Pairing Batteries with Renewables: How Ownership Shapes Operational Incentives and Market Outcomes

Pietro Visaggio*

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Abstract

This paper examines how battery storage ownership structure affects wholesale electricity market outcomes by shaping operational incentives. Using a dynamic dispatch model calibrated to Texas data, I show how transmission congestion creates conditions in which batteries operated jointly with a renewable plant are used strategically to increase the value of renewable production. The strength of this incentive depends on supply elasticity and the timing of renewable production. Co-owned batteries earn roughly 76 percent higher profits than standalone batteries in markets where strategic incentives arise. Despite this strategic behavior, co-owned and standalone batteries produce similar effects on consumer surplus, renewable curtailment, and carbon emissions. While market conditions do not generate enough profits for battery investment to be viable—regardless of ownership—the positive effects on consumer surplus and carbon emissions make batteries desirable from consumers' perspective. Under a uniform subsidy policy, co-ownership's higher profitability makes more batteries viable at moderate subsidy rates. *(JEL L94, Q40, Q42, Q48, Q55)*.

Keywords: Battery storage, renewable energy, electricity markets, ownership structure, market power, transmission congestion, energy subsidies

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1 Introduction

A central problem in economics is how to design policies that encourage investment in projects which, despite generating positive system-wide benefits, are not privately profitable under prevailing market conditions. Electricity storage exemplifies this problem in deregulated wholesale electricity markets. Electricity grids worldwide are undergoing a rapid decarbonization process in which renewable sources such as wind and solar play a central role. Yet their intrinsic intermittency complicates integration into wholesale markets and exposes the grid to reliability risks. Battery energy storage systems (BESS) offer a flexible solution to manage intermittency—charging during off-peak hours, when renewable output is abundant and prices are low, and discharging during peak hours, when renewable output falls and prices rise. Yet despite this role, batteries require substantial upfront investment and, under current market conditions, are rarely profitable on their own. In the United States, for example, by the end of 2024 installed utility-scale storage accounted for only about 2 percent of operating renewable generation capacity. To address this gap, subsidies have been introduced at both the federal and state level. Federal support, initially restricted to batteries co-owned with renewables and charged primarily with electricity from the plant, has only recently been extended to standalone projects. State programs are more heterogeneous, with some covering both ownership types and others limited to co-owned facilities.

My paper answers the question of which battery ownership structure—co-ownership with a renewable plant or standalone—is the most desirable. To investigate this question, I analyze how ownership shapes operational incentives and, through them, market outcomes. Battery operations affect electricity prices. Charging raises prices while discharging lowers them, with the magnitude of these effects depending on supply elasticity. A standalone operator maximizes arbitrage profits by exploiting price differentials across periods. To preserve these differentials, standalone operators target periods when supply is relatively more elastic to trade electricity, as this minimizes the price variations induced by battery operations. By contrast, a co-owner internalizes how battery operations affect renewable revenues. A co-owner may strategically charge during off-peak periods with less elastic supply to induce larger price increases. This strategy is profitable whenever the additional renewable revenues from charging during these periods exceeds the additional storage costs relative to charging during periods with more elastic supply. The strength of this incentive depends crucially on contemporaneous renewable output, as higher production amplifies the revenue gains from price increases.

To study these dynamics, I first develop an illustrative theoretical model of battery utilization, and then I simulate an extended version calibrated to data from the Texas wholesale electricity market. This framework allows me to assess whether the market conditions that generate different incentives arise in practice and what their implications are for prices, emissions, storage profitability, and consumer surplus.

Using the illustrative model, I show that the divergence of operational incentives across different ownership structures can be explained by transmission congestion, supply elasticity, and the timing of renewable production. The model features four periods within a day—off-peak and peak periods, each under congested or uncongested transmission conditions. During uncongested periods, the market operates as a fully integrated system in which all generating resources compete to serve market-wide demand. When transmission congestion occurs, the grid fragments into multiple local markets, each containing a smaller number of generators serving a fraction of total demand. The key distinction is that within off-peak hours, supply is more elastic during uncongested periods, and the same holds for peak hours.

While standalone batteries target uncongested periods for both charging and discharging to minimize price impacts, transmission line congestion can create market conditions under which co-owned batteries find it profitable to charge during congested off-peak hours. This incentive is strongest when renewable output is abundant, as a more inelastic supply curve amplifies the price increase from charging, generating renewable revenue gains that exceed the higher storage costs.

I assess whether these theoretical conditions for divergent operational incentives actually occur by simulating a day-long dynamic dispatch model calibrated to Texas Real-Time Market data from January to December 2021. For each electricity grid node where a renewable plant is operating, I exogenously place a hypothetical battery and solve the model under both ownership structures, obtaining the optimal battery dispatch, operating schedules for other generating resources, and the resulting equilibrium prices. Battery operators make charge and discharge decisions every 15 minutes. Following the structure of the illustrative model, operators behave as price-takers during uncongested periods but act strategically during congested periods when local markets form and battery operations can influence prices. I use node-level Locational Marginal Prices (LMPs) to identify congested periods and, together with S&P Capital IQ data on plant locations, to define the set of plants operating in each local market when transmission line capacity binds.

The simulations yield five main findings. First, ownership does not substantially alter overall battery utilization. Both co-owned and standalone batteries complete approximately 1.65 charge-discharge cycles per day on average, trading a similar amount of electricity. This similarity masks important differences in when batteries trade, which drive divergent market outcomes.

Second, while both ownership types predominantly trade electricity during uncongested periods—selling roughly 98 percent of electricity during uncongested peak hours and purchasing around 76 percent during uncongested off-peak hours—co-owned batteries strategically reallocate approximately 1.3 percentage points of their charging to congested off-peak periods. This reallocation occurs in periods when transmission congestion creates local markets with inelastic supply. Under these conditions, co-owned operators use batteries more intensively than standalone operators because the induced price increase from charging raises renewable revenues by more than it increases storage costs. Co-owned batteries use approximately 5 percent more of their rated power than standalone units when renewable output is low; this gap widens to about 7 percent when renewable production is high.

Third, battery operations reduce renewable curtailment and lower carbon emission costs under both ownership structures, with similar patterns across ownership types. On average, batteries reduce curtailment by approximately 0.9 GWh annually per MWh of storage capacity and reduce carbon costs by around $4500 per MWh of storage capacity annually, using a social cost of carbon of $185 per ton of CO_2 (Rennert et al. (2022)).

By charging during off-peak hours and discharging during peak hours, batteries effectively shift production from marginal producers in peak periods to marginal producers in off-peak periods. The overall effect is that renewable and coal production increase, as these technologies are frequently marginal during off-peak periods, while natural gas and diesel output decreases, even though natural gas also operates at the margin during some off-peak hours. Reductions in natural gas and diesel emissions more than compensate for the increase in coal emissions. This net reduction occurs because avoided renewable curtailment contributes zero-emission electricity that displaces polluting technologies during peak hours.

Fourth, these operational differences generate divergent effects on profitability but similar impacts on consumer surplus. Co-ownership yields substantially higher profits—approximately 76 percent higher in markets where strategic incentives arise—while consumer surplus gains increase similarly across ownership types, by approximately $200k to $440k per MWh of storage capacity. Strategic utilization enables co-owned batteries to internalize the positive effect of battery operations on revenues from selling renewable electricity, whereas standalone batteries earn profits solely from arbitrage. Batteries increase consumer surplus by charging during off-peak hours when prices are low and discharging during peak hours when prices are high, thereby reducing average electricity costs. Strategic charging by co-owned batteries does not alter this result. During congested off-peak hours, co-owned batteries induce larger price increases that affect only local market demand. By contrast, standalone batteries charging during uncongested periods induce smaller price increases that apply to system-wide demand. Because lower elasticity in congested markets is compensated by their smaller market size, consumer surplus gains remain similar across ownership types.

Finally, while neither ownership regime is privately viable at assumed capital costs of $250k per MWh of storage capacity, co-owned batteries require substantially lower uniform subsidies to become profitable. Under a uniform subsidy policy, the first co-owned battery becomes profitable with a subsidy covering 35 percent of capital costs, compared to 55 percent for standalone batteries, because co-ownership allows operators to internalize renewable revenue gains from strategic utilization. This gap persists as subsidy rates increase. Only at approximately 85 percent does the number of profitable batteries equalize across ownership types.

This paper makes two main contributions. First, it extends the literature on storage investment in wholesale electricity markets by showing how ownership structure shapes operational incentives and the value of storage projects. Prior research has shown how market structure–such as market power in storage or vertical integration with dispatchable generation–affects storage operation and market outcomes (Andrés-Cerezo and Fabra (2023b)). Other studies examine how batteries influence nodal prices (Kirkpatrick (2025)), and the value of standalone storage projects in wholesale electricity markets by assuming that the operator can behave either as a price-taker (Butters et al. (2021)) or as a strategic player (Karaduman (2020)). Building on work that shows renewables and storage can be either complements or substitutes depending on market conditions (Andrés-Cerezo and Fabra (2023a)), I focus on storage vertically integrated with non-dispatchable renewables, where the combined firm can switch between strategic and price-taking behavior depending on local congestion. This specification highlights that co-ownership confers operational control on otherwise non-dispatchable generators, enabling them to act strategically. Ignoring ownership structure can therefore lead to biased estimates of both market effects and project profitability.

Second, it contributes to the literature on market power in deregulated electricity markets by identifying a novel channel operating through storage and its interaction with renewable generation. Existing studies show that market size and transmission constraints shape firms' ability to exercise market power (Woerman (2019)), and that incumbents may strategically manipulate supply to influence prices (Borenstein et al. (2002); Mansur (2008); McRae and Wolak (2019); Wolfram (1999)). Some studies examine how ownership of generators with different technologies–such as hydro and thermal plants—allows firms to intertemporally control supply and influence prices (Bushnell (2003)). I develop a framework in which batteries co-owned with non-dispatchable renewables use storage not only to arbitrage inter-period prices but also to enhance renewable revenues during charging periods. By showing how congestion creates localized markets in which a single battery can move prices, the paper identifies a previously overlooked mechanism through which storage and renewables jointly exercise market power.

The remainder of the paper is organized as follows. Section 2 describes the institutional context of Texas electricity market. Section 3 develops an illustrative model to show how transmission congestion, supply elasticity, and the timing of renewable output generate divergent incentives under co-ownership and standalone operation. Section 4 presents the empirical framework, a day-long dynamic dispatch model calibrated to ERCOT data, and explains how congestion and local market definition are incorporated. Section 5 reports the results, focusing on operational incentives, consumer surplus, and profitability across ownership structures. Section 6 concludes by discussing the policy implications of ownership for storage subsidies and market design.

2 Institutional Settings

In the following subsections, I describe the institutional features of the Texas electricity market that provide the foundation for the illustrative and empirical models.

Texas Electricity Market

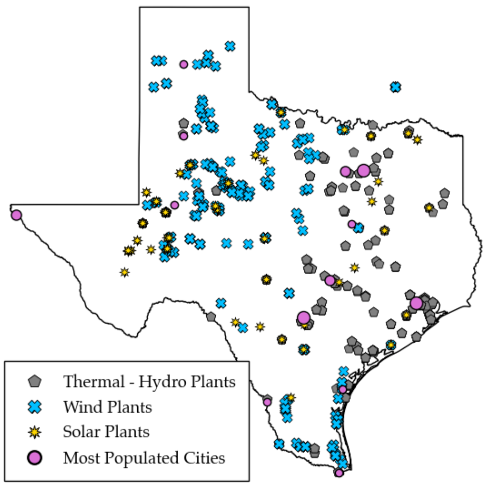
Operated by the Electric Reliability Council of Texas (ERCOT), the independent system operator (ISO), the Texas wholesale electricity market is largely isolated from the rest of the United States grid. As a result, all electricity generated within the state must also be consumed there, and imports and exports are null. ERCOT coordinates the operation of more than 700 generating units that supply electricity to over 26 million consumers, and annual wholesale transactions exceed $40 billion.

The market design in Texas is energy-only, meaning there is no separate capacity market. ERCOT's mandate is to ensure that electricity demand is met at every moment while minimizing system costs and maintaining reliability. To achieve this, ERCOT operates a Security-Constrained Economic Dispatch (SCED) every five minutes in the Real-Time Market (RTM). The SCED uses real-time load telemetry together with the aggregated offer curves submitted by generators to balance supply and demand and to determine the market-clearing price for electricity.

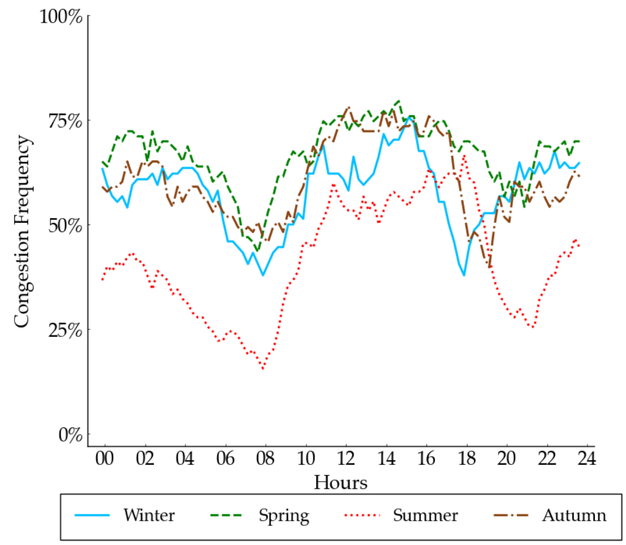
Transmission Line Congestion and Locational Market Definition

Transmission congestion is a defining feature of the Texas electricity market and plays a central role in determining prices. Electricity must be moved across transmission lines because generation and demand are not sited at the same location. While this spatial mismatch exists for all technologies, it is particularly acute for renewables: demand is concentrated in large urban centers, whereas most wind and solar plants are sited in remote areas (Figure 1a). Transmission lines have finite capacity: technical limits on voltage and frequency, as well as thermal constraints, prevent them from carrying unlimited power. Sudden shocks — such as a plant outage, a rapid load increase, or a surge in renewable output — can stress the grid and reduce the amount of power that can safely flow. Moreover, moving electricity generates heat within the line, and if temperatures rise too high the line risks failure. High ambient temperatures exacerbate this problem, lowering the effective capacity of lines and making congestion particularly frequent on hot summer afternoons. Because flows are interdependent across the network, congestion on one path often redirects power and overloads other lines, producing system-wide constraints. As a result, congestion is pervasive throughout the year, binding in more than half of all 15-minutes intervals in 2021 (Figure 1b).

ERCOT addresses these constraints by implementing Locational Marginal Pricing, which assigns a price, the Locational Marginal Price (LMP), to each node that reflects the marginal cost of serving an additional megawatt at that location. When no transmission line is congested, the ERCOT market functions as a single integrated system. In this case, the system operator collects all supply offers from generators and arranges them in increasing order of their submitted prices, forming the aggregate supply curve known as the merit order. The market price is then set by the intersection of this supply curve with demand, equal to the price of the marginal generator. Because electricity can flow freely across the grid, the location of the marginal generator is irrelevant, and the price applies



(a) Power plants and load centers in Texas



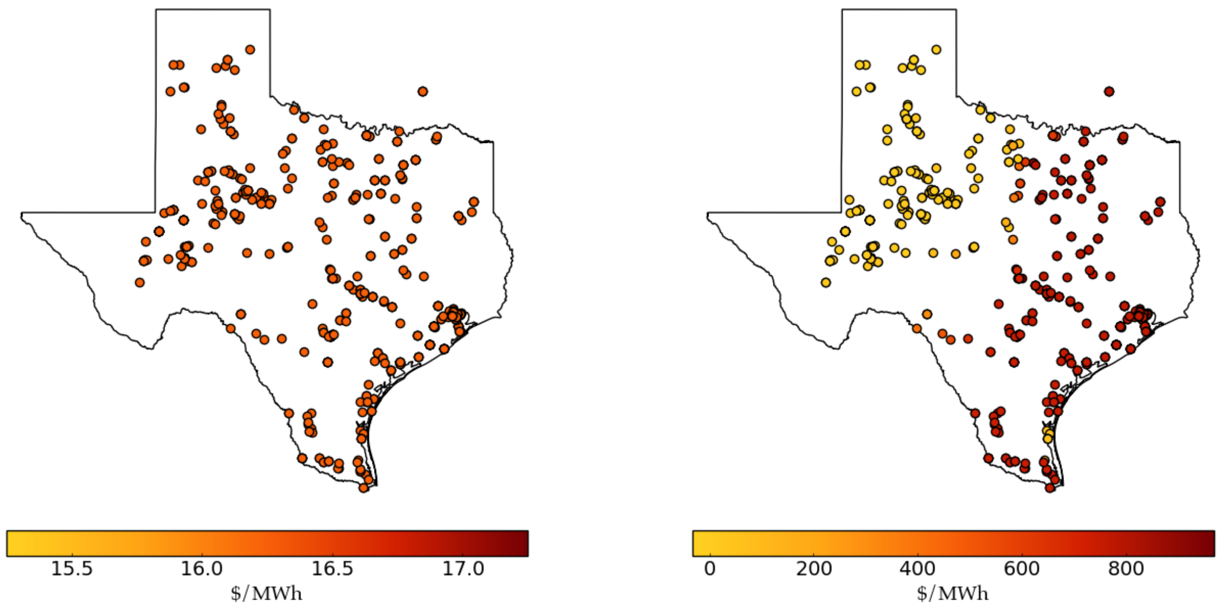
(b) Percentage of 15-minutes periods with at least one congested transmission line, by season.

Figure 1: Transmission congestions in Texas

uniformly at every node. There is a single Locational Marginal Price (LMP), reflecting the marginal cost of producing an additional megawatt from the system-wide marginal unit (Panel 2a).

When transmission lines become congested, ERCOT no longer clears the market at a single system-wide price. Instead, each node is assigned its own Locational Marginal Price (LMP), which reflects the marginal cost of supplying an additional megawatt at that location.

To illustrate how this works, consider a simplified example where the market is represented by just two nodes. One node is a load center with a relatively expensive local generator, while the other hosts a cheaper generator. The two nodes are connected by a transmission line of limited capacity. If the cheaper generator has sufficient capacity to cover the entire load and the transmission line capacity does not bind, then all demand is met by the cheap unit and the LMP is identical across both nodes. Once the line becomes congested before all demand is served, however, the system operator must dispatch the more expensive local generator at the load node. At this point, the market separates into two price zones. The LMP at the cheap generator node remains low, reflecting the marginal cost of the unit whose capacity cannot be fully exported. The LMP at the



(a) Uncongested Market (The data in the figure are from January 2, 2021, 11:15)

(b) Congested Market (The data in the figure are from April 5, 2021, 12:45)

Figure 2: Locational Marginal Pricing in Texas Electricity Market

load node is higher, reflecting the marginal cost of the expensive generator that must be dispatched to meet residual demand (Panel 2b).

Renewable Plants Location

Renewable production is shaped both by plant location and by the inherent variability of their resources. Most wind farms are concentrated in the Panhandle, West Texas, and the Coastal Bend—areas with the strongest wind resources in the state. Solar plants are more widely distributed across West and West-Central Texas, where solar irradiation is highest. Production also varies systematically over the day. Wind output typically peaks at night, when temperatures are lower, and declines around midday as higher temperatures reduce wind speeds. By contrast, solar output peaks around midday and is entirely absent at night.

This geographic concentration of renewables in remote areas, combined with the variability in resource availability, creates conditions for curtailment—situations where renewable plants must reduce production below their potential output. Curtailment can occur for two reasons: excessive renewable supply relative to demand, or transmission line congestion that prevents electricity from reaching load centers. In Texas, transmission congestion is virtually the only cause. When wind or solar resources are abundant, renewable plants in remote regions can generate more electricity than transmission lines can accommodate. Because transmission capacity between renewable-rich areas and load centers is limited, some renewable electricity must be curtailed. This represents a waste of cheap, clean electricity that renewable plants could produce at zero marginal cost.

The geographic distribution of renewable plants not only determines their production potential but also shapes the set of competitors they face when congestion occurs. Plants located near load centers typically share local markets with thermal generators, whereas those in remote areas are often grouped with other renewables alone. This difference directly affects the shape of the local supply curve. In the former case, the curve is generally more inelastic, since thermal generators submit step-shaped offers that reflect rising costs as capacity is utilized more intensively. In the latter, the curve is nearly flat, as renewable plants bid at constant marginal cost, making residual supply close to perfectly elastic under congestion.

Battery Energy Storage Systems in Electricity Markets

Grid capacity investments in storage systems are projected to rank second only to solar in Texas. Almost all planned projects are Battery Energy Storage Systems (BESS) based on lithium-ion technology. A BESS is characterized by four parameters: (i) its power capacity P (MW), the maximum instantaneous rate of charge or discharge; (ii) its duration h (hours), the length of time it can sustain rated power; (iii) its energy capacity E (MWh), defined as the product of power and duration; and (iv) its round-trip efficiency γ^2, the fraction of energy retained over a complete charge-discharge cycle.

Lithium-ion batteries combine high power capacity, moderate duration, and relatively high efficiency, making them well suited for arbitrage in wholesale electricity markets. At the beginning of 2021, only 20 batteries were connected to the Texas grid, with an average power capacity of 12 MW. In practice, these projects were almost exclusively deployed in ancillary-service markets—where grid operators procure services such as frequency regulation and operating reserves to maintain system reliability—and where revenues were initially attractive. However, *"total ancillary demand is small and can be saturated quickly by additional capacity" (Sackler, 2019)*. Industry forecasts therefore indicate that the bulk of storage activity will take place in the energy market. ERCOT operates two sequential markets: a Day-Ahead Market (DAM), where participants can lock in financial positions by committing to buy or sell electricity 24 hours in advance, and a Real-Time Market (RTM), which balances actual supply and demand every five minutes based on real-time conditions. Batteries can participate in either market, but the RTM offers greater arbitrage opportunities due to its higher price variability, making it the expected primary venue for storage operations.

3 Illustrative Model

In this section, I develop an illustrative model to show how transmission congestion, supply elasticity, and renewable production shape battery operational incentives under the two ownership structures—co-ownership and standalone. The model features a single day with four periods: uncongested off-peak, congested off-peak, uncongested peak, and congested peak. A battery operator must fully charge the battery's capacity b during off-peak periods and discharge it during peak periods, when prices are higher. The operator's decision is how to allocate charging across congested and uncongested off-peak periods, and similarly for discharging.

The key distinction in the model is between uncongested and congested periods. During uncongested periods, the electricity market operates as a fully integrated system. The battery faces market-wide demand and competes with the full set of generators across the grid. By contrast, when transmission lines become congested, the battery operates in a local market where demand is limited to local consumption plus whatever electricity can flow through the constrained transmission lines. This fragmentation also reduces the number of competing generators and alters the shape of the supply curve the battery faces.

In each period t, where $t \in \{\text{off-peak, peak}\}$ denotes the time of day, and under transmission status $m \in \{u, c\}$, where u indicates uncongested transmission lines and c indicates congested ones, the supply curve $S_{t,m}$ is modeled as a piecewise linear function with three segments. The initial horizontal segment at price 0 reflects exogenous renewable output, which has zero marginal cost. The remaining two segments, with slopes χ_l and χ_h, where $\chi_l < \chi_h$, represent the supply curve of traditional (thermal) generators.

The key feature is that in off-peak periods, demand intersects the supply curve along the segment with slope χ_l, while in peak periods, demand intersects along the steeper segment with slope χ_h. The value of the slope at the intersection depends on the congestion status m. In each period t, transmission congestion makes supply curves steeper at the relevant intersection points, i.e. $\chi_{t,c} > \chi_{t,u}$.

Figure 3 illustrates the incentives that govern battery utilization under the two ownership structures. A battery that arbitrages price differentials buys electricity during the off-peak period and sells it in the peak period. Since it only stores energy produced by other resources, charging $b_{o,m}$ units during off-peak periods shifts demand from $D_{o,m}$ to $D'_{o,m}$, raising the price from $p_{o,m}$ to $p'_{o,m}$. When the battery discharges in the peak period, I assume that the stored electricity is offered at a price of 0, which allows me to model battery discharging as a negative demand shift. Demand moves from $D_{p,m}$ to $D'_{p,m}$, and the price decreases from $p_{p,m}$ to $p'_{p,m}$.

A standalone operator trades electricity to maximize arbitrage profits exclusively. Consider an operator who has already purchased $b_{o,u}$ units during uncongested off-peak periods and $b_{o,c}$ units during congested off-peak periods, and must now decide when to purchase the final unit to reach capacity b. The operator buys this last unit in the off-peak period with the lowest marginal cost. Charging under market transmission status m would increase the price by $\chi_{o,m}$ up to $p''_{o,m}$. This increase costs in two ways: the $b_{o,m}$ units already purchased become more expensive by $\chi_{o,m}$ (area $B1_m$), and the additional unit itself must be purchased at $p''_{o,m}$ (area $B2_m$). Therefore, the operator buys the unit in the uncongested period if $B1_u + B2_u < B1_c + B2_c$.

An analogous logic applies to discharging. Discharging under market transmission status m would decrease the price by $\chi_{p,m}$ to $p''_{p,m}$. Discharging affects revenues in two

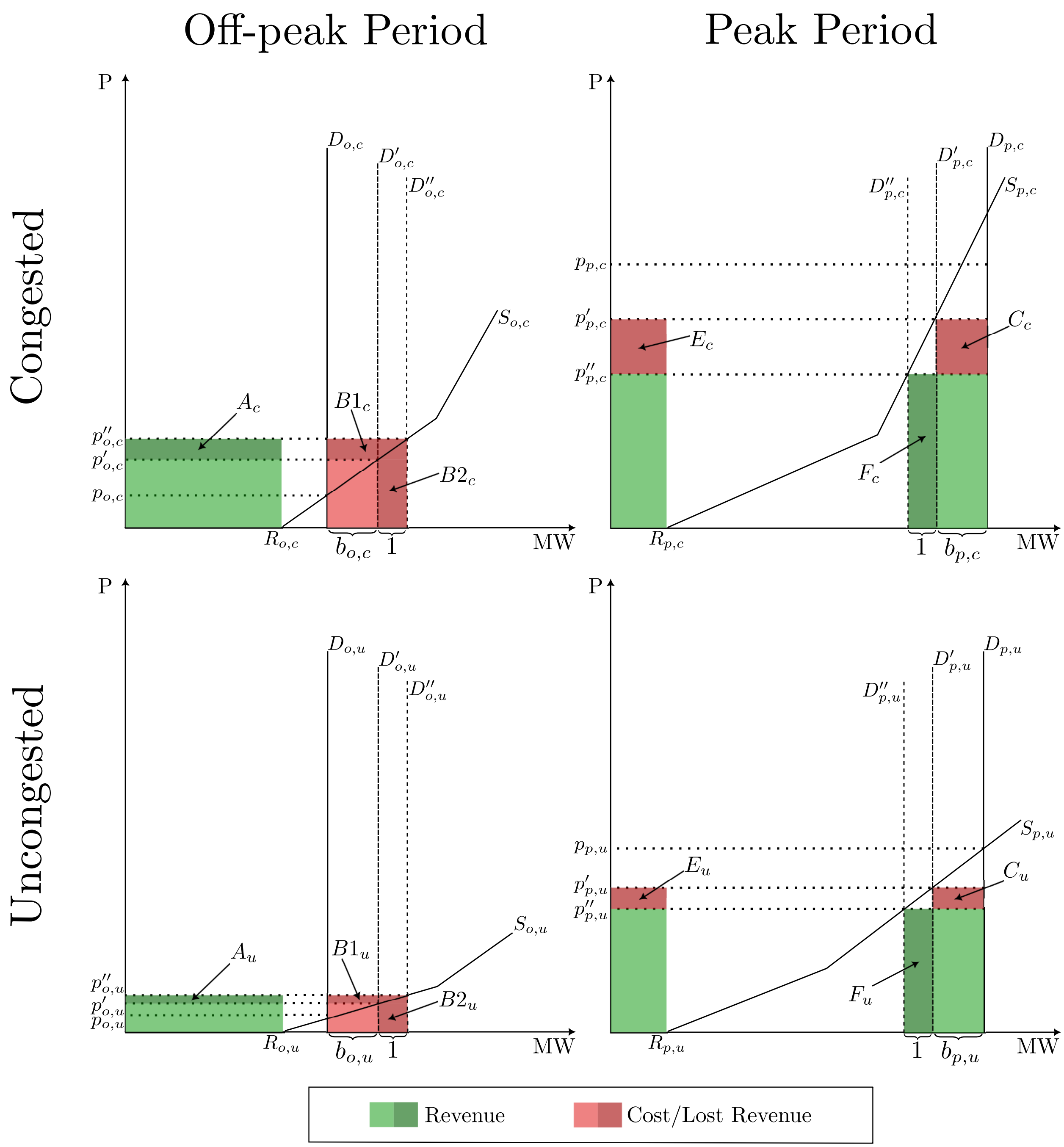


Figure 3: Illustrative Model

opposing ways: it generates revenue $p''_{p,m}$ from selling the additional unit (area F_m), but reduces revenues on the $b_{p,m}$ units already sold by $\chi_{p,m}$ (area C_m). The net marginal revenue from discharging is therefore $F_m - C_m$. The operator sells the unit in the uncongested period if $F_u - C_u > F_c - C_c$.

A co-owned battery operator faces different incentives because it maximizes joint profits from both arbitrage and renewable sales. Unlike a standalone operator, the co-owner internalizes how battery operations affect renewable revenues through price changes.

When charging, the co-owner's marginal cost under market transmission status m is $(B1_m + B2_m) - A_m$, where $A_m = \chi_{o,m} \cdot R_{o,m}$ represents the additional renewable revenues from the price increase. The timing of renewable production and the slope of the supply curve can generate substantially different incentives under co-ownership. If renewable output is particularly high during congested off-peak hours, a co-owner may prefer charging during congestion despite higher storage costs variation. Specifically, the co-owner charges during congested periods when $A_c - A_u > (B1_c + B2_c) - (B1_u + B2_u)$—that is, when the incremental renewable revenue gain from congestion exceeds the additional storage cost.

When discharging, the co-owner's net marginal revenue is $(F_m - C_m) - E_m$, where $E_m = \chi_{p,m} \cdot R_{p,m}$ represents the erosion of renewable revenues from the price reduction (areas E_u and E_c). If standalone batteries prefer to discharge during uncongested periods to minimize price impacts on arbitrage profits, this preference is even stronger for co-owned batteries, as any price reduction from discharging also erodes contemporaneous renewable revenues.

4 Empirical Strategy

To examine whether the theoretical conditions that yield divergent incentives for battery operation under the two ownership structures are observed in practice, I simulate a dynamic battery utilization model under two scenarios: co-ownership with a renewable plant and standalone ownership. In each case, I place a battery at the node of an existing renewable facility in the grid, abstracting from the entry decision, and I compute the optimal dispatch decision of its operator. This exercise is conducted for every renewable plant operating in ERCOT.

The empirical exercise allows me to quantify the implications of ownership for a range of market outcomes—including prices, consumer surplus, and battery profitability—conditional on market conditions. Moreover, by simulating the model for batteries paired with every renewable plant operating in the market, I can also assess how plant characteristics—such as location and technology—influence the magnitude and direction of these ownership effects.

Empirical Model

In the battery-utilization model I develop, the operator participates in the real-time market and utilizes the battery to arbitrage electricity price differentials. The time horizon faced by the operator is a day. This choice reflects empirical evidence on battery utilization patterns. Karaduman (2020) finds that batteries complete approximately 1.5 cycles per day in simulation and 1.7 cycles in observed data, suggesting that storage is predominantly used to exploit intraday price differentials rather than arbitrage opportunities over longer periods. At the beginning of every fifteen-minute period, it has to decide how much electricity to buy (charge) or sell (discharge).

The problem is inherently dynamic because each decision is constrained by the battery's state of charge at the beginning of the period. At $t = 0$, I assume that battery j starts empty ($c_{0,j} = 0$), and I impose that the state of charge is again empty at the end of the day ($c_{96,j} = 0$). Along with the state of charge, the operator's decision depends on electricity demand, supply, and the status of the transmission network. Gross demand for electricity in each period, $\bar{D}_{t,m}$, is assumed to be perfectly inelastic. The reason for this assumption is that the demand side in deregulated wholesale electricity markets is represented by retail providers, which buy electricity to distribute to end-use consumers. While the price paid by the retailers is determined every 15 minutes, the price paid by consumers is represented by fixed rates, which in the short term are disconnected from wholesale prices.

The supply function, $S_{t,m}(p_{t,m})$, is increasing in the electricity price. While in the empirical estimation I model supply from all technologies jointly, in the theoretical framework presented here I treat renewable and thermal generation separately. Renewable output, $\bar{R}_t$, is taken as exogenous and non-dispatchable: all electricity produced by wind and solar plants must be supplied to the market.

Thermal generators cover this residual demand, and their behavior is summarized by an increasing supply function $S^{\text{thermal}}_{t,m}(p_{t,m})$. A key simplifying assumption of the model is that thermal units do not engage in strategic interaction with the battery operator. Instead, they are treated as residual suppliers that adjust output as needed to satisfy net demand at the prevailing price. In other words, thermal generators are not assumed to best respond to the batterys charging and discharging decisions.

At the beginning of each period, the operator observes the status of the transmission network through the congestion indicator $\mathbb{M}_t$, which equals one when lines are congested and zero when the market is fully integrated. In an uncongested grid, every plant operating in the market competes with the full set of generators to serve market-wide load. Each plant produces just a small fraction of the total electricity demanded. Plants can hardly exercise market power in this situation and the market is assumed to be perfectly competitive. In these conditions, the battery operator is assumed not to internalize the effect on the electricity price induced by its operations. On the other hand, when lines are congested the grid splits into multiple local markets. Each plant faces only a handful of competitors to serve a share of total load. With fewer competitors and a smaller load to cover, a plant's opportunity to act strategically grows. When $\mathbb{M}_t = 1$, I assume that the battery operator is a strategic player and internalizes the effect of charging and discharging the battery on the local price.

When choosing $b_{t,j}$, the operator forms expectations about future electricity prices, with uncertainty arising solely from future renewable production. The problem of operator j at time t can therefore be expressed by the following Bellman equation, where the indicator $\mathbb{1}_{j=co}$ distinguishes between a co-owned and a standalone battery operator.

$$V(c_t, t) = \max_{b_t \in B(c_t)} \Big(p_{t,m}(b_t) \cdot \mathbb{M}_t + p_{t,m} \cdot (1 - \mathbb{M}_t) \Big) \cdot \Big(\mathbb{1}_{j=co} \bar{R}_{t,j} + b_t \Big) + \beta \mathbb{E}_{\bar{R}} \Big[V(c_{t+1}, t+1) \Big] \tag{1}$$

s.t.

$$\frac{E - c_{t,j}}{\gamma} \geq b_{t,j} \geq -\gamma c_{t,j} \tag{2}$$

$$\frac{1}{4} P \geq |b_{j,t}| \tag{3}$$

$$c_{t+1} = \ c_t - \gamma \, b_t \cdot \mathbb{1}_{b<0} - \frac{b_t}{\gamma} \cdot \mathbb{1}_{b>0} \tag{4}$$

Equation (1) states that, in each period t, operator j chooses the energy $b_{t,j}$ (in MWh) to inject into or withdraw from the grid, with $b_{t,j} < 0$ indicating charging. The decision is constrained by the technical specifications of the battery: its power capacity P (MW), its duration h (hours), its energy capacity E (MWh), and by its round-trip efficiency γ^2. Within this framework, the first inequality in equation (1) ensures that charging does not exceed the remaining energy capacity: the left-hand side, $\frac{E - c_{t,j}}{\gamma}$, limits purchases once charging losses are considered, while the right-hand side, $-\gamma c_{t,j}$, prevents discharging more energy than is stored, net of discharging losses. The second constraint caps instantaneous power flow at the rating P, expressed in MWh since each interval is one quarter of an hour. Finally, the last equation specifies the law of motion governing the batterys state of charge.

In electricity markets, the operator must constantly balance inelastic gross demand $\bar{D}_t$ with supply and with the electricity traded by the battery:

$$\bar{D}_{t,m} = b_{j,t} + \bar{R}_{t,m} + S^{thermal}_{t,m}(p_{t,m}) \tag{5}$$

The thermal supply function $S_{t,m}(p)$ is strictly increasing in price (hence invertible). This is standard in electricity markets: higher prices bring progressively more (and more expensive) thermal units online along the merit order, so total thermal output rises with

p. Prices can be written accordingly as

$$p_{t,m}(Q_t) = S_{t,m}^{thermal^{-1}}(Q_t) = S_{t,m}^{thermal^{-1}}(\bar{D}_{t,m} - \bar{R}_{t,m} - b_{j,t}), \tag{6}$$

where Q_t denotes total thermal production. The corresponding first-order condition with respect to b_t can be written as

$$\mathbb{M}_t \left[p_{t,m} - \frac{1}{\epsilon_s} \frac{\left(\bar{R}_{t,j} \mathbb{1}_{j=co} + b_t\right) p_{t,m}}{Q_t} \right] + (1 - \mathbb{M}_t) p_{t,m} + \beta \frac{\partial \mathbb{E}_{\bar{R}} \left[V(c_{t+1}) \right]}{\partial b_t} + \mathbf{g}' \boldsymbol{\mu} = 0, \tag{7}$$

where $\mathbf{g}'\boldsymbol{\mu}$ denotes the inner product of the vector of constraint function derivatives with the corresponding Lagrange multipliers.

Equation (7) shows how three market primitives—the supply elasticity ϵ_s, the co-owned plants renewable output $\bar{R}_{t,j}$, and the congestion indicator $\mathbb{M}_t$—generate ownership specific operational incentives. When a standalone battery operates in a congested market ($\mathbb{M}_t = 1$), the operator internalizes only the price effect of its own utilization on the arbitraging profits, captured by the term $-\frac{1}{\epsilon_s} \frac{b_t p_{t,m}}{Q_t}$. When the battery is charging ($b_t < 0$), the term reflects the incremental cost of making stored electricity more expensive; when the battery is discharging ($b_t > 0$), it reflects the reduction in revenues from selling previously stored electricity at a lower price.

By contrast, a co-owned battery operator also faces the additional term $-\frac{1}{\epsilon_s} \frac{\bar{R}_{t,j} p_{t,m}}{Q_t}$, which captures the impact of battery utilization on renewable sales revenues. Charging that raises off-peak prices increases the revenues earned on renewable output in that period, while discharging that depresses peak prices reduces the revenues from renewable sales. Thus, co-ownership creates an additional channel through which battery decisions affect profits: the operator balances arbitrage revenues not only against the costs of stored energy, but also against the induced change in renewable revenues across periods.

Calibration

I calibrate the model with Texas RTM data from 1 January to 30 December 2021. There are three reasons to focus on this interval. First, during this year battery storage was still limited to a handful of small projects used mainly in ancillary-service markets; in the RTM, batteries were dispatched mostly during extreme price spikes. Secondly, aside from the February Storm Uri event, 2021 reflects a return to normal, post-COVID load patterns. Finally, it offers a representative picture of network stress: transmission-line congestion occurred on roughly 70% of days.

To calibrate demand and supply, I use ERCOT's "60-Day SCED Disclosure Reports", which provide plant-level data on bids and realized output at 15-minutes intervals. In the Real-Time Market (RTM), demand is assumed to be perfectly inelastic. Consequently, I measure demand as the total electricity produced within the relevant market—either the statewide system or the local market defined by congestion events.

Aggregate supply curves are constructed by combining thermal generators' bid offers with renewable plant potential output. Thermal generators can submit up to 35 price-quantity pairs in their offer curves, which I aggregate across units to form the thermal supply schedule. I model the renewable part of the supply curve using potential rather than realized production to explicitly incorporate curtailment. The "60-Day SCED Disclosure Reports" include each renewable plant's High Sustainable Limit (HSL)—the maximum electricity output that a renewable plant can produce given current resource availability (wind speed or solar irradiation). The renewable segment of the supply curve has a length equal to the sum of HSL values across all renewable plants in the relevant market, with wind generation offered at -$31.5/MWh (reflecting eligibility for the federal Production Tax Credit) and solar generation offered at $0/MWh.

Energy storage plays an increasingly important role in this environment. Battery Energy Storage Systems (BESS), almost exclusively lithium-ion, are expanding rapidly in Texas and are expected to rank second only to solar in capacity additions over the next decade. To calibrate their characteristics, I use data on advanced-stage projects in Texas. The resulting parameters imply a median capacity ratio of 0.35 relative to the associated renewable plant, a median duration of 1.5 hours, and a round-trip efficiency of $\gamma^2 = 0.9$.

To construct plant-specific local markets and define congestion events, I use ERCOTs five-minute data on LMPs by Resource Nodes, Load Zones and Trading Hubs. Local markets are defined by examining the pairwise differences in LMPs between the node where the battery is assumed to operate and all other nodes across the year. This procedure identifies the set of nodes whose prices move together, providing a market definition specific to each plant. To identify congestion events, I analyze the cross-sectional distribution of nodal LMPs in each period.

Finally, To compute emissions, I use plant-level data from the EIA 923 form for 2021, which reports monthly fuel consumption quantities, heat content per unit of fuel (MMBtu per physical unit), and net electricity generation for each generating unit. I calculate plant-specific heat rates (MMBtu per MWh) by dividing total fuel consumption in MMBtu by total net generation across all months. I combine these heat rates with emission factors from the EPA's GHG Emission Factors Hub (U.S. Environmental Protection Agency (2021)), which provides CO_2 emission rates per MMBtu of fuel consumed. This approach allows me to compute plant-specific CO_2 emissions per MWh of electricity generated and to track how battery operations affect emissions from different generation technologies. I value emissions using a social cost of carbon of $185 per ton of CO_2 (Rennert et al. (2022)).

5 Results

This section presents results from the simulated empirical model. I first describe the operational patterns of standalone batteries. I then identify the market conditions under which co-owned batteries' operational incentives diverge from standalone batteries and assess how these differences affect electricity prices. Next, I examine how battery deployment affects renewable curtailment and carbon emissions. Finally, I analyze the impact on consumer surplus and battery profitability over a 20-year lifetime and discuss the policy implications for subsidy design.

To present results, I classify batteries into five groups according to the characteristics

Group	Off-peak Inelastic Supply	Off-peak Ren. Output	N Batt.	Avg. Storage MWh	Avg. Ren. MW	Solar %	Wind %	Avg. Loc. Mkt. Size
1	Freq.	High	17	73.8	140.6	58.8	41.2	21.4
2	Freq.	Low	11	48.0	91.4	27.3	72.7	20.8
3	Infreq.	High	11	41.5	79.1	54.5	45.5	13.6
4	Infreq.	Low	18	63.2	120.4	72.2	27.8	24.5
5	Never	Any	161	64.5	122.9	13.7	86.3	11.3

Notes: Column "Group" reports the group identifier. **Group 1** = Frequent inelastic supply / high renewable output, **Group 2** = Frequent inelastic supply / low renewable output, **Group 3** = Infrequent inelastic supply / high renewable output, **Group 4** = Infrequent inelastic supply / low renewable output, **Group 5** = Never inelastic supply curve. "N Batt." is the number of simulated batteries in each group. "Avg. Storage MWh" is average battery capacity. "Avg. Ren. MW" is average renewable capacity of the plant located at the same node of the battery. "% Solar and "% Wind" indicate technology shares in each group. "Avg. Loc. Mkt. Size" is the average number of generating resources in the local market in which batteries operate when transmission lines are congested.

Table 1: Summary statistics, by group.

of the nodes where they are located during congested periods. The classification relies on two dimensions. First, how often the local supply curve is inelastic ($\epsilon_s \leq 1$). I compute the fraction of congested periods with inelastic supply at each node. Nodes are classified as "frequent" if their fraction exceeds the cross-node median and "infrequent" otherwise. Second, how often during congested periods the renewable plant located at the battery's node produces above its median output computed across all fifteen-minute periods (congested and non-congested). Groups 1 and 2 consist of nodes frequently exposed to inelastic supply, distinguished by whether renewable output is typically high (Group 1) or low (Group 2). Groups 3 and 4 are exposed to inelastic supply less frequently, again separated by renewable output levels. Finally, Group 5 includes nodes that, when congested, never face an inelastic supply curve. Table 1 reports summary statistics for each group.

Battery Operations

Panel A of Table 2 presents results on the behavior of standalone battery operators during the simulated year. On average, batteries complete slightly more than one and a half full charge-discharge cycles per day. Operators seeking to maximize arbitrage prof-

Group	Off-peak Inelastic Supply	Off-peak Ren. Output	Daily Cycles	Congestion (%)	Buy in Uncong. (%)	Sell in Uncong. (%)
Panel A: Standalone Batteries						
1	Freq.	High	1.66	7.15	74.50	95.93
2	Freq.	Low	1.52	5.09	83.37	95.63
3	Infreq.	High	1.71	7.34	76.09	97.43
4	Infreq.	Low	1.46	2.67	90.00	98.76
5	Never	Any	1.40	8.85	71.66	97.32
Panel B: Co-owned Batteries						
1	Freq.	High	1.68	7.15	73.41	95.98
2	Freq.	Low	1.53	5.09	82.67	95.85
3	Infreq.	High	1.72	7.34	75.85	97.39
4	Infreq.	Low	1.47	2.67	89.64	98.76
5	Never	Any	1.40	8.85	71.61	97.26

Notes: **Group 1** = Frequent inelastic supply / high renewable output, **Group 2** = Frequent inelastic supply / low renewable output, **Group 3** = Infrequent inelastic supply / high renewable output, **Group 4** = Infrequent inelastic supply / low renewable output, **Group 5** = Never inelastic supply curve. "Daily Cycles" reports the average number of complete charge-discharge cycles per day. "Congestion" reports the percentage of time periods experiencing transmission congestion. "Buy in Uncong." is the percentage of electricity purchased during uncongested periods (the remainder is bought during congested periods). "Sell in Uncong." is the percentage of electricity sold during uncongested periods (the remainder is sold during congested periods).

Table 2: Battery operations, by ownership type and group

its target uncongested periods for both charging and discharging. Standalone batteries purchase most of their electricity during uncongested periods (ranging from 72 to 89 percent across groups). Operators target these periods because the supply curve is more elastic, implying that battery charging induces a modest price increase. Group 5 exhibits the highest share of electricity bought during congested periods. Batteries in this group operate in areas where, during congestion, generating resources consist almost exclusively of renewable plants, resulting in relatively elastic supply conditions whether congested or not. Groups 1 and 3 show the second-highest share of charging during congested periods, reflecting that renewable production during congested hours is particularly abundant in the local markets where they operate, which increases the likelihood that renewables are marginal producers during congestion, resulting in more elastic local supply curves.

Similarly, when discharging, operators target uncongested peak periods, releasing 95 to 99 percent of stored electricity during these periods. Operators avoid congested peak hours because the supply curve is particularly inelastic during these periods, meaning that discharging would generate substantial price reductions that erode arbitrage profits by lowering revenues on all stored electricity sold during discharge.

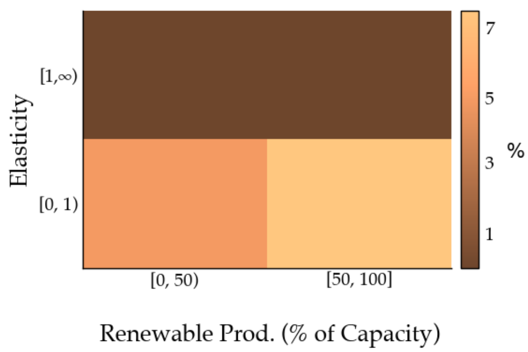
Panel B of Table 2 presents the operational patterns of co-owned batteries. Relative to standalone operations, three key results emerge. First, co-owned batteries complete nearly identical daily cycles, indicating that ownership does not substantially alter overall utilization rates. Second, co-owned batteries in Groups 1 and 2, which more frequently face inelastic supply curves during congested off-peak periods, shift the timing of approximately 1.3 percentage points of charging from uncongested to congested off-peak periods. This reallocation reflects strategic charging incentives during congestion events to raise off-peak prices and increase renewable revenues. Third, co-owned batteries have even stronger incentives to avoid congested periods when discharging, as a price reduction negatively affects both arbitrage profits and revenues from selling renewable electricity.

Divergent Batteries Operational Incentives During Congested Off-peak Periods

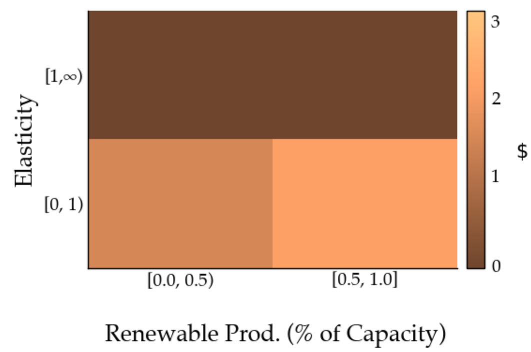
The reallocation of charging to congested off-peak periods documented in Table 2 reflects strategic behavior by co-owned operators. A key feature of the model is that battery operators internalize price variations only when transmission congestion creates local markets with limited competition. In these periods, co-owned operators internalize how charging raises off-peak prices and thereby increases the value of contemporaneous renewable output. Figure 4 illustrates how supply elasticity and renewable production interact to generate these divergent operational incentives during congested off-peak periods. I classify these periods into four groups based on the two factors that explain differences in battery utilization across ownership: the elasticity of the local supply curve and the level of renewable output from the co-owned plant.

Co-owned batteries systematically charge more than standalone units when they operate in congested local markets with inelastic supply. Panel 4a shows that the gap widens with renewable output: when plants operate at a high share of capacity, co-owned batteries use about 7 percent more of their rated power than standalone units. In these cases, co-owned charging also raises local off-peak prices, by up to \$3/MWh relative to the standalone case (Panel 4b). By contrast, when the local supply curve is elastic ($\epsilon_s > 1$), both the utilization difference and the associated price effects largely disappear.

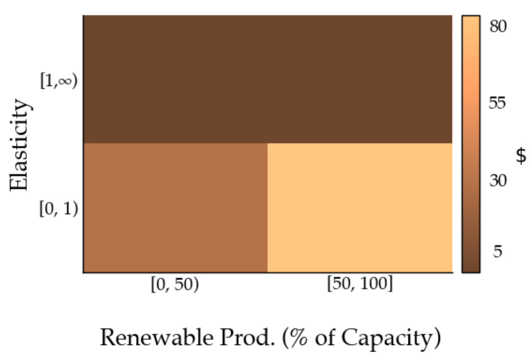
This pattern reflects the strategic behavior of co-owned operators, who deploy the battery to raise off-peak prices and thereby increase renewable revenues. When supply is inelastic, even modest charging pushes prices upward, boosting revenues on all renewable output sold in that period. Panels 4c and 4d illustrate this mechanism. When renewable plants operate at a high share of their capacity co-ownership increases renewable sales revenues by as much as \$80 per MWh of storage capacity, while charging costs rise by up to \$18. Because the revenue gains from renewable sales exceed the additional storage costs, co-owned batteries find it profitable to sacrifice part of their arbitrage margins in order to raise the overall profitability of the plant.



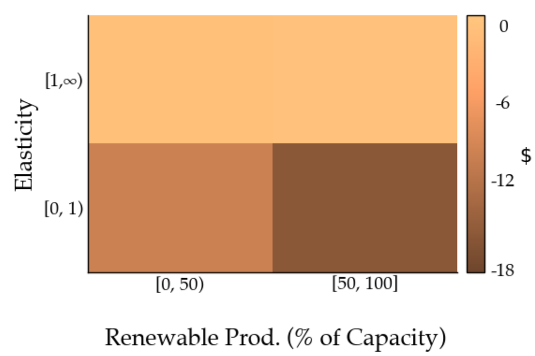
(a) Average percentage difference in utilized rated power (co-owned vs. standalone)



(b) Average difference in price (co-owned vs. standalone)



(c) Average increase in Renewable sales profit under co-ownership (co-owned vs. standalone)



(d) Average difference in stored electricity cost (co-owned vs. standalone)

Figure 4: Battery operational incentives

Group	RW_c (GWh) (1)	RW_s (GWh) (2)	NG_c (tons) (3)	NG_s (tons) (4)	CL_c (tons) (5)	CL_s (tons) (6)	DS_c (tons) (7)	DS_s (tons) (8)	ΔCO_2^c ($) (9)	ΔCO_2^s ($) (10)
1	2.29	2.26	-619	-615	376	388	-305	-305	-6,064	-5,888
2	0.89	0.87	-245	-248	173	177	-173	-173	-4,229	-4,194
3	0.75	0.74	-372	-370	321	320	-234	-235	-5,873	-5,887
4	0.05	0.05	-174	-174	200	204	-154	-155	-1,874	-1,843
5	1.25	1.24	-430	-430	319	320	-259	-259	-4,618	-4,603

Notes: Numbers represent variation with respect to the baseline scenario of no-battery operating in the market. RW reports changes in renewable curtailment (in GWh). NG, CL, and DS report changes in CO_2 emissions from natural gas (NG), coal (CL), and diesel (DS) generation (in tons of CO_2). ΔCO_2 reports the change in total carbon costs ($185 per MWh of storage capacity). Superscript c denotes co-owned batteries, s denotes standalone batteries. Negative values indicate emission or cost reductions; positive values indicate increases. See Table 1 for group definitions.

Table 3: Environmental impacts by ownership type and group

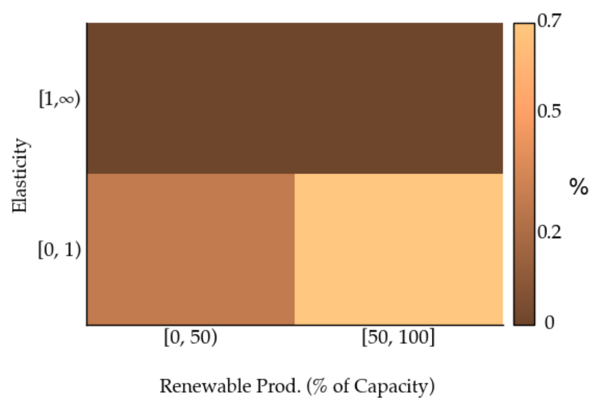


Figure 5: Average percentage of additional rated power used to store otherwise curtailed renewable electricity (co-owned vs. standalone)

Battery Impact on Renewable Electricity Curtailment and Emissions

Columns (1) and (2) of Table 3 report the impact of battery deployment on renewable curtailment. Curtailment reduction does not differ meaningfully across ownership structures, with co-owned and standalone batteries reducing curtailment by nearly identical amounts across all groups. This similarity reflects the characteristics of local markets when curtailment occurs. Curtailment arises during congested off-peak periods when renewable plants are marginal producers and supply is relatively elastic, conditions under which operational incentives tend to coincide across ownership types.

However, co-owned batteries in Groups 1 and 2—which are used strategically more often—reduce curtailment marginally more than standalone batteries. As documented in the previous section, during congested off-peak periods co-owned batteries use approximately 7 percent more of their rated power capacity than standalone batteries. Figure 5 decomposes this additional utilization, showing that roughly 10 percent of this gap comes from storing otherwise curtailed renewable electricity (roughly 0.7 percentage points of additional rated power used).

Columns (3) through (8) of Table 3 report changes in tons of CO_2 emissions by fuel type. Battery operations increase coal emissions but reduce natural gas and diesel emissions under both ownership structures. This pattern reflects how batteries shift production between marginal producers across different periods. By charging during uncongested off-peak periods and discharging during uncongested peak periods, batteries increase production from marginal producers in off-peak hours and reduce production from marginal producers in peak hours. During off-peak periods, marginal producers are typically coal or natural gas plants, meaning battery charging increases output from these technologies. Moreover, during congested off-peak periods when renewable plants are also marginal producers, batteries operating in the same local market absorb curtailed renewable electricity that would otherwise be wasted. When batteries discharge during peak periods, they displace marginal producers—predominantly natural gas and diesel generators during these hours. The net effect across all periods is that renewable and coal production increase, while natural gas and diesel production decrease. Although natural gas plants are marginal during some off-peak periods and thus contribute to battery charging, the displacement of natural gas during peak discharge exceeds this contribution, resulting in a net reduction in natural gas production. Coal emissions increase across all groups (columns 5-6), ranging from 173 to 388 tons of CO_2 per MWh of storage capacity annually. Natural gas emissions decline in all groups (columns 3-4), with reductions between 174 and 600 tons annually, and diesel emissions similarly decrease (columns 7-8), with reductions between 154 and 305 tons annually.

Columns (9) and (10) report the total change in carbon costs, valued at $185 per ton of CO_2. Despite increasing coal production, battery deployment reduces aggregate carbon costs across all groups under both ownership structures. While batteries charge during periods when coal plants operate, they simultaneously reduce renewable curtailment by absorbing otherwise-wasted clean electricity. The net effect is that emission reductions from displaced natural gas and diesel generation, combined with avoided curtailment, more than compensate for the increase in coal emissions. Battery deployment reduces carbon costs by $1800 to $6000 per MWh of storage capacity annually across groups. Importantly, these net emission reductions occur even though round-trip efficiency losses cause batteries to increase off-peak generation by more than they reduce peak generation. Co-owned batteries in Group 1 generate 3 percent larger carbon cost reductions than standalone batteries. This reflects the higher avoided curtailment documented in columns (1) and (2), where co-owned batteries absorb slightly more zero-emission renewable electricity during strategic charging periods. This result provides modest evidence that market power can generate offsetting environmental benefits when negative externalities are present (Buchanan (1969), Asker et al. (2024)). Strategic utilization under co-ownership, while raising prices, generates marginally larger environmental benefits by avoiding more curtailed renewable electricity and generating fewer carbon emission.

Consumer Surplus and Battery Profitability

The operational differences documented in the previous sections occur throughout the simulated year. To assess their economic significance, I now examine their cumulative impact on consumer surplus and battery profitability over a 20-year assumed battery lifetime, without accounting for battery degradation.

Table 4 reports the change in consumer surplus from introducing a battery relative to the no-battery baseline over a 20-year battery lifetime (columns 1 and 2). Because demand is perfectly inelastic in wholesale electricity markets, variations in consumer surplus are equivalent to variations in total electricity costs. Batteries increase consumer surplus under both ownership structures, with each MWh of capacity raising consumer surplus by roughly $200k to $500k. This increase reflects the arbitrage mechanism operating under both ownership types. Batteries charge primarily during off-peak periods and discharge during peak periods, with most transactions occurring in uncongested

Group	Off-peak Inelastic Supply	Off-peak Ren. Output	ΔCS_c (1)	ΔCS_s (2)	ΔCO_2^c (3)	ΔCO_2^s (4)	Π_c (5)	Π_s (6)
1	Freq.	High	245	244	-78	-76	75	43
2	Freq.	Low	372	392	-54	-54	54	42
3	Infreq.	High	407	406	-75	-76	47	46
4	Infreq.	Low	247	249	-24	-24	17	16
5	Never	Any	363	363	-59	-59	31	34

Notes: **Group 1** = Frequent inelastic supply / high renewable output, **Group 2** = Frequent inelastic supply / low renewable output, **Group 3** = Infrequent inelastic supply / high renewable output, **Group 4** = Infrequent inelastic supply / low renewable output, **Group 5** = Never inelastic supply curve. All amounts are in thousands of dollars per MWh of storage capacity over 20 years. Columns (1)–(2) report the average change in consumer surplus relative to the no-battery baseline: ΔCS_c for co-owned batteries, ΔCS_s for standalone batteries. Columns (3)–(4) report the change in carbon costs: ΔCO_2^c for co-owned, ΔCO_2^s for standalone (negative values indicate cost reductions). Columns (5)–(6) report average lifetime operating profits: Π_c for co-owned, Π_s for standalone.

Table 4: Consumer surplus, carbon costs, and battery profitability by group (amounts in $1000s per MWh)

periods. Because supply is more elastic and demand is lower during off-peak periods, the increase in electricity costs from charging is smaller than the reduction in electricity costs from discharging during peak periods.

Comparing across ownership types, consumer surplus gains are similar. This result holds even for batteries in Groups 1 and 2, which are more frequently exposed to inelastic supply during congested off-peak periods and are used strategically by co-owned operators. In these groups, co-owned batteries generate marginally lower consumer surplus gains—$1k less in Group 1 and $14k less in Group 2 per MWh of capacity—but the differences remain small relative to total gains. The limited impact of strategic utilization reflects offsetting market effects. Co-owned batteries in these groups reallocate part of their charging to congested off-peak periods, where more inelastic supply generates larger price increases per unit purchased. However, these larger price impacts affect only local market demand. Conversely, standalone batteries charging in uncongested periods induce smaller price increases that apply to system-wide demand. The lower elasticity in congested periods is thus offset by the smaller market size affected, leaving consumer surplus gains broadly similar across ownership types.

By contrast, co-ownership substantially increases battery profitability compared with standalone ownership in groups where batteries are often used strategically. Standalone batteries earn profits solely from arbitrage, whereas co-owned units also internalize the additional revenues generated by selling renewable output at higher off-peak prices once the battery is introduced. Profitability of a co-owned battery is defined as the lifetime sum of arbitrage profits and incremental renewable revenues relative to the no-battery baseline. Table 4 (columns 5 and 6) shows that strategic use of the battery under co-ownership substantially raises earnings. In Group 1, lifetime profits reach \$75k under co-ownership, against \$43k for standalone units. In Group 2, the advantage persists, though it is smaller (\$54k versus \$42k). When inelastic supply is infrequent (Groups 3 and 4), the two ownership types yield similar outcomes. These profitability estimates reflect only arbitrage revenues from the energy market. Robertson et al. (2025) documents that in ERCOT, batteries derive most revenues from ancillary services markets, which are not modeled here, suggesting that actual battery profitability may be substantially higher than these estimates.

Despite these differences, neither ownership regime delivers sufficient profits to cover investment costs. Assuming capital expenditures of \$250k per MWh[1], projects require subsidies to break even. Even under co-ownership, where profitability is highest, investment remains unviable at current cost levels.

Although investment is not privately viable, subsidizing batteries remains desirable from a consumer's perspective. Battery deployment generates both positive consumer surplus gains from reduced electricity costs and environmental benefits from lower carbon emissions. Combined, these benefits on average exceed the assumed capital cost of \$250k per MWh in all groups, making battery deployment socially desirable even when not privately profitable. This result reflects the "missing money" problem discussed by Joskow (2008), namely the tendency of energy-only electricity markets to generate revenues that are too low to sustain investments which, while beneficial from a social welfare perspective, are not privately profitable. The positive net social benefits justify

[1]The benchmark capital cost is based on BloombergNEF data and on Ziegler, M. S., and Trancik, J. E., "Re-examining rates of lithium-ion battery technology improvement and cost decline," *Energy & Environmental Science*, 2021.

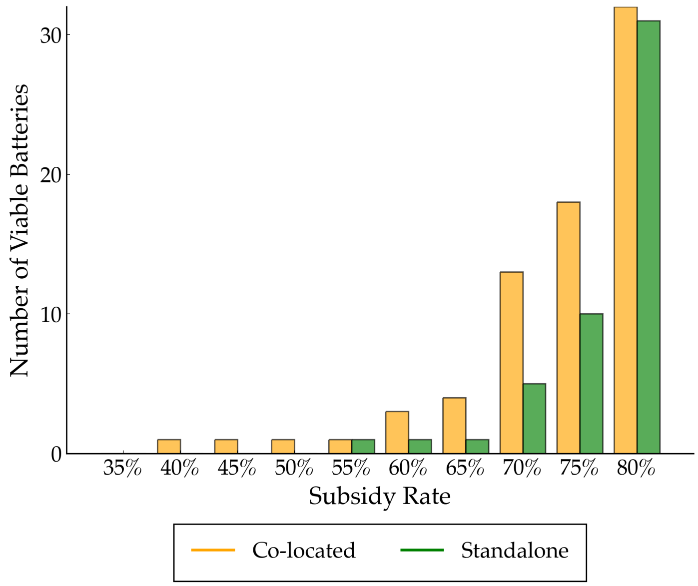


Figure 6: Number of profitable Batteries, by subsidy rate and ownership type

public subsidies to bridge the gap between private profitability and social value.

When policymakers implement uniform subsidy schemes that provide identical support to all projects, higher profitability under co-ownership translates into more simulated batteries being profitable at moderate subsidy rates. Figure 6 shows how many batteries become profitable at different rates, expressed as percentages of capital costs. For subsidy rates below 80 percent, the number of profitable co-owned batteries across simulations is higher than that of standalone batteries, reflecting higher operating profits from strategic utilization.

6 Conclusion

This paper examines how ownership structure shapes battery operation and market outcomes in ERCOT. I develop a simple model that isolates three primitives—transmission congestion occurrence, the elasticity of supply, and the timing of renewable output—and embed it in a day-long dynamic simulation calibrated to ERCOT's 2021 Real-Time Market.

The first result is that co-ownership changes operational incentives. When congestion fragments the grid into local markets with inelastic supply, co-owned operators internalize the price effect of charging on contemporaneous renewable revenues and therefore store more energy. By contrast, peak period behavior is largely uniform across ownership because batteries discharge mostly in uncongested periods, when operators do not internalize price effects.

Strategic charging under co-ownership does not substantially alter consumer surplus, renewable curtailment, or carbon emissions costs compared to standalone operation. At the same time, profitability is substantially higher under co-ownership because operators capture not only arbitrage revenues but also additional renewable revenues generated by the higher off-peak prices.

These findings carry three implications for policy design. First, storage is not privately profitable on average at assumed capital costs, so investments would not occur without external support. Second, from the consumers' perspective, subsidizing batteries is desirable under both ownership structures, since the present value of consumer surplus gains typically exceeds the subsidies required, reflecting the classic missing money problem in energy-only markets. Third, because co-ownership raises profitability, a given subsidy rate makes more batteries profitable than under standalone ownership.

One caveat qualifies these conclusions. The analysis places batteries at nodes with renewable plants, consistent with typical co-owned siting, but standalone projects in practice could choose locations more freely—for example, at major load centers. This restriction may understate the relative advantage of standalone ownership.

In sum, who owns the battery matters when the grid is frequently locally constrained. Co-ownership provides a mechanism to influence prices and increase renewable production value, boosting plant profitability and thereby lowering the subsidy support required to make projects privately viable. These findings highlight that ownership design is central to determining how storage interacts with electricity markets. By shaping both operational incentives and investor profitability while leaving consumer and environmental benefits largely unchanged, ownership structure becomes a key consideration for subsidy policy and market regulation.

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Appendix

A1 Identifying Local Markets During Transmission Congestion

In the empirical model, I assume that when transmission constraints bind, the electricity market fragments into multiple local markets. This section describes the procedure used to identify which nodes operate in the same local market during congested periods.

A1.1 Methodology

The identification strategy exploits variation in Locational Marginal Prices (LMPs) to determine market boundaries. When transmission constraints do not bind, the market operates as a single integrated system and LMPs converge across all nodes. However, when congestion occurs, transmission constraints prevent electricity from flowing freely across the network, causing LMPs to diverge across regions. Nodes that remain price-coupled during congestion—indicated by similar LMPs—operate in the same local market.

For each node i in the ERCOT network, I identify the subset of nodes that operate in the same local market during congested periods using the following procedure:

Step 1: Computing pairwise price differences. Using five-minute interval LMP data for all nodes throughout 2021, I compute the absolute LMP difference for every pair of nodes (i, j) at each time interval t:

$$\Delta LMP_{ij,t} = |LMP_{i,t} - LMP_{j,t}|$$

Step 2: Identifying co-location events. Following Woerman (2019), I classify two nodes as operating in the same market when their LMP difference is less than $1/MWh. For each pair of nodes, I count the number of five-minute intervals in which this condition holds:

$$N_{ij} = \sum_{t=1}^{T} \mathbb{1}(\Delta LMP_{ij,t} < 1)$$

where T represents all five-minute intervals in 2021 and $\mathbb{1}(\cdot)$ is an indicator function.

Step 3: Defining local market membership. The procedure in Step 2 generates a symmetric matrix N of dimension $n \times n$, where n is the number of nodes in the network. Each element N_{ij} represents the number of times nodes i and j operated in the same market throughout the year. I then apply a threshold τ such that node j is considered part of node i's local market during congestion if:

$$N_{ij} \geq \tau$$

Step 4: Geographic validation. To verify that identified local markets reflect genuine transmission constraints rather than spurious price correlations, I compute the geographic distance between all node pairs classified as operating in the same local market. Nodes separated by distances exceeding a thershold δ (in kilometers) are excluded from the local market definition, as such large distances would be inconsistent with binding transmission constraints creating localized price differences.

A2 Identifying Transmission Line Congestion Events

This section describes the procedure used to identify periods when transmission constraints bind and isolate local markets from the rest of the ERCOT system. The identification strategy exploits price differentials between nodes within a local market and nodes in the broader system to detect when transmission congestion fragments the grid.

A2.1 Methodology

For each fifteen-minute interval t and each node i where a battery is simulated, I implement the following procedure:

Step 1: Define the local market. Using the local market definitions constructed in Appendix A1, I identify the set of nodes $\mathcal{L}_i$ that operate in the same local market as node i during congested periods. This set includes all nodes j for which the co-location frequency N_{ij} exceeds the threshold τ established in the previous section.

Step 2: Compute local market price. I calculate the median Settlement Point Price (observed prices use by ERCOT to settle electricity transaction) across all nodes in the local market at time t:

$$p_{i,t}^{local} = \text{median}_{j \in \mathcal{L}_i} \{LMP_{j,t}\}$$

The median is used rather than the mean to ensure robustness to outlier prices that may occur at individual nodes due to measurement error or highly localized constraints.

Step 3: Define the external market. To determine whether the local market is separated from the rest of the system, I identify a set of geographically proximate nodes that are not part of the local market. First, I compute the geographic center of the local market as the median longitude and latitude across all nodes in $\mathcal{L}_i$:

$$(\text{lon}_i^{center}, \text{lat}_i^{center}) = \left(\text{median}_{j \in \mathcal{L}_i} \{\text{lon}_j\}, \text{median}_{j \in \mathcal{L}_i} \{\text{lat}_j\}\right)$$

I then construct the external market set $\mathcal{E}_i$ consisting of all nodes that are (1) not in the local market ($j \notin \mathcal{L}_i$) and (2) located within 200 kilometers of the local market center. The 200-kilometer radius ensures that the comparison reflects nearby market conditions while excluding nodes too distant to be affected by the same transmission constraints.

Step 4: Compute external market price. I calculate the median LMP across nodes in the external market:

$$p_{i,t}^{external} = \text{median}_{j \in \mathcal{E}_i} \{LMP_{j,t}\}$$

Step 5: Identify congestion events. Transmission constraints are classified as binding at node i during period t if the absolute price difference between the local and external markets exceeds a threshold π:

$$\text{Congested}_{i,t} = \mathbb{1}\left(|p_{i,t}^{local} - p_{i,t}^{external}| > \pi\right)$$

This threshold is chosen to identify periods when transmission constraints create economically meaningful price separations while filtering out small price differences that may reflect normal within-market variation rather than binding constraints.

A3 Emissions Calculation Methodology

This section describes the procedure used to compute CO_2 emissions from electricity generation in the simulations.

A3.1 Data Sources

Emissions calculations combine two primary data sources:

1. **EIA-923 Form (2021):** Monthly plant-level data reporting:
   - Fuel consumption quantities in physical units (tons for coal, thousand cubic feet for natural gas, gallons for fuel oil)
   - Heat content per unit of fuel (MMBtu per physical unit)
   - Net electricity generation (MWh)
2. **EPA Emission Factors:** Standard CO_2 emission rates per MMBtu of fuel consumed from EPA (2014):
   - Coal (electric power sector average): 205.3 lbs CO_2/MMBtu
   - Natural Gas: 117.0 lbs CO_2/MMBtu
   - Distillate Fuel Oil (diesel): 161.3 lbs CO_2/MMBtu

A3.2 Heat Rate Calculation

For each generating unit i consuming fuel type f, I calculate the annual heat rate $HR_{i,f}$ as:

$$HR_{i,f} = \frac{\sum_{m=1}^{12} \text{Fuel MMBtu}_{i,f,m}}{\sum_{m=1}^{12} \text{Netgen}_{i,m}} \tag{8}$$

where $\text{Fuel MMBtu}_{i,f,m}$ is the total fuel energy consumed (in MMBtu) by unit i using fuel f in month m, and $\text{Netgen}_{i,m}$ is the net electricity generation (in MWh) from unit i in month m.

The fuel energy consumed is calculated as:

$$\text{Fuel MMBtu}_{i,f,m} = \text{Quantity}_{i,f,m} \times \text{MMBtuPerUnit}_{i,f,m} \tag{9}$$

where $\text{Quantity}_{i,f,m}$ is the physical quantity of fuel consumed and $\text{MMBtuPerUnit}_{i,f,m}$ is the heat content per physical unit.

Only thermal generating units (coal, natural gas, and petroleum products) are included in the heat rate calculation, as renewable and nuclear plants do not consume fossil fuels.

A3.3 Emission Rate Calculation

The emission rate for unit i using fuel f (in tons of CO_2 per MWh) is:

$$ER_{i,f} = \frac{EF_f \times HR_{i,f}}{2000} \tag{10}$$

where EF_f is the emission factor for fuel type f in lbs CO_2/MMBtu, $HR_{i,f}$ is the heat rate in MMBtu/MWh, and division by 2000 converts pounds to short tons.

A3.4 Emissions in Simulations

In each 15-minutes simulation interval t, I compute emissions for each generating unit based on changes in output relative to the baseline (no-battery) scenario:

$$\Delta E_{i,f,t} = \Delta Q_{i,t} \times ER_{i,f} \times 0.25 \tag{11}$$

where $\Delta Q_{i,t}$ is the change in output (in MW) for unit i in interval t, $ER_{i,f}$ is the emission rate, and multiplication by 0.25 converts MW over a 15-minutes interval to MWh.

Total emissions changes are aggregated by fuel type and scenario (co-owned versus standalone) to compute the annual emission impacts reported in the results.