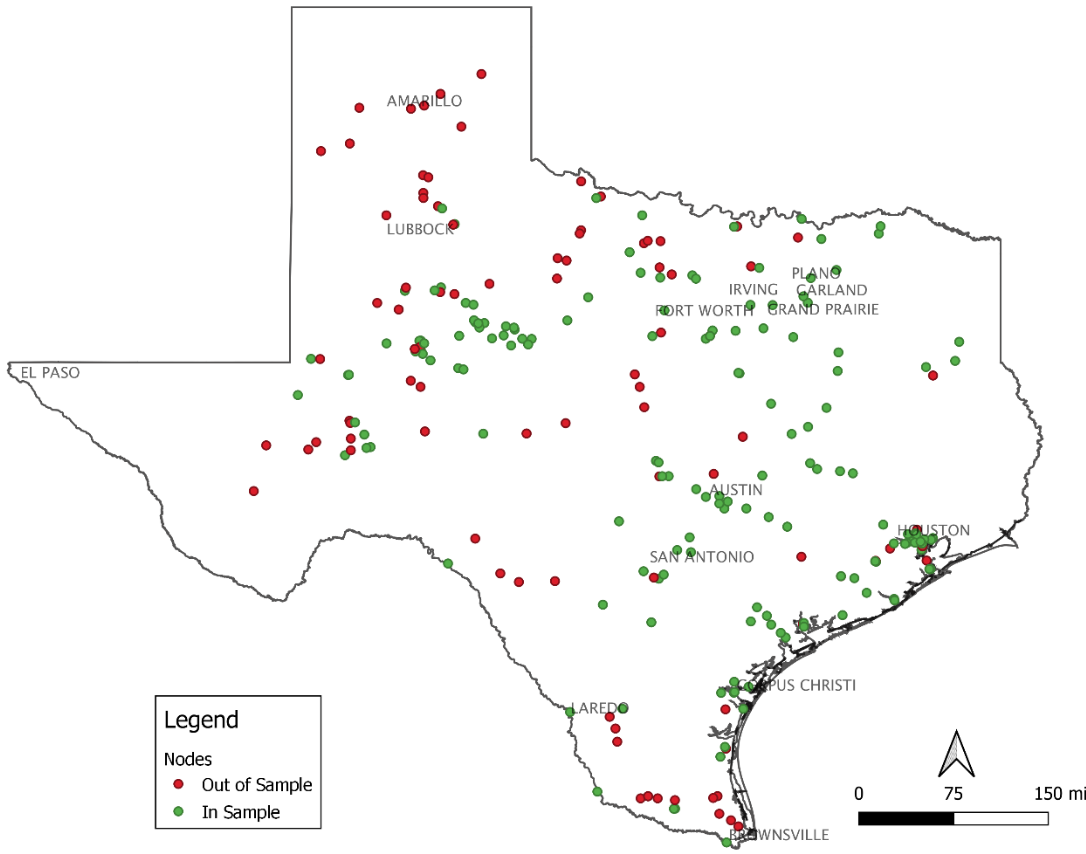

Figure A1. *Nodes in Sample (N=160)*

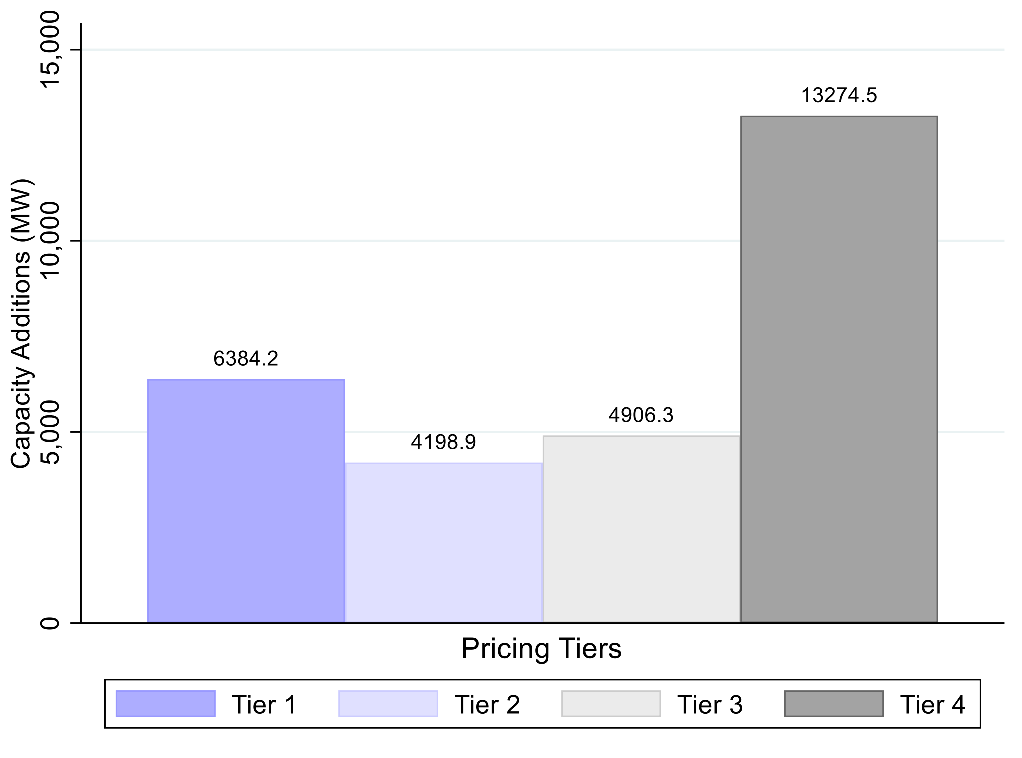

Figure A2*. Capacity Additions (MWs) by Pricing Tiers – Dist. 10 Miles (2012 – 2021)*

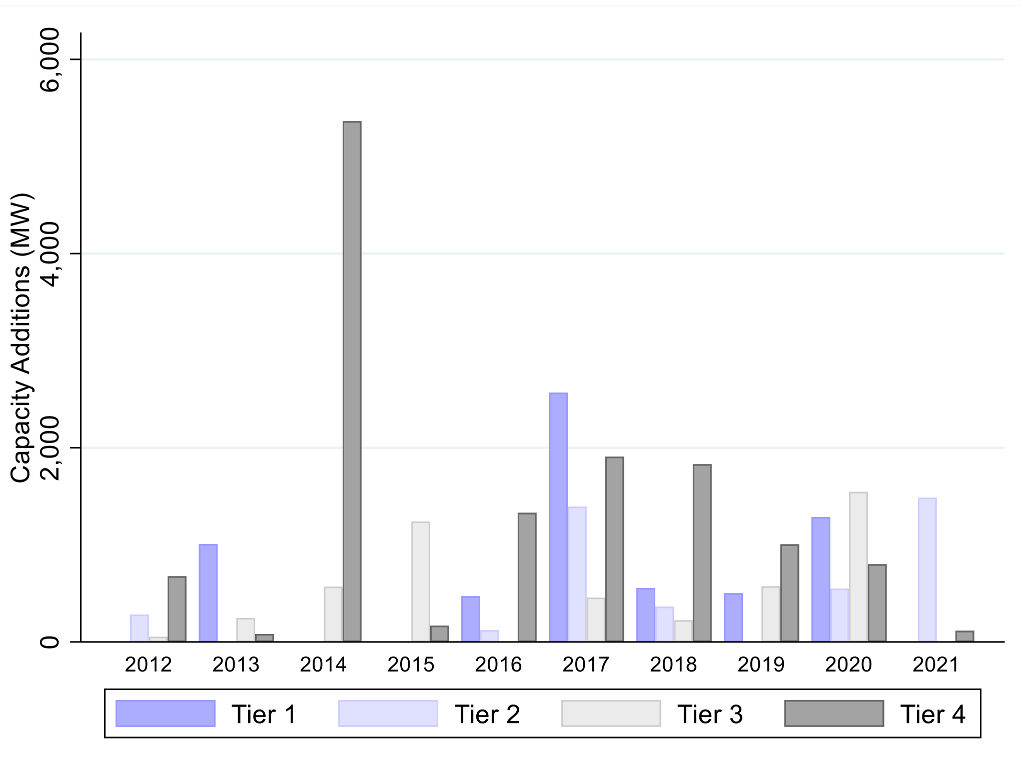

Figure A3*. Capacity Additions (MWs) by Pricing Tiers and Year – Dist. 10 Miles*

Table A1. *New Generation Facilities by Year and Fuel Source (MW)*

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
Wind	370	1,271	150	1,727	3,394	2,517	1,832	1,656	3,995	2,969	300	0	20,181
CT	0	0	103	80	512	0	242	549	297	2,356	409	0	4,548
CCGT	685	0	0	2,570	803	0	2,462	0	0	0	3,010	0	9,530
Solar	30	32	51	44	139	266	645	709	903	1,657	485	0	4,961
Other	887	465	1,011	4	18	276	32	248	45	0	29	317	3,332
Total	1,972	1,768	1,315	4,425	4,866	3,059	5,213	3,162	5,240	6,982	4,233	317	42,552

Notes. Other represents Storage (115), Hydro (1), Biomass (114), Coal (1,887), and Other Gas (1,216).

Table A2. *Average LMPs at Nodes with and without Recent Entry – Nearest Node (1 Year Lag)*

	Non-Entry	Entry					
		All Tech.	CT	CCGT	Wind	Solar	Other
Mean	28.99	26.07	27.05	24.32	25.69	26.01	26.90
Std. Dev.	7.28	5.05	4.99	2.21	5.29	4.79	5.66
Difference		2.92***	1.94	4.67***	3.30***	2.98***	2.09*
in Means		(0.48)	(1.78)	(0.73)	(0.77)	(0.76)	(1.17)

Notes. Difference in means performs a t-test on the equality of means with unequal variances. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

Table A3. *Average LMPs at Nodes with and without Recent Entry – Nearest Node (2 Year Lag)*

	Non-Entry	Entry					
		All Tech.	CT	CCGT	Wind	Solar	Other
Mean	29.05	26.78	26.63	24.38	26.77	26.05	28.31
Std. Dev.	7.29	5.93	4.05	2.96	6.39	5.09	6.91
Difference		2.26***	2.42*	4.67***	2.27***	3.00***	0.73
in Means		(0.46)	(1.14)	(0.71)	(0.74)	(0.68)	(1.06)

Notes. Difference in means performs a t-test on the equality of means with unequal variances. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

***Table A4**. Nodal Entry Logit Regression by Technology – Dist. 10 Miles*

	(1) All	(2) All	(3) CT	(4) CT	(5) CCGT	(6) CCGT	(7) Solar	(8) Solar	(9) Wind	(10) Wind
$\overline{LMP}$	0.0864		0.123*		0.0272		0.0897		-0.0325	
	(0.0651)		(0.064)		(0.309)		(0.0841)		(0.151)	
σ^2_{LMP}	-0.0010	-0.0018	0.00026	-0.038*	0.00479	-0.00681	-0.0018	-0.010	0.00323*	0.0066
	(0.0009)	(0.0028)	(0.0049)	(0.0149)	(0.00522)	(0.0048)	(0.00124)	(0.0083)	(0.0019)	(0.0045)
$\overline{LMP}_{TOD1}$		-0.170		-0.692		-1.062		-0.572		0.0973
		(0.271)		(1.444)		(1.085)		(0.494)		(0.343)
$\overline{LMP}_{TOD2}$		0.307		1.416**		1.917		0.617		-0.0471
		(0.189)		(0.691)		(1.781)		(0.411)		(0.511)
$\overline{LMP}_{TOD3}$		-0.0097		0.498		-0.513		-1.181**		0.458*
		(0.122)		(0.455)		(0.765)		(0.352)		(0.158)
$\overline{LMP}_{TOD4}$		-0.0233		0.760**		0.508		0.389		-0.359*
		(0.100)		(0.222)		(0.781)		(0.276)		(0.197)
$\overline{LMP}_{TOD5}$		0.0566		-2.120		-0.970		0.609		-0.245
		(0.223)		(1.4585)		(3.029)		(0.387)		(0.266)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	57.77***	74.61***	3.12***	15.72***	5.534***	11.80***	22.82***	43.65***	146.5***	274.0***
N	888	888	180	180	158	158	480	480	465	465

Notes. Cluster-robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

__Table A5__. Nodal Entry Logit Regression by Technology – Nearest Two Nodes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All	All	CT	CT	CCGT	CCGT	Solar	Solar	Wind	Wind
$\overline{LMP}$	0.136**		0.128*		0.640		0.127		-0.0056	
	(0.0516)		(0.0692)		(0.390)		(0.0823)		(0.1000)	
σ^2_{LMP}	-0.0009	-0.0030**	-0.0004	-0.0013	-0.0068*	-0.0011	-0.0019*	-0.0065	0.00136	-0.0027*
	(0.0006)	(0.0012)	(0.0005)	(0.0021)	(0.0041)	(0.0059)	(0.0011)	(0.0047)	(0.00112)	(0.0014)
$\overline{LMP}_{TOD1}$		-0.410**		-0.103		0.0498		-0.359		-0.628**
		(0.162)		(0.375)		(0.899)		(0.283)		(0.235)
$\overline{LMP}_{TOD2}$		0.0778		-0.334		-0.0751		0.117		0.320
		(0.142)		(0.550)		(0.418)		(0.302)		(0.188)
$\overline{LMP}_{TOD3}$		-0.158		0.104		-0.499		-0.702**		0.0989
		(0.108)		(0.364)		(0.427)		(0.197)		(0.176)
$\overline{LMP}_{TOD4}$		0.0912		-0.0451		0.00651		0.398**		0.0184
		(0.0840)		(0.343)		(0.212)		(0.176)		(0.191)
$\overline{LMP}_{TOD5}$		0.468**		0.422		1.338		0.752**		0.0483
		(0.212)		(0.391)		(1.204)		(0.292)		(0.268)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	94.78***	120.0***	119.8***	67.87***	36.15***	73.29***	77.67***	78.68***	25.32***	58.37***
N	960	960	270	270	228	228	864	864	465	465

Notes. Cluster-robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

***Table A6**. Nodal Entry Logit Regression by Technology – Nearest Node, Excluding 2017 and 2018*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All	All	CT	CT	CCGT	CCGT	Solar	Solar	Wind	Wind
$\overline{LMP}$	0.201**		0.322**		3.057		0.0493		0.0627	
	(0.0903)		(0.147)		(2.956)		(0.143)		(0.147)	
σ^2_{LMP}	-0.0010	-0.0029	-0.0007	-0.0302	-0.0248	-0.0508*	0.0002	-0.0128	0.0009	-0.0009
	(0.0011)	(0.0024)	(0.0009)	(0.580)	(0.0287)	(0.0301)	(0.0014)	(0.0083)	(0.0014)	(0.0013)
$\overline{LMP}_{TOD1}$		-0.528**		-20.01		-4.084**		-0.467		-0.397
		(0.269)		(113.9)		(1.988)		(0.437)		(0.318)
$\overline{LMP}_{TOD2}$		0.0555		-0.794		1.189		0.486		0.207
		(0.217)		(32.42)		(1.143)		(0.590)		(0.188)
$\overline{LMP}_{TOD3}$		-0.179		-3.556		-1.864*		-1.554**		0.156
		(0.161)		(9.636)		(1.019)		(0.433)		(0.286)
$\overline{LMP}_{TOD4}$		0.0589		1.864		1.502		1.001**		-0.0868
		(0.130)		(42.89)		(0.941)		(0.322)		(0.239)
$\overline{LMP}_{TOD5}$		0.721**		14.74		2.147		1.279*		0.126
		(0.292)		(30.56)		(2.966)		(0.680)		(0.398)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	28.11***	41.38***	29.60***	38.36**	4.822**	48.13***	15.12***	53.78***	14.58**	12.41**
N	592	592	162	162	176	176	556	556	372	372

Notes. Cluster-robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

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