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

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Abstract

Electricity grids are rapidly decarbonizing, with wind and solar generation playing a central role. Their intermittency, however, complicates their market integration and challenges grid reliability. Battery energy storage systems (BESS) are expected to ease these frictions, yet their impact depends critically on ownership. I develop and simulate a dynamic dispatch model of battery utilization, calibrated to ERCOT real-time market data, to study how ownership structure shapes operational incentives. I show that transmission congestion creates market conditions in which co-owned batteries are used strategically: operators charge more during low-price periods, pushing prices upward and thereby increasing the value of contemporaneous renewable output. The strength of this effect depends on supply elasticity and the timing of renewable production. This strategic use has two contrasting effects: it reduces consumer surplus gains relative to standalone operation, but it almost doubles project profitability. As both ownership types require subsidies to be viable, the higher profitability under co-ownership outweighs the smaller consumer gains, making it the more subsidy-efficient option. These findings highlight the importance of ownership design for subsidy policy and market regulation.

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. This tension raises the question of how policy should support such investments and under what forms of organization. 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 means 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% 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. A co-owner, by contrast, 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 concentrated 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 concentrated during peak periods, a co-owner may optimally store no moreand sometimes lessthan 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 charge 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 pricesand 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 then assess whether the theoretical conditions for the divergent operational incentives actually occur. I simulate a day-long dynamic dispatch model that extends the two-period framework, which allows me to measure how different battery's usage across ownership affect prices, consumer surplus, and battery profitability. For each node where a renewable plant is operating, I exogenously place a hypothetical battery and solve the model under both regimes, obtaining the optimal dispatch and the resulting equilibrium prices.

To calibrate the model I use ERCOT Real-Time Market data, from January to December 2021. The main feature of the empirical model is that, in each period, the transmission network is either uncongested or congested. When no lines bind, the system functions as one integrated market. Hundreds of generators compete to meet system-wide demand, and the utilization of a single battery can hardly generate a substantial variation in electricity prices, so I assume the operator behaves as a price-taker. When congestion occurs, the grid breaks into local markets. Each local market contains only a limited set of generators competing to serve a much smaller load, so the batterys deployment can meaningfully influence the local price, and I model the operator as a strategic player. I use node-level ERCOT's Locational Marginal Prices (LMPs) to identify congested periods and, together with S&P Capital IQ data on plant locations, to define the local markets in which each battery operates when lines capacity binds.

First, I show that ownership matters primarily at nodes where transmission congestion frequently generates an inelastic local supply curve. In these cases, a co-owner has the incentive to use the battery strategically – charging on average 7 percent more of rated power than standalone units - because the induced increase in prices raises renewable revenues by more than it raises storage costs. By contrast, when congestion isolates only renewable plants and the local supply curve is nearly perfectly elastic, a single battery cannot move prices and ownership has no effect on dispatch.

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. Relative to the standalone scenario, consumer surplus is roughly $20k less per year under co-ownership. 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, both are desirable from the consumer perspective, with co-owned projects preferred. In both cases, the present value of avoided electricity costs exceeds the subsidies required, making public support worthwhile. Co-owned projects, however, require smaller subsidies because strategic usage raises profitability, more than offsetting the lost consumer surplus gains. As a result, co-owned projects deliver roughly \$1.50 of consumer savings for every \$1.00 of subsidy, compared with about \$1.00 per \$1.00 for standalone projects.

This paper makes two main contributions. First, it extends the literature on storage investment in wholesale electricity markets by emphasizing ownership structure. 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 new channel through storagerenewable integration. 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 a stylized two-period model to illustrate 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 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 $\chi_l < \chi_h$. The 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, and given that demand is higher in the second period, the equilibrium satisfies $p_l < p_h$ in the absence of storage.

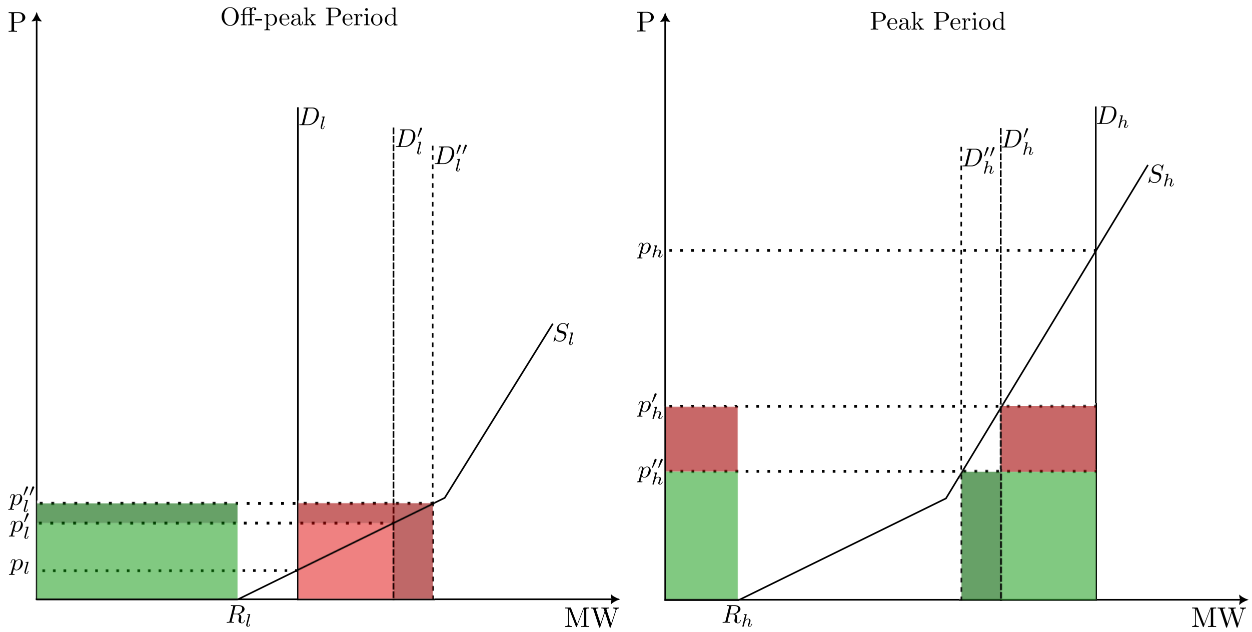
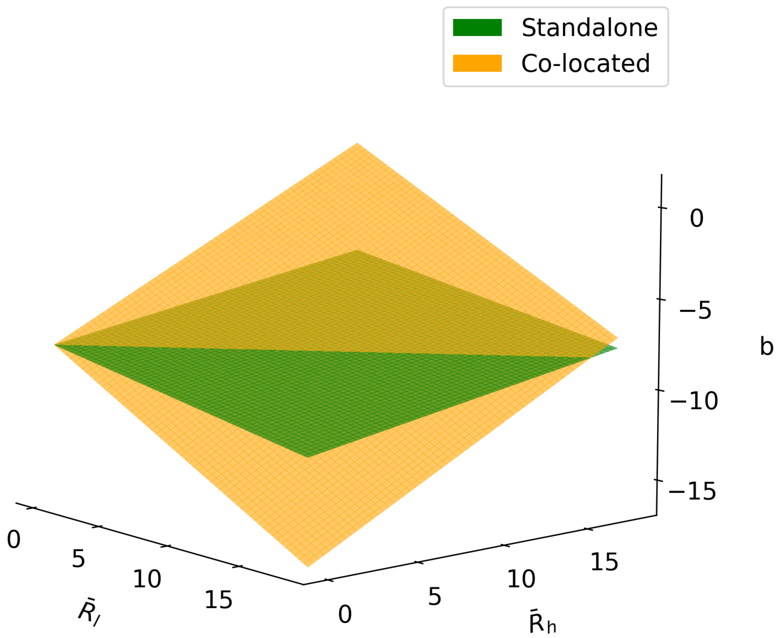


Figure 1: Illustrative Two-Period Model

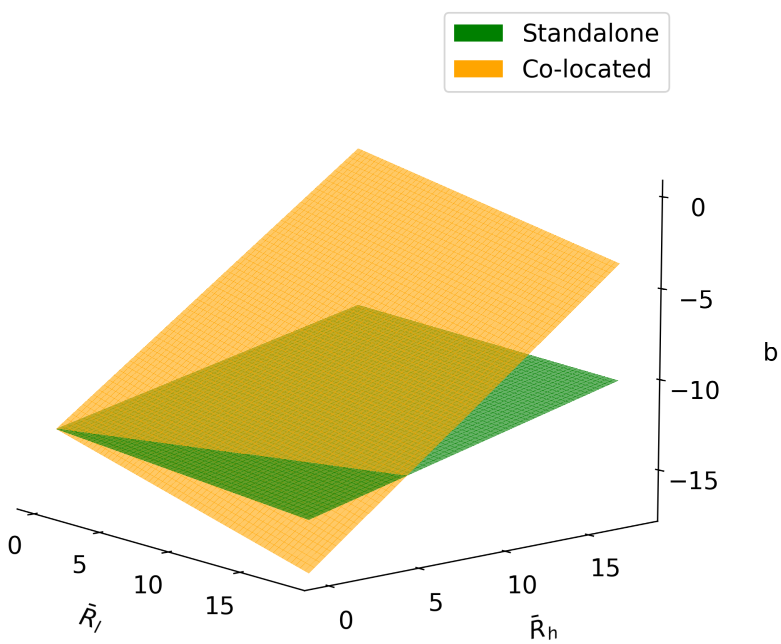
A battery that arbitrages price differentials buys electricity during the off-peak period and sells it in the peak hour. Since it only stores energy produced by other resources, charging b units shifts demand from D_l to D_l', raising the price from p_l to p_l'. When the battery discharges in the peak period, I assume that the stored volume is offered at a price of zero, 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 revenue loss on earlier purchases.

A co-owned battery maximizes joint profits from arbitrage and renewable sales. In



(a) Steeper off-peak hour supply curve



(b) Flatter off-peak hour supply curve

Figure 2: Two-period model: optimal battery utilization for different renewable production availability

deciding whether to store an additional unit, the operator considers five components: the purchase cost of the extra unit, the higher cost of the b units already stored, the revenue from selling the extra unit in the peak period, the revenue loss on the previously stored units, and the net change in renewable revenues across the two periods. Renewable production is exogenous, so all available output must be supplied. When charging raises the off-peak price to p_l'', revenues on R_l increase, while the lower peak price p_h'' reduces revenues on R_h.

Figure 2 illustrates how the timing of renewable output and the slope of aggregate supply curves influence battery incentives under the two ownership structures. Panel 2a shows that when the steepness of the off-peak period supply curve, around the intersection with the demand, is almost as flat as that of the supply curve during the peak hour (i.e. $\chi_l/\chi_h \to 1$), a co-owned battery is charged more than the standalone counterpart, whenever renewable production in the off-peak period is higher than in the peak hour. The increase in the renewable sales revenues generated by the price variation induced by the battery charging during the off-peak hour more than compensate the reduction in arbitraging profits and the reduction in renewable revenues in the peak hours. The incentive weaken and reverse the lower the renewable production in the off-peak price with respect to the second period.

Panel 2b depicts the opposite case, in which the off-peak supply curve is nearly flat ($\chi_l/\chi_h \to 0$). 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 more intensively than the co-owned unit. Because charging barely moves off-peak prices, the increase in renewable revenues is minimal, 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.

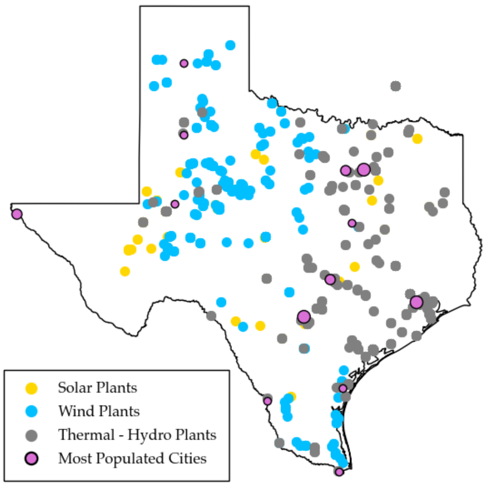
Texas Electricity Market

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.

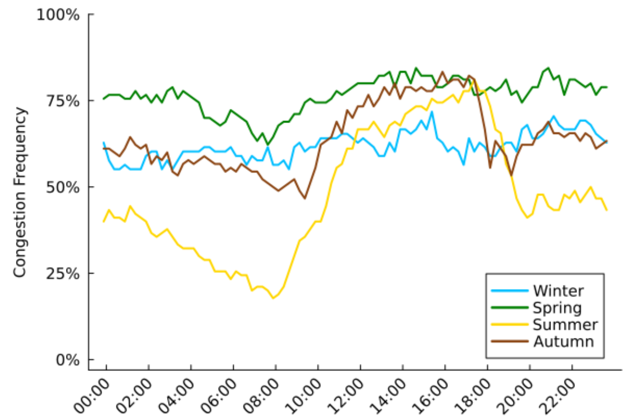
The market design in Texas is energy-only, meaning there is no separate capacity market. ERCOTs mandate is to ensure that electricity demand is met at every moment while minimizing system costs and maintaining reliability. To achieve this, ERCOT operates a Security-Constrained Economic Dispatch (SCED) 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 csited 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 3a). Transmission lines have finite capacity: technical limits on voltage and frequency, as well as thermal constraints, prevent them from carrying unlimited power. Sudden shockssuch as a plant outage, a rapid load increase, or a surge in wind



(a) Power plants and load centers in Texas



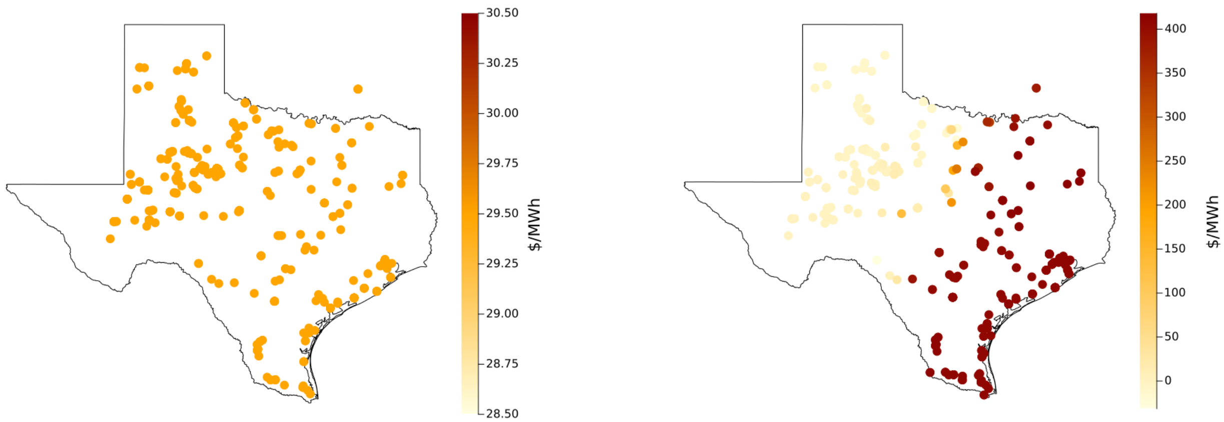
(b) Percentage of 15-minutes periods with at least one congested transmission line, by season.

Figure 3: Transmission congestions in Texas

outputcan 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 intervals during most hours 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 line is congested, the system effectively functions as a single, fully integrated market. Electricity can flow freely across the grid, so the marginal producer is the same everywhere, and the market clears at a uniform price. In these hours, ERCOT conducts a system-wide auction in which all generators are dispatched according to merit order, and every unit of electricity is compensated at the same LMP (Panel 4a). Prices across the grid therefore reflect the cost of the system-wide marginal unit, with no spatial differentiation.

When transmission lines become congested, ERCOT no longer clears the market at



(a) Uncongested Market (b) Congested Market

Figure 4: Locational Marginal Pricing in Texas Electricity Market

a single system-wide price. Instead, each node is assigned its own LMP, which reflects the marginal cost of serving an additional megawatt at that location. Nodes that are not separated by binding constraints share the same price, but when a line binds, prices diverge. In this sense, congestion effectively creates local markets - sometimes encompassing multiple nodes, sometimes reducing to a single node - each characterized by a common LMP determined by the marginal producer within that constrained area. This framework naturally generates a distinction between the export and import sides of a constraint. Generators on the export side of the constraint face lower LMPs, reflecting unused cheap capacity. On the import side, where demand must be met despite limited transmission capacity, more expensive local generators are dispatched and LMPs rise. As a result, congestion produces price divergences across the grid: some areas experience lower prices due to stranded supply, while others face sharp increases as costly units are called upon locally (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 Bendareas 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.

The geographic distribution of renewable plants not only determines their production potential but also shapes the competitive environment they face under transmission congestion. Plants located near major load centers share local markets with thermal generators. When congestion arises in these areas, the resulting local supply curve reflects both renewable and thermal generation. In such cases, the residual supply is frequently inelastic during congested periods.

By contrast, renewable plants located in remote areas far from load centers are often grouped together in local markets composed almost exclusively of other renewables. When transmission lines are congested, the resulting local supply curve is nearly perfectly elastic, as all available renewable output must be supplied regardless of price.

Battery Energy Storage Systems in Electricity Markets

Investments in ESS 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. BESS are characterized by three parameters: its power capacity P (MW), the maximum instantaneous rate of charge or discharge; its duration h (hours), the length of time it can sustain rated power; and its energy capacity E (MWh), defined as the product of power and duration. Because charging and discharging cycles are subject to losses, batteries are also characterized by their round-trip efficiency γ^2, the fraction of energy retained over a complete chargedischarge cycle.

Lithium-ion batteries combine high power capacity, moderate duration, and relatively high efficiency, making them well suited for arbitrage in wholesale electricity markets. In practice, most of the few projects installed in Texas in 2021 were almost exclusively deployed in ancillary-service markets, 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, where batteries exploit real-time price differentials. Given the higher price variability in the RTM, this is expected to be the primary venue for arbitrage opportunities.

4 Empirical Strategy

To examine whether the theoretical conditions that yield divergent incentives 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 outcomesincluding prices, consumer surplus, and battery profitability-conditional on market conditions that generate distinct incentives. Moreover, by simulating the model for batteries paired with every renewable plant operating in the market, I can also assess how plant characteristicssuch as location and technologyinfluence 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 utilize the battery to arbitrage electricity prices differentials. The time horizon faced by the operator is a day-long period. At the beginning of every fifteen minutes 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 batterys 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 ($c_{t=96,j} = 0$). Along with the state of charge, the operators 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 assumed to be 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 perfect 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 their 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:

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

Assume that 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

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

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

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

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 primitivesthe 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 ERCOTs 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 marketeither the statewide system or the local market defined by congestion events.

Aggregate supply curves are constructed by combining thermal generators bid-based offers with the realized output of renewable plants. Thermal generators can submit up to 35 pricequantity 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. BESS are characterized by their power capacity, duration, and round-trip efficiency. 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 $\gamma^2 = 0.9$.

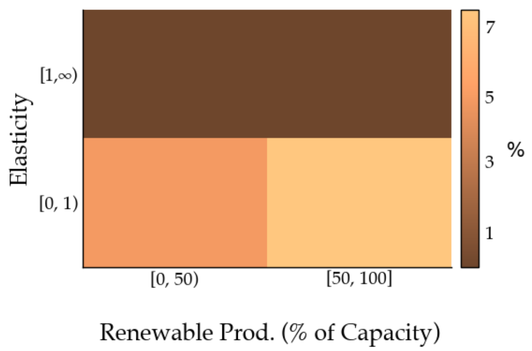
Finally, To construct plant-specific local markets and define congestion events, I use ERCOTs five-minute data on LMPs by Resource Nodes, Load Zones and Trading Hubs. Local markets are defined by examining the pairwise differences in LMPs between the node where the battery is assumed to operate and all 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. A detailed description of the methodology is provided in the Appendix.

5 Results

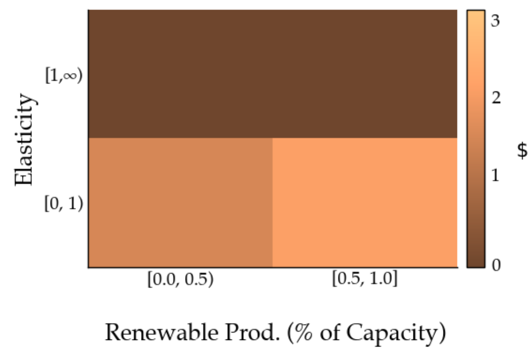
In this section I discuss the results from the simulated empirical model. I start the discussion by illustrating when operational incentives differ across ownership. Next, I show how different incentive affect market outcomes, such as consumer surplus and battery projects profitaility.

Batteries Operational Incentives

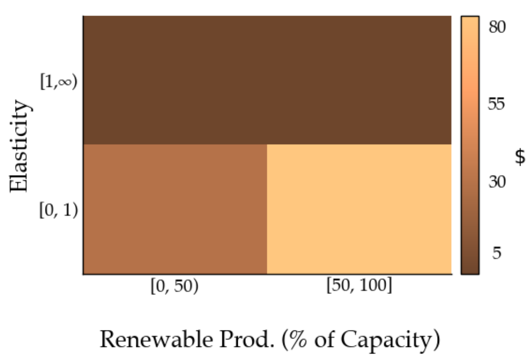
Figure 5 summarizes how ownership structure shapes battery charging decisions during off-peak periods when transmission lines are congested. These periods are categorized into four groups, defined by the interaction of two key factors that drive divergent utilization incentives: the elasticity of the supply curve in the local market where the battery operates, and the level of renewable output from the plant located at the same node. These are the periods in which ownership incentives can matter, since batteries operate in less competitive markets. In my simulations, batteries on average buy about 40 percent of their total stored electricity during congested off-peak periods when co-owned,



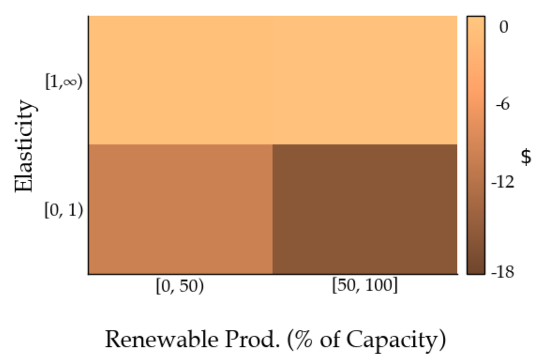
(a) Average percentage difference in utilized rated power (co-owned vs. standalone)



(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

compared to 34 percent when standalone.

Co-owned batteries systematically charge more than standalone units when they operate in congested local markets with inelastic supply. Panel 5a illustrates this by plotting the average percentage difference in utilized rated power between the two ownership structures during off-peak periods in which charging occurs. The gap widens with renewable output: when renewable plants operate above 50 percent of capacity, co-owned batteries use about 7 percent more of their rated power than standalone units. By contrast, when the local supply curve is elastic ($\epsilon_s > 1$), the utilization difference across ownership structures largely disappears. Panel 5b shows the associated average price effect, with co-owned charging raising local off-peak prices by up to $3/MWh compared to the standalone case.

Strategic charging is profitable for co-owned operators because the additional renewable revenues more than offset higher charging costs. Panels 5c and 5d illustrate this mechanism. Co-owned operation increases average renewable sales profits by as much as $80 per MWh of storage capacity during congested off-peak hours (Panel 5c). On the cost side, average harging costs rise by up to $18 per MWh relative to the standalone case (Panel 5d), as higher utilization drives up local off-peak prices. The increase in renewable revenues more than compensates for the higher charging costs, making strategic charging profitable for co-owned operators.

The incentives that distinguish co-owned from standalone batteries arise only during congested off-peak periods. During peak periods, batteries discharge almost exclusively in uncongested markets: on average, 96 percent of stored electricity is released in these periods, regardless of ownership. When transmission lines are not congested, the market is fully integrated and operators do not internalize any price effects from discharging. By contrast, discharging during congested peak periods would lower local prices, thereby reducing both arbitrage profits and renewable revenues.

Together, these results highlight that co-ownership effectively transforms a non-dispatchable resource into a partially controllable one. By coordinating battery operations with renewable output, co-owned operators can use the battery strategically in order to raise the market value of the renewable generation, an incentive absent under standalone ownership.

Consumer Surplus and Battery Profitability

In the previous section I showed that two factors supply elasticity and renewable output during congested off-peak hours are central to explaining differences in battery utilization across ownership structures. To assess how these factors shape market outcomes more broadly, I classify batteries into five groups according to the market conditions faced by the renewable plants located at the same node. The classification is based on

Group	N Batt.	Storage MWh	Renewable MW	% Solar	% Wind	Loc. Mkt. Size
1	17	73.8	140.6	58.8	41.2	21.4
2	11	48.0	91.4	27.3	72.7	20.8
3	11	41.5	79.1	54.5	45.5	13.6
4	18	63.2	120.4	72.2	27.8	24.5
5	161	64.5	122.9	13.7	86.3	11.3

Notes: Column "Group" reports the group identifier. **Group 1** = High inelasticity / high renewable correlation, **Group 2** = High inelasticity / low renewable correlation, **Group 3** = Low inelasticity / high renewable correlation, **Group 4** = Low inelasticity / low renewable correlation, **Group 5** = Always perfectly elastic supply curve. "N Batt." is the number of simulated battery in each group. "Storage MWh" is average battery capacity. "Renewable 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. "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.

two dimensions. The first is the frequency with which the local market, where each simulated battery operates, experiences an inelastic supply curve during congested periods. The second is the correlation between congestion and renewable productionwhether congested hours tend to coincide with high renewable output or, instead, occur when renewable production is relatively low. Groups 1 and 2 correspond to plants frequently exposed to inelastic supply during congestion, but differ in renewable output: Group 1 faces high renewable production, while Group 2 does not. Groups 3 and 4 are exposed to inelastic supply less frequently, again with high and low renewable output respectively. Finally, Group 5 consists of plants that, when congested, always operate in local markets with a perfectly elastic supply curve. Table 1 reports summary statistics for each group after classification.

Table 2 reports the effects of batteries on consumer surplus across groups and ownership structures (columns 1 to 3). Two main results emerge. First, batteries increase consumer surplus regardless of ownership. On average, each MWh of capacity raises consumer surplus by roughly \$200k – \$500k over the batterys lifetime. In this setting, where demand is perfectly inelastic, variation in consumer surplus is measured as the change in total payments to generators: the difference between prices with and without batteries, multiplied by demand. This arises because batteries shift demand from off-peak to peak periods, thereby reducing payments to generatorsthey buy electricity when

Group	ΔCS_c	ΔCS_s	Π_c	Π_s	Sub_c	Sub_s	CS_c^{net}	CS_s^{net}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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 $\Delta CS - Sub$. Group definitions follow Table 1.

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

supply is relatively elastic and sell when supply is less elastic.

Second, the magnitude of consumer surplus gains depends on ownership. The difference is driven by battery incentives during congested off-peak hours. Standalone batteries consistently yield larger gains than co-owned batteries when inelastic supply occurs frequently. For instance, in Group 1, standalone batteries raise consumer surplus by \$204k while co-owned units raise it by \$183k, a gap of \$21k. In Group 2, the gap is smaller but still meaningful, at \$13k. By contrast, when inelastic supply is rare (Groups 34), ownership differences are negligible. The only exception is Group 4, where net consumer surplus is slightly negative (-\$20k to -\$22k per MWh), though the magnitude is economically small relative to subsidy needs. These results are consistent with the mechanism documented above: co-owned batteries are more likely to charge in congested off-peak periods, raising local prices and thus dampening consumer surplus relative to standalone operation.

Turning to profitability (columns 4 to 6 in Table 2), the pattern reverses. Co-owned batteries systematically outperform standalone ones. In Group 1, profitability nearly doubles under co-ownership: average lifetime profits are \$92k for co-owned units, compared with only \$46k for standalone ones. In Group 2, the profitability advantage persists, though it is smaller ($62k versus $41k). This advantage arises because co-owned operators capture not only arbitrage profits but also the additional revenues from selling renewable output at higher off-peak prices. When inelastic supply is infrequent (Groups 34), profitability differences between ownership structures are negligible (around $40k in both cases).

These results carry three main policy implications. First, batteries are not privately profitable on average. Assuming capital costs of $250k per MWh, most projects require subsidies to break even. In the absence of policy support, investment would therefore fall short of socially desirable levels. Second, from the consumers perspective, subsidizing batteries is worthwhile. Under both ownership structures, the discounted increase in consumer surplus exceeds the subsidy required, so net consumer surplus remains positive. The only exception is a negligible case in which net gains are close to zero. Third, consumers would strictly prefer policies that favor co-ownership. While standalone batteries deliver larger gross gains in consumer surplus, co-owned units generate higher revenues, require smaller subsidies, and therefore yield the highest net consumer surplus once subsidies are accounted for.

6 Conclusion

This paper shows that ownership structure shapes battery operation and market outcomes in ERCOT: co-owned batteries charge more in congested off-peak periods, raising prices and profitability, while standalone batteries deliver larger gains in consumer surplus. I develop a simple model that isolates the role of two primitivesthe elasticity of residual supply and the timing of renewable outputand embed it in a day-long dynamic simulation calibrated to ERCOTs 2021 Real-Time Market.

When congestion fragments the grid into local markets with inelastic residual supply, a co-owned operator internalizes the price effect of charging on contemporaneous renewable revenues and therefore stores more energy. In the simulations, this incentive is strongest when renewable output is high during congested off-peak hours; it vanishes when supply is elastic. By contrast, peak period behavior is largely uniform across ownership because batteries discharge mostly in uncongested hours, when operators do not internalize price effects.

The distributional and policy implications follow directly. First, without support, storage is not privately profitable on average at prevailing capital costs. Second, from consumers perspective, subsidizing storage is desirable under either ownership: the present value of reduced payments to generators exceeds the subsidy required in almost all cases. Third, conditional on subsidizing, consumers prefer co-ownership because higher project revenues reduce the necessary subsidy and yield the largest net consumer surplus once subsidy costs are accounted foreven though gross consumer surplus gains are larger for standalone units. These results speak to the design of storage incentives: policies that are neutral across ownership can deliver positive welfare, while modest tilts toward co-located projects may enhance subsidy efficiency.

Two caveats qualify these conclusions. In my simulations, batteries are assumed to be located at nodes that host a renewable plant. This reflects the typical siting of co-owned projects, but it constrains the comparison because standalone batteries in practice can choose their location more freelyfor instance, by installing directly in major load centers. My analysis does not consider this possibility, so the relative advantage of standalone ownership may be understated. Second, the model does not incorporate curtailment events. This omission is unlikely to overturn the main findings, however, as the divergence in incentives across ownership structures emerges when the supply curve is relatively inelasticprecisely the conditions under which curtailment is less likely to occur.

In sum, who owns the battery matters when the grid is frequently locally constrained. Co-ownership confers a lever to reshape prices around renewable production, boosting profitability but dampening gross consumer gains; standalone operation preserves larger gross consumer benefits but requires more subsidy support. Recognizing this trade-off is essential for storage policy in systems where congestion, renewables, and strategic behavior interact.

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