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

Pietro Visaggio*

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 ERCOT 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. Because of this strategic behavior, co-owned batteries reduce consumer surplus gains by approximately $16,000 per MWh of installed storage capacity over their lifetime relative to standalone batteries, but earn $36,000 per MWh higher profits. Market conditions do not generate enough profits for battery investment to be viable, regardless of ownership. Yet if subsidized, co-owned projects yield the highest net consumer surplus, because the additional revenues they generate reduce the required subsidy sufficiently to outweigh their smaller gross consumer gains. Co-owned projects deliver roughly $1.38 of net consumer surplus for every $1.00 of subsidy, compared with about $1.00 per $1.25 for standalone projects.*(JEL L94, Q40, Q42, Q48, Q55)*

*Boston College. E-mail: visaggip@bc.edu. Website: www.pietrovisaggio.com. I am deeply grateful to my advisors Richard Sweeney, Michael Grubb, and Edson Severnini for their invaluable guidance and support. I would also like to thank Theodore Papageorgiou, Rodrigo González Valdenegro, Carlos Eggers Prieto, and Federico Rodari, as well as participants at the Boston College Applied Economics Dissertation Workshop, the Berkeley/Sloan Summer School in Environmental and Energy Economics, and the ISO New England Market Design Workshop, for helpful comments and discussions.

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 when renewable output is abundant and prices are low, discharging 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, 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. A standalone operator arbitrages electricity prices across periods, focusing only on the spread between low and high prices. Conversely, a co-owner also internalizes the effect of battery operations on renewable revenues. Charging during off-peak hours raises prices and thereby increases the value of contemporaneous renewable output, while discharging during peak hours lowers prices and reduces renewable revenues. If renewable production is more abundant in off-peak periods, a co-owned battery may store more electricity than a standalone operator, sacrificing some arbitrage profits to increase renewable revenues. Conversely, if renewable output is higher during peak periods, a co-owner may optimally store no more – and sometimes less – than a standalone operator, in order to avoid eroding the value of renewable generation.

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, storage profitability, and consumer surplus.

Using a two-period model, I show that the divergence of operational incentives across different ownership structures can be explained by the timing of renewable production and by the elasticity of the supply curve. In the first period, an off-peak hour, perfectly inelastic demand intersects supply along a relatively flat segment of the curve, whereas in the second period, a peak hour, the intersection occurs on a steeper segment. When the exogenous renewable production is higher during the off-peak period, a co-owned battery has the incentive to store more. The gap between co-owned and standalone stored electricity widens when the off-peak supply curve is more inelastic, since a given MWh of charging generates a larger price increase. However, if renewable production is higher during the peak hour, the mechanism weakens and can even reverse: anticipating that discharging will depress peak prices – and thus both renewable revenues and arbitrage profits – the co-owner optimally stores no more, and potentially less, than a standalone operator. This reversal is stronger the more inelastic is the peak period supply.

I assess whether the theoretical conditions for divergent operational incentives actually occur by simulating a day-long dynamic dispatch model that extends the two-period framework, with battery operators making charge and discharge decisions every 15 minutes. For each node where a renewable plant is operating, I exogenously place a hypothetical battery and solve the model under both ownership structures, obtaining the optimal dispatch and the resulting equilibrium prices. The model is calibrated using ERCOT Real-Time Market data from January to December 2021.

The central feature of the empirical model is that, in each period, the transmission network is either uncongested or congested. When no transmission line capacity constraints bind, the system functions as a single integrated market. Hundreds of generators compete to meet system-wide demand, and the operation of a single battery cannot meaningfully affect prices, so the operator is modeled as a price-taker. When congestion occurs, by contrast, the grid fragments into local markets. Each local market contains only a limited set of generators serving a smaller load, so a batterys deployment can influence the local price, and the operator is modeled as a strategic player. I use node-level ERCOT 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 markets when transmission line capacity binds.

First, I show that ownership matters primarily when transmission congestion during off-peak periods creates local markets with inelastic supply curves. The divergence in operational incentives across ownership structures widens when the co-owned renewable plant operates at a higher share of its capacity. When the local supply curve is inelastic, a co-owner has the incentive to use the battery strategically because the induced increase in prices raises renewable revenues by more than it raises storage costs. When renewable output is low, co-owned batteries use approximately 5 percent more of rated power than standalone units; this gap increases to about 7 percent when renewable production is high. By contrast, when congestion isolates local markets in which only renewable plants operate, the resulting supply curve is nearly perfectly elastic over the range relevant for battery operations, meaning the portion of the curve spanning the battery's capacity. Under these conditions, a single battery has no ability to affect prices, so ownership does not alter dispatch. Conditions during peak periods do not affect operational incentives because batteries discharge almost entirely when the market is uncongested, where hundreds of generators compete and price effects from battery operations are minimal.

Second, I show that differences in utilization across ownership regimes lead to different effects on both consumer surplus and project profitability. Both ownership structures increase consumer surplus, since batteries typically charge during off-peak hours – when supply is relatively elastic – and discharge during peak hours, thereby reducing consumers payments to generators. Under co-ownership, however, strategic charging during congested off-peak periods raises electricity prices, dampening these gains. Compared with standalone operation, co-ownership reduces consumer surplus gains by roughly $20k per megawatt of installed storage capacity per year. Profitability follows the opposite pattern. While a standalone battery earns only arbitrage profits, a co-owned battery also captures the additional renewable revenues generated by its strategic use, which on average raises project profitability by about 30 percent.

Finally, I show that while neither ownership regime is privately viable at assumed capital costs of $250k per MWh of storage capacity, both are desirable from the consumer perspective when consumers bear the subsidy costs, with co-owned projects preferred. Co-owned projects require smaller subsidies because strategic usage raises profitability, more than offsetting their lower gross consumer surplus gains. As a result, co-owned projects deliver roughly $1.38 of consumer savings for every $1.00 of subsidy, compared with about $1.00 per $1.25 for standalone projects.

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 develops an illustrative two-period model to show how supply elasticity and the timing of renewable output generate divergent incentives under co-ownership and standalone operation. Section 3 describes the institutional context of Texas electricity market. 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 Illustrative Model

In this section, I illustrate how two market primitives – the timing of renewable production and the slope of the aggregate supply curve – yield different incentives for operating a battery under the two ownership scenarios – co-owned and standalone.

Figure 1 illustrates the incentives that govern battery utilization under the two ownership structures, using a simplified two-period setting. The first period corresponds to an off-peak hour, with lower perfectly inelastic demand D_l, while the second is a peak

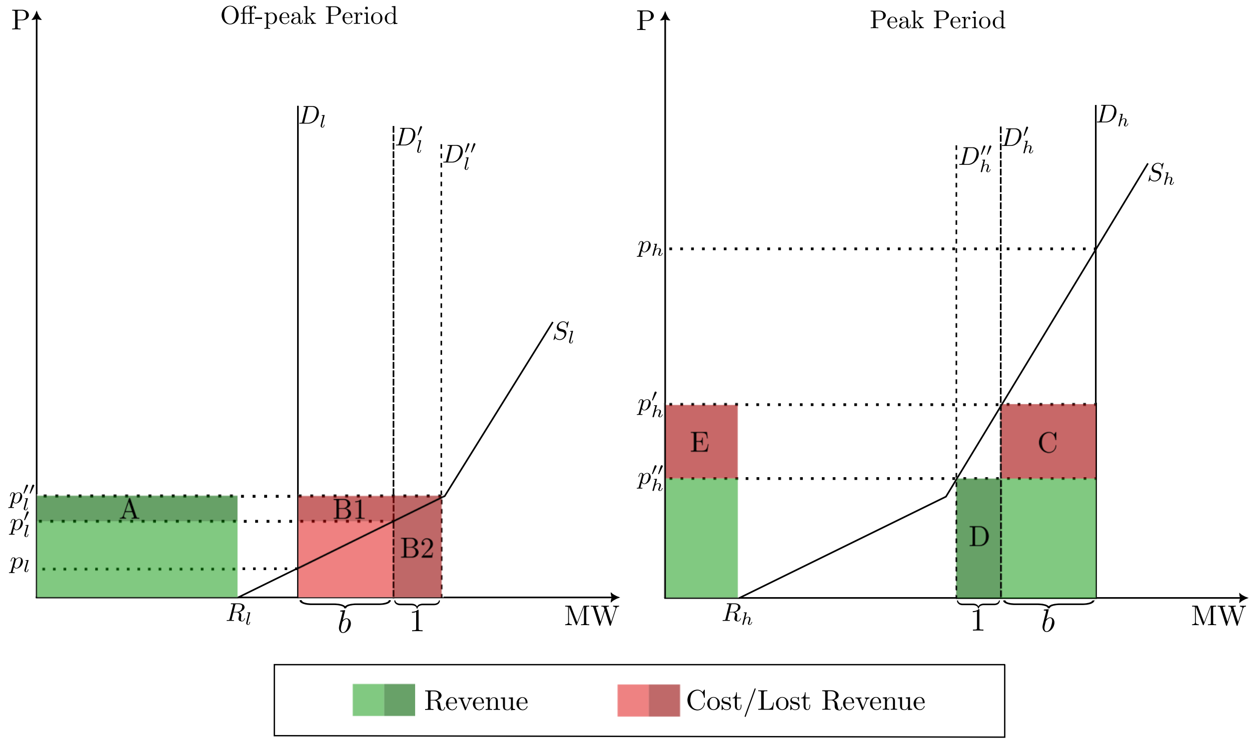


Figure 1: Illustrative Two-Period Model

period with higher demand D_h. In each period, the supply curve S_t is modeled as a piecewise linear function with three segments. The initial horizontal segment at price 0 reflects exogenous renewable output, while the other two segments have slopes χ_l and χ_h, with $\chi_l < \chi_h$. A key aspect of the model is that in each period demand intersects the supply curve at a different slope: in the off-peak period the relevant segment has slope χ_l, while in the peak period it has slope χ_h. Market clearing follows a uniform-price rule, so all electricity is paid at the same price. Under these assumptions, the equilibrium prices are such that $p_l < p_h$.

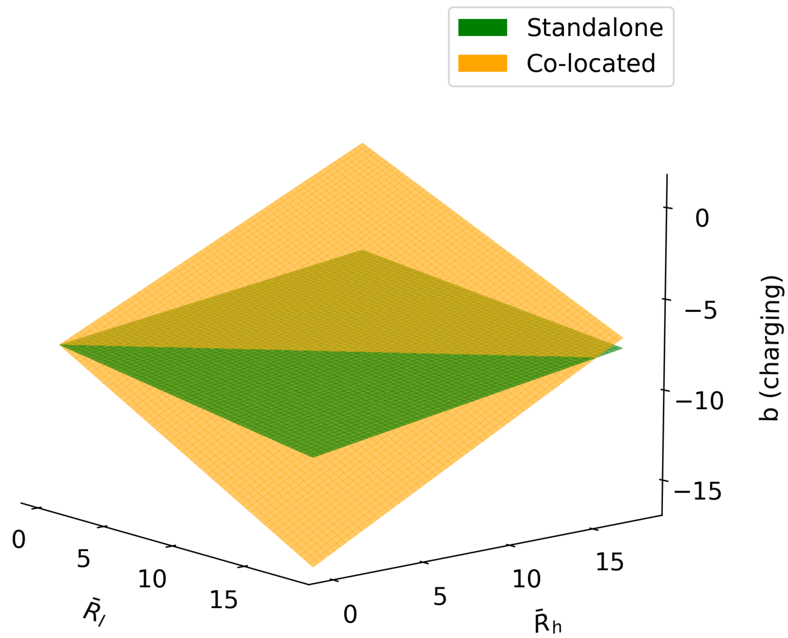
A battery that arbitrages price differentials buys electricity during the off-peak period and sells it in the peak hour. Since it only stores energy produced by other resources, charging b units shifts demand from D_l to D'_l, raising the price from p_l to p'_l. When the battery discharges in the peak 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_h to D'_h and the price decreases from p_h to p'_h.

A standalone operator, who maximizes arbitrage profits, must weigh the marginal cost of storing an additional unit against the marginal revenue from selling it. Buying one extra unit off-peak shifts demand from D_l' to D_l'', raising the price from p_l' to p_l''. This higher price increases costs of stored electricity in two ways: the b units already stored become more expensive by $p_l'' - p_l'$, and the additional unit itself must be purchased at p_l''. When the battery discharges, demand falls from D_h' to D_h'', lowering the price from p_h' to p_h''. Although the operator receives revenue of p_h'' for the extra unit sold, the lower price reduces earnings on the previously stored b units. The operator purchases the additional unit only if the incremental revenue exceeds both the higher off-peak cost and the peak-hour revenue loss (D $\geq$ B1 + B2 + C).

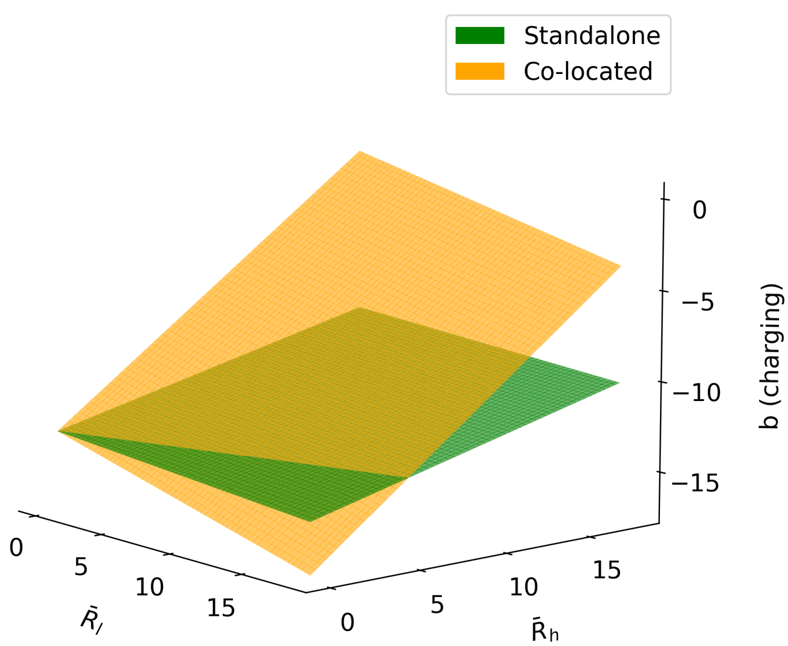
A co-owned battery maximizes joint profits from arbitrage and renewable sales. Unlike a standalone operator, the co-owner internalizes how battery operations affect renewable revenues: higher off-peak prices increase the value of contemporaneous renewable output, while lower peak prices reduce the value of renewable sales in that period. The storage decision therefore balances not only the arbitrage margin and its price effects on stored units, but also the induced changes in renewable revenues across the two periods (A + D $\geq$ B1 + B2 + C + E).

Figure 2 illustrates how the timing of renewable output and the steepness of the supply curves shape battery incentives under the two ownership structures (with negative values of b indicating charging). Panel 2a shows that when the off-peak supply curve, around the intersection with demand, is nearly as flat as the peak-period curve (i.e., $\chi_l/\chi_h = 0.9$), a co-owned battery store more electricity than its standalone counterpart, provided that renewable production in the off-peak period exceeds that in the peak hour, i.e. $R_l > R_h$. In this case, the additional renewable revenues generated by the off-peak price increase more than offset both the loss in arbitrage profits and the decline in renewable revenues during the peak hour.

Panel 2b depicts the opposite case, in which the off-peak supply curve is flatter ($\chi_l/\chi_h = 0.3$). Here, raising off-peak prices through battery charging is profitable only when renewable production in the first period is much larger than in the second. Otherwise, the standalone battery is used to store more electricity than the co-owned unit. Because charging barely moves off-peak prices, the increase in renewable revenues is min-



(a) Steeper off-peak hour supply curve ($\chi_l/\chi_h = 0.9$)



(b) Flatter off-peak hour supply curve ($\chi_l/\chi_h = 0.3$)

Figure 2: Two-period model: optimal battery utilization for different renewable production availability and different first period supply curve slope

imal, while discharging substantially depresses peak prices. As a result, co-ownership provides little incentive to store additional energy: the gain in off-peak renewable revenue is small, while the loss in peak period renewable revenue and arbitrage profits is large.

3 Institutional Settings

In the following sections, I describe the institutional features of the Texas electricity market that provide the foundation for the empirical model.

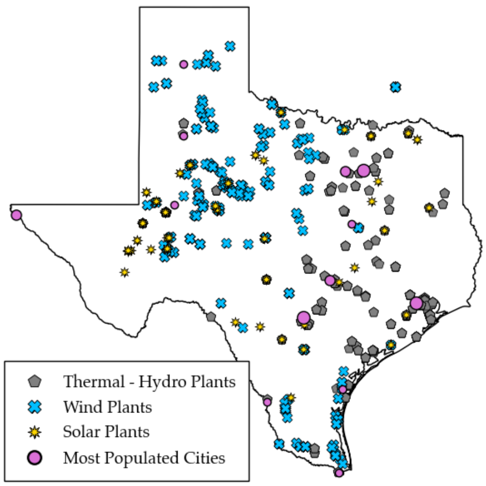
Texas Electricity Market

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.

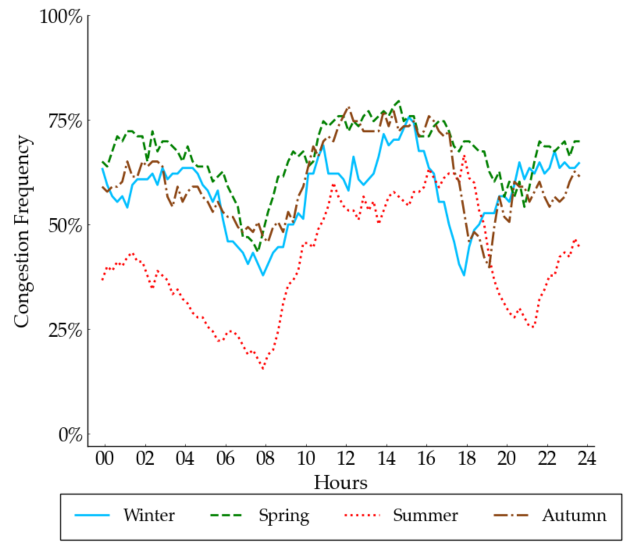
The market design in Texas is energy-only, meaning there is no separate capacity market. ERCOT's mandate is to ensure that electricity demand is met at every moment while minimizing system costs and maintaining reliability. To achieve this, ERCOT operates a Security-Constrained Economic Dispatch (SCED) 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 Congestions 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



(a) Power plants and load centers in Texas



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

Figure 3: Transmission congestions in Texas

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 3a). 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 3b).

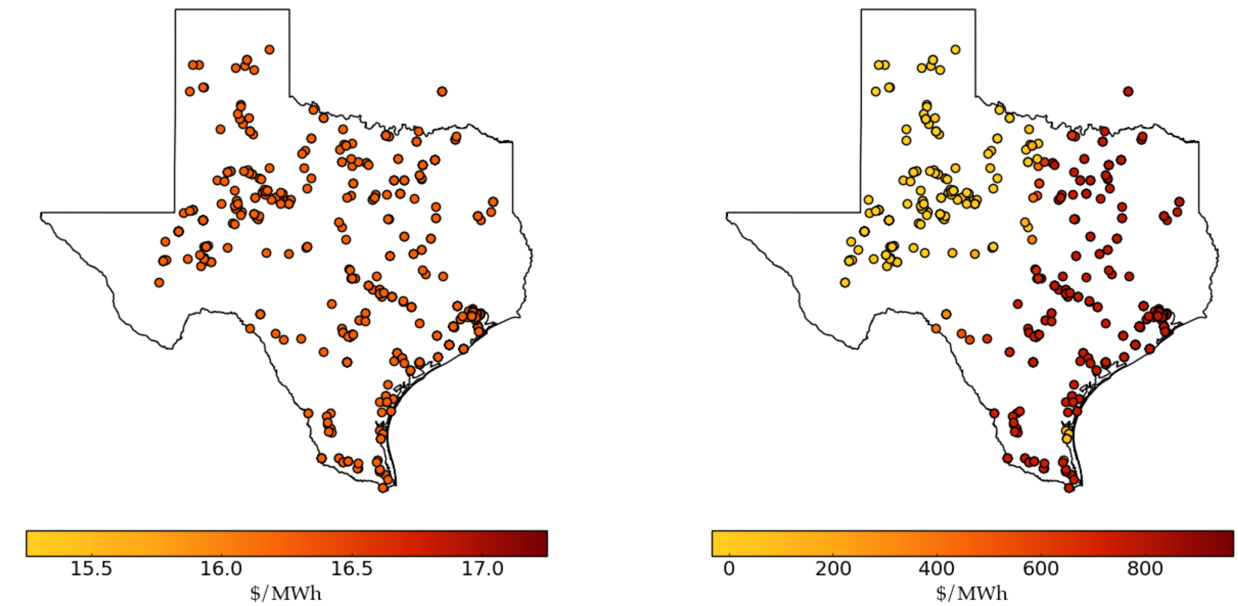
ERCOT addresses these constraints by implementing Locational Marginal Pricing, which assigns a price, the Locational Marginal Price (LMP), to each node that reflect the marginal cost of serving an additional megawatt at that location. When no transmission line is congested, the ERCOT market functions 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 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 4a).

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 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 load node is higher, reflecting the marginal cost of the expensive generator that must be dispatched to meet residual demand (Panel 4b).

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



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

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

Figure 4: Locational Marginal Pricing in Texas Electricity Market

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.

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) by 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.

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. 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 electiricty 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 market is represented by retailer 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. Accordingly, I work with net demand, defined as gross demand minus renewable production, and I abstract from curtailment events.

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 $-\frac{1}{\epsilon_s} \frac{b_t pt,m}{Q_t}$. 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 $-\frac{1}{\epsilon_s} \frac{\bar{R}t,jpt,m}{Q_t}$, 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-minute 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 the realized output of renewable plants. 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. For renewables, I assume that all available output is offered at marginal cost. Wind generation is offered at -$31.5/MWh, reflecting eligibility for the federal Production Tax Credit, while solar generation is offered at zero, consistent with its negligible marginal cost and the absence of the subsidy.

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 $\gamma^2 = 0.9$.

Finally, 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.

5 Results

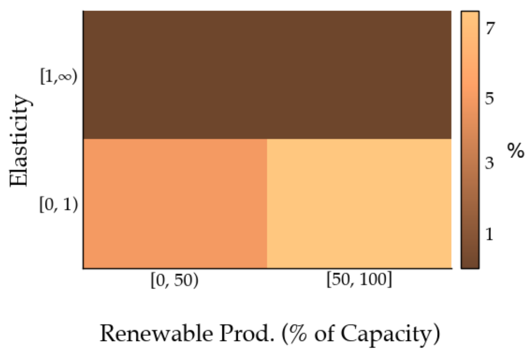
In this section I discuss the results from the simulated empirical model. I start the discussion by illustrating when operational incentives differ across ownership. Next, I show how different incentives affect market outcomes, such as consumer surplus and battery projects' profitaility.

Batteries Operational Incentives

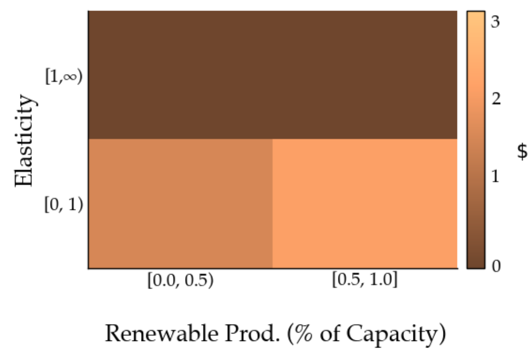
The results I present focus on congested off-peak and peak periods, where charging and discharging decisions reflect the internalization of price effects. A key feature of the model is that batteries internalize the price effects of their operations only when transmission congestion creates local markets. In these periods, the operators are assumed to behave strategically. In uncongested periods, by contrast, the system functions as a single integrated market with hundreds of generators competing, and operators behave as price-takers. This distinction implies that divergent operational incentives across ownership structures can arise only under congestion.

Figure 5 summarizes how ownership structure shapes battery charging decisions during congested off-peak periods. I classify these periods into four groups, according to the interaction of the two factors that, in my theoretical model, 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. In my simulations, co-owned batteries purchase on average about 40 percent of their total stored electricity during these periods, compared with 34 percent for standalone units.

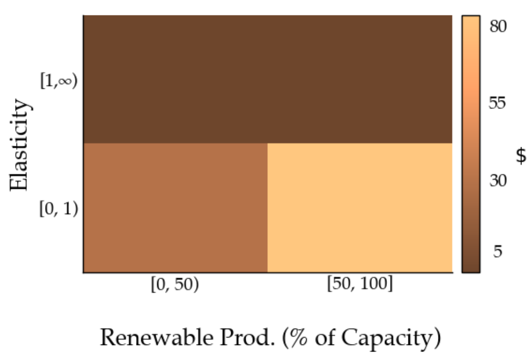
Co-owned batteries systematically charge more than standalone units when they op-



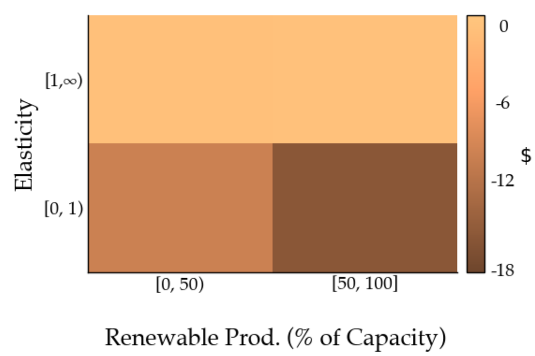
(a) Average percentage difference in utilized rated power (co-owned vs. standalone)



(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 5: Battery operational incentives

erate in congested local markets with inelastic supply. Panel 5a 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 $3/MWh relative to the standalone case (Panel 5b). By contrast, when the local supply curve is elastic ($\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 5c and 5d 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.

Supply elasticity and renewable output during peak periods do not affect operational incentives. The divergence between co-owned and standalone batteries is driven only by conditions in congested off-peak hours. During peak hours batteries discharge almost entirely when the market is uncongested: on average, 96 percent of stored electricity is released when the system functions as a single integrated market. In these conditions, batteries compete alongside hundreds of generators and act as price-takers, so their deployment has only a minimal effect on prices. The reason operators concentrate discharging in uncongested periods is to avoid doing so under congestion, where the resulting price decline would be substantial and would reduce both renewable revenues and arbitrage profits.

Together, these results show that by coordinating battery operations with renewable output, co-owned operators can deploy storage strategically to raise the market value of renewable generation – an incentive absent under standalone ownership. This mechanism illustrates why ownership matters. It shapes operational incentives and determines

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 battery 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.

whether batteries function as pure arbitrage devices or as instruments for influencing market outcomes.

Consumer Surplus and Battery Profitability

In the previous section, I showed that supply elasticity and renewable output during congested off-peak hours drive differences in battery utilization across ownership structures. Those results, however, do not establish whether such differences are economically meaningful, since they might arise only in a limited set of periods. To evaluate their broader relevance, I now examine whether divergent operations translates into systematic differences in consumer surplus and battery profitability. For this purpose, I classify batteries into five groups according to the characteristics of the nodes where they are located, focusing only on congested periods. The classification relies on two dimensions. The first is the frequency with which the local supply curve is inelastic during congested periods. The second is the frequency with which the renewable plant located at the battery's node produces above the median renewable output observed across all fifteen-minutes congested periods. Groups 1 and 2 consist of nodes frequently exposed to inelastic supply, distinguished by whether renewable output is high (Group 1) or low

Group	ΔCS_c (1)	ΔCS_s (2)	Π_c (3)	Π_s (4)	Sub_c (5)	Sub_s (6)	CS_c^{net} (7)	CS_s^{net} (8)
1	183	204	92	46	158	204	25	0.0
2	303	316	62	41	188	209	115	107
3	460	459	41	42	209	208	251	251
4	208	213	20	17	230	233	-22	-20
5	234	234	29	31	221	219	14	15

Notes: All amounts are in \$1000s per MWh of storage capacity. Columns (1)–(2) report the 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 lifetime operating profits: Π_c for co-owned, Π_s for standalone. Columns (5)–(6) report the subsidy required for each ownership type to break even, assuming capital costs of \$250k per MWh. Columns (7)–(8) report net consumer surplus, defined as $\Delta CS - Sub$. See Table 1 for definition of groups.

Table 2: Consumer surplus and battery profitability, by group (amounts in \$1000s)

(Group 2). Groups 3 and 4 are exposed to inelastic supply less often, again separating high and low renewable output. Finally, Group 5 includes nodes that, when congested, always face a perfectly elastic supply curve. Table 1 reports summary statistics for each group.

Table 2 reports the change in consumer surplus from introducing a battery relative to the no-battery baseline (columns 1 and 2). Consumer surplus is computed over a 20-year assumed battery lifetime, without accounting for degradation. Two results stand out. First, batteries increase consumer surplus regardless of ownership. On average, each MWh of capacity raises consumer surplus by roughly \$200k–\$500k. In this setting, where demand is perfectly inelastic, gains in consumer surplus are measured as the reduction in total payments to generators: the difference between prices with and without batteries, multiplied by demand. The increase in consumer surplus reflects the fact that batteries shift demand from off-peak to peak periods, purchasing electricity when supply is relatively elastic and reselling it when supply is less elastic.

Second, the magnitude of consumer surplus gains depends on ownership. Standalone batteries consistently generate larger gains than co-owned units when batteries face inelastic supply more frequently. For example, in Group 1, standalone batteries raise consumer surplus by $204k compared with $183k under co-ownership, a gap of $21k; in Group 2, the gap is $13k. By contrast, when inelastic supply is infrequent (Groups 3 and 4), the differences between ownership types largely vanish, and in Group 3 co-ownership delivers slightly higher gains. The smaller gains under co-ownership reflect operators' strategic use of the battery during congested off-peak periods. This behavior raises local prices relative to the standalone case, increasing consumers' costs of electricity in those periods. Because the savings from lower peak prices are partly offset by these higher off-peak costs, the overall consumer surplus gains are smaller under co-ownership.

While co-ownership dampens consumer surplus gains, it almost doubles battery profitability compared with standalone ownership. Standalone batteries earn profits solely from arbitrage, whereas co-owned units capture both arbitrage profits and the additional revenues generated by selling renewable output at higher off-peak prices once the battery is introduced. Profitability of a co-ownerd battery is defined as the lifetime sum of arbitrage profits and incremental renewable revenues relative to the no-battery baseline. Table 2 (columns 3 and 4) shows that strategic use of the battery under co-ownership substantially raises earnings. In Group 1, lifetime profits reach $92k under co-ownership, against $46k for standalone units. In Group 2, the advantage persists, though it is smaller ($62k versus $41k). When inelastic supply is infrequent (Groups 3 and 4), the two ownership types yield similar outcomes, with profitability of around $40k in both cases.

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. To make the most profitable projects (top decile) viable, capital costs would need to fall by roughly 65 percent.

Although investment is not privately viable, subsidizing batteries remains desirable from consumers' perspective. Under both ownership structures, the discounted increase in consumer surplus exceeds the subsidy required, so net consumer surplus remains

[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.

positive. The only exception is Group 4, where net consumer surplus is slightly negative under both ownership structures. 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 the consumers' point of view, are not privately profitable.

Once subsidies are introduced, the relevant question is which ownership structure delivers greater value per unit of public support. Consumers would prefer to subsidize co-owned projects. While standalone batteries yield larger gross gains in consumer surplus, co-owned units generate higher revenues, require smaller subsidies, and thus achieve higher net consumer surplus. In practice, co-owned projects deliver on average about \$1.38 of consumer savings for every \$1.00 of subsidy, compared with roughly \$1.25 per \$1.00 under standalone ownership.

6 Conclusion

This paper examines how ownership structure shapes battery operation and market outcomes in ERCOT. I develop a simple model that isolates two primitives–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 reduces gains in consumer surplus relative to standalone batteries, as consumers face higher prices during congested off-peak periods. 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, conditional on providing support, consumers would prefer to subsidize co-owned projects. While standalone batteries generate larger gross gains in consumer surplus, co-owned projects require smaller subsidies, delivering the highest net consumer surplus.

Two caveats qualify these conclusions. First, 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. Second, the model does not incorporate curtailment events. However, since the divergence in incentives emerges primarily when supply is inelastic, conditions under which curtailment is less likely, excluding curtailment is unlikely to overturn the main findings.

In sum, who owns the battery matters when the grid is frequently locally constrained. Co-ownership confers a lever to affect price and increase renewable production value, boosting plants' profitability but dampening gross consumer gains; standalone operation preserves larger gross consumer benefits but requires more subsidy support. These findings highlight that ownership design is central to determining how storage interacts with electricity markets. By shaping both operational incentives and the distribution of benefits between consumers and investors, ownership structure becomes a key consideration for subsidy policy and market regulation.

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