Large-scale Battery Storage, Short-term Market Outcomes, and Arbitrage

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November 23, 2021

Introduction

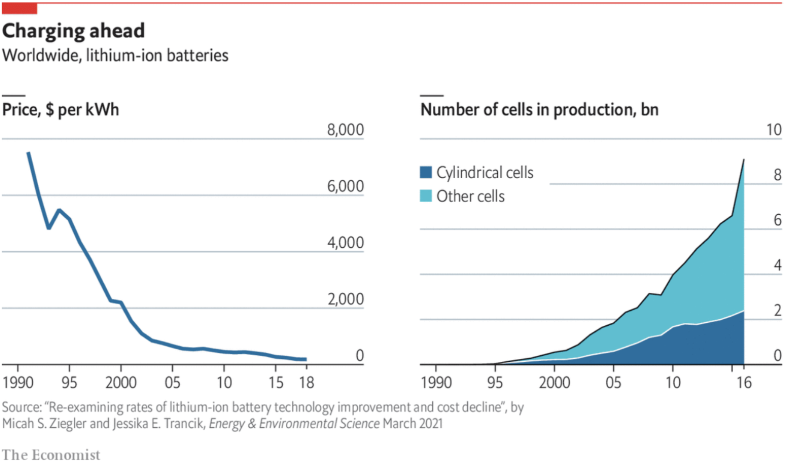
- Share of variable renewable electricity (VRE) in the portfolio mix of generation has more than doubled from 2012 to 2018 in the US (NREL 2018)
- Impacts on emissions, wholesale prices, long-term costs due to the volatility of the electricity supply
- VRE not perfectly forecastable and non-dispatchable
  - **Acceleration of introduction of large-scale, non-hydro, storage technologies such as lithium-ion batteries**
- 1,236 megawatt-hours (MWh) of energy capacity (869 MW of power) installed of batteries across the US at the end of 2018 (EIA 2020)
  - Equivalent to nearly 15 times more power capacity relative to 2010 (EIA 2020)

Research questions

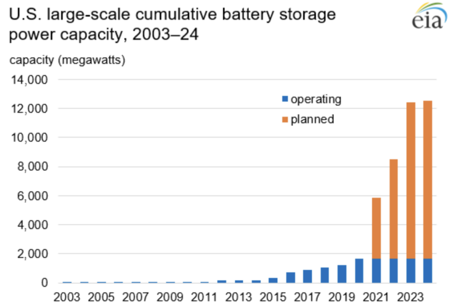
Goal: Characterize the discharging and charging behavior of large-scale battery storage facilities

1. Do storage facilities discharge more or less when load is high?
2. Do storage facilities charge more when wholesale prices are low and sell when they are high in line with a model of optimal arbitrage?
3. Does the addition of new battery capacity affect intra-day price spreads?
4. Are these facilities profitable at current electricity prices and investment costs?

Worldwide lithium-ion batteries



(Planned) battery deployment in the US



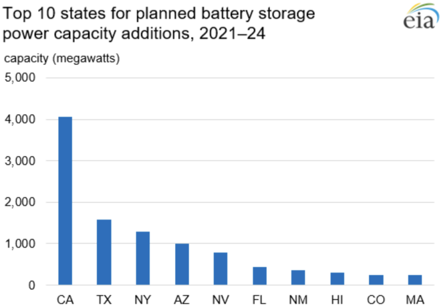


Image: EIA, Electricity Monthly Update.

This paper

Uses novel data on battery storage deployment from the California Independent System Operator (CAISO) 2018-2020

- Descriptive analysis: correlation of battery output with load and prices
- Comparison of actual output data with a stylized model of optimal battery dispatch
  - Representative battery for the California market in 2019
  - Take as input time series of wholesale prices in the CAISO
- Impact of battery deployment on wholesale prices, using 2013-2017 data

Preview of results

- Battery discharging is associated with high levels of load and prices
- Impact of **real-time mkt** (RTM) and **day-ahead mkt** (DAM) prices on battery charging and discharging for different hours of the day provides only partial supporting evidence for optimal behavior of batteries
- New batteries installed capacity associated with approximately 5% decrease in the size of the maximum max-min RTM intraday spread (slightly lower impact for the average max-min intraday spread)
- Current price levels and installation costs not conducive to profitability of batteries

Related Literature

Impact of storage on electricity market outcomes:
Emissions (e.g. Holladay and LaRiviere, 2018), value of storage in ancillary service markets (e.g. Cheng and Powell, 2016); role of storage in integrating VRE (e.g. Black and Strbac, 2007); congestion benefits of batteries (Kirkpatrick, 2020); and impact of market structure on battery investment and social welfare (Andres-Cerezo and Fabra, 2020)

Deployment of batteries in electricity markets (engineering optimization models):
Giulietti, Grossi, Baute, and Waterson, 2018; Sioshansi, Denholm, Jenkin, and Weiss, 2009; among others

Empirical evidence of battery investment and deployment (dynamic models):
Dorsey, Gowrisankaran, and Butters, 2021; Karaduman, 2020

Data sources: CAISO

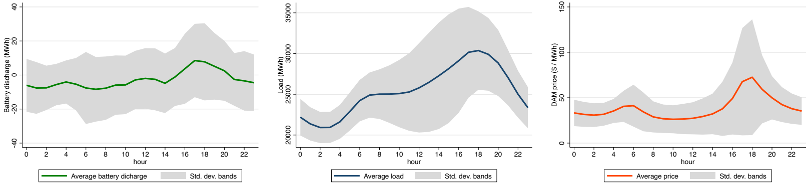
- CAISO/OASIS on aggregate battery output, total load, load forecasts, output of renewables (including large hydroelectric plants) at 5-minute resolution
- Hourly real-time market (RTM) price data from four Default Load Aggregation Points (DLAP)
  - We average the price data from DLAP locations to obtain a unique time series for CAISO (the four DLAP locations are Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), San Diego Gas & Electric (SDG&E), and Valley Electric Associations (VEA))
- Hourly day-ahead market (DAM) price data from 3 main trading zones in California
  - Average of trading zones: NP15, SP15, and ZP26

Additional data sources

- Installed storage capacity in the CAISO from the Energy Information Administration (EIA 860-Form) and Department of Energy (DOE) Global Energy Storage Database
- CAISO started reporting data on battery output in mid-April 2018 & DAM price data starting in June 2018
  - We limit our sample to the period 6 June 2018 to 1 March 2020 to ensure consistent data reporting and to avoid potential confounding effects resulting from the COVID-19 pandemic
- For analysis of battery deployment: data from 2013 - mid 2017 (Bushnell and Novan, 2019) when we observe exact dates of battery entry (DOE)

Descriptive data plots

Figure: Batteries output, load, and prices from the CAISO



(a) Batteries (b) Load (c) DAM prices

Notes: Average battery usage, load profile and Day-Ahead Market (DAM) prices from CAISO +/- standard deviation. Data aggregation: 5-minutes, but DAM prices (hourly). Sample: 6 June 2018 to 1 March 2020.

Operational energy projects (May 2018)

Source: California Energy Commission based on DOE Energy Storage Database.

Batteries characteristics

- Batteries described in terms of **energy capacity** (how much electricity can be stored [MWh]), their **power** (how much electricity can be charged or discharged in any instant [MW]), and **roundtrip efficiency** (how much electricity is not lost in the charging and discharging processes)
- Parameters in our optimization model are inspired by the large-scale facilities already in operation in California:
  - In 2019: 172 operational facilities in the US, of which 47 were in California. Vast majority are lithium-ion batteries
  - Mean **energy capacity** for plants in California is 13.8 MWh and the **median is 7.2**, but there is a facility with a capacity of 120 MWh
  - The mean of **power** for these batteries is 5.3 MW, with a **median of 1.5 MW**
  - The facility with 120 MWh of energy capacity has a power of 30 MW and it is owned by San Diego Gas & Electric

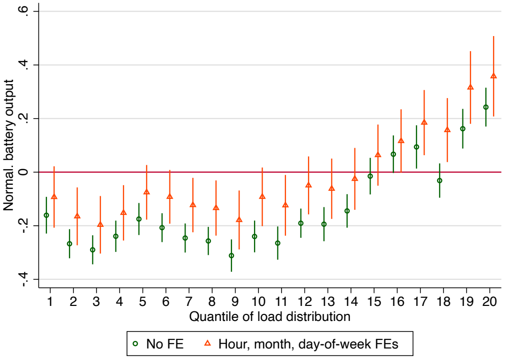
Descriptive analysis

- Similar to Jha and Leslie (2019) and Davis and Hausman (2016), we estimate:

$$Y_t = \sum_{q=1,\dots,20} \beta_q \times \mathbb{1}(X_t \text{ is in quantile } q) + \gamma_\tau + \epsilon_t,$$

- $Y_t =$ battery output / mean of absolute battery output over sample period
  - Normalization allows to interpret coefficients with respect to the average battery dispatch
- $X_t =$ load, hour-ahead forecast of load, load forecast error (defined as the difference between realized load and the hour-ahead forecast of load), or prices
- γ_τ is a vector of time-related fixed-effects: hour, day-of-week, and month
- β_q are the means conditional on quantile q when no FEs or constant added

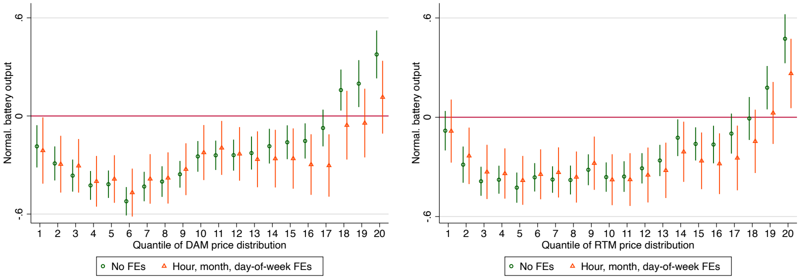
Batteries and load



Notes: Each value represents the effect on battery discharge at each quantile of the distribution of demand. The controls consist of the total output from renewables and large hydro plants. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (6 June 2018 to 1 March 2020).

Batteries and wholesale prices

Figure: Batteries and wholesale prices

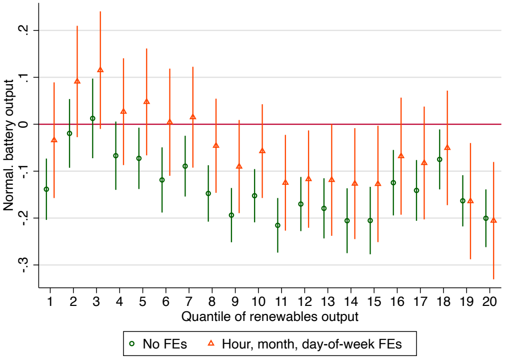


(a) Using DAM prices

(b) Using RTM prices

Notes: Each value represents the effect on normalized battery discharge at each quantile of the distribution of wholesale market prices. Hourly data resolution. Panel(a): DAM prices. Panel(b): RTM prices. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from the CAISO (6 June 2018 to 1 March 2020).

Batteries and renewables



Notes: Each value represents the effect on battery discharge at each quantile of the distribution of renewables output. The controls consist of large hydro plants output and load. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (6 June 2018 to 1 March 2020).

Four facts about batteries output

- Battery output is high when load (demand) is high: $\nearrow$ the value of storage
- Batteries purchase electricity when prices are low or near-median levels and discharge when prices are very high: partial evidence of arbitrage
- Batteries charge when renewables output is high: partial evidence of co-optimization, $\nearrow$ value of storage
- Batteries output responds similarly to unexpected demand increases and unexpected price jumps Hour-ahead forecast load, error forecast, and price increases

A model of profit maximization with constraints

- Following Giulietti et al. (2018) and Sioshansi et al. (2009) we compute the solution to a simple model of a **price-taking** storage facility that maximizes arbitrage value subject to technological constraints:

$$\max_{E_t^{out}, E_t^{in}} \sum_t p_t \times (E_t^{out} - E_t^{in}) \quad \text{s.t.}$$

$$Z_0 = 0 \text{ and } Z_t = Z_{t-1} + \eta E_t^{in} - E_t^{out}$$

$$E_t^{out}, E_t^{in} \leq R^{\max}$$

$$E_t^{out} \leq Z_t \leq S^{\max}$$

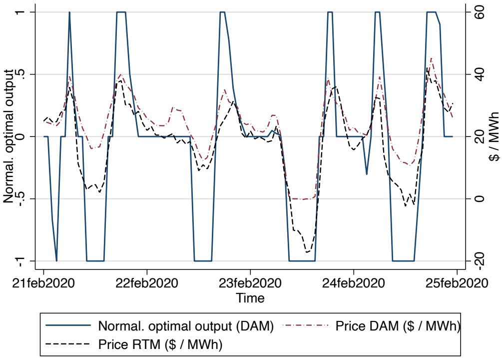
$$E_t^{out}, E_t^{in}, Z_t \geq 0$$

$$R^{\max} = 1.5 \text{ MW}, S^{\max} = 7.2 \text{ MWh}$$

A model of profit maximization with constraints

- Z_t is the amount of electricity stored at time t, p_t is the wholesale electricity price, E^{out} and E^{in} are the amounts of discharge and charge, respectively
- $R^{\max}$ is the power capacity (MW): how much the battery can charge or discharge in period t
- $S^{\max}$ is the energy capacity (MWh): how much electricity can be stored in the device
- Law of motion for Z_t: net change in the amount of energy in the battery is the difference between the amount charged and the amount discharged during the time period t
- We allow for round-trip losses, η
- We fix the values of $R^{\max}$ and $S^{\max}$ at the median values using the data from the EIA (1.5 MW and 7.2 MWh, respectively)
- We solve that problem using GLPK implemented with Pyomo in Python and using DAM and RTM price data from CAISO

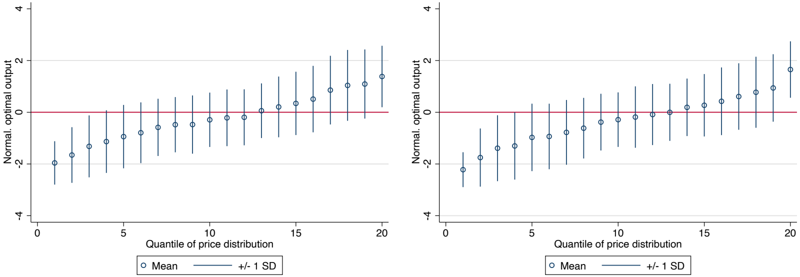
Optimization: battery charge (4 days)



Notes: The battery discharge amounts are the solution to the optimization problem for the representative battery when fed with DAM prices. These amounts are normalized to 1 as the maximum capacity (actual power capacity of the battery is 1.5 MW). The prices on the secondary y-axis are taken directly from the DAM and RTM data. We only present the results for 3 days to ease the visualization, but we solve the problem using all our sample period.

Optimization: mean battery dispatch and price quantiles

Figure: Optimization: mean battery dispatch and price quantile



(a) Using DAM prices

(b) Using RTM prices

Notes: Panel(a): The battery discharge amounts are the solution to the optimization problem for the representative battery using DAM prices in Panel (a) and RTM prices in Panel (b). The horizontal axis refers to the price distribution.

Comparing observed vs optimal battery output

- Goal: To compare the output from the representative battery to the empirical data
  - Key assumption: **price-taking behavior**
- FOCs from optimization model show that current output must be related to past output
  - Not including a lagged dependent variable creates an omitted variable problem $\Rightarrow$ biased coefficients β_j
  - However, addition of lagged variable $\Rightarrow$ biased coefficient α but consistent (if errors IID) and no omitted variable problem

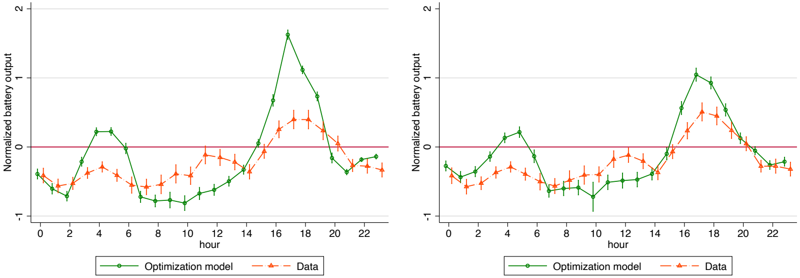
Comparing observed vs optimal battery output

$$Y_t = \alpha Y_{t-1} + \sum_{j=0,\ldots,23} \beta_j \times \mathbb{1}(h(t) = j) \times \text{price}_t + \gamma_\tau + \epsilon_t,$$

- Y_t: normalized battery output
- β_j: extend to which battery owners respond to increases in price at hour-of-day h
- Standard errors correlated within the same day and perform robustness checks regarding this choice (HAC standard errors)
- Additional robustness check: instrument for lagged battery output with battery output at time $t - 25$

Batteries and prices - hourly behavior

Figure: Optimal versus observed battery output

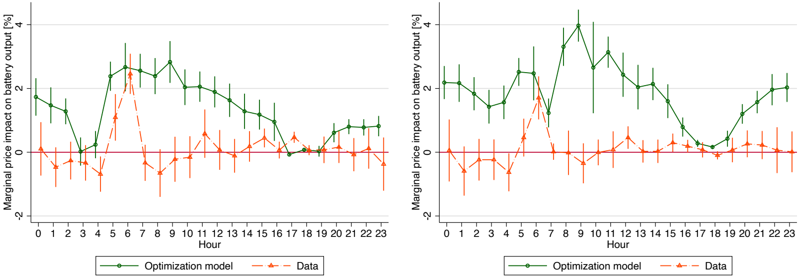


(a) Using DAM prices (b) Using RTM prices

Notes: Linear predictions of normalized battery output for each hour of the day. DAM, Panel(a) and RTM, Panel(b). “Optimization model” refers to the estimates using the battery time series obtained from the optimal dispatch model. “Data” refers to the estimates using observed data in the CAISO (6 June 2018 to 1 March 2020). Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level.

Batteries' response to wholesale price by hour of the day

Figure: Marginal price response



(a) Using DAM prices

(b) Using RTM prices

Notes: Each value represents the marginal impact of changes in wholesale prices (DAM, Panel(a) and RTM, Panel(b)) on normalized battery discharge at each hour of the day. "Optimization model" refers to the estimates using the battery time series obtained from the optimal dispatch model. "Data" refers to the estimates using observed data in the CAISO (6 June 2018 to 1 March 2020). Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level.

Comparison of optimization model with empirical evidence

- Price response and **charging cycles** from optimization model are consistent with the empirical RTM and DAM price responses
- Partial evidence for arbitrage behavior
  - Quantitative responses are smaller for the empirical estimates than for optimization model
  - This occurs mostly during the evening hours
  - Differences likely explained by simplifying modeling assumptions (optimization as “benchmark" abstracts from price uncertainty and dynamic storage consideration)
  - But also because not all batteries dedicated to arbitrage: frequency regulation, ancillary services

Equilibrium prices

- While individual batteries are small, if all batteries optimize charging and discharging decisions $\Rightarrow$ possible impact on equilibrium prices, especially during peak hours
- To test for this, use of a longer time period (2013-mid 2017, Bushnell and Novan) for which we observe the exact dates of battery entry (DOE)
- Estimate a “difference” framework on peak prices and price spreads
- **Key assumption**: exact timing of battery entry is exogenous to current wholesale prices

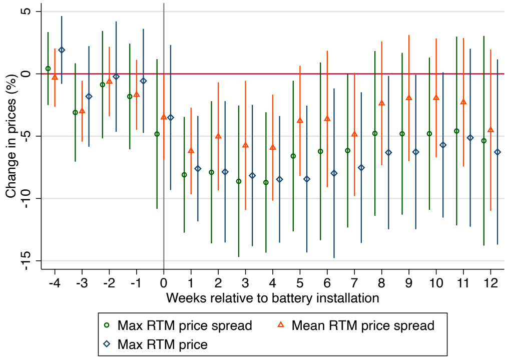
Equilibrium prices

- We aggregate our data at the weekly level and estimate:

$$\log y_t = \beta_0 + \sum_{j=-4,\ldots,12} \beta_j \times capacity_{t-j} + \boldsymbol{\alpha}' \boldsymbol{X}_t + \boldsymbol{\gamma}_\tau + \epsilon_t,$$

- y_t: maximum or mean **daily RTM price spread**, or maximum **daily RTM price**
- *capacity*: new added battery capacity in a given week
- Condition on month and week-of-year fixed effects and include renewable output, large hydro output, and load as controls
- All standard errors are clustered at the monthly level
- $100 \times \beta_j$: semi-elasticity of price spread wrt added capacity

Impact of battery entry on RTM prices



Notes: Each value represents the effect of newly added battery capacity on daily RTM price spreads as well as maximum RTM prices. Unit of data aggregation: weekly. Markers represent 90% confidence intervals. Other data aggregation

Private value of battery storage

- Compare **private value of storage** for optimization model output and observed data
- Objective: provide insights on the value of storage for future battery deployment as well as policy makers

Value of Storage

- Calculate annual storage value for each MWh of installed energy capacity
  - Multiply hourly battery output by the corresponding RTM prices, weighted by the share of volume traded in that hour
    Volume shares
- Assume 66% roundtrip efficiency
- Back-of-the envelope calculation concerning private benefits over lifetime of battery installation

Private value of battery storage

	Predicted hourly output		Actual hourly output	
	optimization	data	optimization	data
Annual revenue ($ per MWh of energy capacity)	11,245.76	-9,032.29	34,797.52	-6,191.94
Representative plant (7.2 MWh):				
9 yr lifetime, non-discounted (m$)	0.729	-0.585	2.255	-0.401
9 yr lifetime, 5% discounted (m$)	0.656	-0.527	2.031	-0.361
Investment cost [m$ - 2018]	1.685	1.685	1.685	1.685
Lifetime profits, non discounted (m$)	-0.956	-2.270	0.570	-2.086
Lifetime profits, discounted (m$)	-1.028	-2.212	0.347	-2.046

Notes: Private value of battery storage arbitrage for the predicted and actual hourly output. Calculations based on hourly responses to prices as well as observed batteries-traded volumes by the hour. Private values assume 66% battery roundtrip efficiency and no degradation over lifetime. Lifetime calculations based on 9 years utilization and 5% annual discount rate. Investment cost of $234 per kWh of storage in 2018 assumed, based on Bloomberg New Energy Finance.

Conclusion

- We document general patterns of the output from large-scale lithium-ion batteries relative to load and wholesale (DAM and RTM) electricity prices in the CAISO
- We benchmark the empirical data against a representative battery installation that takes wholesale prices as given and arbitrages optimally:
  - Data patterns correspond only partially, confirming that batteries in the CAISO perform activities other than arbitrage
- Current price levels and installation costs not conducive to profitability $\Rightarrow$ need for further decrease in installation costs, improved performance, or support policies

Thank you!

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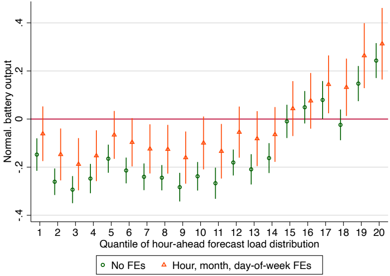
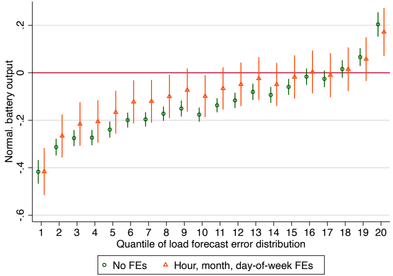
This Project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 772331).

Figure: Batteries, hour-ahead forecast load, and error forecast



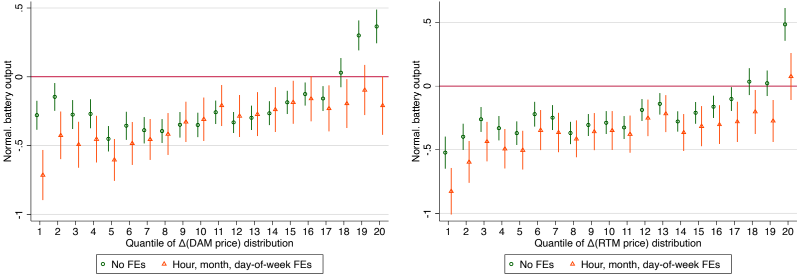
(a) Batteries and hour-ahead forecast load



(b) Batteries and error forecast

Notes: Each value represents the effect on battery discharge at each quantile of the distribution of the hour-ahead load forecast provided by the CAISO to all market participants (Panel (a)) and the difference between the realized load and the hour-ahead forecast (Panel (b)). Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from the CAISO (6 June 2018 to 1 March 2020).

Figure: Batteries and Δ wholesale prices

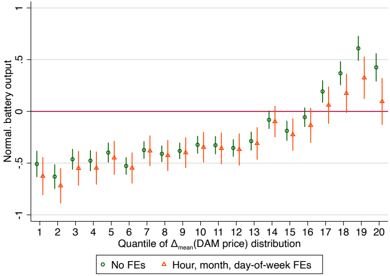


(a) Using DAM prices

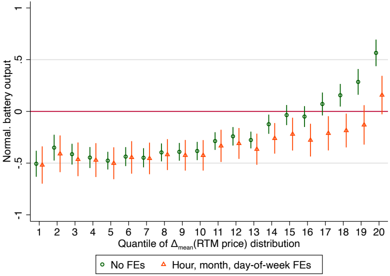
(b) Using RTM prices

Notes: Each value represents the effect on battery discharge at each quantile of the distribution of changes in consecutive hours in the wholesale prices. Panel(a): DAM prices. Panel(b): RTM prices. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from the CAISO (6 June 2018 to 1 March 2020).

Figure: Batteries and Δ_{mean} wholesale prices



(a) Using DAM prices



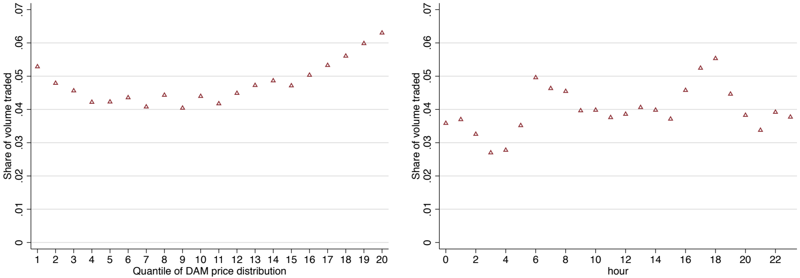
(b) Using RTM prices

Notes: Each value represents the effect on battery discharge at each quantile of the distribution of differences of the hourly price with the daily average price. Panel(a): DAM prices. Panel(b): RTM prices. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from the CAISO (6 June 2018 to 1 March 2020).

▸▸ Batteries, load, and prices

Share of volume traded

Figure: Share of volume traded by quantile of price distribution and by hour

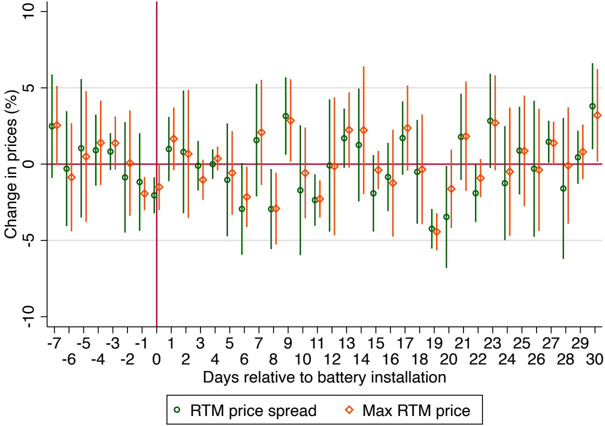


(a) Share of volume traded and price quantiles (b) Share of volume traded by hour

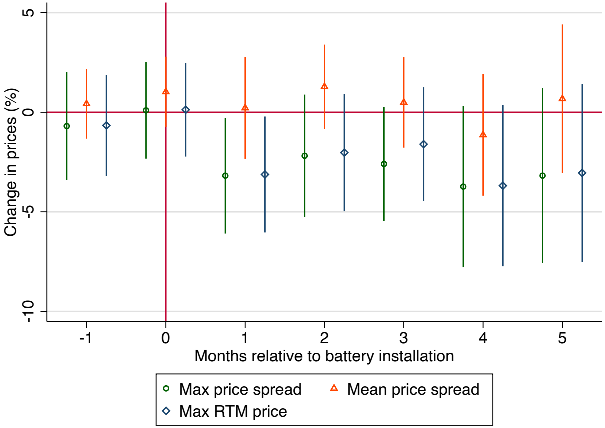
Notes: Share of battery volume traded, measured as battery output (charge or discharge) in a given price quantile (Panel (a)) or in a given hour (Panel (b)) divided by total (absolute) battery output in sample period. Data from the CAISO (6 June 2018 to 1 March 2020).

Value of storage

Equilibrium impact: daily data aggregation



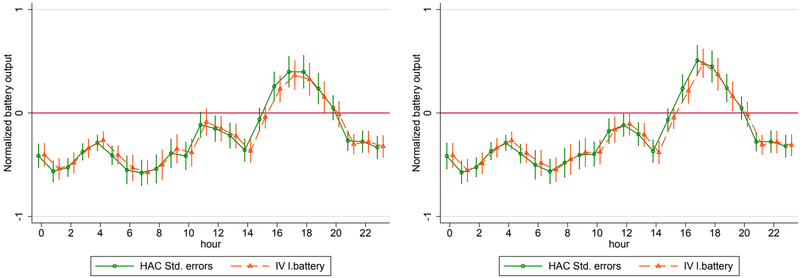
Equilibrium impact: monthly data aggregation



Equilibrium impacts

Robustness: Batteries and prices - hourly effects

Figure: Empirical data: standard errors and IV



(a) Using DAM prices

(b) Using RTM prices

Notes: Linear predictions of normalized battery output for each hour of the day. DAM, Panel(a) and RTM, Panel(b). Observed data in the CAISO (6 June 2018 to 1 March 2020). Bars around markers indicate 95% confidence intervals. HAC standard errors to allow for both arbitrary heteroskedasticity and autocorrelation. “IV l.battery” instruments lagged battery output with lagged output 25 hours ago.