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Abstract

The rapid expansion of intermittent renewable generation has created a sharp increase in net load in the late afternoon and early evening, a gap that thermal power plants have historically filled. This paper asks whether the rapid growth of battery storage in the Electric Reliability Council of Texas (ERCOT), from under 500 MW in 2020 to over 15 GW by 2025, has weakened thermal generators' competitive position during this evening ramp. Using ERCOT's public and proprietary microdata from 2014 to 2025, I provide two pieces of evidence. First, system-wide, the evening price response to daily solar generation fell from \$9.88/MWh per GWh in 2017–2019 to near zero and even negative by 2023–2025, alongside a matching decline in thermal output during the ramp and its replacement by battery discharging. Second, because ERCOT is fragmented by transmission constraints, suggested by an average of 20 to 35 generation sources setting the price simultaneously during evening peaks, a battery's entry can reshape competition locally. Using 155 battery entries and 563 thermal generators whose local markets I identify from nodal price co-movement and spatial proximity, I find that thermal generators lower their offered prices by 1.2 to 1.5 percentage points of the system-wide offer cap at the 65th through 85th percentiles of their capacity, an amount comparable to their own pre-entry offer level. The reduction is concentrated at the top of the offer curve among gas steam, small simple-cycle, and diesel units, reaching 5.7 percentage points of the cap at the 85th percentile. This system-wide and resource-level evidence is consistent with battery expansion narrowing the market power thermal generators previously exercised during the evening ramp.

JEL Codes: L11, L94, Q41, Q42

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1 Introduction

The rapid expansion of intermittent renewable generation changes the diurnal and seasonal profiles of net load that dispatchable generators must meet. As solar output falls in the late afternoon and wind has yet to fully ramp up, net load rises sharply in the evening hours, typically between 5 and 8 PM. Without sufficient storage, this steep evening ramp is predominantly met by thermal power generation plants, especially simple-cycled natural gas power plants (Bushnell and Novan, 2021), which tend to be less efficient (i.e., higher heat rate) and more emission-intensive than combined-cycle gas turbines. In the presence of market power, this ramp also pushes up evening rents: units displaced during the day by cheap solar must incur start-up costs to re-enter the evening market, weakening competitive pressure and allowing low-start-up-cost units to earn substantial rents (Jha and Leslie, 2025).

Battery storage is expected to reduce reliance on thermal power plants during the evening ramp and thereby alleviate the high system costs, emissions, and rents. By absorbing cheap midday energy and releasing it during the evening ramp, batteries reduce the net demand that thermal generation units would otherwise supply. How these effects actually materialize after 2020 during rapid, large-scale battery expansion is an open empirical question.

This paper studies this question by investigating the competition between batteries and thermal power plants in the electricity system under the management of the Electric Reliability Council of Texas (ERCOT), where battery capacity grew from under 500 MW in 2020 to over 15 GW by 2025. This draft of preliminary results answers the two questions: (1) How has the intra-day price and output effect of solar generation evolved as batteries have grown? (2) Has battery storage changed the pricing behaviors of thermal plants? The future work of this paper will look at markup instead of offered price for question (2) by approximating the marginal costs of thermal plants and move on to a third question: whether firms that own both thermal generation and battery storage dispatch their batteries less aggressively to preserve their generators' evening rents. This matters for whether batteries are efficiently used to displace thermal plants' generation.

To answer these questions, I assembled a wide variety of data on the ERCOT system, including the renewable generation and load, detailed microdata on the output and pricing behaviors of each generation resource unit level in ERCOT, and the local marginal price at the nodal level. These datasets are accessed from the ERCOT open data portal or API. They are complemented by EIA860 data and proprietary data from ENVERUS on resource characteristics, such as locations and nameplate capacity.

I first study how the effect of daily solar generation on the intra-day electricity price profile and the intra-day output profile of other types of generation changes by separately looking at period 2014-2016, 2017-2019, 2020-2022, and 2023-2025. The results show that high solar generation of the day causes an evening price spike during the first three periods, most notable in 2017-2019, which is consistent with what Bushnell and Novan (2021) found with California's 2012 to 2016 day. However, this effect disappears and even becomes negative in the period 2023-2025. This alone of course does not suggest that battery expansion enables ERCOT to avoid dispatching expensive generation resources at evening ramping hours because other pricing control policies have been implemented, especially after the outage and price spike caused by Winter Storm Uri (February 2021). However, this result is accompanied by another piece of evidence: the output of small simple-cycled natural gas generators, gas steam generators, and diesel generators have an output spike during evening ramping hours in the first three periods. Especially, in the period 2020 to 2022, they show a dip during daytime and an increase during evening ramping. However, this pattern disappears in 2023-2025. A day of higher solar generation now either reduces the output or has a null effect over the day. The evening ramping output spike is taken over by battery.

Second, I study at the generation resource level how battery entry affects the pricing behaviour of thermal units. I identify the thermal units whose competitive environment a given battery entry plausibly changes, using nodal price co-movement and spatial proximity to define a local market around each entering battery. Where a battery creates an entirely new pricing node, and so has no price history of its own, I locate a price twin for that node and define the local market around the twin; this case turns out to be the majority of battery entries. I then estimate the effect of exposure with a staggered difference-in-differences estimator that compares exposed units to units not yet exposed, on outcomes measured as the offered price at the 65th, 75th and 85th percentiles of a unit's capacity, expressed as a share of the system-wide offer cap. Offered prices fall significantly at all three percentiles, and the reduction is largest at the top of the offer curve among the gas steam, small simple-cycle, and diesel units that previously served the evening ramp.

This paper speaks to three streams of literature. A first stream studies the economics of grid-scale battery storage directly. Butters et al. (2025) model battery entry and dispatch decisions and predict that a large fleet would lower evening peak prices and let conventional units ramp more gradually, using parameters estimated from 2015–2019 data, before the sharp acceleration in deployment since 2020. Karaduman (2023) and Kirkpatrick (2025) take related structural and reduced-form approaches to storage entry and its price effects. Closest to this paper's setting, Allcott et al. (2026) study battery bidding behavior in ERCOT and argue that bidding changes within the existing fleet are unlikely to meaningfully affect thermal generators' ramping or the generation mix. This paper takes the complementary side of that question: rather than characterizing batteries' own bidding, I ask how thermal generators competing with batteries for the same evening load adjust their offer curves once a battery enters their local market, providing reduced-form evidence on a competitive channel this literature has so far only modeled structurally.

This paper is closely related to the literature on market power in wholesale electricity markets, particularly how local transmission constraints and asset ownership shape its exercise. Hortaçsu and Puller (2008) and Hortaçsu et al. (2019) establish, in this same ERCOT market, that strategic bidding is both economically meaningful and sensitive to bidder sophistication. Woerman (2023) shows that transmission congestion shrinking a resource's local market raises markups, and provides the local-market definition and nameplate-percentile markup measures this paper's design in Section 4 builds on directly. Ownership structure compounds these incentives, as in Andrés-Cerezo and Fabra (2023b)'s model of vertical integration between storage and generation, Mercadal (2022)'s evidence on financial players' arbitrage, and Fabra and Llobet (2023)'s study of diversified fossil-renewable portfolios. This paper contributes by using battery entry events as a novel source of local-market-power variation, and by setting up the mixed-asset-ownership question these models raise as a direct extension of this design, described as future work above in Section 1.

The paper builds on the studies of the effect of intermittent renewable generation on the conventional fleet that must accommodate it. Bushnell and Novan (2021) document, using California data from 2012–2016, that high daily solar output raises evening electricity prices, a pattern this paper replicates and extends for ERCOT through 2025. Jha and Leslie (2025) show that the evening net-load ramp created by solar's afternoon decline confers market power on quick-start, low-efficiency thermal units, which must incur start-up costs to re-enter the evening market and so earn substantial rents. Andrés-Cerezo and Fabra (2023a) and Neetzow et al. (2018) study related conditions under which storage complements or substitutes for renewables and transmission investment. This paper connects to this literature directly: since batteries and thermal units can both serve the evening ramp, battery expansion is a natural candidate that changes how the thermal fleet competes in an electricity market of increasing intermittent renewable generation.

2 Background and Data

2.1 ERCOT Electricity Market

ERCOT is the independent system operator for roughly 90% of Texas's electric load. Because it is not synchronously interconnected with the Eastern or Western Interconnections, wholesale transactions within ERCOT largely fall outside the jurisdiction of the Federal Energy

Regulatory Commission, and ERCOT has developed its own market design distinct from other U.S. ISOs. Real-time dispatch and pricing are determined by Security-Constrained Economic Dispatch (SCED), which clears every five minutes and financially settles every 15 minutes using each resource's own submitted stepwise offer curve for each 15-min interval, together with transmission and reliability constraints, to set both dispatch instructions and nodal settlement point prices; these offer curves and dispatch instructions are the resource-level microdata this paper's local-market and treated-unit analyses build on directly. ERCOT also divides system load across eight weather zones, which this paper uses both as a load control and as the level at which several fixed effects are defined.

2.2 Battery Expansion in ERCOT

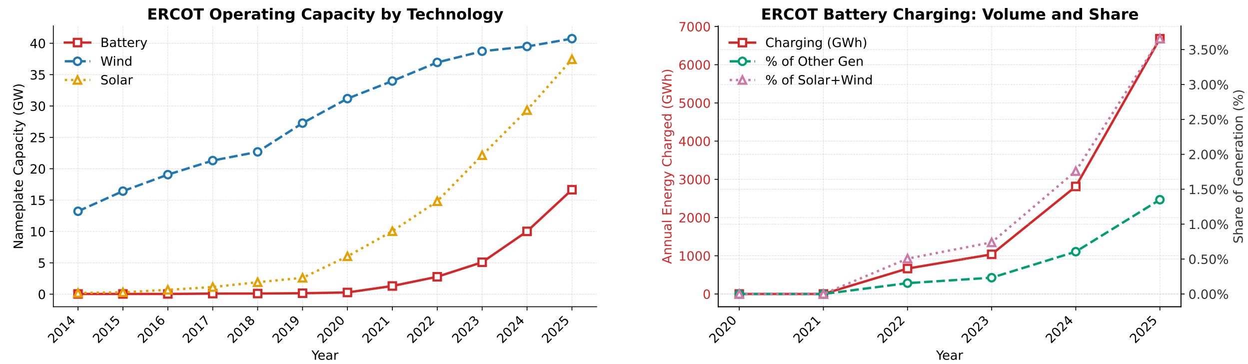
Figure 1 documents the rapid growth of battery storage in ERCOT over the sample period. Panel (a) shows that installed battery capacity was negligible relative to wind and solar through the late 2010s, began accelerating around 2020, and grew from under 500 MW to over 15 GW by 2025, a period over which wind and solar capacity also expanded but far less sharply in relative terms. Panel (b) shows that this capacity growth translated into a rising volume of battery charging and a rising share of total system generation as well as the share of total renewable generation over the years. This timing motivates the paper's four-period split: battery capacity was too small to plausibly affect system-wide dispatch before 2020, making 2014–2019 a useful pre-expansion baseline against which the 2020–2025 periods can be compared.

2.3 Data

This study assembles and matches a variety of ERCOT system data spanning 2014 to 2025. **System-level price, load, and renewable generation.** System-wide outcomes and controls come from three ERCOT public reports: the real-time 15-minute settlement point price averaged across trading hubs from the Real-Time Market price reports; daily solar and wind generation from the Fuel Mix Report; and system-wide hourly load from the Native Load report. These are merged into the 15-minute interval panel used throughout Section 3.

Resource-level output and pricing behaviors. Resource-level microdata come from ERCOT's 60-Day SCED Disclosure Gen Resource Data reports, which record, at each 15-minute SCED interval, every resource's telemetered output (Base Point), operating status, and its own submitted stepwise offer curve. This is the source for the local-market classification in Section 2.4 and the treated-unit offer-curve outcomes in Section 4; summary statistics are reported in Appendix Table A.

Figure 1: Battery Storage Expansion in ERCOT.



(a) (b)

Notes: Panel (a) shows the yearly installed capacity of battery storage (red square) in ERCOT, compared with that of wind (blue circle) and solar (yellow triangle) from 2014 to 2025. Panel (b) shows the yearly charging volume of battery storage in GWM (red square) as well as the proportion of the charged volume over the total generation (green circle) and the generation of solar and wind (dashed, purple triangle); the proportions are on the right axis. Data are collected from Fuel Mix Report and Capacity Changes by Fuel Type Charts March 2026 published by ERCOT.

Nodal locational marginal prices (LMPs) and mapping between nodes and resources. Nodal LMPs come from ERCOT's LMPs by Resource Nodes, Load Zones and Trading Hubs report. Each resource is mapped to its own node, and thus to an LMP, through crosswalks in ERCOT's Settlement Points List and Electrical Buses Mapping. This mapping is essential for identifying which thermal generation resources are potentially affected by a given battery entry: specifically, those located at nodes whose LMPs track the battery's own node closely and that lie nearby geographically, the local-market criteria detailed in Section 4.

Weather zone load and mapping between weather zone, nodes, and resource. Zonal hourly load across ERCOT's eight weather zones comes from the Native Load report. ERCOT provides the mapping between zip codes and weather zones in its Load Profile Guide.[1] I first match each resource to its EIA-860 or Enverus record to obtain its location, including zip code, and then apply this zip-to-weather-zone crosswalk. This mapping also supplies each resource's nameplate capacity, used to define the percentile-based offer-price outcomes in Section 4, and its geographic coordinates, used for the local-market distance gate there.

Natural gas price. The daily Henry Hub natural gas spot price is merged by date (forward-filled over non-trading days) and used throughout as a control for thermal units' output and pricing outcomes, since natural gas prices move the marginal cost of gas-fired

[1]The zip-to-weather-zone crosswalk is in Appendix D of the Load Profile Guide, the Profile Decision Tree.

generation in particular.

2.4 Local Markets and Marginal Generation Sources

I argue that transmission constraints delineate the system into local markets in which generation sources face less competition. Woerman (2023) shows that when higher temperatures reduce transmission capacity and thereby shrink the effective market size, generators earn a higher markup.

To provide direct evidence that the system is indeed delineated into local markets, I visualize below the number of simultaneously marginal generation sources, how this number evolves over time, and which technologies account for it, with particular attention to evening peak hours (i.e., 5 to 9 pm local time). If the entire system were a single unified market, merit-order dispatch would imply exactly one marginal, price-setting source at any moment; if instead the system splits into multiple local markets, each can have its own marginal source and clearing price simultaneously.

At each 15-minute SCED interval, I classify every generation source with a live, price-responsive dispatch instruction as either inframarginal or marginal. I restrict attention to generation sources with telemetered resource status being "on" and a submitted offer curve, which SCED uses for optimization.[2] Within this operating, price-responsive sample, I identify each source's status using the MW breakpoints of its own stepwise offer curve and its output.[3] A source is inframarginal if its output lands exactly on a breakpoint of its own offer curve, either an interior price-tier boundary or the top of its submitted curve, meaning it is fully using every price tier priced below the clearing price and none priced above, without itself setting that price. A source is marginal if its output lands strictly between two consecutive breakpoints of its own offer curve; the only way this can happen is if the local clearing price exactly equals this resource's offered price for that MW range, i.e., this resource is the (or a) price-setting unit.

Figure 2 shows that simultaneous marginal generation sources do indeed exist, presumably each clearing its own local market. To keep the computation tractable while still informative, I sample only Wednesdays. The figure plots the monthly average number of marginal units across all sampled 15-minute SCED intervals during Wednesday evening peaks, from March 2014 through November 2025. Panel 2a shows the total number of simultaneously

[2] This excludes resources operating under other instructions not governed by their own offer curve: self-scheduled or no-bid resources, and resources reported as providing regulation or responsive reserve, RUC-committed, starting up, shutting down, on outage, or in emergency or test status. Specifically excluded status codes: `OFF`, `OUT`, `EMR`, `OFFNS`, `STARTUP`, `SHUTDOWN`, `ONOS`, `ONREG`, `ONRR`, `ONRUC`, `ONEMR`, `ONTEST`.

[3] "Output" refers to the Base Point column in the Generation Resource files of the 60-Day SCED Disclosure reports; that is the resource's MW output level produced by the SCED optimization.

marginal units, summed across thermal plants and battery storage and averaged over the sampled evening-peak intervals in each month; this total has been on an increasing trend since 2023. The annual average has ranged from 20 to 35, implying that the ERCOT system is commonly divided into two to three dozen simultaneous local markets. Panel 2b shows the average number of marginal units for each resource type separately. Marginal sources are not restricted to small gas or diesel units, as large combined-cycle plants appear as well. In addition, batteries have clearly become a notable and growing type of marginal source.

3 System-wide Analysis

In order to study how the expansion of battery storage changes the role of thermal plants in filling the net-load gap after sunset, I carry out an exercise similar to Bushnell and Novan (2021), who study hourly output and prices in California for 2012–2016. I instead use 15-minute intervals and study an electricity system and time period that have experienced significant battery storage expansion.

$$Y_{k,d} = \alpha_{k,m(d)} + \beta_k^s \text{Solar}_d + \beta_k^w \text{Wind}_d + \beta_k^g \text{GasSpot}_d + \theta_k X_{h(k),d} + \varepsilon_{k,d} \tag{1}$$

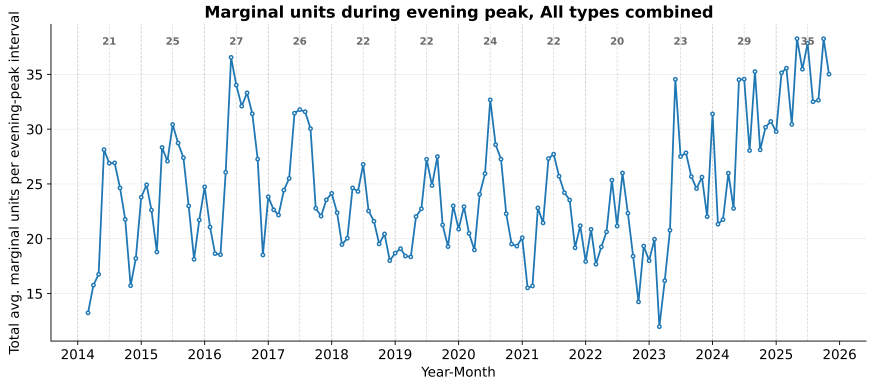
Specifically, I estimate Equation 1 separately for each 15-minute interval of the day, over four time periods: 2014–2016, 2017–2019, 2020–2022, and 2023–2025. Here k denotes the 15-minute interval of the day, taking 96 values; d denotes the date; $m(d)$ is the month of the date; and $h(k)$ is the hour containing interval k.

$Y_{k,d}$ is the outcome variable: either the real-time settlement point price (averaged across hubs) or the output of a given resource type, on date d during interval k. Solar_d and Wind_d denote daily solar and wind generations in GWh, respectively. To control for other factors that could otherwise make output decisions endogenous, I include the Henry Hub natural gas spot price (GasSpot_d) and system-wide hourly load ($X_{h(k),d}$). Standard errors are estimated using the Newey-West HAC estimator with a 7-day lag.

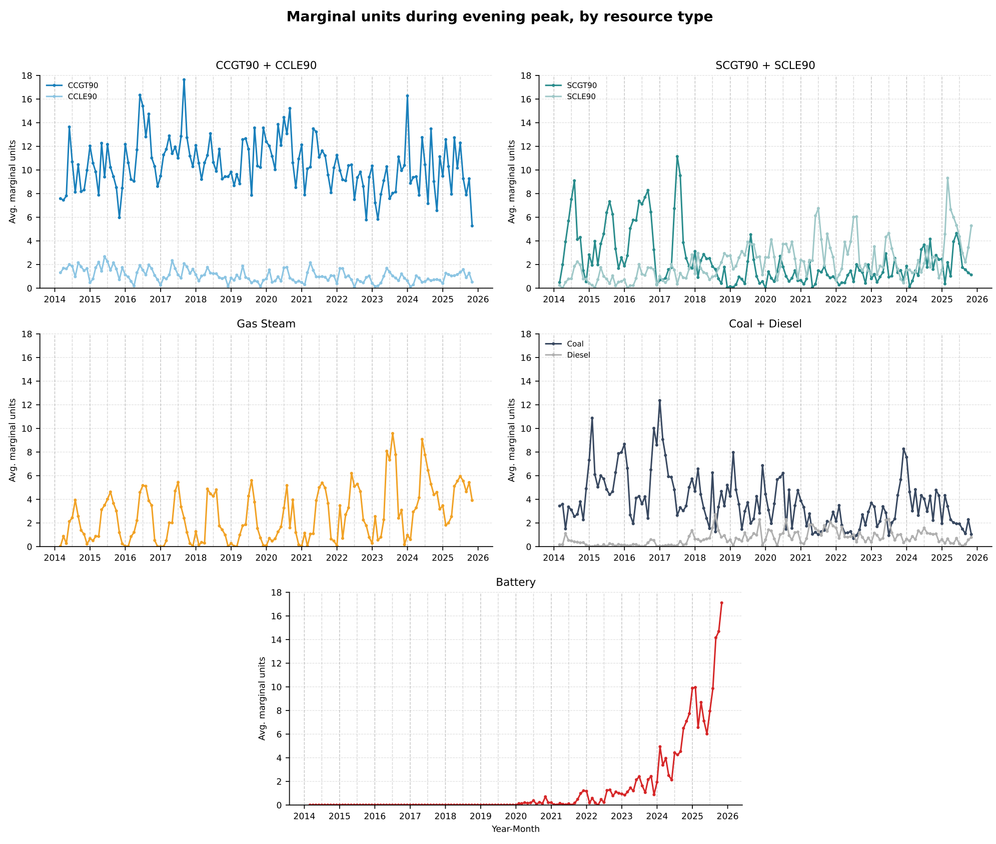
The coefficient of interest is β_k^s, which captures how the outcome changes with daily solar electricity generation, which can largely be regarded as exogenous, since it is primarily determined by weather. One caveat is that solar curtailment could be an endogenous decision; as a next step, I will instrument for solar electricity generation using solar radiation and re-estimate the specification.

Figure 2: Local Markets: Number of Simultaneously Existing Marginal Generation Sources

(a)



(b)



Notes: This figure shows the number of simultaneously marginal generation sources during ERCOT evening peak hours (17:00–21:00), based on the 60-Day SCED Disclosure Gen Resource Data reports. At each 15-minute SCED interval, a source is classified as marginal if its output (Base Point) lands strictly between two consecutive breakpoints of its own submitted stepwise offer curve. The sample is restricted to generation sources with telemetered status "on" and a submitted offer curve used in SCED optimization. To keep the computation tractable, only Wednesdays are sampled; the sample spans March 2014 through November 2025 (December 2025 is excluded because the disclosure reporting structure changed shortly after 2025-12-10). Each monthly point is the average across all sampled Wednesday evening-peak 15-minute intervals in that month. Panel 2a plots the total number of simultaneously marginal sources, summed across all resource types (thermal and battery combined) before averaging across intervals. Panel 2b plots the average number of marginal sources separately by resource type: CCGT90, CCLE90, SCGT90, and SCLE90 are combined-cycle and simple-cycle gas turbines (denoted by nameplate capacity above or below 90 MW); Gas Steam reheat, non-reheat, and supercritical boiler (GSREH, GSNONR, GSSUP); Coal corresponds to CLLIG; and Battery corresponds to grid-scale power storage resources (PWRSTR). Vertical gridlines mark January (year boundary) and July of each year. In Panel 2a, the dark gray number above each year's July gridline reports that year's mean of the plotted series, rounded to the nearest integer.

3.1 Suppressed Evening Peak-time Price Spikes After Battery Expansion

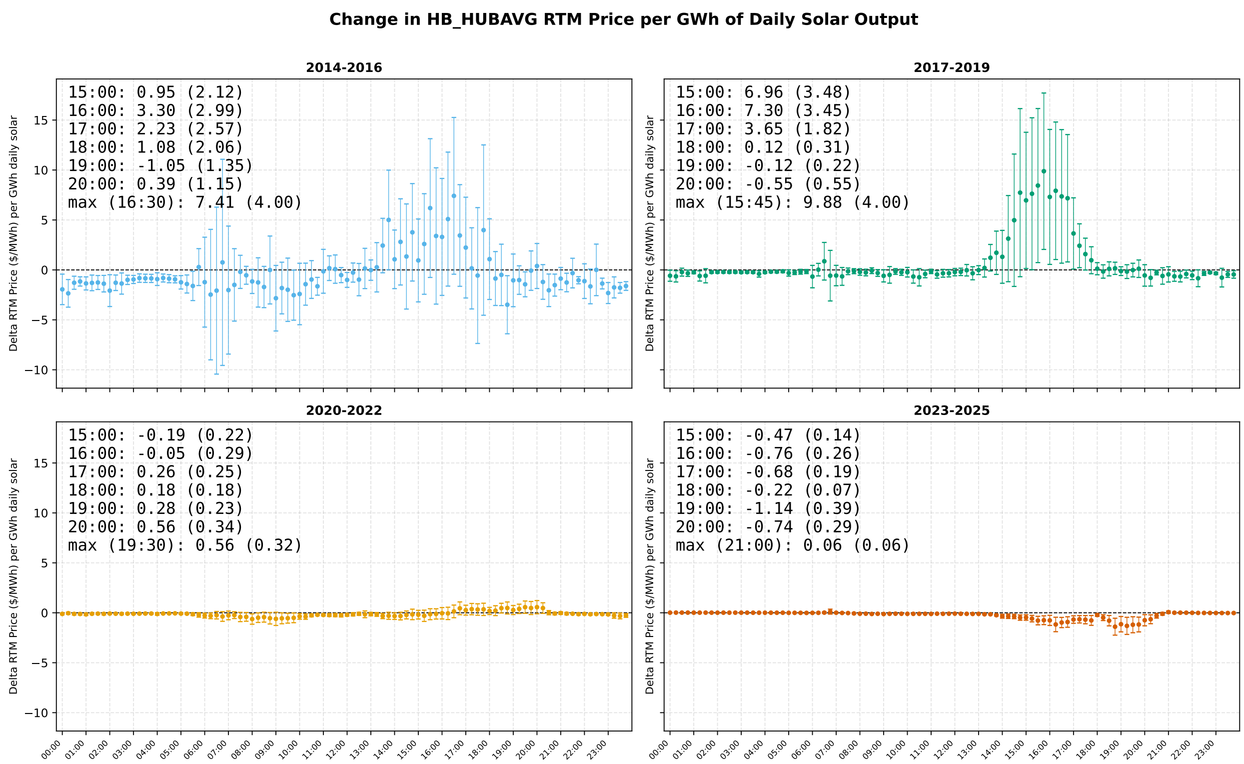
Figure 3 displays the set of 96 coefficients for each of the four periods. In 2014–2016, higher daily solar generation is already associated with modestly higher evening peak prices: the highest coefficient between 15:00 and 21:00 is \$7.41/MWh, at the interval starting at 16:30. This relationship strengthens markedly in 2017–2019, the period with the largest coefficients of the four: the highest coefficient over the same window rises to \$9.88/MWh, at the interval starting at 15:45, meaning that one additional GWh of daily solar generation raises the electricity price by \$9.88/MWh at that time of day. This peak occurs earlier than the typical sunset, possibly because solar generation was not yet abundant during this period, so thermal plants needed to begin increasing output earlier in the afternoon. In 2020–2022, the same evening price spike is still present but visibly attenuated relative to the prior period: the highest coefficient over the same window falls to \$0.56/MWh. Then, starting in 2023, the solar-induced spike in evening peak prices is largely suppressed across the day and even turns negative during some evening intervals: the highest coefficient over the window is just \$0.06/MWh, at 21:00, and on days with more solar generation, evening prices earlier in the window are, if anything, slightly lower rather than higher.

This alone does not establish that battery expansion enables ERCOT to avoid dispatching expensive generation resources at evening ramping hours, since other pricing-control policies have also been implemented, especially after the outage and price spike caused by Winter Storm Uri (February 2021). But the timing lines up with the pattern documented in Section 3.2 below: the same four periods over which the evening price spike strengthens, then attenuates, then disappears are exactly the periods over which quick-start thermal generators show a corresponding output ramp that itself strengthens, attenuates, and disappears, before being replaced by a battery output ramp in 2023–2025.

3.2 Battery's Output Evening Peak Replacing Thermal Generators'

Figure 4 plots the same coefficient, β_k^s, for four generation types: SCLE90, Gas Steam, Diesel, and Battery. In 2014–2016 and 2017–2019, the three thermal types share a common daily shape: output is flat or mildly suppressed during midday hours of high solar generation, then rises sharply during the evening ramp, mirroring the price spike documented in Figure 3 over the same two periods. In 2020–2022, this pattern sharpens into a clearer dip-and-ramp shape: a pronounced daytime dip coincides with a still-larger evening increase, consistent with these units being pushed further out of the midday merit order as solar penetration

Figure 3: **Effect of Daily Solar Generation on Intra-day Price Profile**

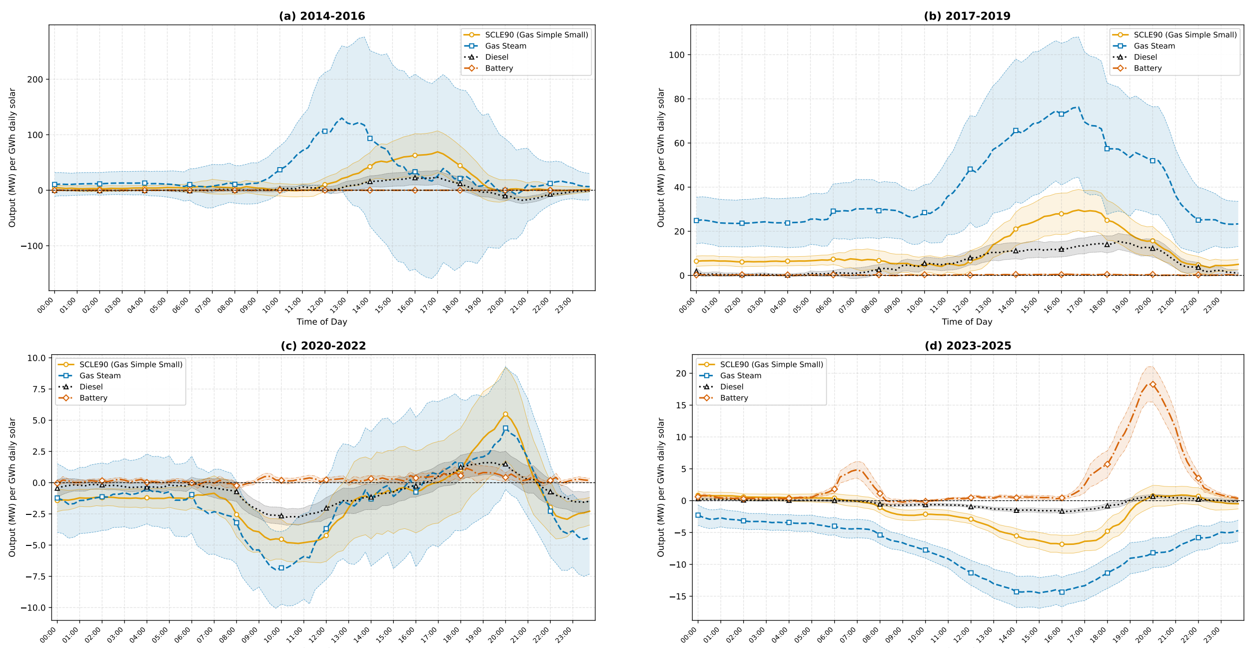


Notes: Each point plots the estimated coefficient β_k^s from Equation 1 for one of the 96 15-minute intervals of the day (k), with a vertical bar showing its 95% confidence interval, where $Y_{k,d}$ is the real-time settlement point price averaged across hubs on date d during interval k. Regressions are estimated separately over four sample periods (2014–2016, 2017–2019, 2020–2022, 2023–2025). β_k^s measures the change in the interval-k price associated with a one-GWh increase in daily solar generation, holding fixed daily wind generation, the Henry Hub natural gas spot price, system-wide hourly loads, and interval-by-month fixed effects. Standard errors are Newey-West HAC with a 7-day lag. Days from February 10–25, 2021 (Winter Storm Uri, during which ERCOT prices repeatedly hit the $9,000/MWh price cap) are excluded from the 2020-2022 period's regressions. Each panel additionally reports, in its upper-left corner, the point estimate and standard error (in parentheses) for the interval starting at 15:00, 16:00, 17:00, 18:00, 19:00, and 20:00, followed by the maximum coefficient over the 15:00–21:00 window together with its standard error and the specific 15-minute interval at which it occurs.

grows, only to be recalled more forcefully once the sun sets. Then, in 2023–2025, the pattern for all three thermal types disappears entirely, and for some hours turns mildly negative: a day rich in solar generation no longer predicts higher thermal output at any hour, day or evening.

Equation 1 is estimated separately for every resource type in the fleet, including combined-cycle plants and large simple-cycle turbines (SCGT90); Figure 4 plots only four types to keep the panel legible. Large simple-cycle output (SCGT90, not plotted) follows a pattern similar to the plotted small simple-cycle type (SCLE90), consistent with the same mechanism operating across simple-cycle technology regardless of size.

Figure 4: **Effect of Daily Solar Generation on Intra-day Output Profile of Other Generation Types**



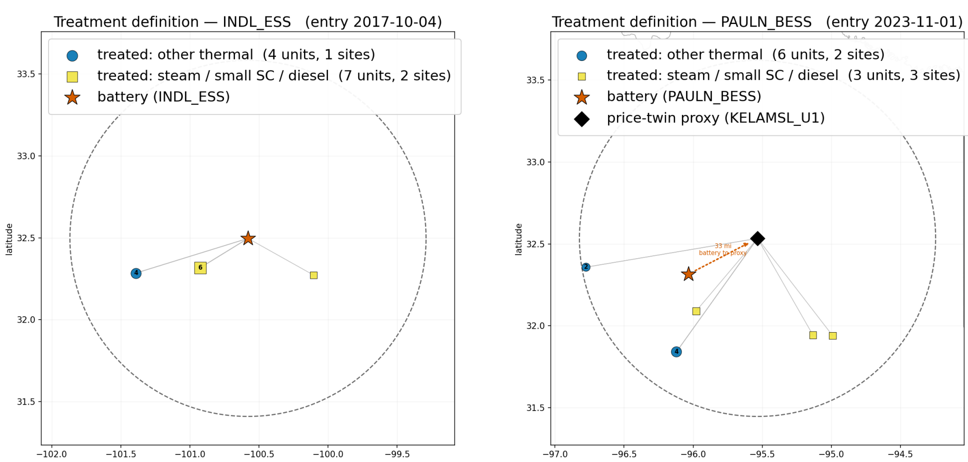
Notes: Each panel plots, for one of four sample periods (panel (a): 2014–2016; (b): 2017–2019; (c): 2020–2022; (d): 2023–2025), the estimated coefficient β_k^s from Equation 1 across all 96 15-minute intervals of the day (k), with a shaded band showing its 95% confidence interval, where $Y_{k,d}$ is the fleet output (MW) of a given generation type on date d during interval k. Four generation types are shown in each panel: SCLE90 (Simple Cycle no larger than 90MW), Gas Steam (gas steam reheat, non-reheat, and supercritical boiler), Diesel, and Battery. β_k^s measures the change in interval-k output associated with a one-GWh increase in daily solar generation, holding fixed daily wind generation, the Henry Hub natural gas spot price, system-wide hourly loads, and interval-by-month fixed effects. Standard errors are Newey-West HAC with a 7-day lag. Days from February 10–25, 2021 (Winter Storm Uri, during which ERCOT prices repeatedly hit the $9,000/MWh price cap) are excluded from panel (c)'s regressions. Note that each panel uses its own vertical scale, as coefficient magnitudes differ by an order of magnitude or more across periods.

The range of the y-axis differs by an order of magnitude or more across the four panels of Figure 4, mirroring the same decline in coefficient magnitude visible in Figure 3: the thermal output response to solar generation was largest exactly when the price response was largest, and both attenuate together through 2020–2022 before disappearing in 2023–2025. This corroborates that the early-period price spikes were driven by the physical necessity of dispatching more from these thermal resources at sunset.

The disappearance of the thermal ramp coincides with its replacement by battery, whose own coefficient becomes positive and, for some hours, of comparable magnitude, in the very panel (2023–2025) where the thermal types go flat. This is consistent with the local-market evidence in Figure 2, which documents batteries becoming an increasingly common marginal, price-setting resource over this same period. The overall evidence suggests that on days rich in solar generation, batteries now charge more at midday and discharge more in the evening, directly substituting for the quick-start thermal capacity that used to serve the ramp and thereby lowering the system cost at that hour.

4 Effect of Battery Entry on Thermal Power Generators' Offer Curves

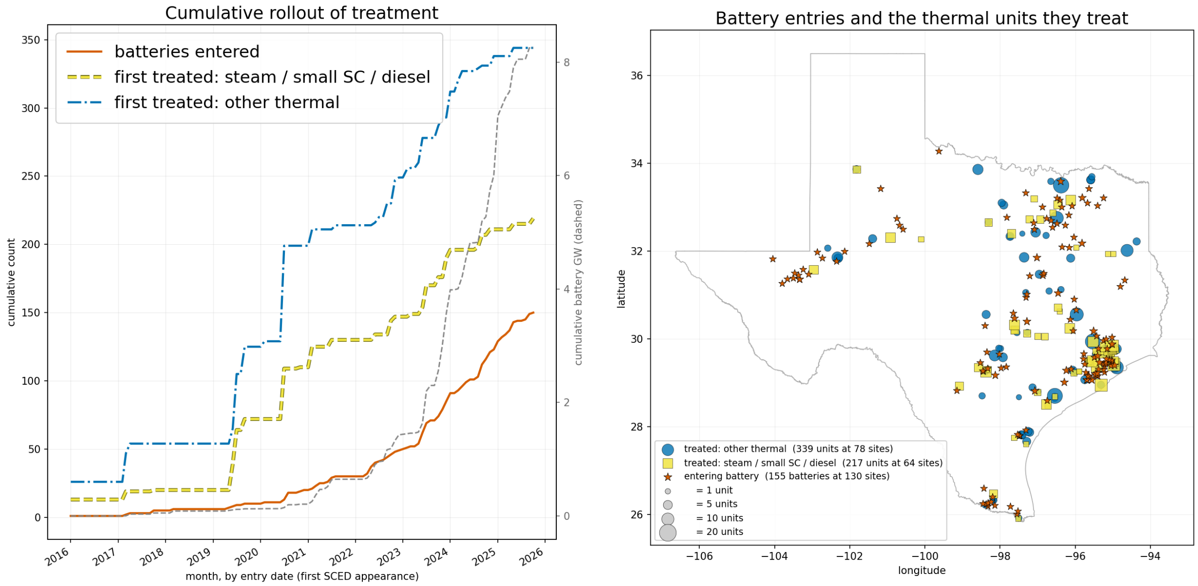
Figure 5: Defining Exposure to Battery Entry



(a) Entering Pre-existing Pricing Node (b) Creating New Pricing Node

Notes: Two illustrative battery entries. In panel (a) the battery enters a pre-existing pricing node, so its own pre-entry price history defines the local market and the 75-mile distance gate (dashed circle) is drawn around the battery itself. In panel (b) the battery creates a new pricing node with no price history; the local market is defined around its price twin (black diamond), and the gate is drawn around the twin rather than the battery. The battery-to-twin distance is reported on the panel but is not itself gated: the gate applies to the distance from the market centre to each thermal unit. Grey lines link the market centre to each treated unit. Marker area, and the number printed inside each marker, give the number of units at that coordinate, because multi-unit plants share one resource node and therefore one point on the map, so one dot per unit would understate the sample. Points are resource-node coordinates, 88 percent of which are generator or plant locations from EIA-860 and Enverus, the remainder electrical bus locations.

Figure 6: Rollout and Spatial Distribution of the Treated Sample



(a) Number of Treated Thermal Generating Units

(b) Spatial Distribution

Notes: Panel (a) shows the cumulative number of battery entries and of thermal units first exposed to one, by month of the battery's first appearance in the SCED record. A thermal unit is counted once, in the month it is first treated by any battery, matching the binary treatment definition. The dashed line gives cumulative battery capacity entered on the right axis. Panel (b) maps every entering battery and every treated thermal unit. Marker area is the number of units at that coordinate, since multi-unit plants share one resource node: 556 treated units occupy 135 distinct coordinates and the largest single site carries 23 units. A unit is treated by a battery if it lies in that battery's local market, defined by price co-movement within \$1/MWh or 1% for at least 90 percent of common hours and a distance within 75 miles of the market centre. Thermal units sharing the battery's own resource node are excluded.

A thermal resource enters this analysis as "treated" if it shares a local market with a battery that interconnects nearby, so that its own competitive environment plausibly changes on the date the battery enters. I identify local markets in the spirit of Woerman (2023) and the local-market evidence in Section 2.4, applying the definition differently to the two ways a battery can interconnect.

For a battery that enters a *pre-existing* pricing node, I compute, over the 365 days before the battery's first appearance in the SCED record, which other nodes track its price closely, within \$1/MWh or 1%, whichever is greater, for at least 90% of the common hours in that window, and lie within 75 miles of it. Every thermal resource at a node satisfying both conditions is treated, with its treatment date set to the battery's first SCED appearance. I require a node to have at least 365 days of price history before entry, so that every treated unit has a usable pre-period. This type of entry almost always means the battery is co-located with another generation source; when that source is itself thermal, I exclude it from the treated group, because a single operator co-optimising the battery and the thermal unit is a different phenomenon from the competitive one this design is meant to capture.

The second case is a battery whose entry *creates* a new pricing node. This does not necessarily require a new substation, but it does create a new electrical bus, and the new node has no price history from which to construct a local market. For these entries I instead use the 365 days *after* entry to find the node whose price most closely tracks the new battery node under the same criteria, its price twin, and then define the local market around that twin using prices from the 365 days *before* the battery entered. This case is the majority of the sample: of the 341 battery resources I classify, 257 create a new node against 52 that enter a pre-existing one, so a design restricted to pre-existing nodes would discard most battery entries. Figure 5 illustrates the two constructions with one entry of each type.

Treatment is a binary indicator equal to one from a unit's first exposure onward. The outcomes are the prices a unit offers at the 65th, 75th and 85th percentiles of its capacity, read off its submitted offer curve. Because ERCOT's system-wide offer cap changed repeatedly over the sample, I express each offered price as a share of the cap in force on that day.[4] All outcomes are then averaged to the monthly level for each resource unit.

I estimate the effect with the staggered difference-in-differences estimator of Callaway and Sant'Anna (2021). For a cohort g of units first exposed in month g and a month t, the group-time average treatment effect is

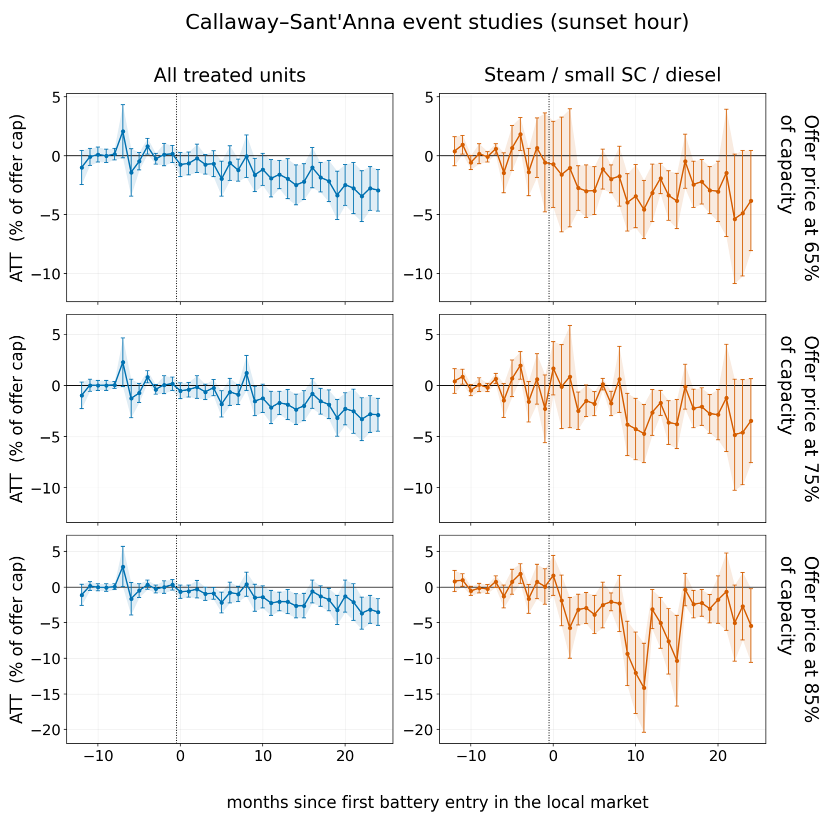
$$ATT(g,t) = \mathbb{E}\left[Y_t - Y_{g-1} \mid G = g\right] - \mathbb{E}\left[Y_t - Y_{g-1} \mid G > t\right] \tag{2}$$

so that unit fixed effects and any shock common to the treated and comparison groups between $g-1$ and t difference out. The comparison group is the set of units *not yet exposed* at t; I do not use never-exposed units, because the location of the battery entry is unlikely to be independent of its local conditions and thus the never-exposed units might evolve quite differently from the treated units in terms of their pricing behavior regardless of battery entry. I estimate $ATT(g,t)$ and report the aggregation that weights cohort-period cells by their share of treated observations as the headline, with the event-time, cohort and calendar-time aggregations reported alongside as robustness. Cohorts are restricted to 2016–2023: by 2024 almost every unit in the sample is already exposed, leaving too few not-yet-exposed units to support a comparison. Unit capacity enters as a time-invariant baseline control variable.

[4]The cap was \$5,000/MWh at the start of the SCED disclosure sample, \$7,000 from 2014-06-01, and \$9,000 from 2015-06-01. Following Winter Storm Uri the Peaker Net Margin threshold was crossed and the cap fell to the low cap of \$2,000 on 2021-03-04, before the PUCT set it at \$5,000 effective 2022-01-01. Two of these changes fall inside the event windows of the 2021–2023 cohorts, so an offered price in dollars would jump mechanically when the cap moved. The ratio is formed at the hourly level before any aggregation.

Because gas steam units (reheat, non-reheat and supercritical), simple-cycle units no larger than 90 MW, and diesel units are the technologies that displayed the clearest duck-curve response to solar output before the battery expansion (Figure 4), I report every specification both for all treated units and for this subsample. Results for the sunset hour are in Figure 7 and Table 1.

Figure 7: Effect of Battery Entry on Offered Prices, Sunset Hour



Notes: Event-study estimates from Callaway and Sant'Anna (2021), computed on the calendar date's own sunset hour. Rows are the capacity percentile at which the offered price is read; columns are all treated units (left) and the gas steam, simple-cycle under 90 MW and diesel subsample (right). The outcome is the offered price as a percentage of the system-wide offer cap in force. The control group is units not yet exposed at that month, cohorts are restricted to 2016–2023, and unit capacity enters as a time-invariant covariate. Event month -1 is the reference and is zero by construction. Bars and shaded bands are 95 percent *pointwise* confidence intervals.

The design rests on 155 battery entries and 563 thermal units, which after the cohort restriction and the requirement that a unit's offer curve actually reach the relevant capacity percentile leaves between 323 and 339 units, 25 cohorts and roughly 24,000 to 25,000 resource-months in the all-unit columns, and 137 units and 16 cohorts in the technology subsample. Figure 6 shows how this sample accumulates over time and where it sits geographically: entries are concentrated in the second half of the sample period, and treated units are

Table 1: Effect of Battery Entry on Offered Prices, Sunset Hour

	65% of capacity		75% of capacity		85% of capacity	
	All	Steam/Small SC/DSL	All	Steam/Small SC/DSL	All	Steam/Small SC/DSL
	(1)	(2)	(3)	(4)	(5)	(6)
ATT (simple)	-1.340^{***}	-1.554^{***}	-1.216^{***}	-1.166^{**}	-1.487^{***}	-5.685^{***}
	(0.476)	(0.553)	(0.400)	(0.570)	(0.500)	(0.662)
ATT (dynamic avg.)	-1.045^{***}	-0.940^{**}	-0.988^{***}	-0.766^{*}	-1.306^{***}	-6.113^{***}
	(0.342)	(0.428)	(0.304)	(0.456)	(0.401)	(0.584)
ATT (cohort avg.)	-1.245^{**}	-2.348	-1.133^{**}	0.004	-1.472^{***}	-8.229^{***}
	(0.508)	(2.119)	(0.446)	(1.988)	(0.547)	(1.871)
ATT (calendar avg.)	-1.116^{***}	-0.776^{***}	-1.030^{***}	-0.538^{*}	-1.242^{***}	-2.761^{***}
	(0.354)	(0.278)	(0.300)	(0.292)	(0.360)	(0.299)
Pre-period mean	1.633	2.454	1.913	2.553	2.304	2.717
ATT / pre-period mean (%)	−82.1	−63.3	−63.6	−45.7	−64.6	−209.3
Cohorts	25	16	25	16	25	16
Units	339	137	334	137	323	137
Observations	24,367	10,431	25,200	11,050	23,731	11,037

Notes: Callaway and Sant'Anna (2021) estimates of the effect of battery entry in a thermal unit's local market on its submitted offer price, expressed as a percentage of the system-wide offer cap in force and measured at three percentiles of the unit's capacity. Estimated on the calendar date's own sunset hour at monthly frequency, with units not yet exposed as the control group, cohorts 2016–2023, outcome regression, and unit capacity as a time-invariant covariate. The four ATT rows are alternative aggregations of the same group-time effects: simple weights cohort-period cells by their share of treated observations, dynamic averages the event-time effects, cohort averages the cohort-specific effects, and calendar averages the calendar-time effects. Analytic standard errors in parentheses. Pre-period mean is the mean of the dependent variable among eventually-treated units before entry; because the estimated effects are of the same order as this mean, the ratio of the two should not be read as a proportional change. Observations are resource-months. Cohorts, units and observations differ across columns because a unit enters a column only if its offer curve reaches that percentile of capacity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

spread across every weather zone and shows some level of concentration at load pockets of the Houston region, Dallas-Fort Worth, and San Antonio and Austin.

The effect on offered prices is negative at every capacity percentile and statistically significant at the 1% level. Among all treated units, offers fall by 1.34 percentage points of the offer cap at the 65th percentile of capacity (s.e. 0.476), 1.22 at the 75th (0.400) and 1.49 at the 85th (0.500). These are economically large relative to the level of the outcome: the pre-entry mean offered price among eventually-treated units is between 1.6 and 2.3 percent of the cap, so the estimated effects are of the same order as the baseline itself.

The technology subsample shows results of the same sign but larger magnitude for the 85th percentile, which is what the mechanism predicts. At the 65th and 75th percentiles the subsample estimates (-1.55 and -1.17) are close to the all-unit estimates, but at the 85th percentile the effect is -5.69 percentage points (s.e. 0.662), roughly four times the all-unit estimate at the same percentile and 3.7 times the subsample's own estimate at the 65th.

The response is concentrated at the *top* of the offer curve, which is the region that sets price on a tight evening and where scarcity rents are earned. Gas steam, small simple-cycle, and diesel units are precisely the technologies whose evening output spike disappears after the battery expansion in Section 3.2, and they are the ones that cut their high-end offers most when a battery arrives in their local market.

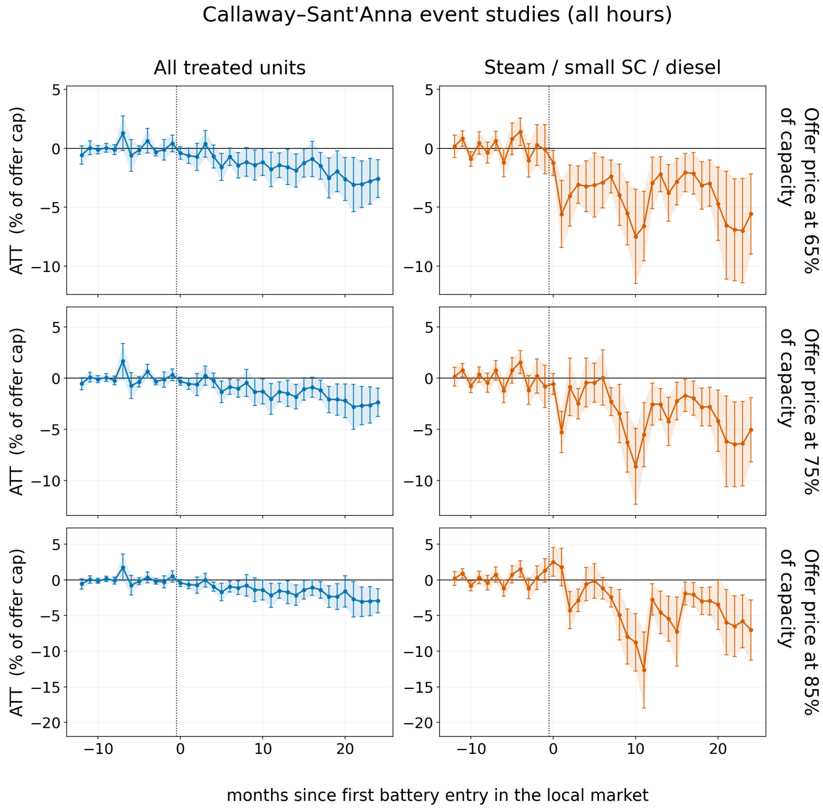
Table 1 also reports three alternative aggregations of the same group-time effects, which differ in how they weight cohorts and periods. For the all-unit columns, the estimate is stable across all four: at the 75th percentile, for instance, the simple, event-time, cohort and calendar-time aggregations give -1.22, -0.99, -1.13 and -1.03, all statistically significant at the 0.01 level. The subsample estimations are less precise because of the smaller sample size. Its cohort-weighted aggregation is imprecise, at -2.35 (s.e. 2.119) for the 65th percentile and $+0.004$ (s.e. 1.988) for the 75th . Nevertheless, the estimates at the 85th percentile are consistently negative and economically large across weighting schemes, ranging from (-8.23) (s.e. 1.871) under cohort weighting to (-2.76) (s.e. 0.299) under calendar weighting.

Figure 7 plots the event-time estimation results. The pre-treatment coefficients for all treated units are close to zero. The post-entry path drifts downward over roughly the first year and a half. The subsample panels are noisier again probably because of the smaller observation size.

Figure 8 and Table 2 repeat every specification using all hours of the day, and the two sets of estimates are close. The reason is that an offer curve, although submitted hourly, moves much less within a day than across days: the within-resource-day component accounts for only 9 to 27 percent of the variance in the offered price at the 75th percentile of capacity, and monthly averaging shrinks that share further. The offer curve does vary systematically over the day, with offers lowest in the late afternoon and a peak-to-trough diurnal profile of about \$21.9/MWh, but at monthly frequency the sunset-hour restriction does not change the estimates much compared with the all-hour sample.

Finally, I estimate the same specifications with the quantity a unit offers as the outcome, reported in Appendix Table B. These results are not conclusive and I do not draw an interpretation from them here, because they are neither internally consistent nor easy to reconcile with the mechanism. Withholding quantity is itself an exercise of market power, so conventional reasoning predicts that a unit facing more local competition offers weakly *more* output, whereas the sunset-hour point estimates are negative: $-30.4\,\mathrm{MW}$ (s.e. 10.7) for all treated units, about 10 percent of their pre-entry mean, and $-67.4\,\mathrm{MW}$ (s.e. 18.0) in the technology subsample. Over all hours of the day the effect is indistinguishable from zero for all treated units ($-0.3\,\mathrm{MW}$, s.e. 6.1) and positive, though insignificant, in the technology subsample ($+9.3\,\mathrm{MW}$, s.e. 7.3), and within that cell the sign changes again across the four

Figure 8: Effect of Battery Entry on Offered Prices, All Hours



Notes: As Figure 7, but computed on all hours of the day rather than the sunset hour. Rows are the capacity percentile at which the offered price is read; columns are all treated units (left) and the gas steam, simple-cycle under 90 MW and diesel subsample (right). The outcome is the offered price as a percentage of the system-wide offer cap in force. The control group is units not yet exposed at that month, cohorts are restricted to 2016–2023, and unit capacity enters as a time-invariant covariate. Event month −1 is the reference and is zero by construction. Bars and shaded bands are 95 percent *pointwise* confidence intervals.

aggregation schemes. The largest estimate is also sensitive to how the outcome is defined. Panel A truncates the offer curve at the unit's High Sustained Limit (HSL), the quantity SCED can actually dispatch, while Panel B uses the curve as filed: the all-unit sunset estimate is essentially unchanged between the two (−33.4 MW, s.e. 11.5, in Panel B), but the subsample estimate falls to −25.0 MW (s.e. 17.6) and is no longer significant at conventional levels. I therefore leave the quantity margin for further investigation.

Overall, system-wide, the evening price and output response to daily solar generation weakens over the same years in which battery capacity expands. At the unit level, thermal resources that share a local market with an entering battery lower the prices at which they offer their capacity, by an amount comparable to their own pre-entry offer level, with the largest reductions at the top of the offer curve and among the technologies that previously met the evening ramp.

Table 2: Effect of Battery Entry on Offered Prices, All Hours

	65% of capacity		75% of capacity		85% of capacity	
	All	Steam/Small SC/DSL	All	Steam/Small SC/DSL	All	Steam/Small SC/DSL
	(1)	(2)	(3)	(4)	(5)	(6)
ATT (simple)	-1.251^{***}	-2.587^{***}	-1.077^{***}	-1.974^{***}	-1.387^{***}	-4.866^{***}
	(0.416)	(0.667)	(0.332)	(0.608)	(0.455)	(0.610)
ATT (dynamic avg.)	-1.017^{***}	-1.717^{***}	-0.891^{***}	-1.278^{**}	-1.202^{***}	-5.052^{***}
	(0.310)	(0.615)	(0.270)	(0.545)	(0.387)	(0.508)
ATT (cohort avg.)	-1.123^{**}	-5.650^{***}	-1.041^{***}	-2.815^{***}	-1.387^{***}	-4.350^{***}
	(0.450)	(1.042)	(0.404)	(0.862)	(0.517)	(1.205)
ATT (calendar avg.)	-0.949^{***}	-1.396^{***}	-0.674^{***}	-1.035^{***}	-1.012^{***}	-2.397^{***}
	(0.303)	(0.306)	(0.212)	(0.286)	(0.313)	(0.281)
Pre-period mean	1.566	2.253	1.848	2.326	2.244	2.521
ATT / pre-period mean (%)	−79.9	−114.8	−58.3	−84.9	−61.8	−193.0
Cohorts	25	16	25	16	25	16
Units	351	137	344	137	334	137
Observations	28,239	12,095	29,063	12,949	27,473	12,854

Notes: As Table 1, but estimated on all hours of the day rather than the calendar date's own sunset hour. Callaway and Sant'Anna (2021) estimates of the effect of battery entry in a thermal unit's local market on its submitted offer price, expressed as a percentage of the system-wide offer cap in force and measured at three percentiles of the unit's capacity. Monthly frequency, units not yet exposed as the control group, cohorts 2016–2023, outcome regression, and unit capacity as a time-invariant covariate. The four ATT rows are alternative aggregations of the same group-time effects: simple weights cohort-period cells by their share of treated observations, dynamic averages the event-time effects, cohort averages the cohort-specific effects, and calendar averages the calendar-time effects. Analytic standard errors in parentheses. Pre-period mean is the mean of the dependent variable among eventually-treated units before entry; because the estimated effects are of the same order as this mean, the ratio of the two should not be read as a proportional change. Observations are resource-months. Estimates are close to the sunset-hour results in Table 1: none of the six comparisons differs by more than 1.19 standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusion and Next Steps

This paper provides preliminary evidence that the rapid expansion of battery storage in ERCOT has begun to erode the competitive advantage that thermal generators historically held during the evening net-load ramp created by solar generation. System-wide, the evening price response to daily solar output fell from \$9.88/MWh per GWh in 2017–2019 to \$0.56/MWh in 2020–2022 and to near zero, turning negative across much of the evening, by 2023–2025; the output response of small simple-cycle, gas steam, and diesel units follows the same trajectory before being replaced by battery charging and discharging. At the resource level, thermal generators exposed to a nearby battery's entry, identified through a Woerman (2023)-style local-market definition applied to 155 battery entries and 563 thermal units and estimated against units not yet exposed, lower the prices at which they offer their capacity by 1.2 to 1.5 percentage points of the system-wide offer cap, with reductions at the top of the offer curve among gas steam, small simple-cycle and diesel units reaching 5.7 percentage points. Together, this system-wide and resource-level evidence points toward battery expansion narrowing the local market power that thermal generators could previously exercise during the evening ramp.

This is a preliminary draft, and several steps remain before these results can support that conclusion more firmly.

The Section 4 outcomes are offered prices, not markups. Approximating each thermal unit's marginal cost, from its heat rate and the daily natural gas price, and re-estimating the design in markup terms would separate a genuine narrowing of market power from a mechanical pass-through of input costs.

The quantity margin is unresolved. The estimated effect on offered MW is inconsistent in sign across hour cuts and whether truncating the offer curve at the HLS. Further investigation is needed to construct a valid outcome variable and test the conventional prediction that weaker market power should, if anything, raise the capacity a unit makes available.

The design identifies the effect from the timing of a unit's *first* exposure, but exposure is repeated: three quarters of treated units are eventually in the local market of more than one battery, and only 63 of the 155 batteries generate any unit's first exposure. Two alternatives will be explored: a dose specification in which treatment is the cumulative nearby battery capacity, and a stacked design in which each battery entry is its own sub-experiment with its own clean controls.

The system-wide design in Section 3 treats daily solar generation as exogenous, but solar curtailment could make it partly endogenous to demand or price conditions. Instrumenting for solar generation with solar radiation would address this.

A natural extension is to ask whether firms that own both battery storage and nearby thermal generation dispatch their batteries less aggressively than an unaffiliated owner would, in order to protect their thermal generators' evening rents, directly testing whether battery expansion is being fully passed through to consumers or partly internalized by vertically integrated owners.

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Appendix

Table A: **Number of Generation Resources in the SCED Reports 2014-2025**

Resource Type	No. of Units	No. of Observations
Gas — Combined Cycle		
Combined Cycle Gas Turbine (>90 MW)	257	23,610,500
Combined Cycle Gas Turbine (≤90 MW)	68	4,700,841
Gas — Simple Cycle		
Simple Cycle Gas Turbine (>90 MW)	38	12,865,409
Simple Cycle Gas Turbine (≤90 MW)	200	51,628,872
Gas Steam		
Gas Steam (Reheat)	34	12,264,909
Gas Steam (Non-Reheat)	18	5,953,504
Gas Steam (Supercritical)	4	1,652,222
Other Fossil		
Coal / Lignite	47	14,084,213
Diesel	29	7,334,665
Renewables		
Solar PV	292	32,628,543
Wind	424	109,929,087
Other Renewables	-	1,614,698
Storage	341	24,909,906
Low-Carbon Dispatchable		
Hydropower	-	9,132,640
Nuclear	-	3,320,960
Total	1,752	315,630,969

Notes: Counts are based on the 60-Day SCED Disclosure Gen Resource Data reports, 2014–2025. No. of Units is the number of distinct resources of each type that appear in the disclosure data at any point in the sample period; No. of Observations is the number of resource-level 15-minute-interval records for that type in the underlying panel. Resource type codes follow the same ERCOT classification used in the notes to Figure 2 (e.g., CCGT90/CCLE90 for combined-cycle, SCGT90/SCLE90 for simple-cycle, GSREH/GSNONR/GSSUP for gas steam); Solar PV corresponds to PVGR and Storage to PWRSTR.

Table B: **Effect of Battery Entry on Offered Quantity**

	All hours		Sunset hour	
	All	Steam/Small SC/DSL	All	Steam/Small SC/DSL
	(1)	(2)	(3)	(4)
Panel A: Deliverable offered quantity (MW)				
ATT (simple)	−0.28	9.29	−30.36***	−67.43***
	(6.12)	(7.33)	(10.67)	(17.99)
ATT (dynamic avg.)	0.01	11.29*	−41.12***	−69.74**
	(6.28)	(6.64)	(14.66)	(28.87)
ATT (cohort avg.)	−4.02	25.07***	−26.15***	−32.96**
	(6.81)	(8.19)	(9.82)	(13.25)
ATT (calendar avg.)	0.07	−2.85	−31.46**	−68.47**
	(4.99)	(5.87)	(13.28)	(28.29)
Pre-period mean	272.2	122.2	299.7	131.9
ATT / pre-period mean (%)	−0.1	7.6	−10.1	−51.1
Panel B: Offered quantity as filed (MW)				
ATT (simple)	−3.54	8.96	−33.42***	−25.02
	(6.90)	(6.96)	(11.54)	(17.64)
ATT (dynamic avg.)	−5.60	9.89	−49.34***	−36.70
	(6.44)	(6.49)	(15.96)	(29.40)
ATT (cohort avg.)	−5.65	12.46*	−26.58**	−2.45
	(7.65)	(7.33)	(10.45)	(11.12)
ATT (calendar avg.)	−3.16	−2.13	−36.07**	−45.69
	(5.09)	(5.48)	(14.48)	(28.02)
Pre-period mean	295.6	135.5	319.9	144.6
ATT / pre-period mean (%)	−1.2	6.6	−10.4	−17.3
Cohorts	26	17	26	17
Units	408	139	393	139
Observations	34,925	13,484	28,839	11,495

Notes: Callaway and Sant'Anna (2021) estimates of the effect of battery entry in a thermal unit's local market on the quantity it offers, in MW, following the same design as Table 1. Columns cross the hour cut with the sample: columns (1) and (3) use all treated units, columns (2) and (4) the gas steam, simple-cycle at or below 90 MW and diesel subsample. Panel A uses the deliverable offered quantity, the top of the submitted offer curve truncated at the resource's High Sustained Limit (HSL), since SCED cannot dispatch a resource above its HSL; Panel B uses the top of the curve as filed, including any tranche standing above HSL in that interval. Estimated at monthly frequency with units not yet exposed as the control group, cohorts 2016–2023, outcome regression, and unit capacity as a time-invariant covariate. The four ATT rows are alternative aggregations of the same group-time effects, defined as in Table 1. Analytic standard errors in parentheses. Pre-period mean is the mean of the dependent variable among eventually-treated units before entry; unlike the offered price, the estimated effects here are a small fraction of that mean, so the ratio can be read as a proportional change. Observations are resource-months. The sample is larger than in Table 1 because offered quantity is defined for every unit-month, whereas a unit enters a price column only if its offer curve reaches that percentile of capacity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.