Lucas Epstein

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EDUCATION

PhD in Environmental Economics, Yale School of the Environment — in progress
Bachelor of Arts in Economics from University of California, Davis — March 2020

RECENT RESEARCH

Ideology, Incidence and the Political Economy of Fuel Taxes: Evidence from the California 2018 Proposition 6 [link] — 2024

Investor Base and Prime Money Market Fund Behavior — 2022
[link]

UNDERGRADUATE RESEARCH

Senior Honors Thesis, UCD Department of Economics — April 2019 – March 2020

- Supervised by Dr. Erich Muehlegger and Dr. Giovani Peri, Associate Professor and Professor of Economics, UC Davis
- Aggregated data from a variety of public and private sources with incongruous geographies
- Conducted multiple regressions to identify casual determinants and valid out-of-sample forecasts
- Implemented data manipulation and analysis in STATA with annotated .do files
- Formally presented original research findings to doctoral candidates and professors

Research Assistant, Dr. Anujit Chakrabory (Econ Professor at UCD) — January – August 2020

- Studied Cournot competition in lab experiments to identify unexplored research questions
- Programmed novel experimental setting in Python using oTree open source software
- Assisted professor troubleshooting various experimental settings for his current research

EMPLOYMENT EXPERIENCE

Research Assistant, Board of Governors of the Federal Reserve — June 2020 - July 2023

- Conduct research with economists
- Process and publish economic data for public release

Campaign Strategist/Coordinator, Ostrander for Assembly 2018 — May – September 2018

- Analyzed demographics and prior electoral results to identify the best path to electoral victory
- Displayed excellent communication and collaboration abilities by coordinating all internal communications between various sectors of the campaign

RECOGNITIONS AND PRESENTATIONS

Special Presentation to the Board of Governors of the Federal Reserve — April 2022
CADem Delegate Appointed from Assembly District 35 — 2019 – 2020
UC Davis Dean's Honor List for the College of Letters and Science — 2018 – 2020
Honors Thesis Research Presentation to Faculty — March 2020

Watts Left Behind: How Battery Investment Turns Fossil Fuel Generators into Stranded Assets

Lucas Epstein

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Abstract

This paper examines how climate policy–driven shifts in the cost of clean energy infrastructure propagate transition risk from electricity markets into financial markets. Specifically, I leverage the Inflation Reduction Act's (IRA) 2022 extension of the Investment Tax Credit (ITC) to stand-alone battery energy storage systems (BESS) in ERCOT to document how subsidized battery investment depresses profits of nearby fossil fuel generators, accelerates asset retirements, and redistributes market value. These market-based observations inform a dynamic discrete choice structural model of generator entry, exit, utilization, and profitability, explicitly designed to quantify fossil fuel asset stranding and identify the firms most exposed to transition risk. Using Simulated Method of Moments to estimate a mean-field equilibrium, I recover fossil asset exit costs parameters, enabling counterfactual simulations of alternative policy paths—including the recent early sunset of ITC subsidies under the "Big Beautiful Bill," which exacerbates regulatory timing risk. Crucially, I link these policy-induced profit declines to firm-level bond market data, empirically demonstrating that fossil-exposed firms experience widening bond spreads and constrained debt issuance as credit markets internalize and price transition risk. Taken together, the findings highlight how climate-aligned subsidies—and analogous private-sector concessional financing from green banks—act as financial levers, simultaneously accelerating the energy transition and reshaping asset values in capital markets.

[Please note this is preliminary work and I don't actually have any structural results yet]

1 Introduction

Transition risk—the financial peril posed by rapid decarbonization—has swiftly emerged as a defining challenge for investors and financial institutions. Unlike the direct threats of physical climate risk, transition risk manifests as sudden shifts in asset valuations driven by policy changes, technological breakthroughs, and evolving investor sentiment. This paper explores how such risk ripples through capital markets, explicitly connecting policy-driven investments in clean energy technology to the financial health and valuation of fossil fuel assets. By examining federal subsidies for utility-scale battery storage, I show that climate policies intended to accelerate decarbonization can significantly alter asset prices and credit conditions for firms exposed to fossil fuel generation.

In 2022, the Inflation Reduction Act (IRA) fundamentally altered the investment landscape for battery energy storage systems (BESS) by extending the Investment Tax Credit (ITC) to standalone storage projects. Previously restricted to solar-plus-storage installations, this policy effectively reduced upfront capital expenditures for new battery installations by 30%. The economic shift was immediate and pronounced in competitive wholesale electricity markets, notably the Electric Reliability Council of Texas (ERCOT), where market transparency and price volatility amplify policy impacts. By dramatically lowering the financial hurdle for battery deployment, the IRA intensified competition with fossil fuel generators, depressing their profitability, accelerating retirements, and reshaping market valuations. The subsequent "Big Beautiful Bill," which unexpectedly advanced the sunset of ITC subsidies, introduced further regulatory timing risk, forcing investors and asset owners to grapple with heightened uncertainty over future returns.

To rigorously evaluate the financial implications of this policy intervention, I first present empirical evidence leveraging both temporal and spatial variations in battery subsidy eligibility under the IRA's "energy community" provisions. Despite other confounding factors this analysis leverages spatial difference in subsidies through energy communities to establish a clear relationship: subsidized battery storage projects directly diminish the profitability of nearby fossil fuel generators, accelerate their exit from the market, and redistribute economic value toward renewables and storage technologies. These stylized facts underscore the mechanism through which clean energy policies trigger tangible transition risk for fossil asset holders, motivating the development of a structural model.

Next, I construct a dynamic discrete choice (DDC) model of generator entry, exit, utilization, and profitability, which integrates detailed dispatch simulations to capture intra-day electricity price dynamics, battery charging behavior, and fossil fuel plant operations under varying market conditions. This structural model explicitly quantifies critical economic parameters such as fossil fuel generator exit costs. Simulated Method of Moments (SMM) estimation techniques allow robust identification of these parameters, facilitating credible counterfactual analyses of alternative policy scenarios, including scenarios reflecting accelerated subsidy sunsets and varying durations of policy support.

The core contribution of this paper emerges clearly as I bridge modeled energy market outcomes to firm-level financial market behavior. By aggregating projected profitability declines at the firm level, I construct a transition risk exposure index that quantifies the vulnerability of fossil-exposed firms to subsidy-driven market changes. Empirical analysis of bond market data reveals that these highly exposed firms face increased bond spreads and reduced bond issuance following the policy shift, clear evidence that financial markets actively internalize and price transition risk.

Crucially, I also frame the ITC subsidy as a policy-induced financing wedge, drawing a direct analogy to private-sector concessional financing mechanisms such as green banks and blended finance programs. While standard green bonds generally offer modest reductions in borrowing costs (5–20 basis points), concessional loans from green banks can lower effective debt costs by 100–300 basis points, substantially replicating the subsidy effect provided by the ITC. By explicitly connecting these policy subsidies to analogous private financing channels, this paper demonstrates how both public policy and private green capital allocation can jointly reshape asset valuations, investment patterns, and credit market conditions.

Ultimately, this research bridges critical gaps between energy economics and climate finance literatures by providing concrete, empirical evidence on how climate-driven policy interventions transmit directly into capital market dynamics. For investors, asset managers, policymakers, and financial regulators, these insights clarify how rapidly evolving climate policies and clean energy investments translate into immediate, measurable financial risks and opportunities.

The remainder of this paper is organized as follows. Section 2 outlines the institutional setting, detailing how the Inflation Reduction Act shapes battery investment subsidies and describing ERCOT's unique market design for battery energy storage systems (BESS). Section 4 describes the data collection and preparation procedures, emphasizing variables central to quantifying market dynamics and financial exposure. Section 3 situates this paper within the broader climate finance and energy economics literature, emphasizing studies related to transition risk, asset stranding, and financial market responses. Section 5 presents reduced-form empirical evidence documenting how subsidized battery deployment depresses fossil generator profitability and accelerates retirements, underscoring channels of transition risk exposure. Section 6 develops a dynamic structural model of generator entry, exit, and profitability, explicitly capturing financial impacts driven by policy-induced shifts in the cost of battery capital. Section **??** uses structural estimation results to quantify the market and welfare implications of battery subsidies, directly relating them to financial metrics. Section 7 conducts counterfactual analyses, including scenarios reflecting early subsidy sunsets under the recent "Big Beautiful Bill," highlighting regulatory timing risk relevant to capital market valuations. Finally, Section 8 leverages the structural results to create a firm-level transition risk index and empirically examines its relationship with bond market outcomes, directly illustrating how capital markets internalize and price policy-driven transition risk. Please

note that there are no empirical results yet available; any reference to "results" should be considered as hypotheses guiding forthcoming analysis.

2 Background

2.1 Inflation Reduction Act and Battery Subsidies

The Inflation Reduction Act (IRA), enacted in August 2022, marked a turning point for utility-scale energy storage in the United States. For the first time, stand-alone BESS became eligible for the federal Investment Tax Credit (ITC), previously available only for batteries paired with solar projects. Under the IRA, qualifying storage projects can receive a base ITC of 30% of eligible capital expenditures, with additional "bonus" credits for projects located in energy communities—areas with a legacy of fossil fuel employment or above-average unemployment—and for projects meeting domestic content and labor requirements. In some cases, total credits can exceed 40–50% of installed cost, substantially reducing effective capital expenditures.

The introduction of this subsidy has accelerated the rapid build-out of BESS capacity, particularly in competitive markets like ERCOT where merchant revenue streams are highly volatile. Developers can now capture arbitrage, ancillary services, and congestion management revenues while facing much lower financing hurdles. In addition to the ITC, the IRA implicitly reshapes market dynamics: by increasing the supply of short-duration storage, it amplifies price arbitrage opportunities, reduces peak-hour fossil utilization, and accelerates the risk of stranded fossil assets. While declining battery costs and operational learning also contributed to the surge in storage investment, the IRA's ITC created a clear inflection point for the economics of merchant batteries.

2.2 Energy Reliability Council of Texas

The Electric Reliability Council of Texas (ERCOT) operates the largest stand-alone electricity grid in the United States, serving roughly 90% of Texas load. ERCOT functions as an energy-only wholesale market, where generators are compensated primarily through locational marginal prices (LMPs) for energy and a set of ancillary service markets, without a forward capacity market. This design makes ERCOT uniquely sensitive to short-term price fluctuations, creating fertile ground for merchant storage and for studying the interaction between battery adoption and fossil generator profitability.

ERCOT's grid is spatially granular, with thousands of generator and load nodes, frequent congestion events, and limited interconnection to other U.S. grids. This nodal architecture allows for localized price effects from battery deployment, renewable intermittency, and transmission constraints. Batteries participate in ERCOT primarily by charging during low-price or renewable-abundant hours and discharging during peak or constrained periods, often reducing peak fossil generation and reshaping intra-day price spreads. Because ERCOT is

transparent in its reporting of SCED (Security-Constrained Economic Dispatch) data, LMPs, and generator outputs, it provides a rich empirical setting to study how battery subsidies accelerate fossil fuel stranding and affect market welfare.

3 Literature Review

The global effort to decarbonize electricity has dramatically increased renewable energy penetration, especially from intermittent sources like wind and solar. While these sources directly displace fossil-fuel generation and reduce greenhouse gases, their intermittency creates significant grid management challenges, requiring backup fossil-fuel capacity to maintain reliability (Bushnell and Novan, 2021; Joskow, 2011). This reliance on fossil backup poses a "missing money" problem, where suppressed wholesale prices undermine investment incentives for dispatchable fossil generators (Bushnell and Novan, 2021). Thus, renewables alone cannot fully eliminate fossil fuels without addressing intermittency.

Battery energy storage emerges as a key technology to resolve these issues. By storing excess renewable energy and releasing it during scarcity, storage smooths renewable output fluctuations, reducing reliance on fossil fuel backup (Gowrisankaran et al., 2016). Recognizing storage's critical role, policymakers have introduced incentives such as the Inflation Reduction Act's 30% investment tax credit to accelerate deployment. This literature review evaluates how battery storage interacts with renewable generation and affects fossil fuel displacement, focusing specifically on the economic rationale for subsidies, historical limits of renewable displacement, the potential role of batteries, and implications for stranded fossil assets.

Economic theory and empirical evidence indicate that subsidies can significantly accelerate renewable and storage deployment but may cause unintended distortions. Borenstein (2012) highlights that renewable subsidies, justified by environmental externalities, can induce inefficient geographic or temporal investment patterns, increasing curtailment. Jaffe, Newell and Stavins (2005) and later work by Fischer and Newell (2008) demonstrate theoretically that subsidies alone may be inefficient relative to combining them with direct carbon pricing, arguing that subsidies can inadvertently promote excess capacity or technological lock-in. Lecuyer and Quirion (2013) further argue that overlapping policies—such as subsidies combined with cap-and-trade—can improve welfare under uncertainty but may encourage redundant or misallocated investments.

Empirical work confirms these concerns. Qiao et al. (2024) find that undifferentiated subsidies in China's wind sector caused geographic overbuilding and higher curtailment, wasting potential renewable output. This literature underscores the importance of subsidy design and targeting, motivating careful analysis of battery storage subsidies to understand their actual market effects.

Historically, renewable expansions have not reliably displaced fossil fuel generation. York (2012) provides global evidence showing renewables displaced fossil energy at a rate below 25%, largely due to renewables adding to overall energy supply rather than substituting for fossil fuels. Similar results appear

in U.S. contexts (Thombs, 2025), indicating that state-level fossil fuel production was largely unaffected by renewable growth from 1997–2020. Cullen (2013) offers detailed analysis for ERCOT, finding wind primarily displaced natural gas generation, with negligible coal displacement. These studies highlight renewables' inability to achieve deep decarbonization alone, particularly due to intermittent production patterns that fail to match demand closely enough to fully eliminate fossil fuel reliance.

Recent research positions battery storage as essential to enhancing renewable displacement of fossil fuels. Butters, Dorsey, and Gowrisankaran (2023) show through calibrated equilibrium modeling that adding battery storage significantly lowers peak electricity prices, undermining profitability for fossil-fueled peaker plants. However, the authors do not consider full equilibrium effects of fossil fuel generator retirements. Duan et al. (2020), modeling Alberta's market, demonstrate that substantial storage capacity paired with wind power reduces reliance on peak gas plants, cutting emissions by approximately 20%. Helm and Mier (2021) theoretically model optimal subsidies for storage and renewables, arguing subsidies initially risk aiding fossil plants but eventually become essential to reducing fossil reliance as renewable penetration grows.

Empirical evidence from California reinforces this dynamic. Lamp and Samano (2022) show battery storage effectively smooths wholesale electricity prices, narrowing peak-to-off-peak price differentials, confirming theoretical predictions that large-scale battery deployment significantly reduces fossil peaker profitability and utilization. Collectively, these studies establish battery storage as a critical enabler for substantial fossil fuel displacement.

As storage and renewables threaten fossil generation viability, the economic literature on stranded fossil assets becomes more relevant.A small but growing literature examines how concessional climate finance such as green bank lending or export credit facilities — can act as a financing wedge, lowering the cost of capital for low-carbon infrastructure and accelerating fossil asset stranding. Campiglio & vanderPloeg (2021) analyze macro-financial transition risks arising from such shifts in financing. Beyene etal. (2024) empirically compare syndicated bank debt to corporate bonds in the fossil sector, documenting divergence in lending terms as transition risk emerges. Blended finance reports by NGFS and LSE further detail how de-risking mechanisms reduce borrowing costs and crowd in private investment for renewables. Together, these findings suggest that green public finance, not just green bonds, can drive the same capex-reducing effects as an Investment Tax Credit—mobilizing capital, reshaping market expectations, and triggering credit responses from fossil-exposed firms.

Hansen (2022) quantifies global fossil asset devaluation under strict climate targets, estimating trillions of dollars in potential losses, primarily driven by decreased fossil fuel prices. Mercure et al. (2018) similarly project significant stranded asset risks due solely to renewable technology diffusion, highlighting substantial financial implications for fossil industries and exporting countries. Chen, Landry, and Reilly (2022) further quantify stranded coal generation capital under aggressive climate policies, emphasizing financial market implications.

Bolton and Kacperczyk (2021) extend this analysis into financial markets, documenting a carbon risk premium where investors demand higher returns from high-emission firms. These studies demonstrate fossil-fuel profitability threats from renewable and storage advances, providing context for battery subsidy impacts on fossil generators, which our paper empirically quantifies.

My study builds on and fills an important gap in the existing literature. While prior studies focus largely on simulations or theoretical modeling, we provide empirical evidence quantifying the actual fossil fuel displacement attributable to battery deployment in ERCOT. We leverage recent battery installations to empirically estimate the marginal impact of storage on fossil generator profitability, utilization, and associated emissions reductions, addressing the gap between theoretical predictions and observed market outcomes.

Our analysis is particularly timely, examining direct impacts from policy-driven storage deployment incentives such as the Inflation Reduction Act's investment tax credit. By combining structural modeling with empirical methods, my research clearly measures how battery storage subsidies alter fossil-fuel generation dynamics and contribute to asset stranding risks. Thus, this paper extends existing knowledge by offering direct, real-world evidence on storage's role in facilitating renewable integration, displacing fossil fuels, and increasing transistion risk associated with fossil generators. Ultimately, our work informs both energy economics literature, climate finance, and practical policy formulation aimed at accelerating energy transition and mitigating climate change risks.

4 Data

4.1 Data sources

High frequency output and price data collected so far for this project only includes a single week in April 2025, but the final project will likely involve a sample period spanning 2022-2025. Thanks to ERCOT's careful record keeping and public distribution, the collection and cleaning process is relatively straightforward. ERCOT reports numerous statistics in 5 minute intervals at a node level across several disparate but interconnected datasets. I gather generation (energy sold) and load (energy bought) data from the Security Constrained Economic Dispatch (SCED) reports (form NP3-965-ER). Both these generation and load have energy that was scheduled to be delivered as well as the telemetered quantity of energy that was actually delivered. This data also includes bid schedules that will be used to directly construct supply and demand curves. The generation data also contains a flag for different technology types. A separate form (NP6-788-CD) contains locational marginal prices (i.e. the market clearing price) at each node. The node names in these three datasets are slightly different from one another but can be merged with relatively straightforward string cleaning and fuzzy matching. The geographic coordinates of each node are not provided by ERCOT, but I was able to gather them from the SNL

database provided by Capital IQ Pro.

Unit level capacity and volume (as well as additional information about the technology in use at each node) can be gathered from EIA form 860 and matched to the ERCOT nodes via fuzzy name matching guided by geographical coordinates. The EIA data also provides the capacity of each generating resource, the date it first operated, and the retirement data for relevant fossil fuel plants. Wind speed and solar radiation (if needed) can be gathered from NOAA's High-Resolution Rapid Refresh system and NREL's National Solar Radiation Database, respectively.

4.2 Construction of pseudo-zones

To reduce the dimensionality of ERCOT's nodal market for empirical modeling, I aggregate nodes into pseudo-zones—clusters of nodes that experience highly similar prices. Hourly SCED LMPs from 2018–2024 are first collected for all generator and load nodes, excluding aggregated settlement points and nodes with substantial missing data. I compute the pairwise correlation of hourly prices and define a distance metric $d_{ij} = 1 - \rho_{ij}$. Using agglomerative hierarchical clustering on this correlation-distance matrix, I identify clusters of nodes that rarely experience differential congestion. To ensure that these zones are geographically contiguous, I cross-check each cluster against HIFLD transmission substation coordinates and nodal latitude/longitude, reassigning outlier nodes to the nearest contiguous cluster when necessary. I will evaluate 4-12 clusters before defining an optimal number of pseudo-zones that strike a balance between computational tractability and fidelity to ERCOT's underlying transmission topology.

Each pseudo-zone is assigned a zone-level price series as the capacity-weighted mean LMP of its member nodes. I validate the aggregation in two ways: (1) over 95% of within-zone price variance is explained by the zone series, and (2) ERCOT's publicly reported binding transmission constraints primarily occur between pseudo-zones, rather than within them. This aggregation preserves the key economic features of the nodal market—particularly spatial price separation driven by transmission limits—while providing a tractable framework for modeling dispatch, battery arbitrage, and fossil retirement decisions.

4.3 Relevant Summary Statistics

- Changes in capacity over time by zone and fuel type
- changes in capacity factor over time by zone and fuel type
- changes in profits per MWh over time by zone and fuel type

5 Descriptive Evidence

This section discusses a collection of reduced form OLS specifications that describe how fossil fuel generation technologies interact with exposure to nearby battery installations across ITC eligibility. Exposure at node i to different generating technologies g on day t is represented by:

$$x^0_{g,i,t} = \sum_{j=1}^{J} \frac{MW_{j,t}}{f(d_{i,j})} \tag{1}$$

where J is a list of all generators of type g. We similarly calculated $x^{\text{vintage}}_{g,i,t}$ separately to determine how much exposure is attributable to each vintage year of batteries. These measures are generally increasing in t as more battery capacity gets added to the grid, but they can also fall suddenly then quickly recover as a result of idiosyncratic outages of nearby generators.[1]

Table 1 shows the impact of battery exposure (measured in a variety of ways) on the daily profits of single cycle gas plants. The simplest model (M0) simply shows that, without controlling for any other factors, exposure to batteries corresponds to lower profits for SC generators. M1 and M2 demonstrate that this relationship dissapears if we control for prices and quantity of output. However, if we break exposure apart by vintage as in M3 and M4, we can see that the newer batteries correspond to smaller profits for SC generators. Furthermore, after controlling for the location of variable generation capacity, I find that exposure to older batteries actually corresponds to larger profits for SC plants.

I should note here that there is not a clean causal interpretation of these coefficients. However M4 provides stylized facts that are consistent with a story of early batteries going to places where peaker plant profits are high but not adding enough capacity to crowd out peaker plant profits. However in recent years the coefficients suggest that subsidized batteries may be crowding out peaker plant profits.

We compare table 2 to table 2 which is nearly identical but estimated on combined cycle (baseload) rather than single cycle (peaker) generator profits. Focusing on M4 I find evidence consistent with a story that older, less sophisticated batteries undercut baseload gas revenues. But newer subsidized vintages raised baseload revenues — perhaps by raising baseload profits in the middle of the day.

[LATER: average daily price curves by year]

To dig into these relationships further, I also run regressions using 15 minute interval generator output dependent variable. Results for single cycle generators are reported in table 3. Column M2, M3, M4 present evidence consistent with a story that exposure to new batteries reduces the total amount of generation

[1] It's possible that some generators were able to begin operations prior to RRAA, but intentionally waited until after IRA took effect in order to collect subsidies. This possibility is considered more carefully in the appendix

Table 1: Daily revenue regression results for single cylce combustion turbines

	M0	M1	M2	M3	M4
LMP		1274.794***	1804.782***	1814.256***	1837.417***
		(45.201)	(85.862)	(85.753)	(88.556)
Generation		32.090***	34.117***	33.975***	34.145***
		(0.897)	(1.246)	(1.332)	(1.351)
All Batteries	−0.388*	0.078	0.094		
	(0.167)	(0.094)	(0.067)		
Batt 2001_21				1.102	1.564*
				(0.787)	(0.786)
Batt 2022				64 257.248	36 455.675
				(43 868.203)	(43 422.082)
Batt 2023				−4231.129	−6406.029+
				(3259.474)	(3276.369)
Batt 2024				−5.017***	−8.430***
				(0.951)	(0.922)
Observations	961	463	463	463	463
Adjusted R^2	0.006	0.833	0.961	0.964	0.966
Fixed effects (resource×dow)			X	X	X
Includes wind & solar controls					X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 2: Daily revenue regression results for combined cylce combustion turbines

	M0	M1	M2	M3	M4
LMP		1657.303***	1871.361	1837.309	1831.663
		(75.267)	(1152.767)	(1140.710)	(1141.229)
Generation		29.485***	33.157***	32.999***	32.900***
		(0.447)	(1.297)	(1.263)	(1.266)
All Batteries	−0.357	−0.621	−0.606		
	(0.831)	(0.479)	(0.933)		
Batt 2001_21				−35.774*	−34.505*
				(13.881)	(15.473)
Batt 2022				−71 794.109	−69 858.236
				(46 002.451)	(45 884.936)
Batt 2023				10.387*	10.343*
				(4.641)	(4.630)
Batt 2024				−0.357	0.270
				(0.947)	(0.635)
Observations	2507	1963	1963	1963	1963
Adjusted R^2	0.000	0.726	0.840	0.842	0.842
Fixed effects (resource×dow)			X	X	X
Includes wind & solar controls					X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

from single cycle plants. No such relationship exists when considering baseload combined cycle plants in table 4.

Table 3: Hourly generation regression results for single cylce combustion turbines

	M0	M1	M2	M3	M4
All Batteries	0.000*				
	(0.000)				
Batt 2001_21		0.001	0.007***	0.007***	−40.352
		(0.001)	(0.002)	(0.002)	(1681.772)
Batt 2022		−76.869***	−54.700+	−53.813+	−62.088
		(13.944)	(27.931)	(27.957)	(99.802)
Batt 2023		−4.331	−30.622***	−31.018***	−39.002*
		(4.180)	(7.244)	(7.352)	(14.514)
Batt 2024		−0.001	0.000	0.003	0.002
		(0.001)	(0.002)	(0.002)	(0.025)
Observations	89 284	89 284	89 284	89 284	89 284
Adjusted R^2	0.005	0.015	0.370	0.371	−1.420
Fixed effects (resource×hour & dow×hour)			X	X	X
Includes wind & solar controls				X	X
Hourly × interactions (battery)					X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Given the high frequency data at our disposal we can examine the times of day where new batteries have a negative relationship with peaker plant generation. To this end I regress generation on interactions between hour of the day and battery exposure (pre and post IRA implementation battery exposure are calculated and enter the regression separately), prices, and fixed effects capturing both resource-hour and hour-day-of-week effects.

The results are presented in figure 1. Which shows results consistent with newer subsidized batteries displacing single cycle plants in the evenings and early mornings. A similar analysis on combined cycle plants does not yield any significant coefficients.

6 Structural Model

The structural model employs a dynamic discrete choice (DDC) framework to analyze quarterly entry and exit decisions of electricity generation technologies, including CC, SC, batteries, wind, and solar, within ERCOT. The model

Table 4: Hourly generation regression results for combined cylce combustion turbines

	M0	M1	M2	M3	M4
All Batteries	0.003*				
	(0.001)				
Batt 2001_21		0.014	−0.010	−0.002	−0.016
		(0.012)	(0.007)	(0.005)	(0.011)
Batt 2022		−46.577	−38.354	−37.053	−92.493
		(43.985)	(38.594)	(38.201)	(68.734)
Batt 2023		−0.008	−0.002	−0.003	−0.001
		(0.011)	(0.004)	(0.004)	(0.009)
Batt 2024		0.004***	−0.001+	−0.001+	−0.001
		(0.001)	(0.000)	(0.000)	(0.001)
Observations	167 050	167 050	167 050	167 050	167 050
Adjusted R^2	0.004	0.006	0.791	0.791	0.792
Fixed effects (resource×hour & dow×hour)			X	X	X
Includes wind & solar controls				X	X
Hourly × interactions (battery)					X

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

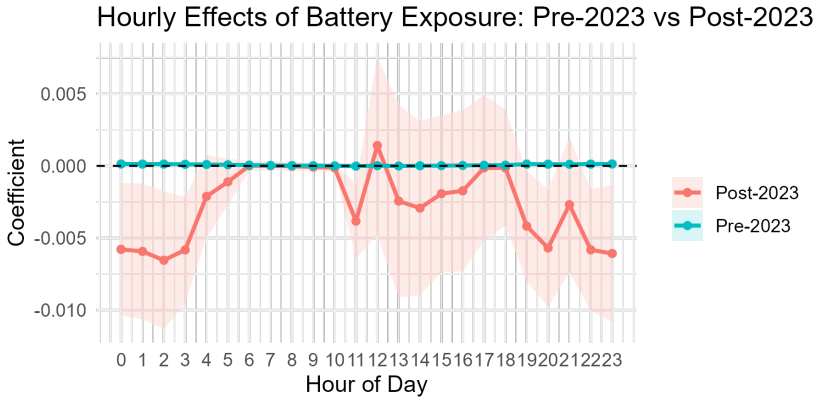


Figure 1: Effect of battery exposure by hour

integrates a merit-order dispatch linear program that simulates intra-day electricity prices, generation dispatch, battery cycling behavior, and operational constraints. Profits derived from this dispatch simulation serve as inputs for the dynamic investment decisions. Investors choose discrete increments of capacity entry or exit based on expected profitability and explicitly modelled exit costs. The modelled exit costs are estimated using Simulated Method of Moments (SMM), matching simulated data to observed empirical moments such as entry and exit patterns, profit dynamics, or policy-driven shifts.

Validation of the dispatch module ensures the structural model generates realistic market outcomes, aligning simulated prices, capacity factors, and operational profits with ERCOT's observed data. Counterfactual simulations assess the impact of different policy scenarios, such as eliminating or extending battery subsidies and introducing carbon pricing. These counterfactuals provide quantitative insights into the dynamic feedback loop where battery adoption depresses fossil generator profitability, accelerates retirements, and reshapes market structure. Section 8 leverages the results of the model to explicitly quantify transition risk exposure at the firm level and links changes in expected fossil profitability to shifts in financial market behavior, including widening bond spreads and reduced issuance activity for firms heavily exposed to risky fossil assets.

6.1 Merit Order Dispatch Model

To compute operational profits, capacity factors, and market-clearing prices for each technology in each zone–quarter, I simulate a dispatch equilibrium over a representative week using a linear program. The model includes five generation technologies—natural CC, SC, battery storage, wind, and solar—and captures key operational constraints, including ramping and battery cycling. Dispatch is determined by cost minimization subject to supply–demand balance and physical limits. Electricity prices are the shadow values on the supply-demand balance constraints (equation A.2) and reflect the marginal cost of meeting demand in each hour. This is similar in principle to how ERCOT chooses which generators to call upon. The key difference is that my model is less sophisticated and makes a "copper plate" assumption within each psuedo-zone where as the ERCOT dispatch system more carefully considered transmission costs and constraints. That being said, I show later that my model is an excellent approximation of dispatch within ERCOT throughout my sample.

The merit order dispatch model is described in detail in the appendix as well as summarized here. In the dispatch model we imagine ERCOT as the social planner that minimizes the the cost of total energy production in a representative week across all technologies and zones. This optimization is subject to constraints that ensure energy produced is equal to energy consumed, that engineering limits on output capacity, thermal unit ramping, battery state of charge, round trip efficiency, and interzonal transfers are respected, and that renewables are not curtailed. The key outputs from this model are zone-hour-technology prices, generation, and most importantly profits. These outputs are critical inputs needed for solving the entry/exit Bellman equations. However, it

would be infeasible to solve this linear program for every potential state space for each Bellman solve. To circumvent this issue I will solve the the linear program once on a sparse grid. I then estimate a "profit emulator" using a ridge regression (Hoerl & Kennard 1970; Dhrymes 1971; Greene 2018).[2] Let the state at time t be:

$$S_{zt} = \left(K_{gzt}^{\text{stock}} \ \forall g,\ \bar{K}_{-z,t},\ \text{FuelPrices}_t,\ \text{Policy}_t\right)$$

I denote the profit emulator as $\hat{\pi}(S_{zt})$. Given the centrality of this function in the structural model, I need to ensure that the outputs of the emulator sufficiently reflects reality. To this end, I will validate model output against observed data to ensure that it closely mimics observed prices and outputs.

6.2 Structural Entry/Exit Model

This section presents the dynamic discrete choice (DDC) structural model of quarterly entry and exit decisions by generation technology. The model is estimated using Simulated Method of Moments (SMM) and is designed to quantify how expected profits and exogenous policy incentives affect investment behavior in ERCOT. The model builds on the dispatch framework described in section A.2 using simulated profits as flow payoffs.

I model each generation technology $g \in \{\text{sc}, \text{cc}, \text{batt}, \text{wind}, \text{solar}\}$ as a representative investor solving a forward-looking dynamic decision problem in each zone z and quarter t. Investors choose whether to:

- **Enter:** Add $k_{gzt}^{\text{entry}} \in \{0, 10, 50, 100, 200\}$ MW of capacity for g in zone z at time t.
- **Exit:** Retire $k_{gzt}^{\text{exit}} \in \{0, 10, 50, 100, 200\}$ MW of capacity for g in zone z at time t.

I impose this discrete and finite action space to ensure tractability in the dynamic program and estimation. All state transitions occur over this limited grid of MW increments. Each decision incurs an investment or scrap cost and leads to future payoffs depending on the evolving state vector.

Where K_{gzt}^{stock} is the installed capacity of technology g in zone z; $\bar{K}_{-z,t}$ is total installed capacity in other zones (captures spillovers); Policy_t is a vector of exogenous policy indicators (e.g., ITC eligibility, counterfactual carbon prices, etc); andFuelPrices_t is vector of zonal fuel prices for fossil generators. The flow payoff in quarter t from owning K_{gzt} MW of technology g in state s_{zt} is given by the profit emulator, $\hat{\pi}_{gzt}(S_{zt})$. Entry and exit costs are specified as:

$$\text{EntryCost}_{gzt} = \left(\text{Capex}_{g0} \cdot (1 - \text{Subsidy}_{gt}) \cdot f_g(t)\right) \cdot a_{gzt}^{\text{entry}}$$

$$\text{ExitCost}_{gzt} = \phi_g \cdot a_{gzt}^{\text{exit}}$$

[2] A ridge regression is essentially an OLS with an additive penalty term to keep the magnitude of coefficients small. This sort of regression has been shown to produce better out of sample predictions.

Where ϕ_g represents exit cost per MW for fossil technology g; Capex_{g0} is baseline capital cost; Subsidy_{gt} is the policy subsidy rate (e.g., 0.3 if 30% ITC); and $f_g(t)$ is a price path for technology g monotonically declining in t. ϕ_g will estimated by the model where as the rest of the parameters here are externally calibrated.

Let $V_{gzt}(s_{zt})$ be the value function for technology g in zone z at time t. The Bellman equation I solve is:

$$V_{gzt}(s_{zt}) = \max_{a_{gzt} \in \mathcal{A}} \{\hat{\pi}_{gzt}(S_{zt}) - \text{Cost}_{gzt}(a_{gzt}) + \beta \cdot \mathbb{E}\left[V_{g,z,t+1}(s_{z,t+1}) \mid S_{zt}, a_{gzt}\right]\}$$

Where $\mathcal{A}$ is the finite set of entry/exit actions (e.g., $\{0, 50, 100, 200\}$ MW). (These are placeholder values in the current version); and β: quarterly discount factor (fixed)

6.3 Estimation Approach

I estimate the exit cost per MW, ϕ_g, for fossil technologies using a computationally tractable structural procedure. The key device is to solve for a mean-field equilibrium (MFE) rather than a full Markov Perfect Equilibrium (MPE). In an MPE, each firm best-responds to the full vector of other firms' strategies, which requires solving the entire set of strategies jointly. In high dimensional spaces, such as the state space of my model, solving a multi firm MPE would become computationally infeasible. The MFE solution algorithm circumvents part of this dimensionality problem by solving each technology–zone problem separately while still capturing the aggregate influence of the rest of the system. considering each zone separately. The solution algorithm, described in more detail below, assumes a law of motion for other zones, generates best responses given this conjectured law of motion for aggregates, simulates to update that law, and iterates to a fixed point. This fixed-point approach substantially reduces dimensionality and is one of the key simplifications necessarily to solve this model.

We should be careful to note that MFE and MPE are precisely identical. Rather, I am relying on a standard result that in dynamic industries with many agents, equilibria of the finite-player game converge to mean-field (or oblivious) equilibria, and that mean-field best responses provide accurate approximations to MPE outcomes in large systems (Weintraub, Benkard & Van Roy 2008, 2010).

To preserve cross-zone realism, I summarize outside capacity using technology-specific aggregates, $K_{-z,g}$, across five buckets: CC, SC, storage, wind, and solar. The profit emulator is trained on dispatch linear program runs that respect interzonal transmission limits. Profits in zone z therefore respond to both own capacities $K_{z,\cdot}$ and outside aggregates $K_{-z,\cdot}$ in a way consistent with network constraints.

To further manage computational burdens, I discretize the state space on a coarse grid: six grid points for each own capacity K_g (for all five technologies) and three grid points for each outside bucket $K_{-z,g}$ (for all five tech-

nologies). Policy is treated as a regime indicator, so I solve the pre-IRA and post-IRA problems separately rather than introducing an additional state dimension. Fuel prices follow an AR(1) process and enter through the emulator. In the Bellman expectation I integrate over a small quadrature set of realizations (low/medium/high with weights) rather than gridding fuel directly, which avoids state-space explosion while still allowing fuel to meaningfully shift profits.

The equilibrium-finding algorithm begins with an initial guess for the law of motion governing outside aggregates, for example of the form

$$K_{-z,b,t+1} = a_b + \rho_b K_{-z,b,t} + \gamma_b \, IRA_t + u_{b,t}.$$

Given this conjecture, I solve each zone's Bellman problem using policy iteration, which yields technology–zone-specific policy functions conditional on the proposed law of motion. These policies are then used to simulate the entire system forward, producing artificial histories of capacity evolution across all zones and technologies. From these simulated paths, I re-estimate the law of motion for the aggregates, and then replace the initial conjecture with a damped update toward this new estimate. By repeating this process, the law of motion and the induced policies converge to a fixed point: the simulated evolution of aggregates implied by the policy functions is consistent with the law of motion that agents were presumed to take as given.

Once the mean-field equilibrium has converged, I forward-simulate the model to compute empirical moments.

To identify ϕ_g, I use eight moment conditoins. The first two moments involve profit-exit responsiveness in fossil fuel generators. For each each of $g \in \{sc, cc\}$, I match the slope of exit hazards on a lagged profitability index $\tilde{\Pi}_{i,t} = \sum_{k=0}^{L} \delta^k \Pi_{i,t-k}$:

$$\Pr(E_{i,t} = 1) = \alpha_g + \beta_g \, \tilde{\Pi}_{i,t} + \lambda_{\text{age}} + \lambda_z + \lambda_t + \varepsilon_{i,t},$$

with moment definitions being

$$m_g^{\text{slope}} = \hat{\beta}_g^{\text{data}} - \hat{\beta}_g^{\text{sim}}(\phi).$$

Higher ϕ_g dampens responsiveness, so m_g^{slope} should shrink toward zero as exit costs rise.

The next six moments capture the equilibrium path of fuel mixes. For each fossil technology $g \in \{sc, cc\}$, I estimate in data and in simulations the panel regression

$$\Delta K_{gz,t} = \alpha_g + \lambda_z + \lambda_t + \beta_g^{(W)} \, \text{WindShare}_{z,t-1} + \beta_g^{(S)} \, \text{SolarShare}_{z,t-1} + \beta_g^{(B)} \, \text{StorageRatio}_{z,t-1} + \varepsilon_{gz,t},$$

where $\Delta K_{gz,t}$ is the net change in fossil capacity (MW) by zone and year, and λ_z, λ_t are zone and year fixed effects. WindShare, SolarShare are the shares of generation or capacity from wind and solar, and StorageRatio is a measure of storage penetration (e.g., MW of storage relative to peak load). Moments are defined as the differences in estimated coefficients between data and simulation:

$$m_g^{\text{wind}} = \hat{\beta}_g^{(W),\text{data}} - \hat{\beta}_g^{(W),\text{sim}}(\phi), \quad m_g^{\text{solar}} = \hat{\beta}_g^{(S),\text{data}} - \hat{\beta}_g^{(S),\text{sim}}(\phi), \quad m_g^{\text{stor}} = \hat{\beta}_g^{(B),\text{data}} - \hat{\beta}_g^{(B),\text{sim}}(\phi).$$

For fossil technologies, the expected sign of all three is negative: greater penetration of wind, solar, or storage should accelerate fossil exit.

Together, these eight moments (two hazard–profit slopes and six fuel mix) provide over-identification for the two parameters $\phi_{\text{sc}}, \phi_{\text{cc}}$, balancing direct identification of exit costs with discipline on the interactions between different technologies of interest. I am also considering including a set of conditions that disciplines the relationship between technology types across different zones as well as the the MFE fixed point identification.

7 Counterfactuals

In this section I will compare baseline results to counterfactuals associated with three possible policy alternatives. The first counterfactual answers the question: what would have happened if the IRA had not extended ITC to BESS. I compute this counterfactual by setting $\text{subsidy}_{b,t} \quad \forall t$ equal to zero in all periods and projecting forward from an initial date of 2022Q4. Next I consider the effects of the new law that sets ITC to expire in 2028. Similar to the first counterfactual I set $\text{subsidy}_{g,t} = 0 \quad \forall t > 2027q4$ and project forward from 2025Q1. Finally I examine what the effects of a carbon tax would be. For this counterfactual I calculate the emissions from different fuel times and adjust the fuel type variable as needed. For each of these counterfactuals plus the baseline, I will chart the following statistics.

- capacity by technology over time
- capacity factor for fossil fuel plants over time
- total generation by technology over time
- Emission pathway
- NPV of changes to producer surplus per technology relative to baseline
- NPV of changes to consumer surplus relative to baseline
- NPV of total welfare both including and excluding SCC

8 Extension to Financial Markets

8.1 Measuring Firm-Level Transition Risk Exposure

I define transition risk as the economic exposure of a firm to declining fossil fuel profits arising from the energy transition, including battery adoption, renewable

penetration, and policy-induced retirements. The structural model produces zone- and technology-specific expected profits for each period t:

$$\hat{\pi}^{\text{baseline}}_{g,z,t}, \quad \hat{\pi}^{\text{no policy}}_{g,z,t},$$

where g indexes generation technology (e.g., sc, cc), z indexes pseudo-zones constructed from nodal price correlations, and t indexes time. Let $K_{f,g,z}$ denote the capacity of firm f in technology g and zone z. We define firm-level transition risk exposure as the expected decline in profits under a transition scenario:

$$\Delta\Pi_f = \sum_{g,z} K_{f,g,z}\Big(\hat{\pi}^{\text{baseline}}_{g,z} - \hat{\pi}^{\text{no policy}}_{g,z}\Big), \tag{2}$$

where a negative value indicates a loss in continuation value as a result of ITC extending to batteries.

To facilitate comparison across firms of different sizes, we also construct a normalized transition risk index:

$$\text{TRI}_f = \frac{\Delta\Pi_f}{\sum_{g,z} K_{f,g,z}\hat{\pi}^{\text{no policy}}_{g,z}}, \tag{3}$$

which measures the percentage decline in expected profits relative to the no policy baseline.

8.2 Linking Transition Risk to Financial Markets

I next examine whether financial markets price this transition risk. Using firm-level bond issuance data from S&P Capital IQ Pro, I match generation firms to their parent company debt (via DUNS numbers) and construct a panel of bond-level yields and spreads relative to matched-maturity Treasury securities.

We exploit quasi-experimental variation from the passage of the Inflation Reduction Act (IRA) and the contemporaneous acceleration of battery adoption in ERCOT. Specifically, we estimate a difference-in-differences specification comparing firms with high vs. low transition risk exposure before and after the policy event:

$$\text{Spread}_{f,t} = \alpha + \beta\Big(\text{HighRisk}_f \times \text{PostPolicy}_t\Big) + \gamma_f + \lambda_t + \varepsilon_{f,t}, \tag{4}$$

where:

- $\text{Spread}_{f,t}$ is the bond yield spread (or new-issue coupon) for firm f at time t;
- HighRisk_f is an indicator for firms in the top quartile of the Transition Risk Index (3);
- PostPolicy_t is an indicator for periods after the IRA passage or other salient transition policy;

- γ_f and λ_t are firm and time fixed effects.

The coefficient β measures the differential change in financing costs for highly exposed firms following the policy shock. A positive and significant β would indicate that credit markets recognize and price the transition risk associated with fossil asset exposure in the presence of growing battery penetration and anticipated retirements.

I complement this yield-based analysis with a volume-based test, examining whether high-risk firms issue fewer bonds post-policy, consistent with restricted market access rather than pure repricing.

9 Conclusion

This paper highlights how climate policy-driven investments in battery storage reshape electricity markets and transmit significant transition risk to financial markets. Leveraging the 2022 extension of the Investment Tax Credit (ITC) to standalone battery storage systems under the Inflation Reduction Act (IRA), I demonstrate how subsidized battery investment materially depresses the profitability of fossil fuel generators, accelerates their retirements, and triggers substantial redistribution of market value toward clean energy infrastructure. These empirical observations provide a clear mechanism through which climate policy interventions directly translate into tangible financial risk for firms holding fossil-based assets.

The core contribution of this analysis emerges clearly from the development and estimation of a dynamic discrete choice structural model, which quantifies fossil asset stranding and explicitly links these market outcomes to firm-level credit risk. Using Simulated Method of Moments (SMM) estimation, the model credibly identifies fossil exit costs, enabling robust counterfactual analyses under varying policy scenarios — including the recently enacted "Big Beautiful Bill," which accelerates the ITC subsidy sunset and highlights how regulatory timing uncertainty compounds financial risks.

Critically, this paper extends beyond market-level insights, directly connecting policy-driven shifts in asset profitability to observable financial market outcomes. By constructing firm-level measures of transition risk exposure from modeled profit trajectories, I document clear responses in bond markets: fossil-exposed firms face elevated financing costs and reduced debt issuance consistent with capital markets actively internalizing and pricing the climate-related transition risks. Additionally, by explicitly characterizing the ITC subsidy as analogous to a financial "wedge" introduced by private concessional lending mechanisms—such as green banks and blended finance programs—the analysis bridges a crucial gap between energy economics and climate finance literature. This framing emphasizes how public subsidies and private green finance function as complementary financial levers, jointly reshaping asset values and investment patterns during the energy transition.

Ultimately, this research contributes a timely and rigorous empirical demonstration of how climate policy and private-sector green capital allocation prop-

agate through financial markets, influencing asset valuations, investment risks, and credit conditions. For financial regulators, policymakers, asset managers, and investors navigating an economy in rapid transition, the insights offered here underscore the critical need to understand and proactively manage transition risks in portfolios exposed to carbon-intensive industries.

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A Dispatch Model

A.1 Description

Let:

- $h = 1, \ldots, 168$ index the hours in a representative week.
- $g \in \{\text{combined cylce (cc)}, \text{single cycle (sc)}, \text{batt}, \text{wind}, \text{solar}\}$ index generation technologies.
- K_g: installed capacity (MW) of technology g in the zone.
- D_h: hourly electricity demand in the zone.
- $A_{gh} \in [0, 1]$: availability factor of technology g in hour h. For wind and solar, this is exogenous; for dispatchable technologies, $A_{gh} = 1$.
- MC_g: marginal cost of generation for technology g.
- $\eta \in (0, 1)$: battery round-trip efficiency.
- $b^{\max}$: maximum battery charge/discharge rate (MW).
- $E^{\max}$: maximum battery energy stock (MWh).
- R_g: hourly ramp rate limit for fossil technologies (fraction of capacity).
- $I^{\max}$: maximum interzonal import/export (MW).

Decision Variables

- q_{gh}: output of technology g in hour h.
- b_h^{charge}, $b_h^{\text{discharge}}$: battery charging and discharging in hour h.
- m_h: net imports in hour h from other zones (positive if importing).

Optimization Problem

$$\min_{\{q_{gh},b_h,m_h\}} \quad \sum_{h=1}^{168} \sum_{g\in\{\text{cc,sc}\}} MC_g \cdot q_{gh} \tag{A.1}$$

$$\text{s.t.} \sum_{g\in\{\text{cc,sc}\}} q_{gh} + b_h^{\text{discharge}} + \sum_{g\in\{\text{w,s}\}} A_{gh}K_g + m_h = D_h + b_h^{\text{charge}} \ \forall h \tag{A.2}$$

$$0 \le q_{gh} \le K_g \quad \forall g \in \{\text{sc}, \text{cc}\},\ \forall h \tag{A.3}$$

$$|q_{g,h+1} - q_{gh}| \le R_g \cdot K_g \quad \forall g \in \{\text{cc}, \text{sc}\},\ \forall h < 168 \tag{A.4}$$

$$0 \le b_h^{\text{charge}} \le b^{\max}, \quad 0 \le b_h^{\text{discharge}} \le b^{\max} \quad \forall h \tag{A.5}$$

$$e_{h+1} = e_h + \eta \cdot b_h^{\text{charge}} - \frac{1}{\eta} \cdot b_h^{\text{discharge}} \quad \forall h < 168 \tag{A.6}$$

$$0 \le e_h \le E^{\max} \quad \forall h, \quad e_0 = \bar{e} \tag{A.7}$$

$$q_{gh} = A_{gh} \cdot K_g \quad \forall g \in \{\text{wind}, \text{solar}\},\ \forall h \tag{A.8}$$

$$m_h \in [-I^{\max},\ I^{\max}] \quad \forall h \tag{A.9}$$

Model Outputs
Solving this linear program yields:

- **Hourly electricity prices** P_h: the shadow value on constraint A.2.
- **Generation** q_{gh} for dispatchable technologies and battery operations.
- **Technology-specific profits:**

$$\pi_g = \sum_{h=1}^{168} (P_h - MC_g) \cdot q_{gh}$$

- **Battery arbitrage profits:**

$$\pi_{\text{batt}} = \sum_{h=1}^{168} P_h \cdot (b_h^{\text{discharge}} - b_h^{\text{charge}})$$

- **Capacity factors for dispatchable technologies:**

$$\text{CF}_g = \frac{1}{168 \cdot K_g} \sum_{h=1}^{168} q_{gh}$$

These model-generated profits π_g enter the dynamic investment model as technology-specific flow payoffs. Because prices and dispatch respond endogenously to the installed capacity mix in each zone–quarter, this approach allows the model to capture key interactions such as price suppression from renewables and battery arbitrage.

A.2 Validation

To ensure the credibility of the dispatch model described above, I validate its outputs against observed data from the ERCOT market. Although the dispatch model is not formally estimated, its purpose is to generate realistic prices, generation levels, capacity factors, and profits for each technology, which in turn inform the structural investment model. This validation step is crucial for confirming that the dispatch model produces behavior that approximates actual market outcomes.

I simulate the dispatch model for a representative week in each zone–quarter using the observed capacity mix, fuel prices, and technology availability profiles (wind and solar). I then compare the model outputs to corresponding empirical metrics from ERCOT data, focusing on four key dimensions:

1. **Electricity Prices:** I compare the model-implied hourly prices (the shadow prices on the supply–demand constraints) to observed ERCOT real-time or day-ahead locational marginal prices (LMPs) at zonal hubs. report the average price level, standard deviation, and intraday patterns.

2. **Technology Dispatch:** For each dispatchable technology (cc, sc, battery), I compare model-implied generation to observed generation in the same zone–quarter. For renewable technologies, I match generation using exogenous availability profiles. Discrepancies in dispatch are interpreted in terms of marginal cost calibration or binding operational constraints.

3. **Capacity Factors:** I compute the model-implied capacity factor for each technology as:
$$\mathrm{CF}_g = \frac{1}{168 \cdot K_g} \sum_{h=1}^{168} q_{gh}$$
and compare to empirical averages derived from ERCOT's Generator Output data. This provides a key diagnostic of whether dispatchable technologies are producing realistic levels of output.

4. **Profits per MW:** I calculate the operational profit per installed MW for each technology. These profits are compared to estimates from reduced-form regressions or accounting-based benchmarks, and are used as flow payoffs in the dynamic investment model.

For each of the above dimensions, I compute validation metrics such as root mean squared error (RMSE) and show graphical comparisons.

Close alignment between model and data on these dimensions indicates that the dispatch model is a credible engine for generating policy-relevant counterfactuals and technology-specific profitability signals. Moderate discrepancies can be interpreted in terms of uncertainty in marginal cost calibration, battery cycling behavior, or miscalibration of import/export frictions. If substantial gaps are observed, I can iteratively refine model inputs (e.g., fuel costs, availability factors, interzonal import constraints) in an ad hoc fashion and revalidate until the model reasonably replicates patterns shown in the ERCOT data.