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 battery activity correlates with load and real-time prices. We further propose an instrumental variable strategy to estimate the short-term impact of prices on battery discharge. The empirical findings are consistent with the optimal solution of an arbitrage maximizer, indicating that battery owners respond to price incentives. In addition, we provide evidence that battery deployment in the years 2018 and 2019 lowered average wholesale equilibrium prices in California by about 0.8%, impacting private returns of battery investment.

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 [2020]), 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) do the activities of newly available storage facilities affect the equilibrium prices in electricity markets?

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

[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]).

effects of technology adoption (Dorsey et al. [2021], 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 for the causal impact of prices on battery activity, instrumenting wholesale real-time market (RTM) prices with natural gas prices, a cost shifter. This retrospective analysis lets us assess 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 first empirical evidence on the impact of aggregate large-scale battery usage on equilibrium prices using errors in the hourly load forecast to instrument for battery deployment.[5] This is important since the presence of battery storage can lower electricity prices and therefore, limit future arbitrage possibilities for battery owners, reducing incentives for storage investment.

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. We also estimate the impact of RTM prices on battery charging and discharging for different hours of the day, using the above mentioned instrumental variable (IV) strategy, that confirms the presence of arbitrage behavior from battery owners. 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.

[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]).

[5] One notable exception is Karaduman [2020] who models the electricity market in Australia using a supply function equilibrium and finds that storage can have non-negligible decreasing effects on equilibrium prices.

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 capacity and power comparable to the median battery operable in California as of 2019 that takes for inputs the time series of load and wholesale prices in CAISO. Qualitatively, we find a similar price response for both the optimal model dispatch and the empirical data, indicating that battery owners take advantage of arbitrage opportunities in this market. Yet, the quantitative response in the empirical data is significantly smaller, especially during evening peak hours. We discuss potential differences between the optimal model solution and our empirical findings, that indicate that the assumptions used in the optimal dispatch model are too rigid in practice. In addition, we calculate the average yearly return per kilowatt-hour (kWh) of storage and find that the empirical values are only about 1/5 of the total returns from the optimization model solution.

Finally, we show that battery deployment during 2018 and 2019 reduced equilibrium prices by about 31 cents per MWh, representing an approximate price decrease of 0.8%, when evaluated at the average RTM price. The effects are particularly strong during the evening peak load from 6pm to 9pm. Yet, we also find significant price reductions during the day. These findings highlight that batteries can be effectively used to decrease ramping needs at peak hours and to flatten the overall load profile in electricity markets with a large share of VRE generation. On the other hand, battery investment is only profitable if there are enough arbitrage possibilities. The fact that battery deployment lowers prices, in particular during peak hours, means that future battery investment will be less profitable if this effect scales with the growth in storage capacity. Policies aimed to incentivize lithium-ion batteries deployment should take this fact into account. To illustrate this effect, we calculate counterfactual RTM prices had there not been any batteries installed and we find that the storage value under the optimization model would have increased by about 1.5% relative to the case with actual prices, whereas this effect is about one order of magnitude smaller in the empirical data (actual prices and actual storage output). This finding indicates that at current levels of battery deployment, the effects of prices on investment profitability are still negligible. While our empirical analysis focuses on California, the results are broadly applicable to other liberalized electricity markets with an increasing VRE share and to storage facilities worldwide.

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 the empirical estimation strategy and results for short-term market outcomes. Section 4 provides a simple model of optimal storage management, which we solve with data from CAISO. Finally, section 5 estimates the effect of battery usage on equilibrium prices and section 6 concludes.

2 Data

2.1 Batteries output, load, and wholesale prices

We use publicly available data obtained from 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.[6] While data on load, batteries, and renewable output are available at 5-minute intervals, we retrieve hourly real-time market (RTM) price data from four Default Load Aggregation Points (DLAP). Similar to Bushnell and Novan [2020], we average the price data from DLAP locations to obtain a unique time series for CAISO.[7] An alternative dataset would be to employ price data from the day-ahead market (DAM). Yet, the fact that batteries can be employed to respond to short-term imbalances in load as well as price fluctuations makes RTM prices more attractive for our analysis, as DAM prices mainly reflect day-ahead expectations of market participants.[8] Moreover, we obtain fuel prices for natural gas power plants from OASIS. These plants are typically considered to be the marginal (price-setting) technology in CAISO. These data are available at a daily

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

[7] 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.

[8] While a large share of electricity is traded in the DAM, prices from the DAM and the RTM are highly correlated (see for instance discussion in Bushnell and Novan [2020].

frequency for 79 fuel regions.[9]

We combine these data with information on installed storage capacity in CAISO from the Energy Information Administration (EIA), as well as the Department of Energy (DOE).[10] Appendix Figure A.1 shows the location of the main storage facilities in California in 2018. Based on these locations, we obtain detailed temperature data from the National Oceanic and Atmospheric Administration (NOAA) for three main climatic regions in line with the location of the main battery capacities.[11]

CAISO started reporting data on battery output in mid-April 2018. We therefore limit our sample to the period 1 May 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.[12]

We start our analysis by plotting in Figure 1 the average battery charging profile, load profile, and RTM prices together with one-standard deviation bands to highlight the uncertainty of these variables. There are several things worth noting. First, battery activity, displayed as battery discharge in MWh in Panel (a), is centered around zero for a 24-hour period. 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) of the same figure). RTM 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 larger degree of price uncertainly during those same hours.

[9]CAISO reports fuel prices for each gas flow day, reported as $/million british thermal unit (mmBtu) independently for each of the fuel regions. Similar to DLAP prices, we average the natural gas prices to obtain a univariate time series.

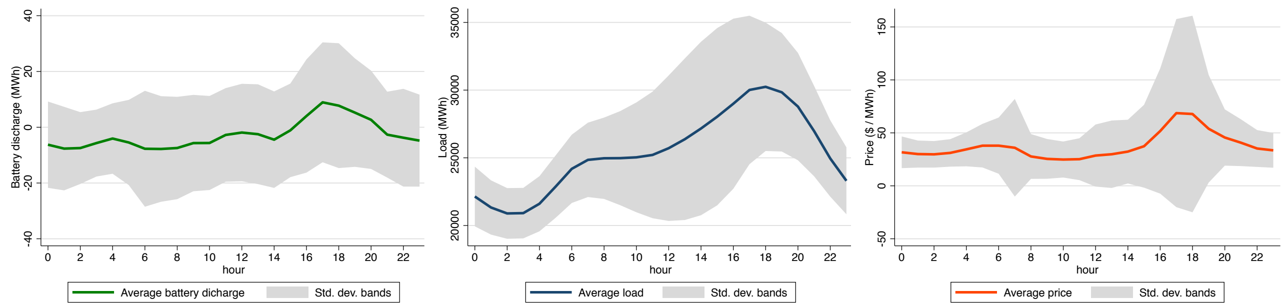
[10]EIA-860 Form reports generator-level specific information about existing generators and storage facilities with 1 megawatt of power capacity or greater. The DOE Global Energy Storage Database is an open-access resource for detailed energy-storage project in the US and worldwide.

[11]To generate a uniform temperature time series for California, we focus on the weather stations in Sacramento, San Diego, and Los Angeles and take a battery capacity-weighted average.

[12]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.

Figure 1: Batteries output, load, and prices from CAISO

a: Battery b: Load c: RTM prices



Notes: Average battery usage, load profile and Real Time Market (RTM) prices from CAISO +/- standard deviation. Data aggregation: 5-minutes, but RTM prices (hourly). Sample: 1 May 2018 to 1 March 2020.

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.[13] 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". In particular, 7 out of the 8 largest batteries (by energy capacity) are labeled as "arbitrage", which altogether have 363 MWh of energy

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

capacity (51% of the storage energy capacity in California). The other plant out of these 8 largest batteries is labeled as “spinning reserve”.

3 Short-term Market Outcomes

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 and Figure A.3. Battery output is symmetric around 0 with positive and negative values. 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). RTM 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 one 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 other relevant variables and a rich set of fixed effects.

3.1 Load, prices, and battery output

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 [2019] and Davis and Hausman [2016] as follows:

$$\text{battery output}_t = \sum_{q=2,\ldots,20} \beta_q \times \mathbb{1}(Z_t \text{ is in quantile } q) + \boldsymbol{\alpha}'\boldsymbol{X}_t + \boldsymbol{\gamma}_\tau + \epsilon_t, \quad (1)$$

where $\boldsymbol{X}_t$ is a vector of controls and $\boldsymbol{\gamma}_\tau$ is a vector of time-related fixed-effects: hour, day-of-week, and month.

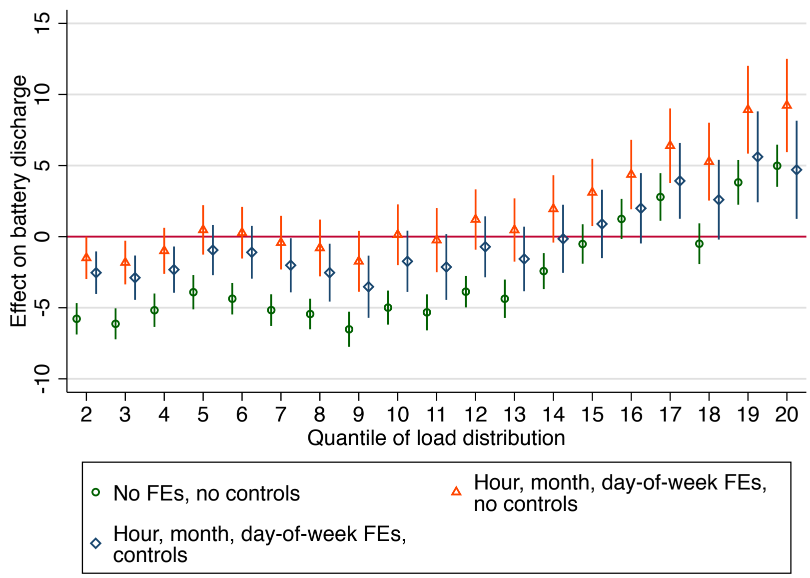
The term $\mathbb{1}(\cdot)$ is equal to 1 if the expression inside the parentheses is true and 0 otherwise. The advantage of this specification over a linear model with one single coefficient is that we can distinguish different levels of correlation at different levels of the independent variable distribution. Z_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), and prices. In the main section of this paper we focus on the relationship between batteries and load quantiles as well as price 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 Z_t is equal to load under three different specifications shown in Figure 2. The first specification has no controls nor fixed-effects. Specification two includes hour, month, and day-of-week fixed effects, which capture well-documented patterns of cyclicality in demand and production of renewables. The month fixed-effect controls for any aggregate changes in CAISO. Specification three controls additionally for total output from renewables and large hydro plants. The underlying assumption in this regression is that demand and renewable output can be considered exogenous once we control for the rich set of fixed effects. This is less clear for output from large hydro plants, which might be correlated with unobservables, but we include it because it may affect how lithium-ion batteries output is determined. Hydro output can be considered as a proxy for how constrained the electric grid is in terms of more traditional forms of storage.[14]

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 clearly from the coefficient values: they are relatively constant and negative for the first 10 quantiles of the demand and then almost monotonically increase and become positive when load is in the highest quantiles of its distribution. This same pattern emerges in the three specifications we estimate. In fact, once the cyclical patterns of the demand are taken into account through the fixed effects, the coefficients on high demand levels indicate that batteries discharge increases by between 5 and 10 MWh, which is roughly as much as twice the mean of the batteries power capacity (5.3 MW, see section 2).

[14]The coefficient on this variable is positive and statistically significant. The regression coefficients for the load quantiles are unaffected when omitting large hydro output from the set of control variables.

Figure 2: 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 (1 May 2018 to 1 March 2020).

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 Z_t equal to the hour-ahead load forecast provided by CAISO. This simply represents an inaccurate version of demand that is available to all market participants. The results from this regression are shown in Figure A.4 in the Appendix. We find that the results are fully aligned with and there are almost no differences with the results previously shown in Figure 2 above.

Similarly, we set Z_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 discharge at any given quantile of the demand forecast, which can be seen in Figure A.5 in the Appendix. Taken together, these findings reinforce our hypothesis that batteries supply the grid with more energy when demand is higher, or higher than forecasted.

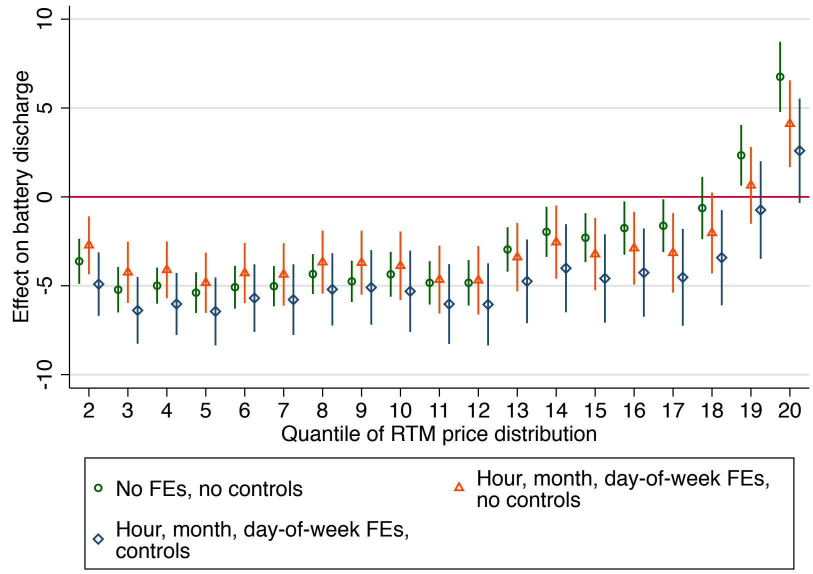
We repeat the same analysis for prices. In this case, we estimate Equation 1 with Z_t equal to RTM prices and we add load as one of the controls. Figure 3 shows the coefficients for the same three types of specifications (no fixed-effects and no controls, fixed-effects, fixed-effects and controls). The 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.[15] Nevertheless, when testing for the hourly impact of prices on battery output in subsection 3.2, we propose an instrumental variable (IV) strategy to deal with possible endogeneity, that might result from the fact that these variables are jointly determined in market equilibrium. However, for now, we assume they are exogenous and estimate regression model (1).

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 at a constant level otherwise. This pattern is robust to our three different specifications varying fixed-effects and controls. If we assume exogeneity for the price, this results suggest that batteries engage

[15] 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 arbitrage.

Figure 3: Batteries and prices



Notes: Each value represents the effect on battery discharge at each quantile of the distribution of RTM prices. The controls consist of the total output from renewables, large hydro plants output, and load. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (1 May 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.7 in the Appendix shows the share of the absolute amount of energy traded by quantile of the price distribution. At quantiles 19 and 20, the share of volume traded is the highest at a share of around 7%.

We also examine the correlation between batteries output and changes in the RTM price from one hour to the next. These results are shown in Appendix Figure A.6 and confirm that, in the aggregate, discharging is positively correlated with price increases and the larger the price increase, the larger the amount discharged by the battery in line with arbitrage behavior.

3.2 Causal impact of prices on battery output

Since battery output and prices are defined jointly in equilibrium, we propose an IV strategy to estimate the causal impact of prices on battery charging and discharging decisions. To do so, we estimate regression model Equation 2, where we instrument RTM prices with the daily spot price for natural gas,

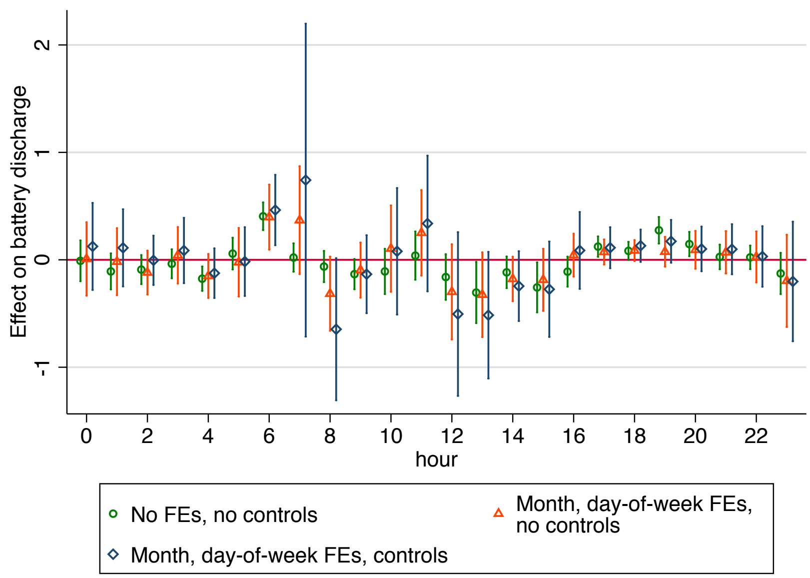
$$\text{battery output}_{hd} = \beta_{0h} + \beta_h \times \text{RTM price}_{hd} + \boldsymbol{\alpha}_{\boldsymbol{h}}'\boldsymbol{X}_{hd} + \boldsymbol{\gamma}_{h\tau} + \epsilon_{hd}. \tag{2}$$

This regression additionally conditions on the same vector of controls as the price regression Equation 1. As we observe natural gas prices only at the daily frequency we estimate this equation for each hour h of the day separately and henceforth include only month and day-of-week fixed-effects. The coefficient β_h thus captures the extend to which battery owners respond to increases in RTM prices at hour h. The index d corresponds to the different days in our sample. Similar to the above regressions, we allow standard errors to be correlated within the same day, yet we perform robustness checks allowing for Newey-West standard errors that are autocorrelated up to 7-days, similar to Bushnell and Novan [2020].

Natural gas prices are a suitable instrument for RTM prices as gas-fired power plants are typically considered the price-setting (marginal) technology in CAISO, and thus gas prices are clearly related to RTM prices. On the other hand, battery charging and discharging decisions are short-term decisions as there are several load-cycles during a 24-hour period. Battery charging and discharging should therefore not be affected by changes in the daily input prices for gas-fired power plants. Consequently, gas prices can be seen as a suitable cost shifter for the marginal technology in CAISO that does not have any direct impact on battery output decisions.

The relevance of the instrument is supported by a strong F-statistic from the first stage for each of the hours. The average first stage F-statistic (over all hours) for the regression model with fixed-effects and control variables is 13.76. We plot the coefficients β_h, one for each hour of the day, in Figure 4, again showing three specifications for robustness. Table A.1 in the Appendix reports the numerical values for the main regression model with fixed-effects and control variables and reports the first stage F-statistic for each hour separately, supporting the fact that for most hours of the day the instrument is not weak.[16] Similarly, for robustness, we report the three regression specifications with Newey-West standard errors in Appendix Figure A.9 to account for potential autocorrelation of the error terms. In the main text, we report the coefficients with clustered standard errors, as these lead to more conservative inference.

Figure 4: Batteries and prices - hourly effects



Notes: Each value represents the effect of RTM prices, instrumented with natural gas prices, on battery discharge at each hour of the day. The controls consist of the total output from renewables, large hydro plants output, and load. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (1 May 2018 to 1 March 2020).

Figure 4 highlights the existence of several load cycles during a 24-hour period. Battery discharge responds to high prices around hours 6 and 7 in the morning. Similarly, we find a significant increase in battery discharge during the evening peak hours (18-21). Load cycles can be of different lengths. According to our estimates, a \$1 increase in RTM prices during the morning peak at 6am leads to an approximate increase of 0.46 MWh discharge of batteries, representing an increase of 2.2% of the standard deviation of battery discharge at this hour. The increase in discharge during the evening is spread out over several hours,

[16] Only for 4 out of the 24 hours, we find a first stage F-statistic that is smaller than 5.

yet summing up the individual coefficients for hours 18 to 21, we find a similar total impact. The figure also highlights that for most hours of the day, the individual coefficients are not statistically different from zero. In these hours, battery output does not respond to prices. This is consistent with our second observation above in the previous section if we combine the information from Panel (c) in Figure 1 and Figure 3. Those graphs suggest that on average, high prices occur around hours 6 and 18 and that batteries discharge only when prices are very high. Whether we looked at variations across quantiles of the price distribution or by the hour of the day, the batteries behavior is to discharge only when prices are at their highest levels. This effect is stable across all three specifications for this same model.

One reason for the fact that we see relatively large standard errors for most estimates is related to the nature of our data, as we only observe aggregate battery output for CAISO rather than the output of individual batteries over time. If individual batteries are not fully synchronized or batteries are employed for other purposes than arbitrage (e.g. frequency control, ramping / spinning reserves) as explained in subsection 2.2, the aggregation will induce some noise in the dependent variable. While this would still allow us to estimate unbiased point estimates, we will only be able to detect statistically significant effects for relatively large impacts.

4 Optimal Storage

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 compare the empirical observations from section 3 to some stylized 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 help us understand the patterns that we document based on the data. The problem and the constraints are given by

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

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.

$R^{\max}$ 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).

We further assume 100% roundtrip efficiency for both charge and discharge, otherwise we would have a constant $\eta < 1$ multiplying E_t^{in} and E_t^{out} in the equation for Z_t as follows $Z_t = Z_{t-1} + \eta \times (E_t^{in} - E_t^{out})$ and also the net amount of energy traded.[17] 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.[18]

The problem is solved using the GLPK solver implemented with Pyomo in Python and using the RTM prices and load data from CAISO.[19] Note that we assume perfect foresight

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

[18] 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.

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

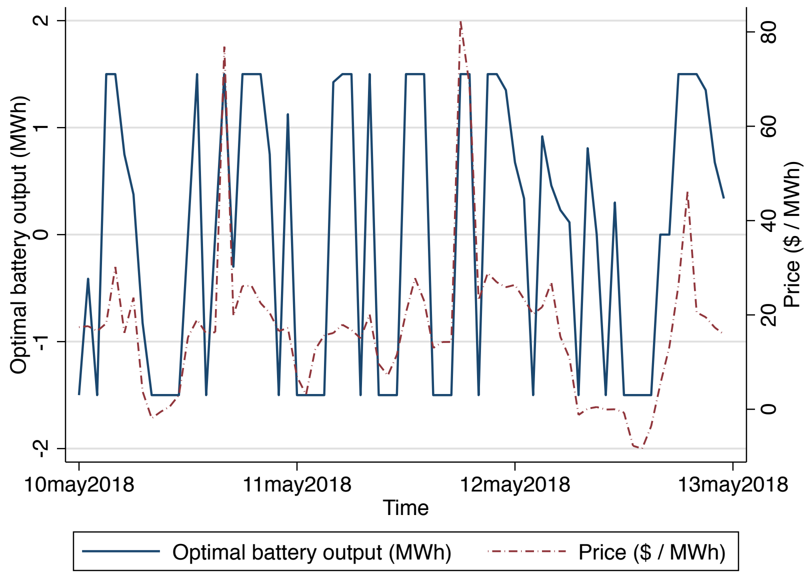
since we use the contemporaneous price data when making decisions at time t. Therefore, our results in this section should be interpreted as the best case scenario and this interpretation is useful since we want to compare the data analysis from the previous section against the best a storage facility can do.

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 three consecutive days only, 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, 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 is 0.35, which is more than three times the correlation (0.1) between those same prices and the observed aggregate net amount of discharge.

When we vary the value of the roundtrip efficiency, the parameter η above, 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 increases monotonically from 0.35 when $\eta = 1$ to 0.46 when $\eta = 0.6$.

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 purchase energy when the prices belong to quantiles 11 and below as measured by the mean of $E^{out} - E^{in}$. However, the same is true for quantiles 15 and below when measured instead by a one-standard deviation band around the mean. 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 quantiles. This fact can be due to several reasons. First, our optimization solution assumes perfect information on wholesale 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

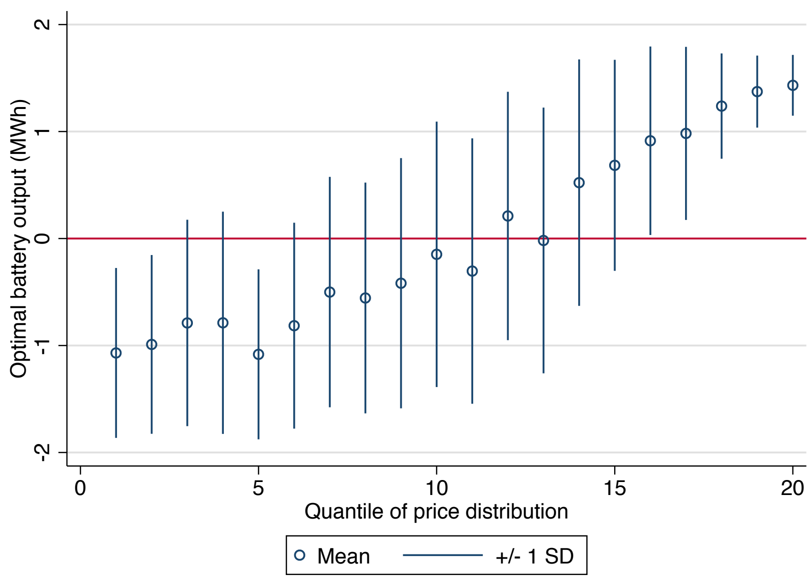
Figure 5: Optimization: battery charge (3 days)



Notes: The battery discharge amounts are the solution to the optimization problem for the representative battery. These amounts are bounded between −1.5 and +1.5 MWh because we set the power capacity of the battery at 1.5 MW. The prices on the secondary y-axis are taken directly from the RTM data. We only present the results for 3 days to ease the visualization, but we solve the problem using all our sample period.

of the battery facilities exercise market power or strategically respond to opponents' storage behavior.[20] 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 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. Keeping those factors in mind, we are confident that this stylized model of optimization returns battery output patterns that are consistent with those in the data.

Figure 6: Optimization: battery charge and price quantiles



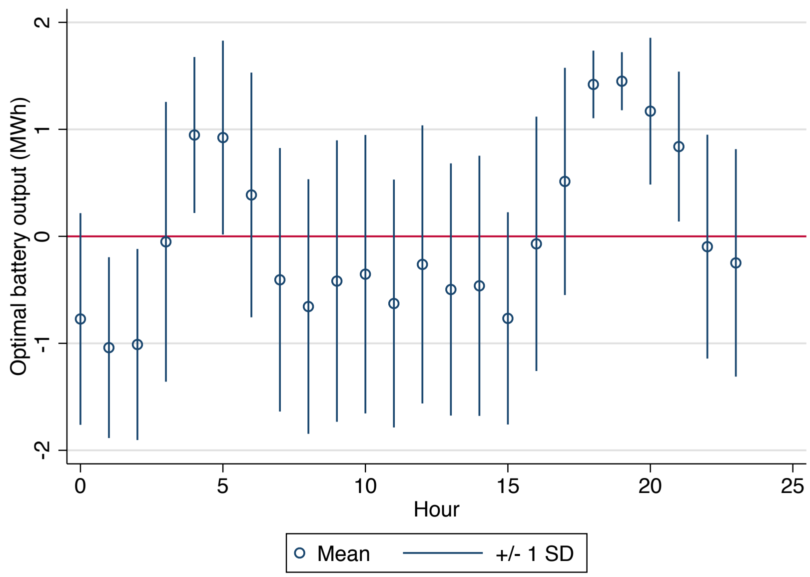
Notes: The battery discharge amounts are the solution to the optimization problem for the representative battery. The horizontal axis refers to the RTM price distribution.

Next, we aggregate the battery output from our optimization problem at the hourly level. This is presented in Figure 7. Our price-taking battery enters discharging mode at around 4 to 5am and 6pm (hour 18). During the rest of the hours the battery has a wide distribution that covers both charging and discharging except at 1am and 2am when the +/-1 standard

[20] 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.

deviation distribution is completely in charging mode. This pattern is consistent with that seen in the RTM prices from Panel c in Figure 1 in which prices are higher at around 6am and 6pm. Therefore, our optimal battery exercises some arbitrage by discharging when the revenues are higher. This is also consistent with Figure 4 in that the only hours in which we found a positive statistically significant effect on battery discharge were 6am and 7pm (in at least one of the three regression models). Yet, the quantitative responses are smaller for the empirical estimates than for the optimization model, in particular, during the evening hours.

Figure 7: Optimization: battery charge by hour of the day



Notes: The battery discharge amounts are the solution to the optimization problem for the representative battery. These amounts are aggregated at the hourly level.

Altogether, we conclude that in the aggregate, the batteries in the data make decisions whose outcomes are highly consistent with those from a price-taking battery that maximizes arbitrage opportunities. The differences that we find between the two approaches can be likely explained by the simplifying modeling assumptions. We will further elaborate on this in the next section, where we test for equilibrium price effects of battery deployment.

5 Effect of Batteries Output on Wholesale Prices

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, if all battery owners optimize their charging and discharging decisions in line with prices, they might have an impact on equilibrium prices, especially during peak hours. We test for this possibility in the present section, where we also discuss what this potential price reduction means for private returns for battery owners both under the modeling assumptions as well as in the empirical data.

To test for the possibility that battery output impacts equilibrium prices, we estimate the following regression model:

$$\text{price}_t = \beta_0 + \beta \times \text{battery output}_t + \boldsymbol{\alpha}'\boldsymbol{X}_t + \boldsymbol{\gamma}_\tau + \epsilon_t, \tag{3}$$

where we condition on the same vector of controls and vector of time-related fixed-effects as in Equation 1. Since our previous analysis has shown that battery owners do engage in arbitrage in the aggregate and respond to price incentives, battery output is clearly endogenous in equation (3). Therefore, we instrument battery output with the forecast error in load, defined as the difference between realized load and the hour-ahead load forecast. Our main identification argument is based on the fact that batteries are predominantly used to provide short-term energy. While the hour-ahead load forecasts are widely used to schedule the dispatch of traditional electricity generation units, errors in the load forecast, should be directly related to increased battery activity (as also highlighted in Appendix Figure A.5). On the other hand, as our regression framework controls for renewable output, large hydro output, as well as realized load, this "surprise" in load should be exogenous to other factors influencing prices. While it is not possible to test for this identifying assumption, we provide a robustness check by including additional controls that might affect demand in a non-linear way, namely heating and cooling degree days (HDD and CDD, respectively) as well as natural gas prices as the main price-setting technology in CAISO.

We report both the ordinary least squares (OLS) regression estimates and the IV results in Table 1. While we find a positive impact of battery output on prices in the OLS estimates

(Columns (1) and (2)), the coefficient turns negative and is significantly larger in size in the IV estimates in Columns (3) and (4), consistent with the endogeneity concern discussed above. The IV results show that battery deployment lowers average equilibrium prices by roughly 31 cents / MWh (around 0.8% when evaluated at the average RTM price). As shown in Column (4), the inclusion of additional control variables does not impact the main coefficient on batteries, supporting our main identifying assumption. We find a strong first stage F-statistic of about 20 in both IV models. The first stage results are reported in Appendix Table A.2 that again show that battery discharge is positively and significantly correlated with the forecast error of load.

Table 1: Impact of batteries on equilibrium prices

	(1) OLS	(2) OLS	(3) IV	(4) IV
Batteries	0.079***	0.044	-0.306**	-0.312**
	(0.030)	(0.029)	(0.123)	(0.122)
Renewables		-0.004***	-0.004***	-0.002**
		(0.000)	(0.000)	(0.001)
Large hydro		-0.002	-0.001	0.002
		(0.002)	(0.002)	(0.002)
Load		0.005***	0.005***	0.002***
		(0.001)	(0.001)	(0.001)
Natural gas price				0.004***
				(0.001)
HDD				1.822***
				(0.399)
CDD				-0.062
				(0.586)
Observations	15,742	15,694	15,694	15,670
R^2	0.189	0.304	0.281	0.294
Fixed-Effects	Y	Y	Y	Y
Controls	N	Y	Y	Y
First state (F-stat)	-	-	20.49	20.19

Notes: Dependent variable: RTM prices. IV estimates (Columns 3 and 4) instrument battery deployment with the forecast error in load, defined as the difference between realized load and the hour-ahead load forecast. Data from CAISO (1 May 2018 to 1 March 2020). Robust standard errors clustered at the date level in parenthesis. * $p < .1$, ** $p < .05$, and *** $p < .01$.

As the impact of batteries on equilibrium prices is likely heterogeneous for different hours of the day, we proceed by estimating a variation of Equation 3 in which we interact battery output with hour of the day. The model otherwise includes the same set of controls and fixed-effects. We do this for both the OLS and the IV estimates.[21] The main results for

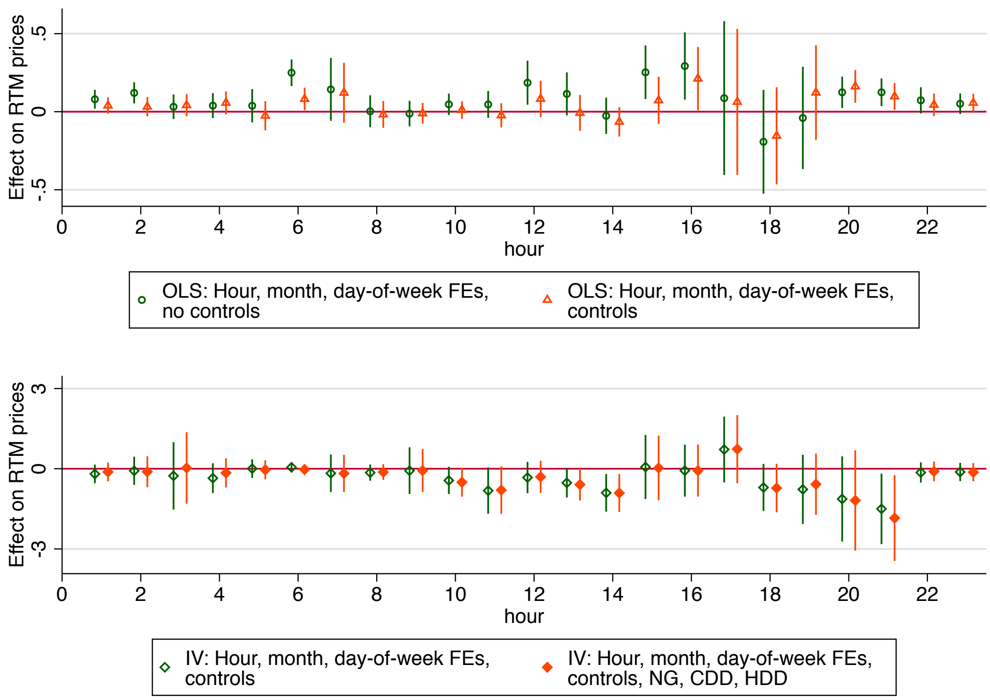
[21] For the IV estimates we instrument battery output for each hour of the day with the load forecast error interacted with each hour of the day.

the hourly effect of battery usage on RTM prices are reported in Figure 8. The upper panel refers to the OLS results, while the lower panel reports the IV estimates. In line with the average effect from Table 1, we find that most of the hourly OLS coefficients are positive, except during peak hours at 6pm when the marginal impact of battery deployment on prices turns negative.

When focusing on the IV estimates in the lower panel of the same figure, we find that most individual point estimates turn negative, yet are not statistically significant at the 95% confidence interval. However, we find significant impacts at the 90% confidence interval for 5 out of the 24 hours. Overall, the IV results indicate that the presence of batteries impacts RTM prices mostly during the late morning and early afternoon (10am to 2pm) in line with peak production from solar plants, as well as during the evening hours (mostly 6pm to 9pm) in line with ramping needs during peak demand. The magnitude of the impacts is considerably larger during these hours, reaching up to \$1.5 at 9pm, which represents an impact of almost 3.7% of the average RTM price during this hour. One caveat of the hourly results is that the instrument becomes relatively weak when interacting the load error forecast with the hour of the day. The first stage F-statistic in this case is only 1.6. Yet, the hourly results provide additional insight on the timing when battery deployment has its largest impact on prices.

Finally, to put our results further into context, we use the estimated marginal price responses from the empirical analysis (Figure 4) as well as the optimal arbitrage solution from the representative battery owner (Figure 7) to provide estimates on the "value of storage" in 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 interesting benchmark of "optimal" arbitrage, to which we can compare our empirical results. Following the findings from this section that show an equilibrium price effect of storage, we calculate counterfactual prices to show what the value would have been for the first MW of installed storage capacity in this market. This can provide useful insights for future battery investors as well as policy makers, as the associated "value of storage" is likely to decrease with additional capacity in the future.

Figure 8: Impact of battery use on RTM prices by hour



Notes: Each value represents the effect of battery discharge on RTM prices. The upper panel reports OLS estimates, while the lower panel reports IV estimates in which battery discharge has been instrumented with the load forecast error. The estimation follows Equation (3) in which we interact battery output with hours of the day. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (1 May 2018 to 1 March 2020).

To calculate the annual storage value for each kWh of installed capacity, we multiply the average price response for each hour in either the optimization model or the empirical results by the RTM prices weighted by the share of volume traded for a given hour (see also Appendix Figure A.8). We assume 100% roundtrip efficiency for our calculation. We further calculate the counterfactual RTM prices subtracting the estimated equilibrium impacts from our preferred IV specification (FEs and standard controls) from the observed RTM prices and recalculate the annual storage value. The results are summarized in Table 2, which shows the values of a simple back-of-the-envelope calculation concerning the private benefits over the lifetime of a battery installation.

Table 2: Private value of battery storage

	Optimization model		Data	
	Actual prices	CF prices	Actual prices	CF prices
Storage yearly returns per 1 kWh [$]	71.248	72.304	13.819	13.838
Lifetime profits, median plant (7.2MWh):				
Lifetime value [m$]	4.159	4.221	0.807	0.808
Investment cost [m$]	1.685	1.685	1.685	1.685
Lifetime profits [m$]	2.474	2.536	-0.878	-0.877

Notes: Private value of battery storage arbitrage for the optimization model in section 4 and for the empirical estimates from Figure 4. Calculations based on hourly responses to prices as well as observed batteries-traded volumes by the hour. Counterfactual (CF) prices take into account the equilibrium effect of battery deployment. Private values assume 100% battery roundtrip efficiency and no degradation over lifetime. Lifetime calculations based on 10 years utilization and 5% annual discount rate. Investment cost of $234 per kWh of storage in 2018 assumed, based on Bloomberg New Energy Finance.

We find that the average yearly return is about $71.2 in the model and $13.8 per kWh in the empirical data. These stark differences are likely driven by the model assumptions and the fact that the model predicts large arbitrage opportunities in the evening hours when prices are highest.[22]

Under the counterfactual prices, we find that the storage value under the optimization model would increase by about 1.5% but this same effect is about one order of magnitude smaller in the empirical data. While the total impact on profits from the counterfactual

[22] Interestingly, Karaduman [2020], who builds on a dynamic structural model to estimate the equilibrium impacts of storage, finds similar discrepancies.

prices may seem small, recall that currently there are only about 1.2 GWh of capacity and 0.9 GW of power of storage installed in CAISO. If the effects we found persist for larger storage capacities, equilibrium prices will likely decrease further as well as the private return of battery investors. Note that our findings focus exclusively on the private returns and abstract from any additional impacts on producer and consumer surplus in electricity markets.

Finally, our calculations highlight that under current conditions it is not profitable for battery owners to operate in this market, when purely relying on arbitrage. 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.

6 Conclusion

This paper documents general patterns of the output from large-scale lithium-ion batteries relative to load and wholesale (RTM) electricity prices in CAISO. We further estimate a causal effect of prices on batteries output using natural gas prices as an instrument for wholesale prices. When we benchmark those aggregate patterns to what we would observe for a representative battery installation that takes wholesale prices as given, we find that those patterns closely 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. In addition, we provide first reduced form evidence for the impact of aggregate battery deployment on RTM prices in equilibrium using a novel instrumental variable strategy based on the error of the forecast that is released by the system operator to all market participants.

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 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 typically made in the energy economics literature is reasonable.

The analysis also highlights that batteries that solely rely on arbitrage opportunities (at given rates of deployment) could lead to negative lifetime profits and that this would likely limit investment in large-scale battery capacity. Battery investment could be supported by allowing batteries to compete for other services, such as frequency regulation, as well as capacity markets. The effect of the storage output on wholesale equilibrium prices will be also related to how much storage gets committed to the capacity market needs. 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.[23]

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

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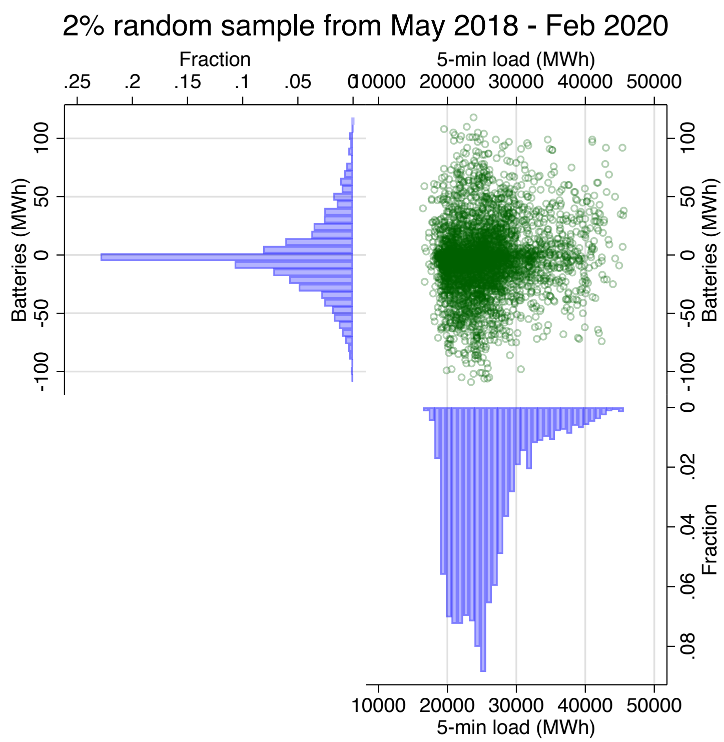
Appendix: Additional tables and figures

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

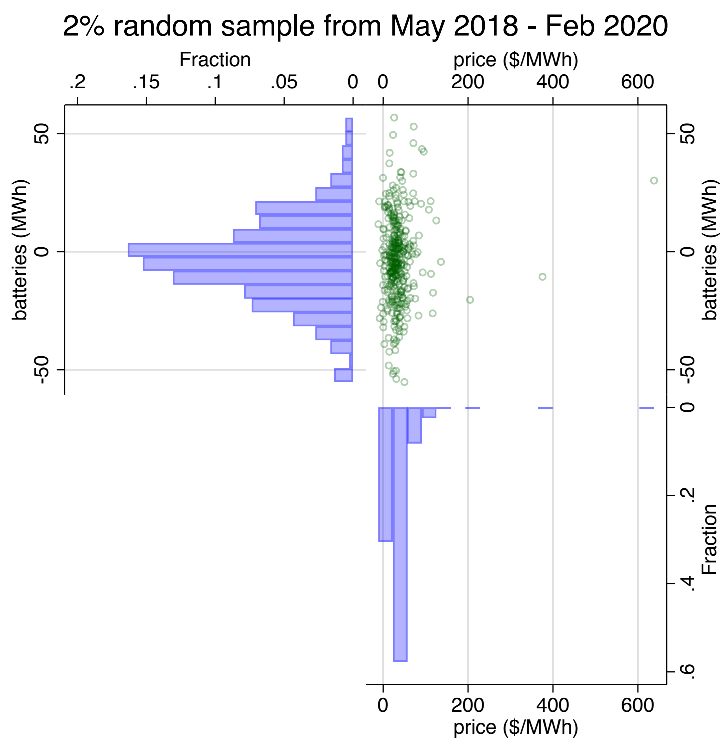
Notes: Source: California Energy Commission using DOE Energy Storage Database.

Figure A.2: Batteries output and load



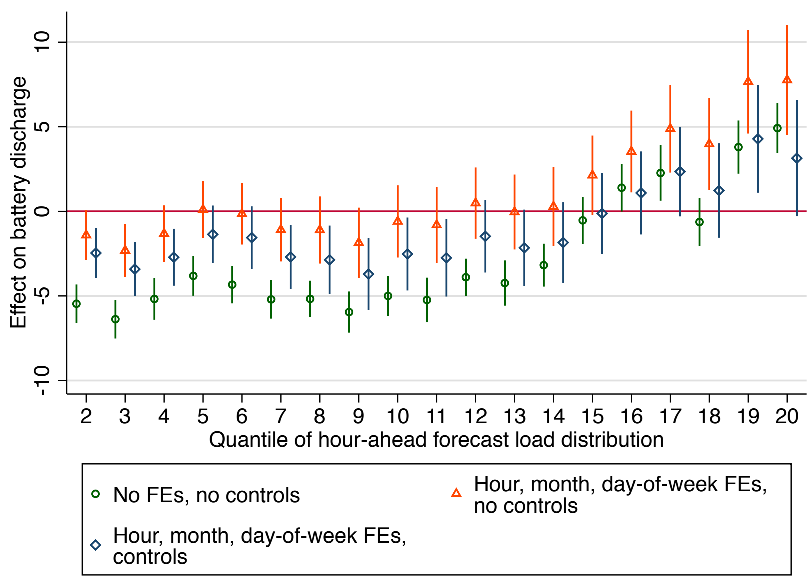
Notes: Empirical distributions of batteries output and load as well as their correlation. Data from CAISO (1 May 2018 to 1 March 2020).

Figure A.3: Batteries output and RTM prices



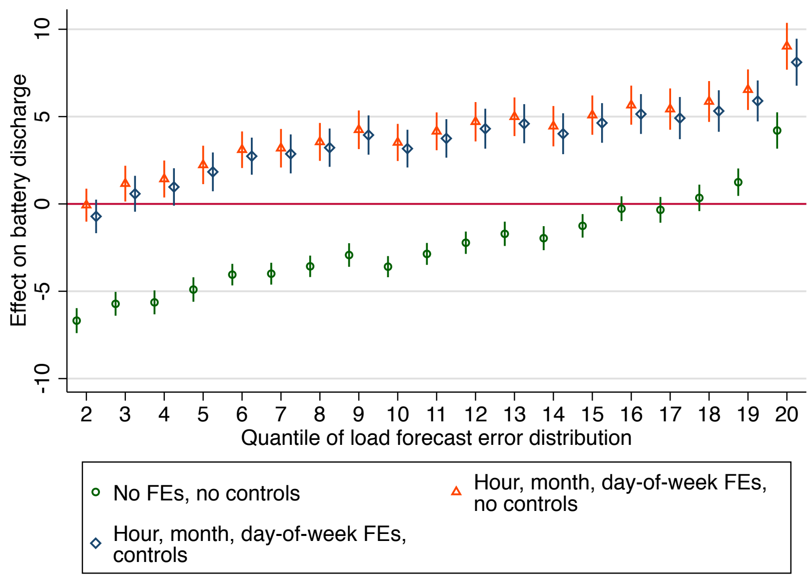
Notes: Empirical distributions of batteries output and RTM prices as well as their correlation. Data from CAISO (1 May 2018 to 1 March 2020).

Figure A.4: Batteries and hour-ahead forecast load



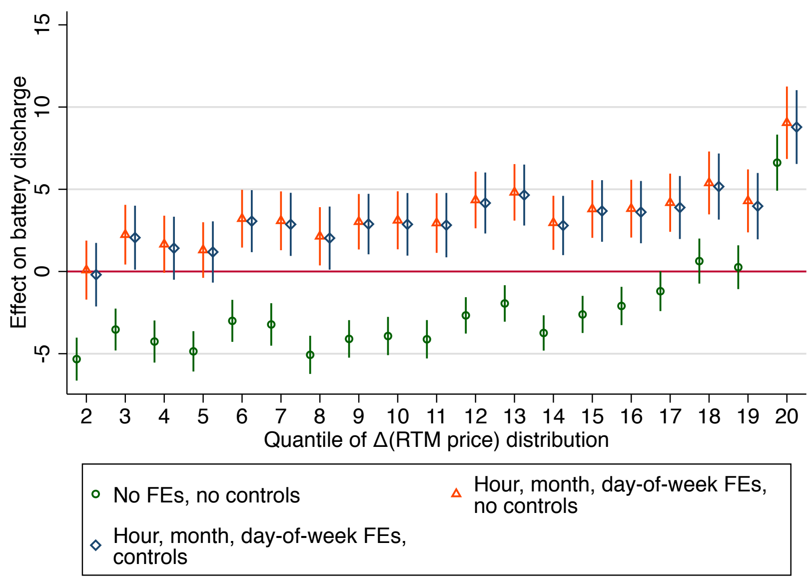
Notes: Each value represents the effect on battery discharge at each quantile of the distribution of hour-ahead load forecast provided by CAISO to all market participants. The controls consist of the total output from renewables and large hydro plants. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (1 May 2018 to 1 March 2020).

Figure A.5: Batteries and error forecast



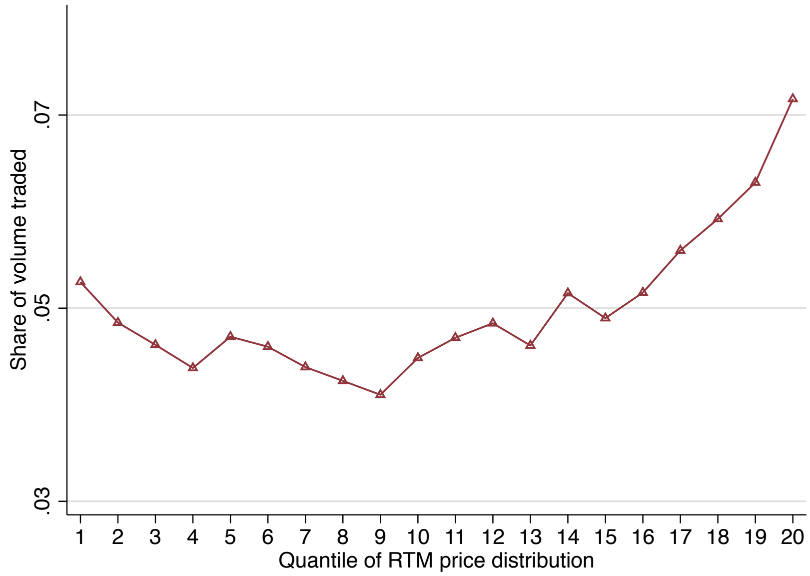
Notes: Each value represents the effect on battery discharge at each quantile of the distribution of the difference between the hour-ahead load forecast provided by CAISO to all market participants and the realized load. The controls consist of the total output from renewables and large hydro plants. Bars around markers indicate 95% confidence intervals. Standard errors clustered at the date level. Data from CAISO (1 May 2018 to 1 March 2020).

Figure A.6: Batteries and Δprice



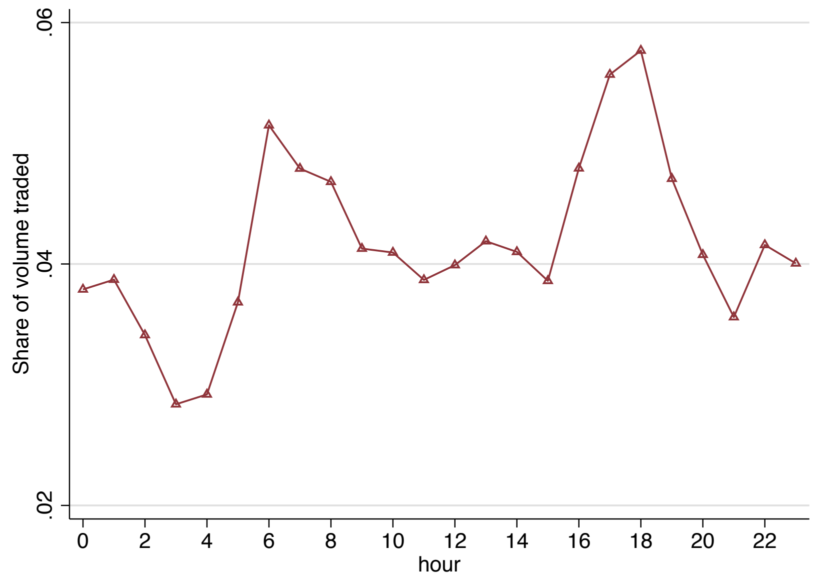
Notes: Each value represents the effect on battery discharge at each quantile of the distribution of changes in consecutive hours in the RTM prices. The controls consist of the total output from renewables, large hydro plants output, and load. Bars around markers indicate 95% confidence intervals. Standard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

Figure A.7: Share of volume traded and price quantiles



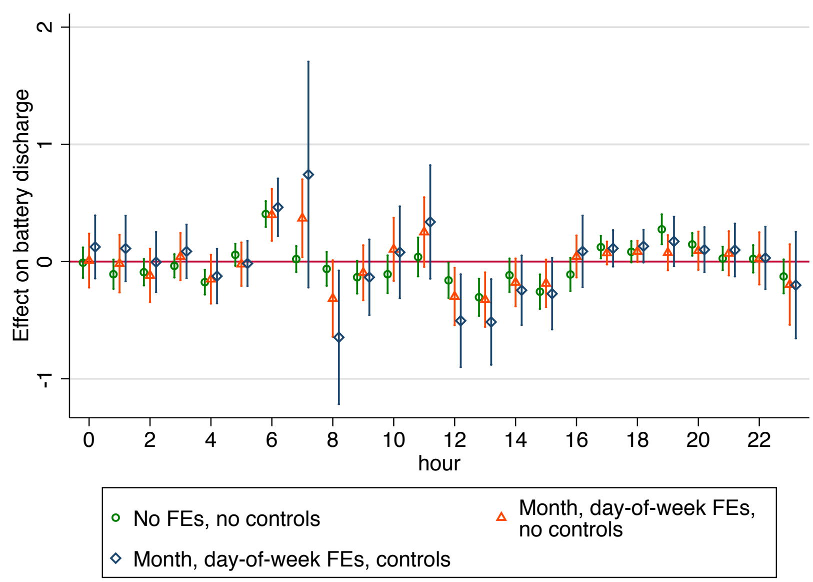
Notes: Share of battery volume traded, measured as absolute battery charge / discharge, by price quantiles. Data from CAISO (1 May 2018 to 1 March 2020).

Figure A.8: Share of volume traded by hour



Notes: Share of battery volume traded, measured as absolute battery charge / discharge, by hour of the day. Data from CAISO (1 May 2018 to 1 March 2020).

Figure A.9: Battery output and prices - hourly (Newey-West)



Notes: Each value represents the effect of RTM prices, instrumented with natural gas prices, on battery discharge at each hour of the day. The controls consist of the total output from renewables, large hydro plants output, and load. Bars around markers indicate 95% confidence intervals. Newey-West standard errors allow for autocorrelation for up to 7 days. Data from CAISO (1 May 2018 to 1 March 2020).

Table A.1: Battery output and prices (IV regression)

Hour	**Beta**	**Standard error**	**95% Conf. interval**	**F-stat (first stage)**
0	0.125	(0.207)	[-0.281; 0.53]	25.581
1	0.112	(0.183)	[-0.248; 0.471]	28.508
2	-0.005	(0.117)	[-0.234; 0.225]	24.582
3	0.087	(0.155)	[-0.218; 0.391]	25.169
4	-0.124	(0.118)	[-0.356; 0.107]	20.991
5	-0.016	(0.164)	[-0.337; 0.304]	17.583
6	0.463***	(0.167)	[0.135; 0.791]	14.263
7	0.742	(0.743)	[-0.715; 2.199]	1.538
8	-0.646**	(0.338)	[-1.308; 0.016]	8.803
9	-0.134	(0.185)	[-0.497; 0.229]	13.465
10	0.079	(0.301)	[-0.51; 0.668]	9.3
11	0.338	(0.322)	[-0.294; 0.97]	7.875
12	-0.505	(0.389)	[-1.267; 0.258]	4.776
13	-0.515*	(0.301)	[-1.105; 0.074]	8.833
14	-0.245	(0.166)	[-0.57; 0.08]	8.791
15	-0.274	(0.227)	[-0.718; 0.17]	5.203
16	0.087	(0.183)	[-0.271; 0.446]	3.323
17	0.113	(0.098)	[-0.079; 0.304]	4.18
18	0.131*	(0.077)	[-0.02; 0.282]	5.43
19	0.172*	(0.102)	[-0.028; 0.372]	13.565
20	0.101	(0.106)	[-0.107; 0.31]	19.519
21	0.099	(0.119)	[-0.135; 0.332]	18.82
22	0.031	(0.144)	[-0.251; 0.314]	24.267
23	-0.201	(0.284)	[-0.758; 0.355]	15.949

Notes: Each row corresponds to a separate regression for each hour of the day of battery discharge on RTM prices, where RTM prices are instrumented with natural gas prices. The regression includes month and day-of-week FEs and additionally controls for renewable and large hydro generation as well as total load. Robust standard errors clusterd at the date level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: First stage regressions for Table 1

	(1)	(2)
Dependent variable	Battery discharge	
Load forecast error	0.018***	0.018***
	(0.004)	(0.004)
Renewables	0.001***	0.001***
	(0.000)	(0.000)
Large hydro	0.004***	0.004***
	(0.000)	(0.000)
Load	-0.000	-0.000
	(0.000)	(0.000)
Natural gas price		0.000
		(0.000)
HDD		-0.083
		(0.158)
CDD		-0.086
		(0.165)
Constant	-14.671***	-13.940***
	(1.622)	(2.177)
Observations	15,694	15,670
R^2	0.108	0.107
Fixed-Effects	Y	Y

Notes: First stage regression for the IV results in Columns 3 and 4 of Table 1. Robust standard errors clusterd at the date level. * p< 0.1, ** p < 0.05, *** p < 0.01.