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

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Abstract

The expansion of the share of renewable energy in the portfolio mix of the electricity generation sector has accelerated the development and integration of large-scale battery storage facilities. We document charging and discharging patterns in the California market and show how the utility-scale batteries' activity correlates with load and real-time prices during 2018 and 2019. The empirical findings are partially consistent with the optimal solution of an arbitrage maximizer, indicating that battery owners respond to price incentives only at certain hours of the day. In addition, we provide evidence that battery deployment in the years 2013 through 2017 lowered average intra-day wholesale price spreads and that current market conditions limit the profitability of batteries in this market.

JEL codes: Q41, Q42, Q48, Q55

Keywords: Battery storage, electricity markets, renewable energy, equilibrium prices.

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1 Introduction

The share of variable renewable electricity (VRE) in the portfolio mix of generation has more than doubled from 2012 to 2018 in the US.[1] This rapid increase of the VRE share has caused dramatic changes in the electricity market. Several implications have been discussed in the literature, for example, impacts on emissions (Cullen [2013], Callaway et al. [2018], Novan [2015]), impacts on wholesale prices (Bushnell and Novan [2021]), and on the long-term costs due to the volatility of the electricity supply (Lamont [2008], Gowrisankaran et al. [2016]), just to name a few. Since VRE is not perfectly forecastable and non-dispatchable, one consequence of those changes has been the acceleration of the introduction of large-scale, non-hydro, storage technologies such as lithium-ion batteries. According to the EIA, there were 1,236 megawatt-hours (MWh) of energy capacity installed of this type of facilities across the US at the end of 2018, with altogether a power (the maximum amount electricity that can be discharged in any instant) of 869 megawatt (MW). This represents an increase of nearly 15 times in power capacity relative to 2010 (EIA [2020]).[2]

A natural question is to characterize the discharging and charging behavior of these large-scale battery storage facilities, particularly relative to the well documented load and wholesale price patterns. In this paper, we focus on the following three questions, (i) do storage facilities discharge more or less when load is high?, (ii) do storage facilities charge more when wholesale prices are low and sell when they are high in line with a model of optimal arbitrage?, and (iii) does the entry of new storage capacity affect wholesale electricity prices?

Some of those questions have been assessed through models that extrapolate the optimal responses of a storage facility to the entire market (Diaf et al. [2008], Giulietti et al. [2018], Sioshansi et al. [2009]), models that study the interaction of storage and nodal pricing (Antweiler [2018], Kirkpatrick [2018], Leslie et al. [2021]), and more recently by using dynamic models to assess the equilibrium effects of technology adoption (Dorsey et al. [2021],

[1] Sun et al. [2018]

[2] This is comparable to about half of the production capacity of the San Onofre Nuclear Generating Station (SONGS), which provided about 8% of the electricity generated in California in 2012 and that was shut down the same year (Davis and Hausman [2016]).

Karaduman [2020]).[3]

We take a different approach and use the most recent data on charging and discharging output of large-scale batteries in California published by the California Independent System Operator (CAISO).[4] We do not assume that batteries are necessarily optimizing a known objective function, but rather, we describe the aggregate patterns and document whether they correlate to key market outcomes: load and wholesale electricity prices. Furthermore, we provide evidence on whether these facilities' actions are consistent with the behavior of an arbitrageur, which is the typical behavior that is assumed in most models of large-scale batteries (see for instance Sioshansi et al. [2009]). Finally, while individual batteries are price-takers, we provide evidence on the impact of aggregate large-scale battery capacity on daily price spreads under the assumption that the exact time of entry is exogenous. To the best of our knowledge, this is the first paper to use actual data from battery output to study the behavior of battery facilities.

Our results show that battery discharging is associated with high levels of load and prices, indicating that large-scale batteries are mostly employed during peak load and that they may be engaging in arbitraging behavior. Charging and discharging patterns during the day follow the wholesale electricity price movements, mainly during the morning hours and during peak load in the evening. To compare these patterns to the optimal responses of a profit-maximizing battery owner, we solve for the optimal solution of a battery with energy and power capacity comparable to the median battery operating in California as of 2019 that takes for input the time series of wholesale prices in the CAISO. Qualitatively, we find a similar response to prices in both the optimal model dispatch and the empirical data, indicating that battery owners take advantage of some arbitrage opportunities in this market. Yet, the quantitative response in the empirical data is significantly smaller, especially during

[3]In addition, other studies have concentrated on the development of patents related to electricity storage that promote innovation in both renewable and conventional energy technologies (Lazkano et al. [2017]), on the theoretical implications that the market structure has on the equilibrium outcomes when there is storage in the system (Andrés-Cerezo and Fabra [2020]), on the interactions of support policies for renewables and storage (Abrell et al. [2019], Tabari and Shaffer [2020]), as well as on alternative storage technologies, such as liquid air (Lin et al. [2019]).

[4]The share of VRE is approximately 23% of total generation in this market ([Sun et al., 2018]).

evening peak hours. We also estimate the marginal impact of wholesale prices on battery charging and discharging across the different hours of the day both for the output obtained from the optimization model and for the observed data after applying a normalization that allows to compare those two types of data. We find that in the observed data there is much less responsiveness to prices compared to the output from the optimal model. We discuss the differences between the optimal model solution and our empirical findings in light of the assumptions made in the optimal dispatch model. In addition, using a simple difference framework, we show that addition of battery capacity over the years 2013 to 2017 has led to significant decreases in the maximum daily price spread in the real-time market. This finding indicates that in the aggregate, batteries can reduce peak prices, affecting market outcomes and future profitability of battery investment. Finally, we calculate the average yearly revenue per megawatt-hour (MWh) of current storage capacity and find evidence against profitability in the data.

The rest of the paper is structured as follows. Section 2 introduces the data and describes the current storage facilities in California. Section 3 presents patterns between batteries output and short-term market outcomes. Section 4 provides a simple model of optimal storage management, which we solve with data from the CAISO and present the comparison against the observed data. Finally, section 5 estimates the effect of entry on price spreads and a back-of-the-envelope analysis of profitability. Section 6 concludes.

2 Data

2.1 Batteries output, load, and wholesale prices

We use publicly available data obtained from the CAISO and OASIS on aggregate battery output (net charge or net discharge), total load, load forecasts, output of renewables (including large hydroelectric plants), and prices.[5] While data on load, batteries, and renewable output are available at 5-minute intervals, we retrieve hourly real-time market (RTM) and

[5]These main data sources can be accessed through the following links: CAISO and OASIS.

day-ahead market (DAM) price data.[6] Since the largest share of energy (about 90 to 95%) is traded in the DAM (Bushnell and Novan [2021]), we focus primarily on DAM prices for our main results. The DAM might allow battery owners to lock in production decisions with certainty. On the other hand, as batteries can be employed to respond to short-term imbalances in load as well as price fluctuations, we will also report our main results employing RTM prices.

We combine these data with information on installed storage capacity in the CAISO from the Energy Information Administration [EIA, 2021], as well as from the Department of Energy [DOE, 2020].[7] Appendix Figure A.1 shows the location of the main storage facilities in California in 2018.

The CAISO started reporting data on battery output in mid-April 2018 and we have access to DAM prices starting in June of the same year. Therefore, we limit our main 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 and the mandatory stay-at-home orders implemented in March 2020.[8] In addition, to study equilibrium impacts of new battery capacity investment in section 5, we use hourly data from the CAISO on DAM and RTM wholesale market prices from Bushnell and Novan [2020] over the period 1 January 2013 to 31 May 2017.

We start our analysis by plotting in Figure 1 the average battery charging profile, load profile, and DAM prices together with one-standard deviation bands to highlight the uncertainty of these variables. There are several things worth noting. First, battery activity,

[6] RTM prices are available from four Default Load Aggregation Points (DLAP). Similar to Bushnell and Novan [2021], we average the price data from DLAP locations to obtain a unique time series for the 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). The price within each DLAP is the sum of the marginal energy price and the congestion and loss prices. The energy component, which is by far the largest component of the DLAP prices, is constant across DLAPs, leading to a high correlation across DLAPs. Similarly, we obtain DAM prices from the three CAISO trading zones (NP15, SP15, and ZP26) and average these time series to obtain a unique time series for DAM prices.

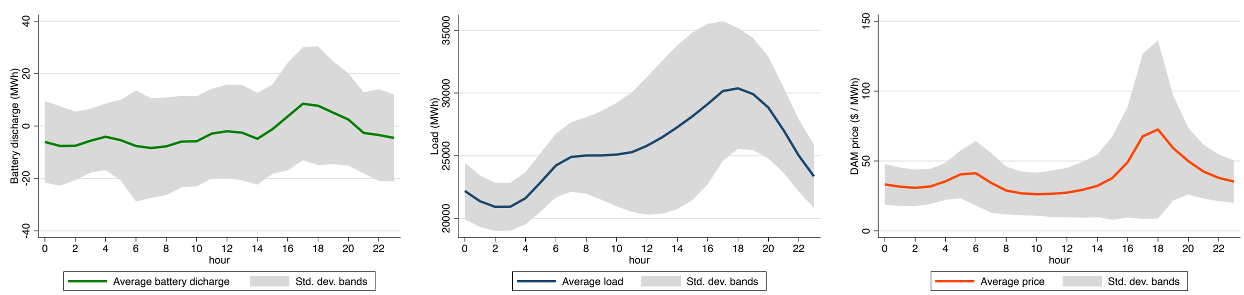
[7] EIA-860 Form reports generator-level specific information about existing generators and storage facilities with 1 megawatt of power capacity or greater. The DOE Global Energy Storage Database is an open-access resource for detailed energy-storage project in the US and worldwide.

[8] The state of California declared in Executive Order N-33-20 state of emergency on March 4, 2020, followed by a mandatory statewide stay-at-home order issued on March 19.

displayed as battery discharge in MWh in Panel (a), illustrates the losses due to the current battery technology. When we divide the sum of the discharge amounts of the batteries by the absolute value of the charge amount of the batteries we obtain a ratio of 0.66 (= 84,221.5 MWh / 127,581.8 MWh). Therefore, the roundtrip efficiency (how much of the energy charged can be used in the discharging process) of the fleet as a whole is slightly lower than what other studies have used in their simulations. The ratio found here is the same than the one we use later in subsection 4.1.[9] On average, batteries charge during the night and discharge mainly during the evening hours, between 6pm to 8pm, coinciding with peak load (shown in Panel (b)). DAM prices (Panel (c)) show two spikes, coinciding with ramping needs during the early morning hours as well as during peak load in the evening. The standard deviation measure highlights a large degree of price uncertainly during those same hours.[10]

Figure 1: 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 the CAISO +/- standard deviation. Data aggregation: 5-minutes, but DAM prices (hourly). Sample: 6 June 2018 to 1 March 2020.

[9]Our ratio is below the US average reported by the EIA (https://www.eia.gov/todayinenergy/detail.php?id=46756) of 0.82. This EIA statistic is based only on those facilities that filled Form EIA-923 in 2019 and not from the entire fleet of batteries, which may explain the gap between our ratio and the EIA's.

[10]While DAM and RTM prices are highly correlated ($\rho = 0.57$), RTM prices are more volatile, especially during peak hours.

2.2 Storage facilities

Lithium-ion batteries are typically described in terms of their energy capacity (measured in MWh) and their power (measured in MW). The former refers to how much electricity can be stored in the battery whereas the latter refers to how much electricity can be charged or discharged in any instant. Batteries are also characterized by their roundtrip efficiency, which measures how much electricity is not lost in the charging and discharging processes.

The parameters in our optimization model are inspired by the large-scale facilities already in operation in California and documented in the EIA-860 Form. As of 2019, there were 172 operational facilities in the US, of which 47 were in California. The vast majority are lithium-ion batteries. The mean of the energy capacity for those 47 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 those same batteries is 5.3 MW, with a median of 1.5 MW.[11] The facility with 120 MWh of energy capacity has a power of 30 MW and it is owned by San Diego Gas & Electric. Several of these facilities are recorded as "Arbitrage" of which a subset of those are also recorded as "Frequency Regulation".[12] In particular, 7 out of the 8 largest batteries (by energy capacity) are labeled as "Arbitrage", which altogether have 363 MWh of energy capacity (51% of the storage energy capacity in California). The other plant out of these 8 largest batteries is labeled as "Ramping / Spinning Reserve".

By taking the ratio of the sum of the capacity in each of those three categories relative to the total storage capacity installed, we obtain that 66% of the energy capacity is labeled as "Arbitrage", 38% is labeled as "Frequency Regulation", and 37% as "Ramping / Spinning Reserves" with a strong overlap between the last two categories, which we can label in general as ancillary services. Pooling the last two categories together, the ratio is 44%. Note that those ratios are weighted by nameplate capacity. Altogether this suggests that most of these facilities self-report that they concentrate on arbitrage and less than half of them concentrate on ancillary services.

[11] In our stylized optimization model we assume equal input and output power capacity.

[12] Frequency regulation is the ability to stop a frequency deviation in the electricity supply (60 Hz in the CAISO). This occurs for example when there is an unexpected outage.

We also compute how much energy each battery can provide measured in hours (this is another common way to express the capacity of a battery). Specifically, we divide the nameplate energy capacity (MWh) by the nameplate capacity (MW). On average a battery has a capacity of 3.7 hours (maximum of 7 and minimum of 0.5 hours). Assuming the maximum depth of discharge (the battery is completely depleted of energy before recharging and it is charged to its maximum capacity) and a symmetric duration for charging and discharging, we would have full cycles of $2 \times 3.7 = 7.4$ hours on average, and of 14 hours as a maximum. This implies that the cycles are completed in less than a day. However, there is degradation from full discharges and the CAISO is aware of such costs but we do not have any specific information on how each individual battery manages such costs since we only observe the aggregate data.[13]

3 Descriptive evidence on load, prices, and battery output

The availability of high-frequency data makes it possible to study how battery owner's charging and discharging decisions correlate with load and prices. To get a first sense of the range and mode of those variables, we provide histograms and scatterplots in Appendix Figure A.2. Positive values indicate that, in the aggregate, the batteries supply electricity to the grid, i.e. they discharge. Negative values indicate that, in the aggregate, batteries store electricity (charge). Load has a skewed distribution with most of its values roughly between 20 and 40 gigawatthours (GWh). Prices have a stronger skewness, some prices are negative, and some are an order of magnitude larger than the mode. Neither the scatter plot between batteries output and load nor the ones of batteries output and prices show any obvious correlation between those variables. Our regression analysis in this section extracts meaningful correlations after splitting the data and controlling for a rich set of fixed effects.

To allow for a flexible relationship between load, prices, and battery output, we estimate a regression model inspired by the work in Jha and Leslie [2021] and Davis and Hausman

[13] CAISO Energy Storage and Distributed Energy Resources Phase 4 Stakeholder Workshop 2019, accessible through the following link.

[2016] as follows:

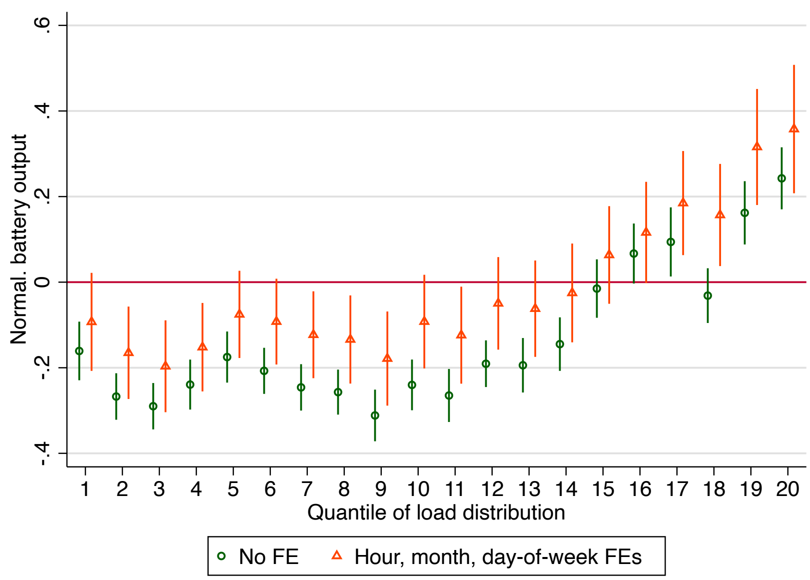
$$Y_t = \sum_{q=1,\ldots,20} \beta_q \times \mathbb{1}(X_t \text{ is in quantile } q) + \boldsymbol{\gamma}_\tau + \epsilon_t, \tag{1}$$

where $\boldsymbol{\gamma}_\tau$ is a vector of time-related fixed-effects: hour-of-the-day, day-of-week, and month. The term $\mathbb{1}(\cdot)$ is equal to 1 if the expression inside the parentheses is true and 0 otherwise. The data in X_t are sorted and split into 20 equally spaced bins or quantiles (ventiles). We do not include a constant so that we can estimate one coefficient for each quantile. As it will become clear in the next section, we will compare observed battery dispatch data and optimal battery dispatch outcomes, therefore, in order to make those two types of data comparable, we define Y_t as the normalized observed battery output. Specifically, Y_t is equal to the battery output divided by the mean of the absolute battery output over our sample period. This normalization allows us to interpret coefficients with respect to the average battery dispatch.

When there are no controls or fixed effects added to Equation 1, the coefficients β_q are equal to the conditional means of X_t given quantile q. The addition of fixed effects captures the well-known cyclicality in the electricity markets and β_q become the mean at quantile q corrected by those cyclical effects. The month fixed-effect moreover captures any aggregate changes in CAISO, such as capacity additions. X_t is one of the following: load, hour-ahead forecast of load, load forecast error (defined as the difference between realized load and the hour-ahead forecast of load), prices, and renewables output. In the main section of this paper we focus on the relationship between batteries and load, price, and renewables output quantiles and report the remaining regression results in the Appendix. We report standard errors clustered at the date level to allow for correlation of errors within the same day.

We start with the case when X_t is equal to load under two different specifications, this is shown in Figure 2. Our first observation confirms an intuitive hypothesis, which is that batteries, on the aggregate, discharge when demand is high and charge when demand is low. This can be seen from the coefficient values from the model without fixed effects: they are relatively constant and negative for the first 14 quantiles of the demand distribution and then almost monotonically increase and become positive when load is in the highest quantiles. This

Figure 2: Batteries and load



Notes: Each value represents the effect on normalized battery discharge at each quantile of the distribution of demand. 5-minute data resolution. 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).

same pattern emerges in the two specifications we estimate. The inclusion of fixed effects centers the lower quantiles of the load distribution around zero. Once the cyclical patterns of the demand are taken into account, the coefficients on high demand levels indicate that batteries discharge increases by about 0.4 times the average absolute output of 13.6 MWh, representing an absolute increase of about 5.4 MWh or roughly as much as the mean of the batteries power capacity (5.3 MW, see section 2).

The regression above uses contemporaneous demand as the main explanatory variable but it is entirely possible that storage facilities do not have perfect information about what the demand will be. Therefore, we estimate the same model by setting X_t equal to the hour-ahead load forecast provided by the CAISO. This simply represents an inaccurate measure of demand that is available to all market participants. The results from this regression are shown in Figure A.3a in the Appendix. We find that there are almost no differences with the results previously shown in Figure 2 above. Similarly, we set X_t equal to the difference between the realized load and the hour-ahead forecast. This indicates by how much batteries respond to errors in the hourly load forecast. We find that batteries reactions tend to be to charge when realized load is smaller than the hourly forecast and to discharge otherwise, which can be seen in Figure A.3b in the Appendix. Altogether, these findings reinforce our hypothesis that batteries supply the grid with more energy when demand is higher, or higher than forecasted.

We repeat the same analysis for prices. In this case, we estimate Equation 1 with X_t equal to DAM and RTM prices separately. Figure 3 shows the coefficients for the same two types of specifications (no fixed-effects and with fixed-effects). The implicit assumption in this regression is that prices can be considered exogenous to the batteries decisions. As individual battery capacities are relatively small, this is a common assumption in electricity market models.[14]

The correlations obtained from this regression lead us to our second observation: batteries tend to discharge only when prices are at the highest levels and charge the rest of the hours

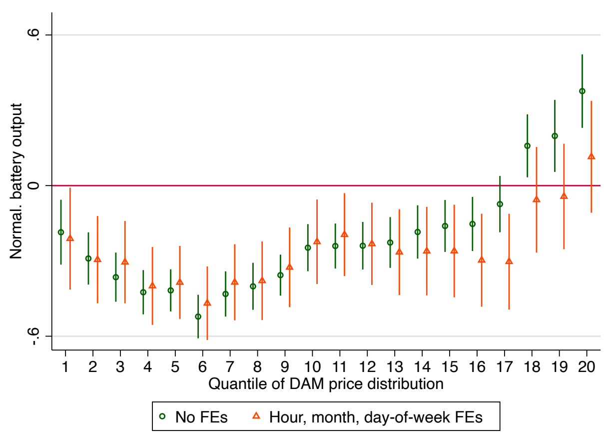
[14]The largest storage facility in California has a power capacity of approximately 30 MW. Yet, most of the mass of the load distribution is between 20,000 and 40,000 MWh.

in the day. This pattern is robust to our two different specifications and holds for both DAM and RTM prices. If we assume exogeneity for the price, these results suggest that batteries engage in arbitrage.

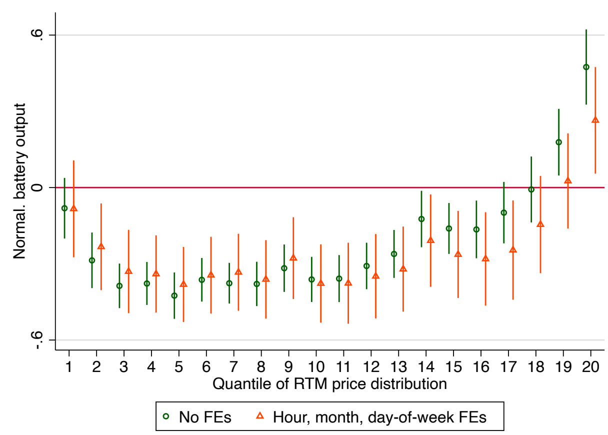
We could also add controls such as load or renewables output to Equation 1. The result when doing so is a collection of mostly negative coefficients because batteries in the end are net consumers: they do not actually produce any new energy and due to the roundtrip efficiency of less than 100% there are losses. So netting out all other effects, the batteries are net buyers (negative coefficients).

Figure 3: 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).

The results in Figure 2 and Figure 3 only give the aggregate effect by quantile of the distribution but they do not convey any information of how much volume the batteries traded in each of those quantiles. Even though the measured effects are only positive at the highest quantiles, there is more energy traded by the batteries precisely at those quantiles than in other regions of the price distribution. Figure A.6a in the Appendix shows the share of the absolute amount of energy traded by quantile of the RTM price distribution. At quantiles 19 and 20, the share of volume traded is the highest at a share of around 6%.

We also examine the correlation between batteries output and changes in the wholesale price. To do so, we study both the battery response to changes in wholesale prices from one hour to the next (Appendix Figure A.4) as well as differences between the hourly price and the average price level that day (Appendix Figure A.5). These results confirm that, in the aggregate, discharging is positively correlated with price increases from one hour to the next and the larger the price increase, the larger the amount discharged by the battery in line with arbitrage behavior. Similarly, we show that most of the discharging occurs at prices that are well above the average price level on a given day.

To end this descriptive section, we examine in Figure 4 the batteries activity with respect to the renewables output. The coefficients in this case are very different from the previous graphs. Generally, the higher the quantile of the renewables output, the higher the batteries' purchases of energy. This suggests that some storage facilities may be co-optimizing with renewables output and perhaps alleviating some congestion issues in the grid.[15]

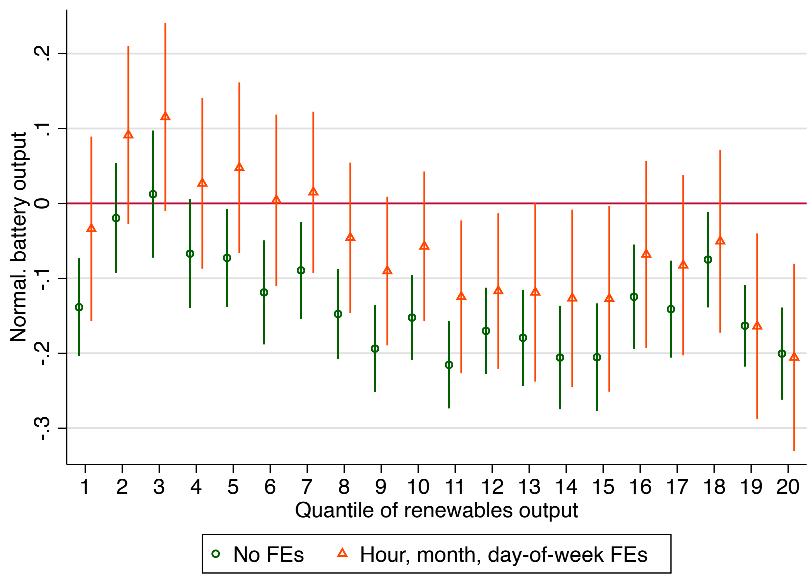
4 Optimal Storage

4.1 Model

In this section, we use a similar setting as in Giulietti et al. [2018] and Sioshansi et al. [2009] and compute the solution to a simple model of a price-taking storage facility that maximizes arbitrage value subject to technological constraints. Our goal is to benchmark the empirical observations to the optimal outcomes of a representative battery in the same market. We do not attempt to calibrate the output of this battery to the data, but rather to understand the patterns that we document based on the data. The problem and the constraints are given

[15]For completeness, Appendix Figure A.7 shows the correlation between net load, defined as load net of renewables output, and normalized battery activity. The coefficients are comparable to the main results for load in Figure 2. The relation between storage capacity and the correlation of net load with renewables output is an active topic of research, see for example Andrés-Cerezo and Fabra [2021].

Figure 4: Batteries and renewables



Notes: Each value represents the effect on normalized battery discharge at each quantile of the distribution of renewables output. 5-minute data resolution. 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).

by:

$$\max_{E_t^{out}, E_t^{in}} \sum_t p_t \times (E_t^{out} - E_t^{in}) \quad \text{s.t.}$$
$$Z_0 = 0 \text{ and } Z_t = Z_{t-1} + \eta E_t^{in} - E_t^{out}$$
$$E_t^{out}, E_t^{in} \leq R^{\max}$$
$$E_t^{out} \leq Z_t \leq S^{\max}$$
$$E_t^{out}, E_t^{in}, Z_t \geq 0$$
$$R^{\max} = 1.5 \text{ MW}, S^{\max} = 7.2 \text{ MWh},$$

where 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. The law of motion for Z_t simply states that the net change in the amount of energy in the battery is given by the difference between the amount charged and the amount discharged during the time period t. The parameter $\eta < 1$ is the fraction of energy that is not lost during the charging and discharging processes, this is known as the roundtrip efficiency. We assume $\eta = 0.66$ based on our data.[16] Larger values of this parameter do not have a large effect on our main results as discussed below.

$R^{\max}$ is the power capacity (MW), which is how much the battery can charge or discharge in period t. Both E^{in} and E^{out} are bounded by this constant. $S^{\max}$ is the energy capacity (MWh), which is how much electricity can be stored in the device. This constant bounds from above the state variable Z_t. We fix the values of $R^{\max}$ and $S^{\max}$ at the median values using the data from the EIA as explained in subsection 2.2 above (1.5 MW and 7.2 MWh, respectively).

Note that because we model a price-taker storage facility, we assume that the battery has no effect on the system's residual demand and therefore, no effect on p_t.[17]

The solution to this problem is found using the GLPK solver implemented with Pyomo

[16] Sioshansi et al. [2009] uses $\eta = 0.8$ for their initial simulations and then they perform robustness checks with $\eta = 0.5, \ldots, 0.9$.

[17] A battery whose actions affect the equilibrium price would maximize $\sum_t p_t(L_t - E_t^{out} + E_t^{in}) \times (E_t^{out} - E_t^{in})$ subject to the same constraints as in the price-taking problem, and where L_t is the load and $p_t(\cdot)$ is the inverse demand function.

in Python and feeding the DAM and RTM prices, separately, into the model.[18] Note that we assume perfect foresight since we use the contemporaneous price data when making decisions, either when using DAM or RTM prices. Therefore, our results in this subsection should be interpreted as the best case scenario and this interpretation is useful since we want to compare the observed battery output against the expected optimal behavior.

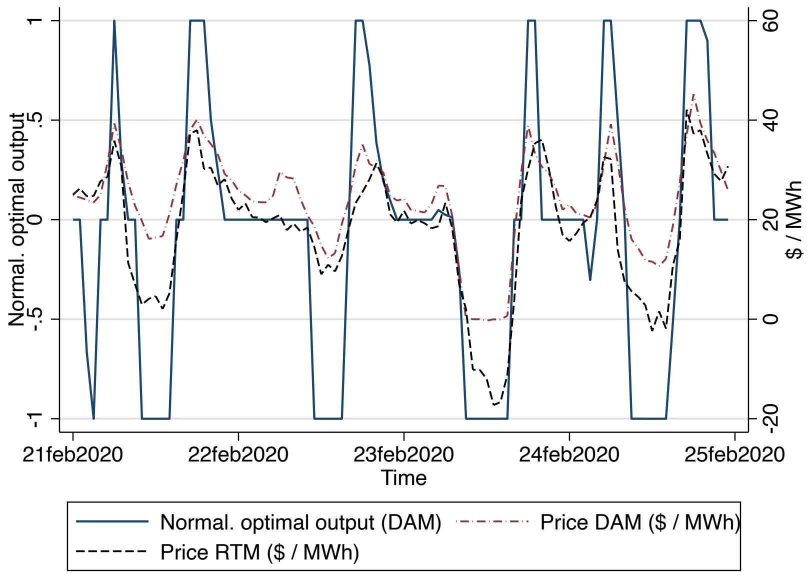
The solution to the constrained maximization problem is shown in Figure 5 by plotting the net amount of discharge $E^{out} - E^{in}$ over time, specifically for four consecutive days only and for the case of DAM prices, to ease visualization. The oscillating behavior is typical to the solutions to this type of problems. The oscillations are largely correlated with changes in the wholesale prices (either DAM or RTM), which we also plot in the same graph. It is evident that our optimal battery discharges when prices are high and charges when prices are low. The correlation between these two time series over the entire sample period for DAM prices is 0.43, which is more than three times the correlation (0.13) between those same prices and the observed aggregate net amount of discharge.

When we vary the value of the roundtrip efficiency η, we obtain qualitatively the same results as with $\eta = 1$. However, by decreasing the roundtrip efficiency, the variance of the battery output −at any given quantile of the price distribution and at any given hour of the day− decreases as well but the means remain practically unchanged. The correlation between the observed prices and the simulated battery output decreases monotonically from 0.46 when $\eta = 0.6$ to 0.35 when $\eta = 1$.

Figure 6 shows the distribution of the net amount of discharge for each of the twenty quantiles of the wholesale price distribution. Consistent with Figure 5, our optimal battery injects energy to the system more often when prices belong to the upper quantiles of the distribution and purchases energy when the prices belong to quantiles 12 and below as measured by the mean of $E^{out} - E^{in}$. Qualitatively, this is a similar pattern than the one found in Figure 3 using the actual data on batteries output. The main difference is that in the data, discharging only occurs for the last two to three quantiles. This fact can be due to several reasons. First, our optimization solution assumes perfect foresight on wholesale

[18] https://www.gnu.org/software/glpk/

Figure 5: Optimization: battery charge (4 days)

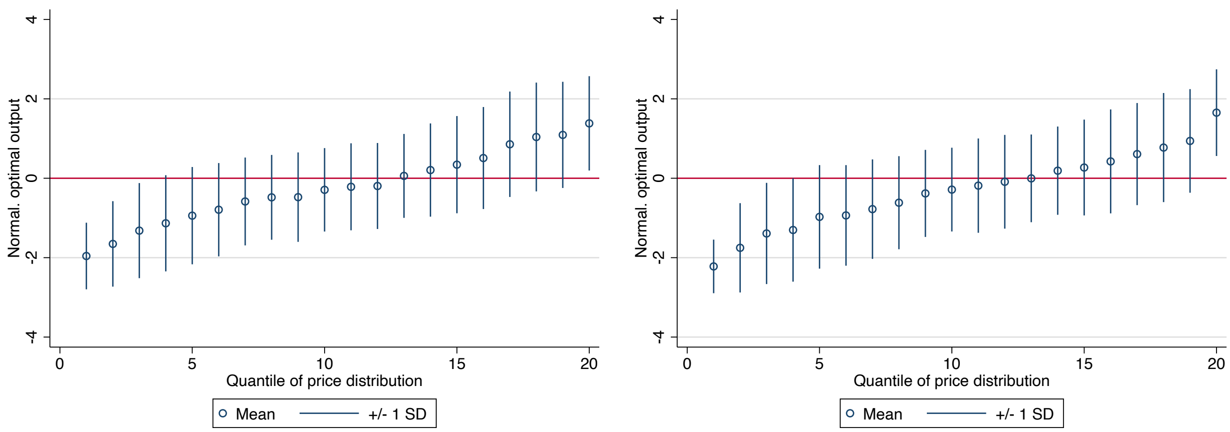


Notes: The battery discharge amounts are the solution to the optimization problem for the representative battery when fed with DAM prices. These amounts are normalized to 1 as the maximum capacity (actual power capacity of the battery is 1.5 MW). The prices on the secondary y-axis are taken directly from the DAM and RTM data. We only present the results for 4 days to ease the visualization, but we solve the problem using all our sample period.

prices, which is not true in reality. Second, our optimization model captures the behavior of a price-taker storage facility, it is possible albeit unlikely that some of the battery facilities exercise market power or strategically respond to opponents' storage behavior.[19] Third, our optimization model uses parameter values for a representative battery, but we know from the discussion in subsection 2.2 that there are large differences in the power and capacity sizes of the batteries in the CAISO. Finally, the optimal storage problem is more complex in reality than in our stylized model since we do not take into account dynamic charge and discharge decisions.

Figure 6: Optimization: battery charge and price quantiles

(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.

4.2 Comparing the empirical data to optimal storage

To understand in how far battery owners follow the same pattern as predicted by the optimization model, we estimate a regression that is motivated by the state equation in subsec-

[19]Market power is also related to the nature of the owner of the facility. Bahn et al. [2021] and the references therein have quantified the implications that the portfolio composition of an owner of a VRE plant has on market power. Andrés-Cerezo and Fabra [2020] study theoretically the equilibrium properties of markets with and without vertical integration between storage facilities and production as well as when including market power exercised by storage facilities.

tion 4.1. Since battery activity is a direct function of the amount of electricity stored and this is related to past battery output, we include the lagged battery output in our empirical model as explanatory variable.[20]

To make the coefficients comparable for both the battery output from the representative battery and from the empirical data of the CAISO battery fleet, we define Y_t as the battery output (observed or optimal) divided by the mean of the absolute dispatch over our sample period. This is the same definition as in the previous section. The respective means of the normalized battery output from the optimization model are -0.207 (when feeding in DAM prices) and -0.208 (when using RTM prices), while the mean of the normalized observed battery output is -0.212.[21] The regression model is

$$Y_t = \alpha Y_{t-1} + \sum_{j=0,\ldots,23} \beta_j \times \mathbb{1}(h(t) = j) \times \text{price}_t + \boldsymbol{\gamma}_\tau + \epsilon_t, \tag{2}$$

where price_t represents the wholesale price at time t, $h(t)$ is the hour of the day at time t, and $\mathbb{1}(\cdot)$ is the indicator function. This regression additionally conditions on the same vector of time fixed-effects as the price regression Equation 1 and on the lagged value of the normalized battery output Y_{t-1}.[22]

As highlighted in the previous section, individual batteries are small and thus price-taking behavior is a common assumption. In line with the modeling framework in subsection 4.1, we therefore assume that battery owners take wholesale prices as given. Since the inclusion of a lagged dependent variable can affect the autocorrelation of the error term in equation (2), for robustness, we estimate the model with HAC standard errors that are robust to both arbitrary heteroskedasticity and arbitrary autocorrelation. Similarly, as lagged battery

[20]The first order conditions of the optimization problem in subsection 4.1 contain lagged terms of E_t^{out} and E_t^{in}, which implies that the simplest regression model for battery output must include at least one lag of the output as explanatory variable. If it was not included, there would be an omitted variable problem in the regression. However, the estimation of this model by OLS results in biased but consistent estimates. Given the large amount of data at our disposal, we opt for avoiding the bias from an omitted variable.

[21]To interpret the results in terms of MWh the coefficients need to be multiplied by the mean of the absolute dispatch: 13.38 MWh in the empirical data and 0.64 MWh and 0.62 MWh in the optimization model with DAM and RTM prices, respectively.

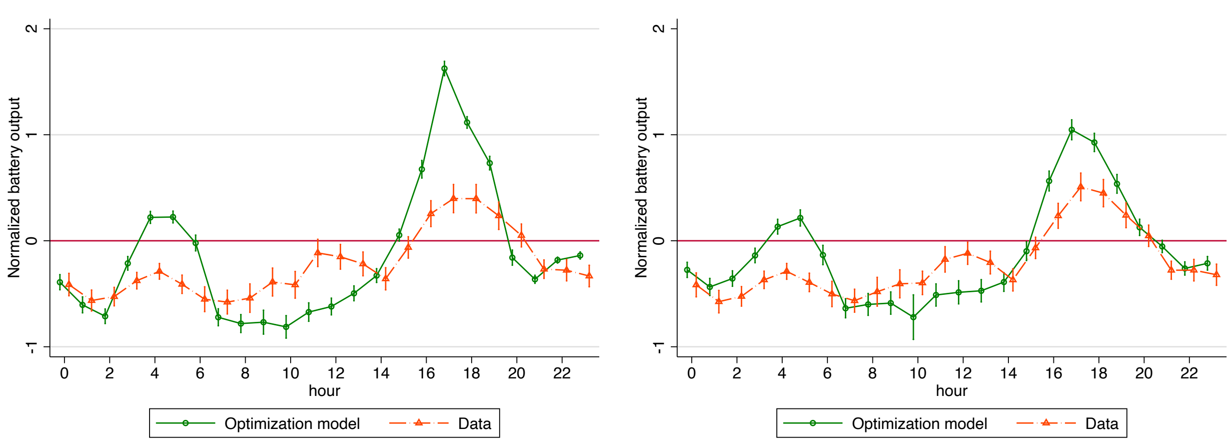
[22]We omit additional control variables from the regression as these are not taking into account by the optimization model. The results when including additional control variables in the model with the empirical data are available from the authors upon request.

output is likely correlated with the error term, we estimate an alternative model in which we instrument lagged battery output at $t-1$ with lagged battery output one day before (at $t-25$). As batteries typically optimize within a given day, we expect this equation to be less affected by potential endogeneity concerns.[23]

Using the same empirical model for the two time series of battery output separately (observed output and optimal output), allows us to directly compare the predicted output and coefficients for the battery activity obtained from the optimization model and the empirical data. We plot the predicted hourly battery activity in Figure 7. Panel (a) shows the total predicted battery output when $price_t$ is equal to DAM, while Panel (b) employs RTM prices. These effects are evaluated at mean values of the data.

Figure 7: 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 subsection 4.1. "Data" refers to the estimates using observed data in CAISO (6 June 2018 to 1 March 2020). Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level.

There are several things worth noting. First, the optimal output follows closely the wholesale market prices. We see two main discharging cycles in line with the price spikes, one at hours 4 to 5 in the morning and the second one at hours 16 to 19 during the evening

[23]We report these results in Appendix Figure A.8. Our estimates are robust to these alternative modeling choices.

peak. The rest of the day the batteries are typically in charging mode. This pattern is consistent with that seen in the DAM prices from Panel (c) in Figure 1 in which prices are higher at around 5am to 6am and 6pm. This cyclical pattern exists for both DAM and RTM prices, although the increase in discharge is larger for DAM prices.

The predicted battery output from the empirical data is generally less pronounced, although we see evidence for the same charging cycles. However, in this case only the evening hours are related to a positive and significant discharge. Overall, the quantitative responses are smaller for the empirical estimates than for the optimization model.

Those differences between optimal arbitrage and the empirical data can be explained by a variety of factors. First, the model assumes battery owners have perfect foresight about market prices, which clearly is not given in practice. Second, our predictions compare optimal arbitrage from a single representative battery to the current fleet of batteries in California. If individual batteries are employed for purposes other than arbitrage (e.g. frequency control, ramping / spinning reserves) as explained in subsection 2.2, these batteries will not necessarily respond to short term price signals. As we only observe aggregate battery output for the CAISO rather than the output of individual batteries over time, we are unable to make this distinction. Finally, there might be additional constraints in battery usage that are not captured by the simple model of optimal arbitrage.

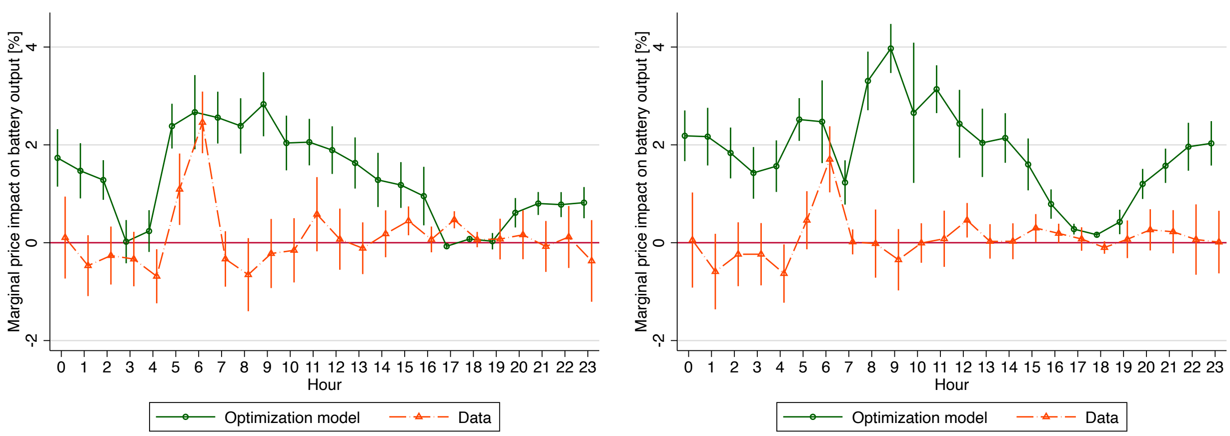
To better understand how the two types of batteries respond to changes in the wholesale price, we plot in Figure 8 the marginal effect of DAM and RTM price changes on battery discharge for each hour of the day. This marginal effect is captured by the β_j coefficients from Equation 2, which are allowed to vary by hour of the day. As the regression model additionally controls for month, day-of-week, and hour-of-the-day fixed effects, these coefficients are net of all cyclical components and aggregate shocks to battery deployment.

If batteries engaged in arbitrage, we would expect that an increase in wholesale prices triggers an increase in battery discharge for most hours of the day. We do find such evidence for optimal battery output in Figure 8, where the estimated price coefficient is either positive or zero for all hours. The marginal price effects are zero in hours in which the battery is operating at full capacity at peak charge or discharge, at about 3-4am and 5-7pm, in the

DAM market. To put it differently, an increase of wholesale prices in these hours does not longer lead to an expansion of battery discharge. We see a similar pattern for RTM prices. However, in this case all coefficients are positive, indicating that the battery will respond to price increases at all hours with additional discharge. This is in line with batteries being the most flexible asset type that can respond almost instantaneously to price fluctuations. Note that the total marginal effect is rather small. We estimate a maximum response of about 3% and 4% relative to the mean absolute battery output at 9am for a 1 \$/MWh increase in DAM and RTM prices, respectively. The positive price coefficients indicate that batteries will either discharge more with higher prices or charge more with lower prices.

Figure 8: 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 in subsection 4.1. "Data" refers to the estimates using observed data in CAISO (6 June 2018 to 1 March 2020). Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level.

By comparing this "optimal" response to the observed data, we find that the CAISO battery fleet only responds positively to marginal price increases during the early morning hours around 5am and 6am and a small, yet significant increase at hour 5pm for DAM prices, and at hours 12pm, 3pm and 4pm for RTM prices. These findings indicate that batteries are less flexibly employed than would be foreseen by an optimal arbitrageur. In line with the description in subsection 2.2, batteries seem to be active also during the day for other purposes, such as frequency control in hours in which renewable output is high. While the battery fleet overall is less responsive to price changes than our optimal solution, the batteries in the data make decisions whose total outputs are somehow consistent with those from a price-taking battery that maximizes arbitrage opportunities.

5 Batteries Output and Wholesale Prices

5.1 Price spreads and new storage capacity

The fact that individual storage units are small compared to the overall market size makes the price-taking assumption in the storage model in section 4 reasonable. Yet, there is the possibility that all battery owners optimize their charging and discharging decisions in line with prices, in which case those operations may have an impact on the market equilibrium, especially during peak hours. A linear regression of wholesale prices on battery output would thus suffer from endogeneity. The aggregate nature of our data makes it hard to find a suitable instrument for battery deployment. Instead, we use a more direct approach, estimating a "difference" framework of battery capacity additions on equilibrium price spreads and peak prices. The key assumption is that the exact timing of battery entry is exogenous to current wholesale prices.

Since for the time period in the dataset used up to this point in the paper we do not have the exact dates of entry of new capacity, we opt for using a longer time period (January 2013 to mid-2017, (as in Bushnell and Novan [2021]) for which we observe the exact dates of battery entry (the DOE-Global Energy Storage Database (DOE-GESD), DOE [2020]). We use the facilities for which we observe the exact "commissioning" date. Appendix Figure A.9 plots the cumulative capacity of installed power as reported in both the DOE-GESD and the EIA Form-860.

As daily data on price spreads can be noisy and there is some uncertainty about the exact timing of full battery capacity availability, for the main analysis, we aggregate our data at the weekly level and estimate:

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

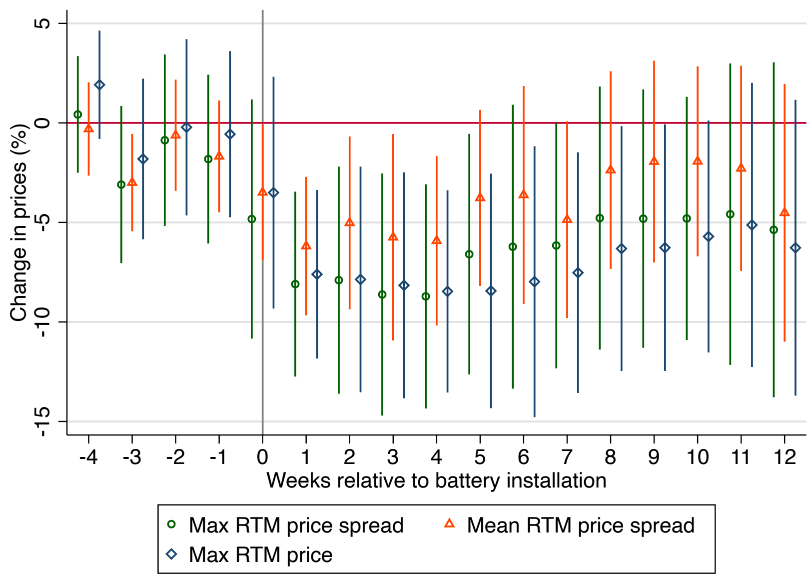
where y_t is the maximum or mean daily RTM price spread, or the maximum daily RTM price. The variable capacity_{t-j} is the *new* battery capacity. When $j < 0$, no new capacity has been added yet. Positive values of j represent weeks after the entry event. We condition on month and week-of-year fixed effects ($\boldsymbol{\gamma}_\tau$) and include renewable output, large-hydro output, and load as controls. Standard errors are clustered at the monthly level. The coefficients of interest are β_j, which give the semi-elasticity of the price spread with respect to added capacity. For a 1 MWh of new capacity, the spread changes by $100 \times \beta_j$ percentage points.

Figure 9 shows that for our three different price statistics there is a negative and statistically significant effect (at the 90% level) in the weeks following the addition of new storage capacity in the system. The significance of this effect fades away after five weeks, yet the mean point estimates remain negative. In the four weeks leading to the entry event the coefficients in all but one specification are not statistically different from zero, consisting with our hypothesis that the timing of the battery entry is exogenous and not foreseeable. We perform robustness checks regarding the data aggregation at the daily and monthly frequency and present those results in Appendix Figure A.10. The monthly-level specifications reflect some of the same behavior as in the case of weekly frequency data, while the daily data aggregation is more noisy, and no clear data pattern can be identified.

5.2 The private value of battery storage

To put our results further into context, we use the predicted battery output from the empirical analysis (Figure 7) as well as the actual battery output and optimal arbitrage solution from the representative battery owner (Figure 5) to provide estimates on the private value of storage in the CAISO. Recall that the model maximizes profits from arbitrage for a representative installation, and makes several assumptions concerning information on prices as well as price-taking behavior. While these assumptions do likely not hold fully in practice, the model provides an appropriate benchmark of "optimal" arbitrage, to which we can compare

Figure 9: Impact of battery use on RTM prices spreads



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. Standard errors clustered at the date level. Data from CAISO (1 January 2013 to 31 May 2017).

our empirical results.

To calculate the annual storage value for each MWh of installed energy capacity, we multiply the average battery output for each hour of the day in either the optimization model or the empirical results times the corresponding hourly value of the RTM prices weighted by the share of volume traded in that hour (see Appendix Figure A.6).[24] We assume 66% roundtrip efficiency for our calculation. The results are summarized in Table 1, which shows the values of a simple back-of-the-envelope calculation concerning the private benefits over the lifetime of a battery installation.

Table 1: 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 RTM prices as well as observed batteries-traded volumes by the hour. Data from 6 June 2018 to 1 March 2020. 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.

The average annual revenue is between -9.0 and 34.8 $ per kWh. These stark differences are explained by the model assumptions and the fact that the optimization model predicts large arbitrage opportunities in the evening hours when prices are at their highest level but the observed output has much lower responses as discussed in the previous section. The batteries are only profitable in the third column (actual output from optimization model). The last column (actual observed battery output) shows substantial negative profits. This simple

[24] We obtain very similar results if instead we multiply each observed price times the corresponding battery output for each hour in our sample and then take the sum.

calculation is model-independent and it shows that regardless of what the true objective function the fleet may have, even the annual revenue is negative at current prices.[25] Note that our findings focus exclusively on the private returns and abstract from any additional impacts on producer and consumer surplus in electricity markets.

Our calculations highlight that under current conditions it is not profitable for battery owners to operate in this market. While the model predicts positive (and sizeable) lifetime profits, these are not met in the empirical data, indicating that without additional policies or other sources of revenues, e.g. from ancillary services, profit maximizing firms would not enter this market.

Finally, our results from subsection 5.1 show that battery deployment can have an impact on min-max price spreads and maximum prices in the RTM market. While the focus on arbitrage possibilities can improve the profitability of batteries in the short-run, the entry of new battery capacity could reduce future profit opportunities in the medium and long-run, making investment less attractive.

6 Conclusion

This paper documents general patterns of the output from large-scale lithium-ion batteries relative to load and wholesale (RTM and DAM) electricity prices in the CAISO. When we benchmark those aggregate patterns to the output from a representative battery installation that takes wholesale prices as given, we find that those patterns only partially correspond to the optimal behavior of the CAISO's median-size storage facility. By doing so, this paper presents first empirical evidence for the widely made assumption in the literature regarding the arbitrage behavior of this type of facilities.

While our results are robust to model specifications and robustness checks, they should be interpreted with caution. First, we only observe aggregate battery responses and do not

[25] We repeated this back-on-the-envelope analysis using DAM prices instead of RTM prices. The only column with sizeable differences is the third column (actual output from optimization model). With DAM prices, the discounted lifetime profits are more than eight times larger (2.506 m$) than when using RTM prices. However, the discounted lifetime profits when using the actual observed battery output and DAM prices (fourth column) are −2.077 m$, which represent a difference of only 1.5% with respect to the RTM case.

have access to a panel dataset on the individual storage plants output. Second, our simple model abstracts from more complex, dynamic storage considerations a battery owner faces in reality. Yet, comparing the average battery response to a simple model for a representative battery owner provides a useful benchmark on how far the owners optimize their behavior with respect to arbitrage. Our findings furthermore highlight that the assumption of arbitrage for storage facilities typically made in the energy economics literature should be made with wariness.

The analysis also highlights that batteries at current wholesale price levels and investment costs may be facing negative lifetime profits and that this would likely limit investment in large-scale battery capacity. In the future, the effect of the storage output on wholesale equilibrium prices will also be related to how much storage gets committed to the capacity market needs, provided it exists. Batteries have recently successfully participated in capacity market auctions in PJM and the UK, and are expected to be a potential game changer in Spain, where a new capacity market has been announced.[26] These are interactions left for future research.

[26]See for instance recent developments following these links for PJM, the UK, and Spain.

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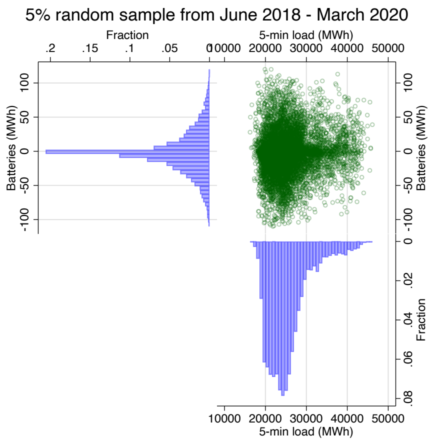
Appendix: Additional tables and figures

Figure A.1: Operational energy projects (May 2018)

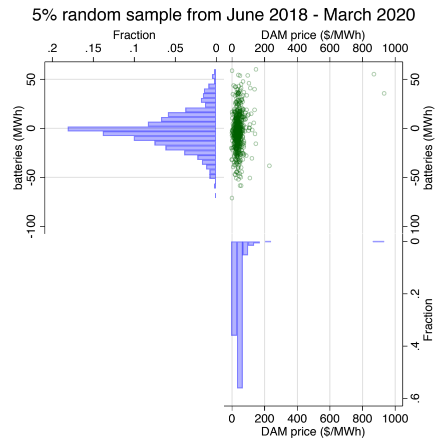
Notes: Source: California Energy Commission using DOE Energy Storage Database.

Figure A.2: Batteries output, load, and prices from the CAISO

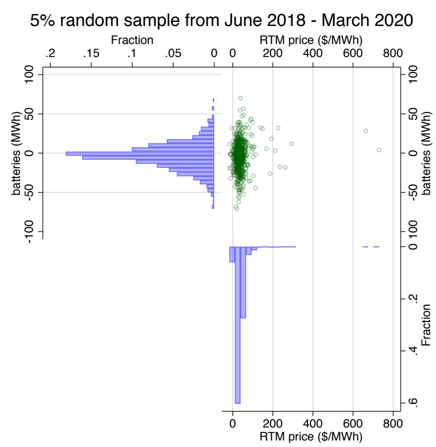
(a) Batteries output and load



(b) Batteries output and DAM wholesale prices



(c) Batteries output and RTM wholesale prices

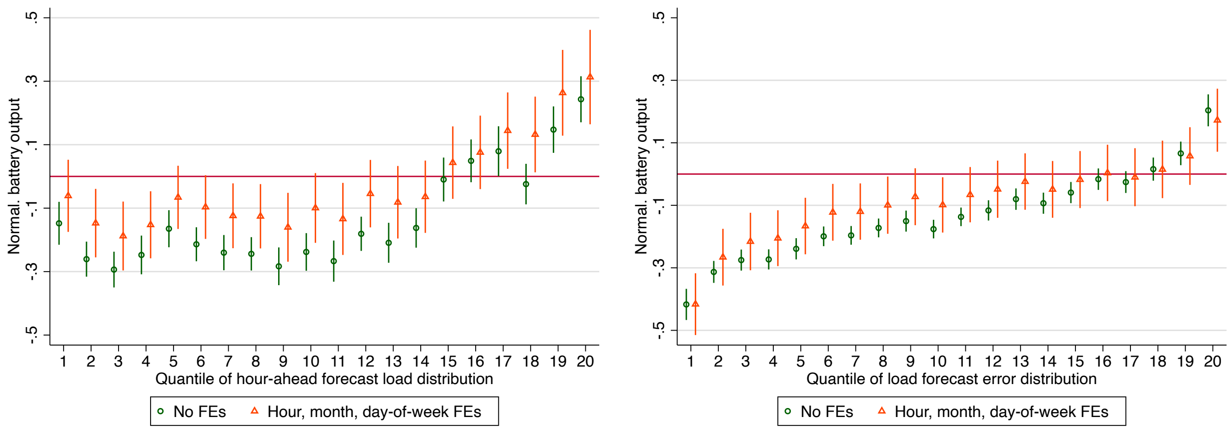


Notes: Empirical distributions of batteries output, load, DAM, and RTM prices as well as their correlation. Data from the CAISO (6 June 2018 to 1 March 2020).

Figure A.3: Batteries, hour-ahead forecast load, and error forecast

(a) Batteries and hour-ahead forecast load

(b) Batteries and error forecast

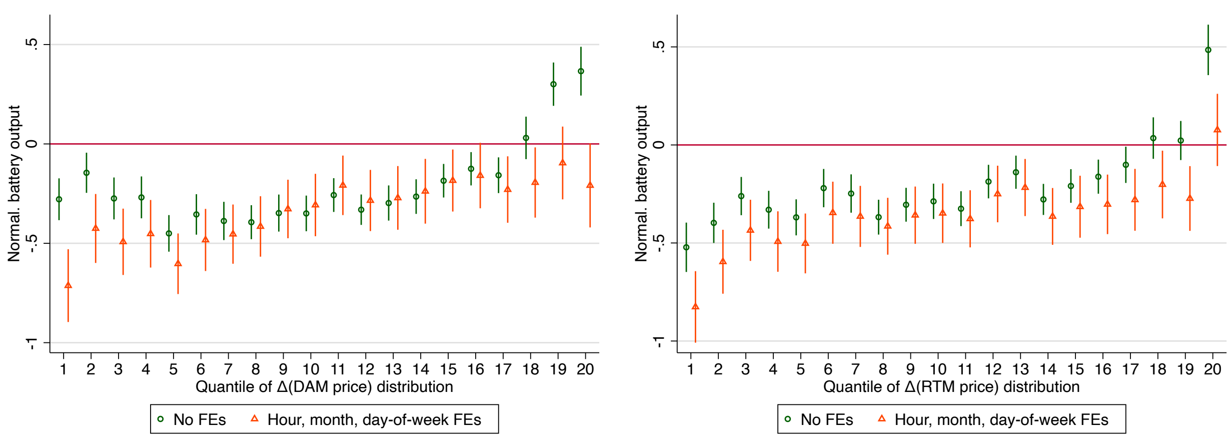


Notes: Each value represents the effect on battery discharge at each quantile of the distribution of the hour-ahead load forecast provided by the CAISO to all market participants (Panel (a)) and the difference between the realized load and the hour-ahead forecast (Panel (b)). Bars around markers indicate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

Figure A.4: Batteries and Δ wholesale prices

(a) Using DAM prices

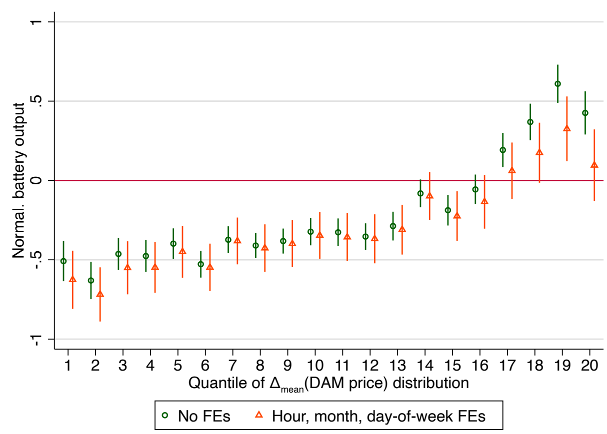
(b) Using RTM prices



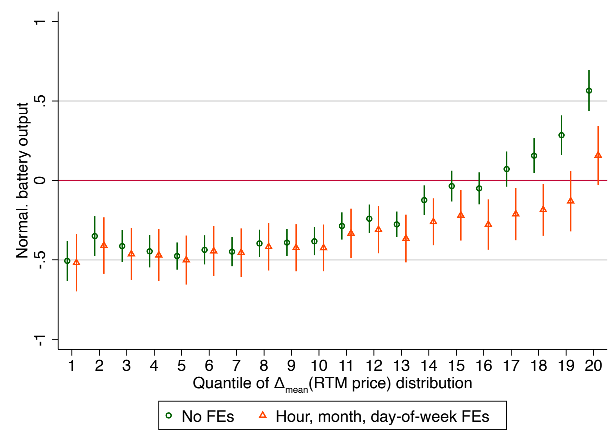
Notes: Each value represents the effect on battery discharge at each quantile of the distribution of changes in consecutive hours in the wholesale prices. Panel(a): DAM prices. Panel(b): RTM prices. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data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

Figure A.5: Batteries and Δ_{mean} wholesale prices

(a) Using DAM prices



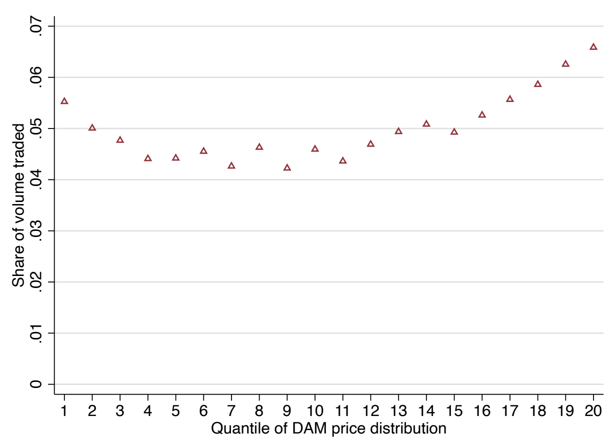
(b) Using RTM prices



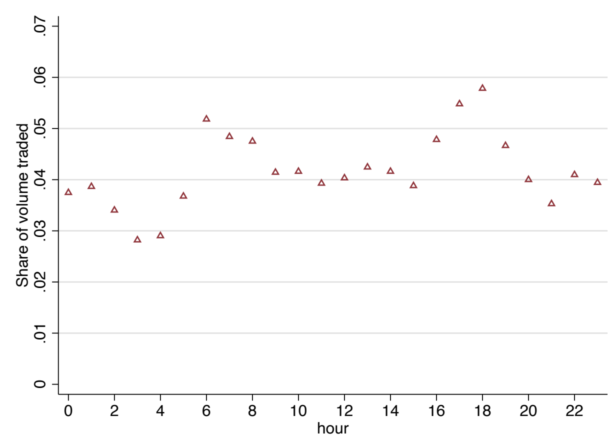
Notes: Each value represents the effect on battery discharge at each quantile of the distribution of differences of the hourly price with the daily average price. Panel(a): DAM prices. Panel(b): RTM prices. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level.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

Figure A.6: Share of volume traded by quantile of price distribution and by hour

(a) Share of volume traded and DAM price quantiles

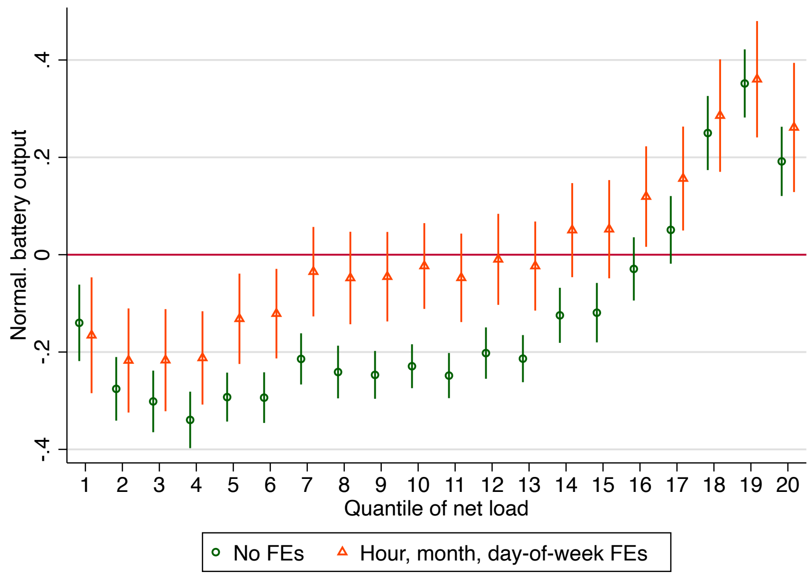


(b) Share of volume traded by hour



Notes: Share of battery volume traded, measured as battery output (charge or discharge) in a given DAM 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).

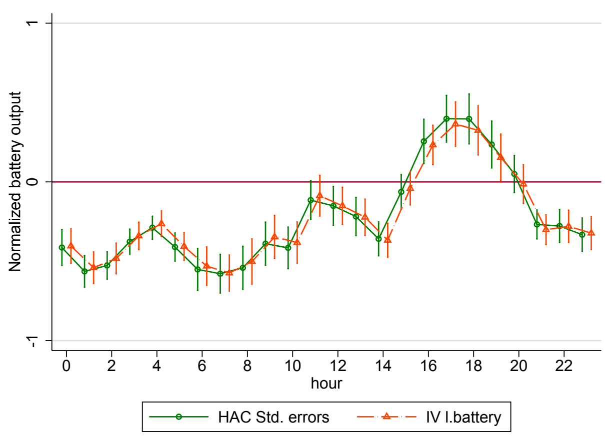
Figure A.7: Batteries and net load



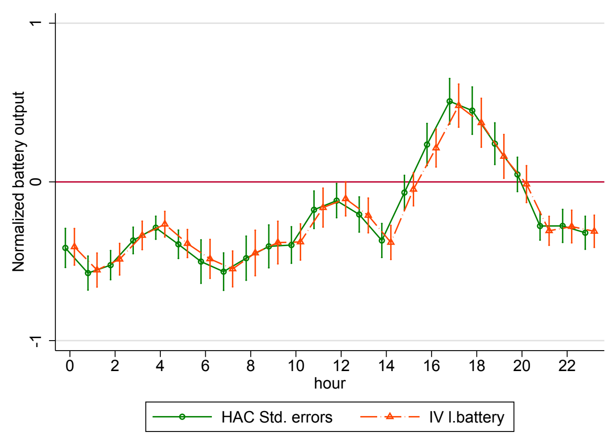
Notes: Each value represents the effect on normalized battery discharge at each quantile of the distribution of demand net of renewables. 5-minute data resolution. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from the CAISO (6 June 2018 to 1 March 2020).

Figure A.8: Robustness checks: observed battery output, standard errors and IV

(a) Using DAM prices

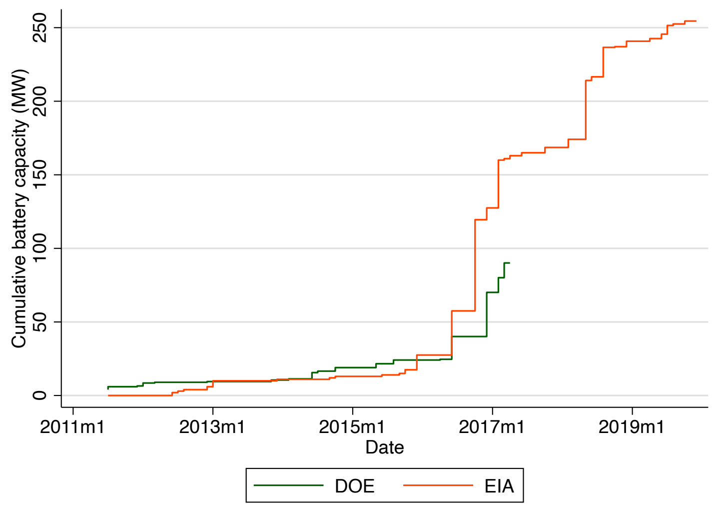


(b) Using RTM prices



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.

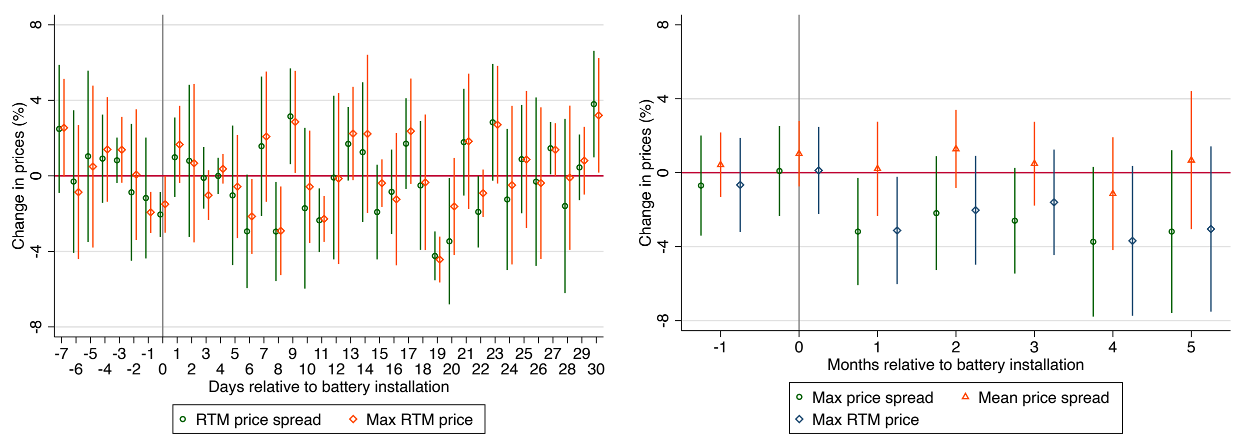
Figure A.9: Installed battery capacity CAISO



Notes: Cumulative installed battery capacity in CAISO. Sources: DOE Energy Storage Database (green line) and EIA form 860 (red line).

Figure A.10: Impact of battery use on RTM prices spreads

(a) Daily data aggregation (b) Monthly data aggregation



Notes: Each value represents the effect of newly added battery capacity on daily RTM price spreads, maximum RTM price spread, as well as maximum RTM prices. Unit of data aggregation: daily in Panel (a) and monthly in Panel (b). Panel (a) includes month and day-of-month FEs, while Panel (b) uses year and month-of-year FEs in addition to the main control variables as in the main text. Markers represent 90% confidence intervals. Standard errors clustered at the date level. Data from CAISO (1 January 2013 to 31 May 2017).