Soaking Up the Sun: Battery Investment, Renewable Energy, and Market Equilibrium

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Abstract

Battery storage provides a potentially valuable complement to renewable energy. Thus, policymakers have recently incentivized and mandated storage as a means to integrate renewable energy and meet climate goals. This paper evaluates the equilibrium value and adoption trajectory of utility-scale batteries using California data, focusing on the impact of falling battery capital costs, complementarities with renewable energy, and market power. We develop linked competitive dynamic equilibrium models of battery adoption and operations. We forecast electricity load and prices using an approach that allows for a a non-linear and time-variant marginal cost curve of electricity. We have several main findings: (1) the value of battery storage increased sharply between 2016-19 as solar generation increased, (2) battery investment exhibits decreasing returns-to-scale—the per-unit value of batteries drops significantly with total installed battery capacity, (3) battery operations increase California's 2018 expected discounted social surplus from the electricity market by $6.5 billion or $4.35 per MWh of solar energy generated, and (4) California would require a 17% subsidy on batteries to meet its 2024 storage mandate of 1.3 GW of power capacity.

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1 Introduction

Growth in renewable electricity generation has been dramatic over the past 10 years, in the U.S. and worldwide. By displacing generation from fossil fuels, renewables reduce greenhouse gas emissions. However, almost all recent growth in renewables comes from sources such as solar photovoltaics (PV) that are *intermittent*: a solar farm cannot generate electricity after the sun sets, or when a cloud passes overhead. Absent the ability to store electricity, integrating these intermittent sources into the electricity grid requires the capability both to produce electricity at times with low expected renewable production and to adjust production suddenly when renewable production fails. Intermittency adds to the social costs of renewables through the costs of building, maintaining, and operating additional fossil fuel generators (Bushnell and Novan, 2018; Gowrisankaran et al., 2016; Joskow, 2011). Battery storage is a potentially important complement to intermittent renewable energy: it can lower the social costs of renewables by storing energy when renewable production peaks and releasing it when it plummets.

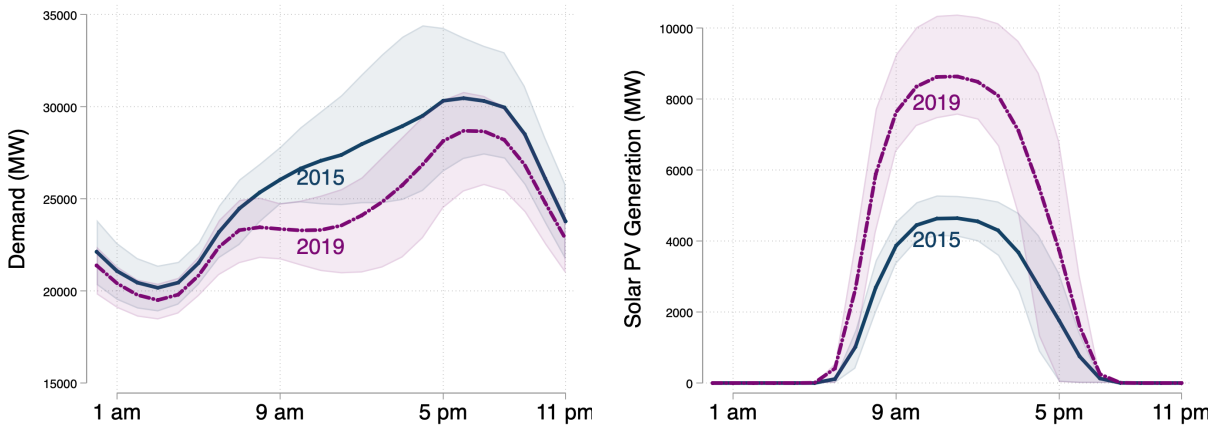
We illustrate these points with data from California, a leader in adding solar generation capacity.[1] Figure 1 Panel A displays average electricity demand for electricity and Panel B displays average solar generation, over the hours of the day and separately for 2015 and 2019. Solar generation increased dramatically over this period, but this generation typically occurs in the middle of the day and not in the evening, when demand is highest. Figure 2 displays *net load*, which is the difference between total demand and renewable generation, and hence the portion of demand that is supplied by non-renewable generation. Net load in 2019 plummets in the middle of the day but rises again in the early evening to a similar level as in 2015, resulting in a double-humped curve. The double humps raise the social costs of renewables for two reasons. First, they imply that solar does not produce in the evening when net load, and hence marginal costs, are highest. Second, they increase the ramping costs that generators bear every time they turn on or off (Cullen, 2010; Mansur, 2008; Reguant, 2014).

Utility-scale batteries in California can lower the social costs of solar generation by storing energy starting at noon—when the sun is shining—and releasing it from 6PM on. Batteries can help both in using solar to replace fossil fuel generation when marginal costs are highest and in lowering ramping costs. However, the equilibrium value of large-scale batteries is limited because each additional battery, acting as an arbitrageur, will raise prices at noon and lower prices in the evening, thereby flattening the humps and lowering values.

In conjunction with these trends that affect the revenues from storage, the capital costs of lithium-ion battery cells have dropped 85% from 2010 to 2018 with projections of 50% further cost drops over the next 10 years (Cole and Frazier, 2019; Goldie-Scot, 2019). Not coincidentally, the 2019 Nobel Prize in Chemistry was awarded for the development of lithium-ion batteries. Despite these dramatic cost decreases, the central impediment to utility-scale battery storage remains its high capital costs. For this reason, the private market is unlikely to install batteries in the near future in the absence of mandates or subsidies.

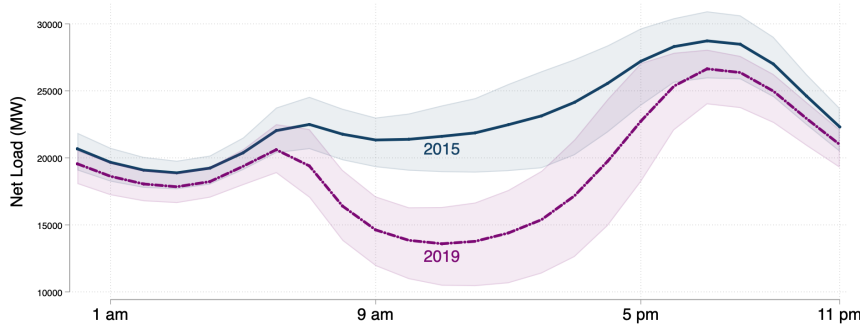
[1] California has a mandate that 60% of generation must be from renewable sources by 2030 and 100% by 2060.

Figure 1: Solar generation and electricity demand by year in California



Note: Panel A shows the mean and 25th and 75th percentiles of electricity demand, by year and hour of day. Panel B shows the mean and 25th and 75th percentiles of solar generation by year and hour of day. Figures calculated by authors from CAISO data.

Figure 2: The "duck curve": net load distribution by year in California



Note: The figure shows the mean and 25th and 75th percentiles of net load, by year and hour of day, calculated by the authors using CAISO data.

Recognizing the complementarity between renewable energy and batteries and also these high capital costs, states have paired renewable energy mandates with battery storage requirements. In 2013, California passed a requirement for utilities and other companies to procure 1.3 GW of storage power capacity by 2024, with the specific justification that batteries can help optimally integrate the renewable energy resources.[2] Other states—notably AZ, MA, NJ, NY, and OR—have also implemented battery procurement requirements as a complement to their renewable energy standards.[3]

This paper has two main goals. First, we seek to evaluate the equilibrium value and adoption trajectory of utility-scale batteries. Specifically, we examine how falling battery capital costs, complementarities with renewable energy, and market power affect the equilibrium adoption

[2]The legislation stated "Additional energy storage systems can optimize the use of the significant additional amounts of variable, intermittent, and offpeak electrical generation from wind and solar energy..."

[3]The Federal Energy Regulatory Commission (FERC) Order 841 requires all electricity markets to remove barriers that would inhibit participation of storage resources in wholesale energy markets.

of battery capacity and their value given adoption. Second, we seek to understand the role of renewable energy mandates and battery subsidy policies in affecting values and adoption levels. Specifically, we investigate the level of subsidies necessary to meet battery mandates and how much a battery market lowers the costs of renewable energy mandates.

Our study adds three innovations to the economics and engineering literature on battery operations decisions. First, we model the equilibrium effects of large-scale battery operations decisions, which are important because battery operators act as arbitrageurs, and undercut their own values. To understand the equilibrium effects of large-scale battery operations, we model the electricity cost curve, and not just market price. Second, we develop a frontier time series forecasting model of load and the electricity cost curve. This is challenging, because the marginal cost curve for electricity is highly nonlinear and sensitive to supply and demand conditions that vary over time. It is also important, because the value of large-scale batteries fundamentally depends on the expectation of future electricity marginal costs. Finally, we link together a capacity adoption model with a battery operations model. The operations model microfounds the revenues that batteries earn across solar penetration and battery capacity. The adoption model is ultimately necessary to understand the value of a battery market, the time path of battery adoption, and the role of subsidies in affecting these variables.

We proceed by developing and solving competitive dynamic equilibrium models of battery capacity adoption and battery operations. Our capacity adoption model specifies an infinite mass of identical potential battery operators. Each potential battery operator can adopt at one point in time. It makes its decision of whether to adopt in each period after forming rational expectations regarding future capital adoption costs and equilibrium adoption levels. The gross value of adoption at any point point in time is a function of the battery's ability to arbitrage prices, which depends on the total battery capacity and solar generation. We estimate these values from our operations model.

In our operations model, each battery operator in each five-minute interval of the month observes the current net load and real-time market price and decides what percent of its capacity to charge or discharge, up to its technological constraints. To make dynamically optimal decisions, the battery operator must forecast the future price distributions, which will be affected by market-level battery operations decisions. Our operations model incorporates a number of features that we believe are important in this context: deterministic within-day fluctuations in net load that vary by month; a restriction of the information set of the forecasting model to that of a real-time market participant; serial correlation of the shocks to net load and marginal cost curve of electricity due to the dynamics created by weather and ramping costs; a non-linear marginal cost curve of electricity that evolves over time; a loss in energy from charging and discharging the battery; and the depreciation of batteries from operation, particularly with deep cycles. We estimate electricity load and marginal cost curves using data from the California Independent System Operator (CAISO)—which covers 80% of California's electricity demand—from 2015-19. This setting allows us to assess empirically the complementarity between solar generation and the value of storage. We estimate current and future battery capital costs from data maintained

by the National Renewable Energy Laboratory (NREL).

We identify the complementarity between battery storage and solar generation from the relation between the solar penetration and the value of battery storage—computed from the operations model—over the months of our sample. The variation in solar energy penetration over the months in our sample allows us to identify this effect. A limitation of this identification strategy is that our adoption model uses an out-of-sample projection to a future with more solar generation than currently exists. We identify the effect of battery capacity on battery value by evaluating the extent to which increases in capacity lower the per-unit value of batteries, which occurs because the batteries, acting as arbitrageurs, moderate extreme price fluctuations. We do this by estimating how the additional charge or discharge at any time period would affect the marginal cost of electricity. Thus, we identify the effect of large-scale batteries as a counterfactual of our dynamic optimization process. Our counterfactuals here capture the dynamics of ramping constraints, by allowing both the amount generated and the deviation of the amount generated between successive periods to affect the electricity marginal cost curve. Our identifying assumption on the counterfactuals is that the time-series process on the marginal cost evolution is invariant to the amount of installed battery capacity.

Relation to literature. Our study builds on several literatures. First, our work relates to an engineering and economics literature that investigates the value of storage in wholesale electricity markets. Early engineering papers in this literature modeled the storage decision using a finite-horizon framework and assumed that the storage device operator had perfect foresight about future prices or relied on historical prices when making discharge and charge decisions (Sioshansi et al., 2009; Sioshansi and others, 2011; Walawalkar et al., 2007). More recent engineering studies relax the perfect foresight assumption and model storage decisions given uncertainty about future prices (Mohsenian-Rad, 2015; Mokrian and Stephen, 2006; Xi et al., 2014).[4] Our operations model uses substantial inputs from the engineering literature and extends this literature by considering the equilibrium effects of large-scale storage and the impact of monopoly or competitive storage markets. A recent economics working paper, Kirkpatrick (2018), empirically estimates the effect of recent utility-scale batteries installations on electricity market prices and transmission line congestion in California. Finally, a contemporaneous economics working paper to ours, Karaduman (2019), also seeks to understand the value of energy storage in an equilibrium setting. Our equilibrium model is complementary to Karaduman (2019), with different approaches to modeling demand and price residuals to allow for dynamics and equilibrium effects of large battery capacity. Our use of California data, which provides large variation in solar generation, allows us to evaluate directly the impact of solar energy on battery values.

Second, we contribute to an economics literature that explores market impacts of new energy technologies. Bushnell and Novan (2018), Craig et al. (2018), Cullen (2013), Novan (2015)

[4]Other related work has considered the effects of storage on emissions (Carson and Novan, 2013; Hittinger and Azevedo, 2015; Holladay and LaRiviere, 2018), the value of storage in ancillary service markets (Berrada et al., 2016; Cheng and Powell, 2016; Kazemi et al., 2017), and the role of storage in integrating intermittent renewable power plants (Black and Strbac, 2007; Garcia-Gonzalez et al., 2008; Paatero and Lund, 2005).

Wolak (2018), and Woo et al. (2016) measure the environmental and market effects of renewable energy generation. Burr (2014), Reddix (2015), Feger et al. (2017), Langer and Lemoine (2018), and De Groote and Verboven (2019), evaluate the impact of solar subsidies on adoption. We add to this literature with a dynamic model of investment and subsidies in battery capacity. While previous work developed dynamic models of investment in a renewable energy, we are the first paper to develop a dynamic model of investment in battery storage. Unlike solar adoption, battery charge and discharge decisions are themselves a difficult, dynamic problem and thus, our adoption model integrates a dynamic operations model.

Third, our work also relates to the literature investigating the time series properties and forecasting of electricity load and real-time prices. In particular, our model for the evolution of prices is motivated by the specific time series features of electricity prices experienced both systematically across most electricity markets (e.g., see Weron (2014) for a comprehensive review) and also for the California CAISO market in particular (Knittel and Roberts, 2005).[5] By combining both a time series model of net load together with a structural model of supply, our model for the evolution of prices is closest in spirit to Kanamura and Ōhashi (2007). Given our empirical setting, however, we estimate our model at a much higher frequency, accommodate a much richer set of seasonal patterns, and conduct the analysis within a psuedo out-of-sample forecasting framework.

Finally, our work relates to a literature on the computation of high-frequency dynamic models of electricity supply. Following (Cullen and Reynolds, 2017), we simplify the computation burden by solving the social planner single agent dynamic problem, which yields equivalent decisions to the competitive dynamic equilibrium problem. Our computational techniques were developed concurrently with Reynolds (2019).

Findings. We find that the gross social value (not accounting for capital costs) of a small (5000 MWh) utility-scale competitive battery market would be about $180 per kWh in 2019, where renewable energy share is 12% of generation. This contrasts with the reported battery capital costs from NREL of about $378 per kWh in 2019. Thus, battery capacity is not yet at a break-even point. Because of the rapid reduction in battery costs, expected battery capital costs will be $180 per kWh in 202x. Thus, this would be the break-even point for a small competitive battery market, if California's solar generation were to remain constant.

We find a strong complementarity between the gross social value of utility-scale batteries and renewable energy generation. In particular, if renewable energy share were to equal xx% of generation, the 2019 gross social value of batteries would be $378 per kWh. Combining the mandated increase in renewable energy share in California with the expected decrease in battery costs, the small utility-scale battery installation will be expected to break even by 202x. Due to its role as an arbitrageur, the per-unit value of battery capacity declines significantly in the installed capacity: 25,000 MWh of batteries would add a social value of $xxx while 50,000 MWh of batteries

[5] Some of the features of wholesale electricity prices including the skewness and volatility are closely connected to the need to constantly balance demand and supply of electricity, and the inability to hold negative inventories (Deaton and Laroque, 1992).

would add a social value of $xxx, both per kWh in 2019. Correspondingly, we find that the 25,000 MWh batteries lower prices at 6PM an average of xxx while the figure is xxx for the 50,000 MWh batteries.

Despite the fact that we are not far from reaching a break-even point, battery adoption will likely be slow for several years in the absence of a battery mandate or subsidy. The reason for this is that, given that battery costs are declining, there is an option value of waiting for further technological change instead of adopting at the break-even point. In order to reach California's mandate of 5,200 MWh by 2024,[6] a competitive battery market would require a subsidy of $47 per kWh or a 17% subsidy. Without a battery mandate, we would expect to see virtually no installed capacity by 2024 and would have to wait until 2029 to see this level of installed capacity.

Overall, allowing a competitive battery market in 2018 would increase discounted social welfare in California by $6.5 billion, which amounts to $4.35 per discounted MWh of solar energy that will be produced in California under their renewable energy mandate. In contrast, a monopoly battery market would install at approximately double the rate of a competitive battery market but would less in discounted social surplus.

The remainder of our paper is structured as follows. Section 2 discusses our institutional features and data. Section 3 discusses our model and estimation. Section 4 presents our results and counterfactuals, and Section 5 concludes.

2 Data and Institutional Setting

Worldwide investment in utility-scale batteries is expected to expand rapidly in the coming decade. The trajectory of battery investment over time will hinge on both batteries' expected costs and the expected value (i.e., benefits) of deploying battery resources over time. Thus, we employ two primary data sets to estimate and compute our model battery investment. First, we use data on future projections of utility-scale battery costs. Second, we use historical electricity market data to estimate the value of deploying battery storage and how that value changes over time as more renewable power plants come online. In the following subsections, we describe our primary data sources and discuss relevant institutional details.

2.1 Capital Cost of Battery Storage

Some energy storage technologies such as pumped hydroelectric storage have been established for decades, but the majority of recent utility storage installations use battery technologies. More specifically, lithium-ion based batteries now dominate the US market—accounting for over 90% of battery storage capacity (EIA, 2020). Nearly all lithium-ion battery resources were installed after 2014. This recent deployment of batteries has been driven by a surge in private R&D efforts and government policies that encourage or mandate battery investment.

[6] California's original mandate specifies 1,300 MW of battery power. Using a batteries with four-hour storage duration, this translates to 5,200 MWh of energy storage.

Although the stock of utility-scale batteries is growing quickly, the overall battery fleet remains relatively small. As of 2018, there was only 0.9 GW of aggregate battery power capacity in the US (1.2 GWh of energy capacity), a power capacity similar to that of a typical combined-cycle natural gas power plant (EIA, 2020). Due to the lack of historical data on utility-scale battery capital costs, we use forward-looking projections of battery capital cost from the literature to model the evolution of future battery costs. In particular, we use data from the National Renewable Energy Laboratory (Cole and Frazier, 2019) that compiles cost projections from over 25 publications that consider utility-scale storage costs.

Cole and Frazier (2019) compile data on utility-scale lithium-ion batteries cost projections published between 2016 and 2018. The exact cost of a battery installation will depend on the battery's specifications such as round-trip efficiency and duration. A battery's round-trip efficiency measures the percentage of stored energy that is available for later usage, a more efficient battery typically entails higher costs.[7] The battery's duration indicates the amount of time the battery is able to discharge at its rated power capacity. For example, a 2-hour duration battery could discharge at full power capacity for 2 hours. Although battery systems can be developed with a range of specifications, we follow Cole and Frazier (2019) and focus on the most common type of battery system currently being added in US markets—batteries with 4-hour duration and 85% round-trip efficiency.[8]

Figure 3 demonstrates variation in cost projections for battery storage over time in $/kWh.[9] Each point in the figure represents a normalized cost projection for a particular year from a single publication, and the orange line plots the quadratic line of best fit.[10] These data allow us to quantify expectations and uncertainty about future capital cost of storage. In Section 3 we discuss our battery capacity adoption model in more detail and explain how we pair these cost projection data with our model.

2.2 The Wholesale Electricity Market

In addition to battery capital costs, another key input to the battery storage investment problem is information about the present discounted value of owning a battery system. To evaluate the value of a battery system, we develop a model of *battery operations*. We then combine our model of battery operations with electricity market data to solve for the optimal sequence of charge-discharge decision and the associated value of storage operations.

The source of data for our operations model is the California Independent System Opera-

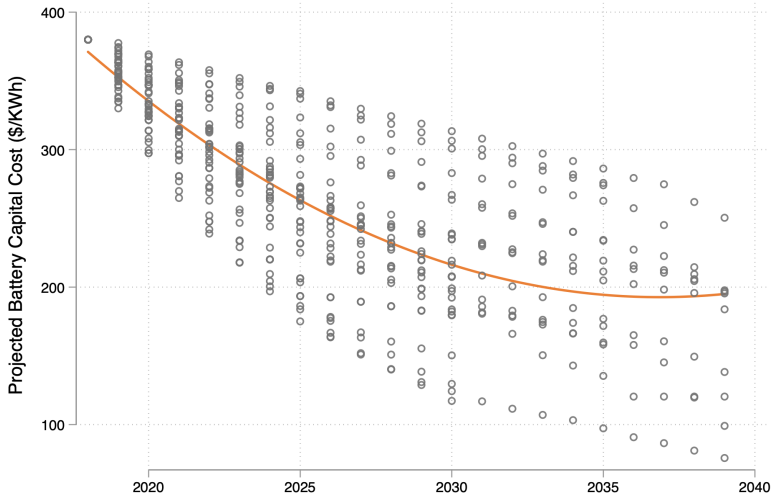
[7] Round-trip efficiency is always below 100% because some energy is lost during the charge-discharge cycle.

[8] According to EIA and the DOE Storage Database, the majority of the batteries have a 4-hour storage duration and have round-trip efficiency between 75 and 95%. Batteries with shorter duration (less than 2 hours) are relatively better suited for ancillary service applications, whereas batteries with longer duration (e.g., 4-hour) are relatively better suited for energy arbitrage applications.

[9] $/kWh costs can be converted to $/kW costs simply by multiplying by the duration (e.g., a $500/kWh, 4-hour battery would have a power capacity cost of $2000/kW)

[10] NREL normalizes the cost projections so that each publications' projection starts at the same baseline cost of $380 in 2018.

Figure 3: Battery Capital Cost Projections



Notes: Figure constructed by the authors using data from Cole and Frazier (2019). Each point represents a future cost projection for a particular year from a single publication. The orange line plots the expected cost.

tor (CAISO).[11] The CAISO, a non-profit independent system operator (ISO), dispatches over 200 million megawatt-hours of electricity to 30 million consumers each year. California deregulated its electricity sector in 1998, and consequently designated the CAISO to manage the state's new wholesale electricity market. The CAISO is connected to the Western Interconnection and also regularly imports and exports power to other utilities and power producers across the western US. At each instant, the CAISO balances supply and demand to ensure electricity is delivered to consumers reliably and cost-efficiently. To that end, CAISO runs two distinct market processes: a day-ahead market (DAM) and a real-time market (RTM).

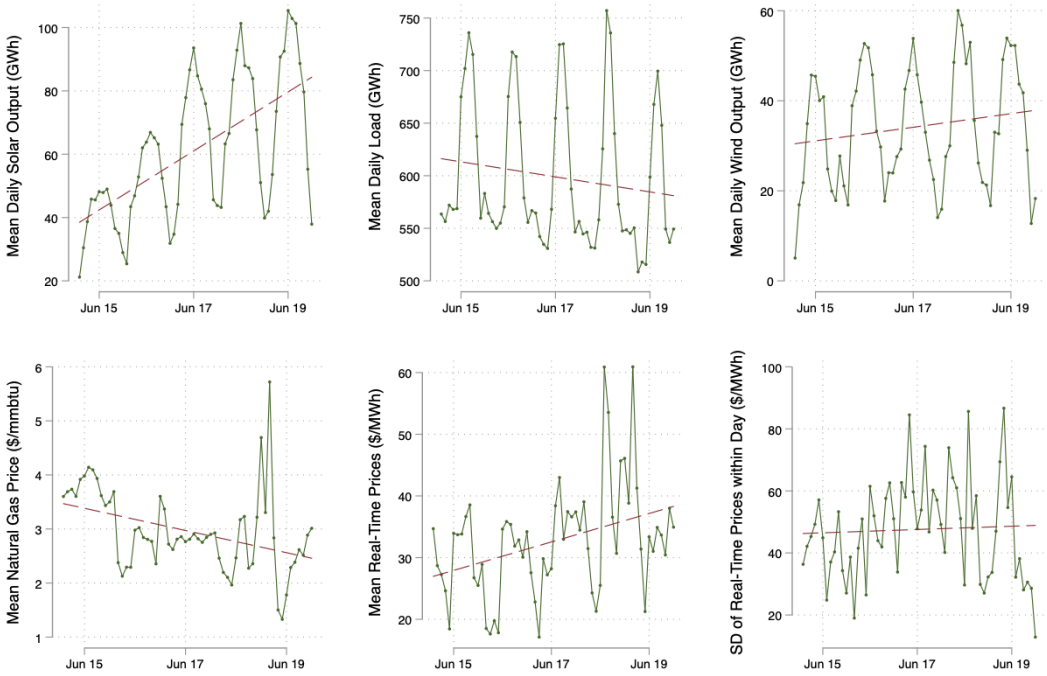
In the day before power is delivered, the system operator conducts 24 energy auctions, one auction for each hour of the day. For each of the 24 energy auctions in the day-ahead market, market participants submit bids to either buy or sell energy and CAISO then computes production quantities and prices to clear each of the hourly auctions. CAISO also uses the day-ahead market to secure energy reserves, these reserves are held ready and available for the ISO to use if needed, and can be called upon to quickly increase or decrease output if there are any unexpected changes in electric supply or demand at the last minute. At the close of the day-ahead market, each power producer is scheduled hourly for a quantity of production (possibly zero), and a capacity allocated for reserves.[12] CAISO allocates production and reserves to meet demand at the lowest cost, subject to reliability and other physical constraints of the system. On the day of energy delivery, CAISO utilizes the real-time market to re-adjust generator production schedules in response to unplanned outages or deviations from the expected day-ahead demand schedule.

[11] We obtain the data used for the analysis from the CAISO Open Access Same-time Information System (OASIS) portal. OASIS provides real-time data related to the ISO transmission system and its markets, such as system demand forecasts, transmission outage and capacity status, market prices, and market result data.

[12] Market participants that do not wish to directly participate in the day-ahead market can also submit self-scheduled hourly production plans to the ISO for planning purposes.

Market participants can submit real-time market bids until 75 minutes before the delivery hour. During the delivery hour, the system operator continuously updates the demand forecast and dispatches the lowest-cost generators every five minutes.[13] Any unanticipated supply-demand imbalance that occurs within the last 5 minutes before electricity is delivered must be met using reserve generators.

Figure 4: Market Trends

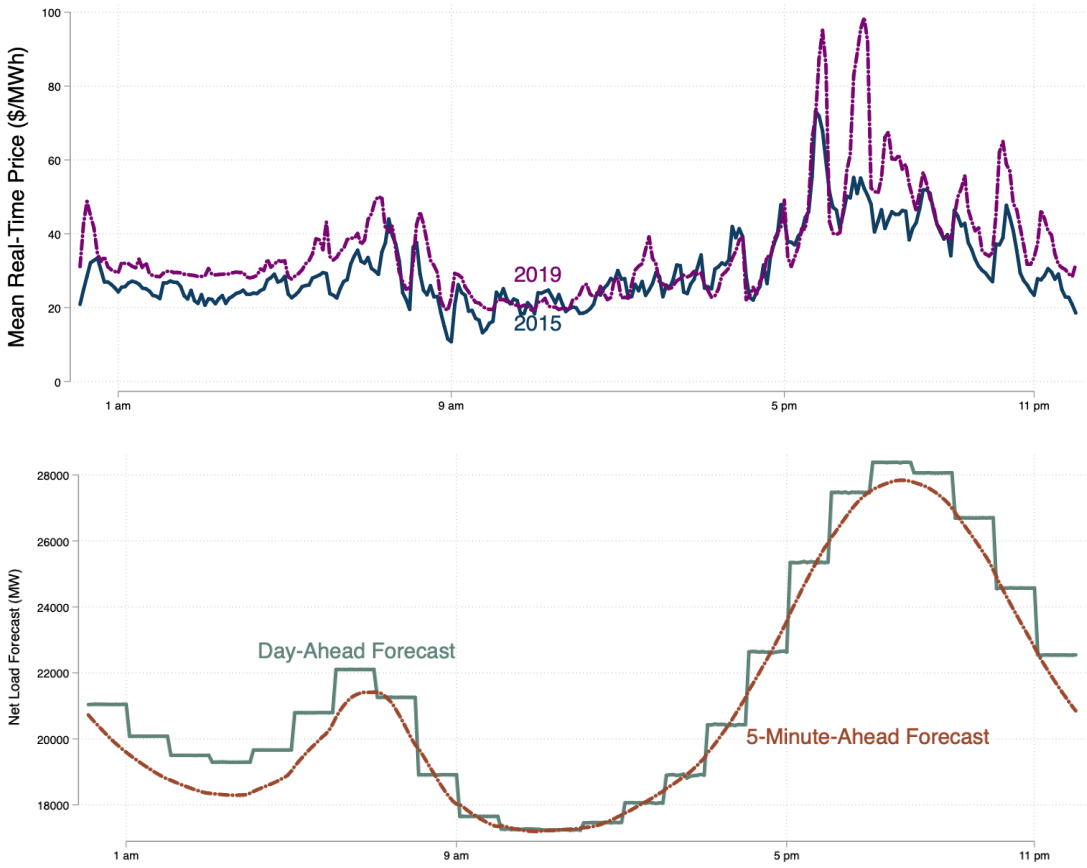


California's grid is currently undertaking a dramatic transition away from fossil-fueled power sources towards renewable resources. The renewable energy transition is, in turn, disrupting market outcomes in CAISO's wholesale markets. The most notable disruption, is the growth of solar PV. As of 2015, California already hosted the largest capacity of solar PV panels in the US, and state lawmakers voted to boost renewable energy further by mandating that 60% of electricity come from renewable sources by the year 2030, and 100% by 2060. The top panel of Figure 4 shows that during the sample period of our study, January 2015 - December 2019, utility scale solar more than doubled from under 40 GWh/day to over 80 GWh/day. At the same time, average demand (load) for electricity remained relatively stable, falling by 7.5%. Average wind power production increased slightly from 28 GWh/day to 36 GWh/day. Figure 4 shows that prices for natural gas, the predominant fossil fuel generation source in CAISO, hovered around $3/MMBtu for much of the sample period. Modest reductions in demand coupled with increasing solar PV investment led to a 13% generation share for solar by 2019. In fact, during some afternoons in 2019, solar PV accounted for over half of the energy supply. While this

[13]Generators can only submit on bid curve to the entire trading hour but the market price can change every five minutes due to demand shocks, transmission congestion, or supply outages.

unprecedented expansion of solar production has reduced California's carbon footprint, it also introduced new challenges in managing the electric grid. The "duck curve" in Figure 2 illustrates that as solar PV output continues to climb during daytime hours, other power plants must make larger and faster adjustments each evening when the sun sets. For example, on January 1st 2019, fossil fuel generators had to ramp up output by 15,000 megawatts over a three hour period. In the two bottom right panels of Figure 4, we see that as solar generation increased, mean prices in the real-time market have also trended upwards by nearly 20%. Real-time prices have also become more volatile, with the standard deviation of real-time prices increasing through most of the sample period.[14]

Figure 5: Market Prices in California



The top panel of Figure 5 demonstrates how market price dynamics have changed as more solar PV has come online in California. In particular, each line shows the mean real-time market price at each five interval of the day for a given sample year. Throughout the sample, real-time prices were relatively low during the middle of the day when solar PV generation hits its daily peak. On the other hand, as total solar generation has risen each year, real-time prices have increased significantly in the evening hours when solar PV generation falls and fossil-fuel plants are called on to quickly ramp up. Table 2 in the appendix shows that for the 6 pm hour, prices rose by 16% between 2015 and 2019. Bushnell and Novan (2018) and show that wholesale price

[14] All prices are for the California South Hub Trading Zone (SP15).

increases in the morning and evening can be explained by an increase in generation from flexible, high marginal cost natural gas turbines during those hours.[15]

Over the sample period, prices within each hour of the day have also become more sporadic. For instance, mean prices at 5:05 pm barely changed between 2015 and 2019, but prices at 5:55 pm increased by more than 50%. More generally, systematic differences between beginning-of-hour prices and end-of-hour prices have become more pronounced. The increased within-hour price variation was also driven by the new production profile imposed by the "duck curve". The bottom graphic of Figure 5 provides intuition about why the "duck curve" could increase within-hour price variation. In particular, Figure 5b shows the average day-ahead forecast of net load (demand minus solar & wind) as well as the five-minute ahead net-load forecast across the day. In the day-ahead market, forecasts are made hourly and CAISO schedules power plants in hour-long blocks to meet the anticipated demand. However, if the next day arrives and net load exceeds the day-ahead forecast value, new generators can be called upon in the real-time market to meet unplanned demand increments or unexpected reductions in solar output. We see in Figure 5b that during the evening ramp up period, the day-ahead forecast is systematically too low at the beginning of each hour and too high at the end of each hour. As a result, during early evening hours generators must reduce output relative to the day-ahead schedule at the beginning of each hour, and they must increase output relative to the day-ahead schedule at the end of each hour. These adjustments lead to larger price spreads within hours that we observe in Figure 5a. This systematic imbalance in the real-time market has become further exacerbated over time as solar PV's generation share has expanded and faster fossil plant ramp ups are needed each evening.

Higher and more volatile market prices in California are a signal of the strains of operating a grid with significant presence of intermittent renewables. These challenges will persist as California and other grids work to reach ambitious renewable energy targets. A key policy question is to understand how to achieve renewable energy targets while avoiding extreme price increases for rate-payers and maintaining a reliable grid that is not prone to regular blackouts. One potential solution is to utilize battery storage to help smooth out adjustment costs and mitigate the risks of price spikes and blackouts.

Battery Operations in the Electricity Market

Realizing the challenges imposed by renewable energy requirements, policymakers have passed new legislation aimed to increase electricity storage investment. In early 2018, the Federal Energy Regulatory Commission (FERC) issued Order 841, which requires independent system operators to remove any existing barriers that would inhibit participation of storage resources in wholesale markets. In addition, the California Public Utility Commission mandated that the state's investor-owned utilities must procure 1,300 megawatts (power capacity) of storage by 2020, with installations required to be operational no later than the end of 2024. Following the announce-

[15]Early evening prices have risen because there is only a limited amount of plants that are physically capable of ramping up production in very short time frames, furthermore, ramping power plants quickly can impose start-up costs and additional maintenance costs.

ment of the mandate, California's utilities have rapidly increased investment in storage. By 2019, utilities had enough battery storage to discharge up to 126 MW at a given instant.[16]

The CAISO has made efforts to integrate these new storage technologies into their wholesale markets and ensure compliance with FERC Order 841. CAISO allows batteries to participate in both ancillary service and energy markets as non-generator resources (NGRs).[17] CAISO allows batteries to submit either demand bids or supply bids in both day-ahead and real-time energy auctions. A battery can submit a set of prices and associated quantities at which the battery is willing to discharge energy, with the possibility of submitting negative quantities to indicate battery would like to charge. Batteries also provide the ISO with information about the device's physical constraints such as energy capacity (how much energy the battery can hold in stock), and power capacity (how much the device can charge/discharge at any moment). Under a simple bidding strategy, a battery could submit a single price at which they would be willing to discharge (sell energy), and a lower price at which they would charge (buy energy). Apart from the energy market, batteries also have the option to supply reserve capacity (ancillary services).

We model a battery operating in the real-time energy market. By doing so, we allow storage to respond to price signals both within and across hours. Within-hour adjustments are likely to be an important source of value for storage resources on a grid with high renewable energy penetration. The main data input for our battery operations model is a multi-year time series of real-time prices. In our analysis, we use prices from the CAISO South Zone Trading Hub (SP15) because it currently contains the largest share of utility scale battery installations within CAISO.[18]

A limitation of our approach is that we do not allow our battery to provide reserve services. Our choice not to model reserve operations warrants some discussion considering that in 2019, more than 75% of battery capacity in CAISO was scheduled to provide reserve services not energy (see Figure 10 in the Appendix). Although many of the earliest battery operators are providing reserve services, it unlikely that reserve services will be the primary battery storage application in the long-run. Sackler (2019) emphasized this point as follows:

> *"Battery storage investors, however, should be wary of building investment cases primarily based upon future ancillary service market value expectations. ...while frequency regulation has historically been one of the most lucrative ancillary services markets (and exemplifying a service that [batteries] can outcompete traditional providers in), most ISOs only require 100-400 MW of the product in any given hour."*

To support this point, Figure 9 in the Appendix shows that CAISO procured less than 800

[16] 126 MW was the maximum aggregate output by batteries reported by CAISO between May 2018 and December 2019.

[17] An NGR is a resource that a can both inject and withdraw energy from the grid and change back and forth quickly between withdrawal and injection without bearing a start-up cost.

[18] The trading hub prices are calculated by CAISO as a load-weighted average of all the locational marginal prices in the region.

MW of average hourly regulation reserves[19] in all but five months of our five-year sample. Furthermore, demand for regulation services in CAISO did not grow substantially over time. For this reason, we focus our analysis on battery operations in the energy market to understand long-run market impacts of large storage investments.

In the next section, we discuss our model of battery capacity investment as well as our model of battery of battery operations.

3 Model and Estimation

Our dynamic equilibrium model of battery storage includes two components. The first component, the *capacity adoption model*, solves agents' decisions of whether to make a capital investment in storage capacity in a given year. The second component, the *operations model*, solves agents' short-run dynamic decisions regarding when to charge and discharge their storage systems. We allow agents with storage capacity to choose charge and discharge quantities at every five-minute interval throughout each year. This section first details the capacity adoption model, then the operations model, and finally our estimation.

3.1 Capacity adoption model

Our capacity adoption model considers an infinite mass of ex-ante identical potential battery operators, or agents for short. Each agent i has the ability to install a unit capacity of storage technology, $k = 1$, at one point in time. The unit capacity is sufficiently small that each agent takes electricity market prices as given.

Agents face an infinite horizon dynamic problem with uncertainty and discount the future with factor β. Each year, agents that have not yet adopted storage observe the current state and decide whether to adopt storage, or wait and preserve the option to adopt storage in the future. Adopters bear a fixed cost of obtaining storage but can then use the storage to earn future flow profits, by acting as arbitrageurs in the energy market. Each agent has room for exactly one storage system and cannot replace the system once installed. Hence, agents solve an optimal stopping problem of when to invest.

Agent decision problem

We now discuss the decision process at each year t. At this point, agents that have not previously adopted make a binary decision of whether or not to invest in storage capacity. Agents that adopt must pay a fixed cost, c_t, that is the cost net of any subsidy available at year t. At year t, agents observe c_t but do not know future adoption costs. We assume that these costs evolve stochastically, declining over time in expectation due to technological advances. It is common knowledge that agents have rational expectations over future adoption costs and hence form

[19]This calculation includes both regulation up and regulation down services, which are the two most lucrative reserve products offered by CAISO.

accurate distributions over future trajectories. Accordingly, a benefit of waiting to invest is that capital costs are likely to be lower in the future. As above, adoption costs depend on subsidies that the government offers for battery investments in year t. We consider subsidy paths that evolve deterministically and are known to market participants.

Besides costs, agents must also forecast the expected current and future revenues from their system. The annual per-unit revenues depend on both the aggregate capacity of storage present in the market and the year. Aggregate storage capacity matters because, with additional capacity, storage owners will arbitrage away more of the intertemporal price differentials, reducing the per-unit payoff of storage. The year matters both because the expansion of renewable energy generation over time will likely increase the value of storage by increasing intertemporal price fluctuations and also because the year may affect available subsidies. We model renewable energy market share as evolving exogenously and deterministically over time. We motivate this modeling choice by the policy environment in California, where the state has specified a renewable portfolio standard that rises before reaching a 60% renewable requirement by 2030. Consequently we capture the impact of renewable energy share on the storage payoff through the calendar year, t.[20]

Define K to be the aggregate capacity present in the market at the start of a period. The aggregate state space can then be written as (c, t, K). The individual state includes the aggregate state plus the agent's battery capacity k, which starts out at $k = 1$ upon installation. Define $K^*(c, t, K)$ to be the equilibrium aggregate storage capacity following adoption at state (c, t, K); K^* includes the existing capacity K plus the capacity from the new adopters. Given the rational expectations assumption, agents can accurately predict $K^*(c, t, K)$ conditional on the state.

Owners of storage capacity buy and sell energy to maximize expected discounted profits in every small time interval of each year. Define the expected revenues per unit of capacity from storage at year t to be $\pi(t, K^*)$. We approximate $\pi(t, K^*)$ as a log-linear function of the solar generation share and equilibrium battery capacity K^*. For a series of values of t and K^*, we microfound $\pi(t, K^*)$ with our operations model that we discuss in Section 3.2. Namely, using the implied storage values from the operations model, we regress the equilibrium revenues across months and K^* on the above characteristics and controls, and use the fitted values in the capacity adoption model.[21] We allow for capacity investments to depreciate over time from usage at a rate $\delta(K^*)$.[22] Thus, a battery owner that installs a battery system at state (c, t, K) will have $\delta(K^*(c, t, K))$ of capacity at year $t + 1$.

[20] We assume the renewable generation share follows the state RPS schedule—and interpolate the share for years without a target—until reaching 60% in 2030. After 2030, we assume that renewable generation share stays constant at 60%. We also assume that this increase is divided between solar and wind proportionally according to the relative increase in capacity that we observe between the two technologies during our sample.

[21] This type of approximation is consistent with a long literature in industrial organization and macroeconomics (e.g. Gowrisankaran and Rysman, 2012; Hendel and Nevo, 2006).

[22] Implicitly, $\delta(K^*)$ and $\pi(t, K^*)$ incorporate the fact that agents will modulate usage of their battery to lower depreciation, and that usage may be lower with a higher K. We discuss this point further in Section 3.2.

We now formally exposit the agent's decision problem as a Bellman equation:

$$
\begin{aligned}
&V(k,c,t,K) = \\
&\mathbb{1}\{k=0\}\Bigg[\max\Bigg\{\overbrace{\pi(t,K^*) - c + \beta\int V\Big(\delta\left(K^*\right),c',t+1,\delta\left(K^*\right)K^*\Big)dG(c'|c,t)}^{\text{Value from adopting}}, \\
&\overbrace{\beta\int V\Big(0,c',t+1,\delta\left(K^*\right)K^*\Big)dG(c'|c,t)}^{\text{Value from waiting}}\Bigg\}\Bigg] \\
&+\mathbb{1}\{k>0\}\Bigg[\underbrace{\pi(t,K^*)k + \beta\int V\Big(\delta\left(K^*\right)k,c',t+1,\delta\left(K^*\right)K^*\Big)dG(c'|c,t)}_{\text{Value if invested before } t}\Bigg],
\end{aligned}
\tag{1}
$$

where $dG(c'|c,t)$ is the integral over the conditional density of the next period's costs net of subsidies given the year and current period's costs, and where K^* abbreviates $K^*(c,t,K)$.

In (1), an agent that has not already adopted can invest (the second line) or wait (the third line). These agents face an important tradeoff in their capacity investment problem. On the one hand, agents that do not invest maintain the option to invest in future years when capital costs will likely be lower (though subsidies may also have expired). On the other hand, agents that wait and do not invest forgo $\pi(t,K^*)$. Finally, agents that invested before t (the fourth line) face no further choices but see their capacity depreciate over time.

Equilibrium of model

A market equilibrium consists of values of $K^*(c,t,K)$ for all values of the aggregate state such that no potential adopters want to deviate from their strategy given this equilibrium capacity level. The equilibrium condition specifies that potential entrants must be indifferent between adopting and not adopting for all states with positive investment:

$$
\begin{aligned}
&\overbrace{\pi(t,K^*) - c + \beta\int V\Big(\delta\left(K^*(c,t,K)\right),c',t+1,K^*(c,t,K)\delta\left(K^*(c,t,K)\right)dG(c'|c,t)}^{\text{Value from adopting}} \\
&= \underbrace{\beta\int V\Big(0,c',t+1,K^*(c,t,K)\delta\left(K^*(c,t,K)\right)\Big)dG(c'|c,t)}_{\text{Value from waiting}}, \quad \forall c,t,K \text{ s.t. } K^*(c,t,K) > K.
\end{aligned}
\tag{2}
$$

In addition, in equilibrium, for all states with zero investment, $K^*(c,t,K) = K$, the value from adopting (the left side of (2)) must be less than or equal to the value from waiting (the right side of 2).

Finally, we discuss computation of this model. We compute the social planner's problem, which will generate the same state-contingent adoption rates as the competitive dynamic equilibrium but is easier to compute since it does not require that an equilibrium condition analogous

to (2) must be satisfied (Hopenhayn, 1992; Ljungqvist and Sargent, 2012; Lucas and Prescott, 1971; Prescott and Mehra, 1980). For each aggregate state (c, t, K), the planner chooses a non-negative quantity of capacity to add. The planner Bellman equation can be written:

$$\mathcal{V}(c,t,K) = \max_{K^* \geq K} \left\{ K^* \pi\left(t, K^*\right) - c\left(K^* - K\right) + \beta \int \mathcal{V}\Big(c', t+1, \delta\left(K^*\right) K^*\Big) dG(c'|c,t) \right\}, \quad (3)$$

where K^* again abbreviates $K^*(c,t,K)$. Comparing (3) to (1), the planner's faces incentives on its last unit of investment that are equivalent to the those of the agents in the competitive equilibrium.

We compute the planner solution by discretizing both c and K. We choose a range for these values that is sufficiently broad to avoid constraining the solution and a discrete grid that is sufficiently fine to approximate the optimal solution well.

3.2 Operations model

Our dynamic investment model uses $\pi(t, K^*)$ as an input, for a range of values of t and K^*. Since our data contain essentially no variation in battery capacity, we calculate $\pi(t, K^*)$ by solving π for different values of K^* as counterfactuals from a dynamic competitive equilibrium operations model. We also solve the operations model separately for each month of our sample in order to account for changes to the value of storage across seasons and from different levels of renewable penetration.

We now describe the modeling that we use to perform this calculation. Within each month, we model each day as homogeneous, for computational tractability,[23] and K^* as fixed. Battery operators, or agents, buy and sell energy in the real-time electricity market in every five-minute time interval with the goal of maximizing their expected discounted profits from being arbitrageurs. We model agents as solving an infinite-horizon dynamic problem, where the ex-ante equivalent days are repeated in perpetuity. We believe that this is a reasonable approximation because we focus on battery technology with relatively short storage duration—batteries that can completely fill or empty within a few hours—so expectations about prices several days in the future will have relatively little influence on charging decisions today.

Each agent's charge decision at each time interval is a function of its charge level and current market characteristics. Since each agent controls a small capacity of storage, it takes real-time electricity prices as given. Although each agent acts as a price-taker, we allow the aggregate battery charge quantity to impact equilibrium market prices. We operationalize this by estimating a marginal cost curve for electricity produced by generators. Battery charging will increase the net load—which is the quantity of electricity produced by generators—and thereby likely increase marginal costs and prices, while discharging will do the opposite. Analogously to the

[23] We assume the days within the month are the same only in our estimation of the optimal policies. When we estimate the value of storage, we apply our policies to the actual time series of net load, and market prices that we observe over our sample. On this dimension, we are likely understating the value of storage to the extent that there is some additional gains that could be obtained by more finely tuning our policy functions.

investment model, each agent forms rational expectations about the evolution of net load and of aggregate quantity supplied by storage owners, which allows it to form rational expectations about generator prices.

Storage technology

Our model captures three critical components of the battery technology, and their influence on how they can be operated. First, a battery's power capacity F determines what fraction of the battery can be charged or discharged in each five-minute interval and therefore how *quickly* the battery can transition from full to empty and vice versa. We model battery technology that can fully discharge within a four-hour period. We focus on four-hour duration batteries because they are the most common battery specification currently operating in the CAISO market. For these batteries, $F = \frac{1}{4\times 12}$.

Second, we model the round-trip efficiency of the battery, υ, which determines the percentage of energy that is lost during a charge/discharge cycle from a given level of energy to a higher level and back to the original level. We focus on a round-trip efficiency of $\sqrt{\upsilon} = 0.85$ because the storage capital costs projections from NREL are based on lithium-ion batteries with these parameters.

Finally, we model capacity fading, which occurs when the amount of energy a battery can hold decreases with repeated use. Lithium-ion batteries, as well as most other batteries, will exhibit capacity fading. The extent of capacity fading depends on the number of round-trip cycles the battery has made, the calendar age of the battery, and the characteristics of each cycle.[24] Capacity fading is likely to play an economically important role in a storage operator's decisions. Specifically, a storage operator may not want to engage in arbitrage if the expected difference in prices across the charge/discharge periods is not substantially large to justify the additional capacity fading that the battery will endure to complete a cycle.

We model capacity fading using the capacity degradation model of Xu et al. (2016). This model takes each a series of charge/discharge decisions over a time interval, calculates cycle ends and the characteristics of each cycle, and returns a value for how much capacity degradation would occur over this time interval. Appendix XX provides details on our application of this model. It would be computationally difficult to model agent's optimization over the amount of capacity fading in the operations model. Instead, as we detail in Section XX, we develop a heuristic optimization process to account for capacity depreciation in our model. Our heuristic decreases the agent's perceived round-trip efficiency υ to account for capacity fading. In so doing, we account for capacity fading in the agent's charge decision, though using a functional form that is an approximation to the true functional form as represented by Xu et al. (2016).

[24] For instance, deeper cycling (such as going from 0% to 100% and back to 0% one time) can cause more capacity degradation than shallow cycling (such as going from 40% to 60% and back to 40% five times).

Agent decision problem

At each five-minute time interval s, each agent seeks to maximize the sum of expected discounted profits, making charge/discharge decisions over the interval.[25] We let S denote the number of time intervals within a day and D the number of days within a year. The per-period discount factor is then $\beta^{\frac{1}{SD}}$.

The agent bases its dynamic operations decisions on a state that is composed of two components. First, the state includes the fraction of the battery's capacity that it has stored as energy. Denote the battery's fraction of charge as $f \in [0, 1]$. Second, the state includes the current market price P_u and the agent's perceived distribution of future market prices at time interval u, which we denote $G^u(P_{u+1}, P_{u+2}, \ldots)$. Because of our perfect competition assumption, the agent only cares about market prices and not the actions of other battery operators, though other agents' actions will affect prices in equilibrium.

We can express the operations Bellman equation as:

$$\begin{aligned} W(f, P_u, G^u(P_{u+1}, P_{u+2}, \ldots)) = \max_q \Big\{ & P_u \times (\mathbb{1}\{q > 0\} q\upsilon + \mathbb{1}\{q < 0\} q/\upsilon) + \\ & + \beta^{\frac{1}{SD}} \int W(f - q, P_{u+1}, G^{u+1}(P_{u+2}, P_{u+3}, \ldots)) d(G^{u+1} | G^u) \Big\}, \\ & \text{s.t. } -F\upsilon \leq q \leq F/\upsilon \text{ and } 0 \leq f - q \leq 1, \end{aligned} \tag{4}$$

where q is the fraction of the battery's capacity that it discharges.[26] Equation (4) states that the agent maximizes its total current profits from charging, which are equal to price times quantity supplied (the first line), plus the expected future value of the position next period, where the agent's energy held next period is $f - q$ (the second line). This maximization is subject to the battery's power capacity of F and the constraint that it cannot be less than empty or more than full (the third line). The quantity supplied in the first line reflects that some energy is lost through charging and discharging. We assume that these energy losses occur symmetrically across charging and discharging.[27]

Equilibrium of model

We focus on a symmetric equilibrium, where all battery operators start each period with the same fraction already charged and then choose the same charge/discharge fraction each period. Define $Q(q)$ to be the quantity of electricity supplied to the grid by battery operators at a period

[25] CAISO has both a fifteen-minute ahead market (cleared 4 times per hour) and a five-minute ahead market (cleared 12 times per hour). We focus on the five-minute ahead market.

[26] For simplicity, equation (4) defines G^{u+1} to be a function of G^u only, rather than other information available at time u.

[27] If we instead assumed that energy was only lost while charging, the last term of the first line of Equation 4 would be $\mathbb{1}\{q > 0\} q + \mathbb{1}\{q < 0\} q/\sqrt{\upsilon}$).

where this (common) discharge fraction is given by q:

$$Q(q) = K^* \times \Big(\mathbb{1}\{q > 0\} q\upsilon + \mathbb{1}\{q < 0\} q/\upsilon \Big).$$

To model equilibrium, we need to consider how $Q(q)$ affects equilibrium prices and in turn affects charge/discharge decisions. We do this by developing a structural time series model of electricity demand and supply.

We model electricity *net load*—the electricity demanded by users net of the amount produced by intermittent renewable sources—as an autoregressive process whose mean depends on the time of day. The amount of electricity that needs to be supplied by dispatchable generators (which are all generators except intermittent renewable sources) at any time interval is then net load minus $Q(q)$. The price of electricity is a function of the amount supplied by dispatchable generators, the time of day, and an additional independent autoregressive process. The residuals of these processes may depend on weather, generator outages, transmission congestion, ramping costs, and other events that impact net load and prices relative to their means at a given time interval of the day.

We let ε^L and ε^P denote the residuals of the autoregressive processes on net load and price, respectively. They are observable to agents at the start of each short interval and have a distribution $d\varepsilon(\cdot, \cdot)$ conditional on their lagged values. Net load at any interval of the day $s \in 1, \dots S$ is $X_s^L + \varepsilon^L$, where X_s^L is a fixed effect for interval s. By our perfect competition assumption, wholesale electricity price at interval of day s is equal to marginal cost, yielding:

$$P(s, Z, \varepsilon^P) = \overline{MC}(Z) + X_s^P + \varepsilon^P, \tag{5}$$

where $\overline{MC}(Z)$ is the mean marginal cost function, Z is the amount of electricity supplied by dispatchable generators, and X_s^P is a fixed effect for interval s. Price (and marginal cost) is the sum of $\overline{MC}(Z)$, X_s^P, and ε^P.

Define f^a to be the aggregate fraction that agents have charged at the start of any period. Any agent can determine the future equilibrium charge/discharge decisions and hence the future price distribution $G(\cdot)$ from f^a, the interval of day s, and the autoregressive residuals ε^L and ε^P. Since f^a is the same as f by the symmetry assumption, these four elements indicate the state for an agent at any time interval.

Defining $q^*(f^a, s, \varepsilon^L, \varepsilon^P)$ to be the equilibrium quantity discharged at that state, we can rewrite the Bellman equation imposing the equilibrium conditions as:

$$\begin{aligned} W(f^a, s, \varepsilon^L, \varepsilon^P) = \\ \max_q \Big\{ P(s, X_s^L - Q(q^*(f^a, s, \varepsilon^L, \varepsilon^P)) + \varepsilon^L, \varepsilon^P) \times (\mathbb{1}\{q > 0\} q\upsilon + \mathbb{1}\{q < 0\} q/\upsilon) + \\ + \beta^{\frac{1}{SD}} \int W(f - q, s + 1 - \mathbb{1}\{s = S\} S, \varepsilon^{L\prime}, \varepsilon^{P\prime}) d\varepsilon(\varepsilon^{L\prime}, \varepsilon^{P\prime} | \varepsilon^L, \varepsilon^P) \Big\}, \\ \text{s.t. } -F\upsilon \leq q \leq F/\upsilon \text{ and } 0 \leq f - q \leq 1. \end{aligned} \tag{6}$$

In a competitive dynamic equilibrium, $q^*(f^a, s, \varepsilon^L, \varepsilon^P)$ must be the value of q that maximizes (6) for every state $(f^a, s, \varepsilon^L, \varepsilon^P)$.

Analogously to our approach for solving the equilibrium in the investment stage, we recast the battery operations problem as a social planner's problem. We rewrite the problem as the single-agent planner's problem whose allocation is then equivalent to the competitive equilibrium problem. The objective of the social planner is to maximize welfare. Electricity demand is perfectly inelastic in the short-run, therefore the planner will meet demand by choosing the state-contingent battery discharge fraction $q^*(f^a, s, \varepsilon^L, \varepsilon^P)$ that minimizes the total expected discounted cost of electricity production. Let $TC(s, q, \varepsilon^L, \varepsilon^P)$ denote the total cost of production for any state. It is the integral of marginal cost from zero to net load plus aggregate battery output:

$$TC(s, q, \varepsilon^L, \varepsilon^P) = \int_0^{X_s^L - Q(q) + \varepsilon^L} P(s, Z, \varepsilon^P) dZ. \tag{7}$$

Although $TC(\cdot)$ includes an unknown constant, we normalize the constant to zero because the optimal solution to the planner's problem is invariant to the the value constant.

We then write the social planner's Bellman equation as:

$$\begin{aligned} \mathcal{W}(f^a, s, \varepsilon^L, \varepsilon^P) = \max_q \Big\{ &- TC(s, q, \varepsilon^L, \varepsilon^P) + \\ +\beta^{\frac{1}{SD}} \int \mathcal{W}(f^a - q, s + 1 - \mathbb{1}\{s = S\} S, \varepsilon^{L\prime}, \varepsilon^{P\prime}) dG(\varepsilon^{L\prime}, \varepsilon^{P\prime} | \varepsilon^L, \varepsilon^P) \Big\}, \\ \text{s.t. } -Fv \leq q \leq F/v \text{ and } 0 \leq f^a + q \leq 1. \end{aligned} \tag{8}$$

For a similar model to ours, Cullen and Reynolds (2017) prove that a solution to the planner's problem exists, that the solution and associated state-contingent prices are equivalent to all competitive equilibria, and that a competitive equilibrium exists.

We also use the same framework to compute the optimal operation and the associated value of a monopolist storage operator relative to a competitive battery market. The monopolist's operation problem is also a single agent problem so computation is similar to the competitive problem, the only difference is that the flow payoff for a monopolist is equal to $P(s, X_s^L - Q(q) + \varepsilon^L, \varepsilon^P) \times Q(q)$ instead of $-TC(s, q, \varepsilon^L, \varepsilon^P)$. In words, the monopolist values its total revenues as opposed to (the negative of) total cost.

3.3 Estimation

To investigate the value of storage and how that informs our adoption model of the battery technology, we require estimates of both the evolution of capital costs for battery investment as well as the optimal (dynamic) operations policy of a battery operator to microfound the gross value of storage in our adoption model. We describe the steps towards estimation of both of these steps in this subsection.

Evolution of Battery Costs

We postulate the appropriate dynamic process for the costs of the storage technology, C_t, in question is given by unit root with drift process given by:

$$C_t = C_{t-1} e^{\delta} e^{\eta_t}, \quad \eta_t \sim N(0, \sigma^2) \tag{9}$$

with C_{2018} as the (initial) cost assessment of battery technology in the year 2018, and with δ and σ^2 governing the size of the drift and future uncertainty involving the level of costs. To the extent that $\delta < 0$, the costs of storage will generally trend down over time. The uncertainty involved around the size of these future declines in costs is captured by the process η_t.

The motivation for these modelling choices are encapsulated in the cost projections collated by the National Renewable Energy Laboratory (NREL) summarized in figure 3. These future cost assessments display several patterns critical to our modelling choices including: (i) a non-linear trajectory, (ii) a downward trend in costs, (iii) uncertainty at future horizons, (iv) positive skewness in the distribution of future costs, and (v) a general increase in the uncertainty of the cost assessments throughout the over 30 years of the projection.

Each of these patterns guide the modelling approach for the dynamic process of costs. The (almost) certain downward trend in costs motivates the drift term in our model, the non-linear trajectory motivates the exponential formulation. Additionally, the increasing level of uncertainty in the forecast uncertainty motivates the unit-root (in logarithms) formulation of the model, and the positive skewness in the cost assessments motivates the log-normal distribution for the shock process.

Given these modelling choices the remaining parameters required to formulate the dynamic process involve the current assessment of the size of the downward drift (δ), and the size of the shock process governing the level of uncertainty (σ) around the assessment going forward in the future.

To estimate both of these parameters, we assume the dynamic process above and find the parameters that best fit the full path of forecast confidence intervals given by NREL. To do this we must take a stance on the confidence level the High-Low spread of the NREL cost assessments (see figure 3). We assume this range constitutes a 95 percent confidence level.

It is easy to show that given the formulation of the dynamic process that consistent estimates of the drift parameter and the shock variance can be recovered from linear regressions of the logarithm of the "Mid" cost assessment on a linear trend, and the range of the logarithm of the "High" and "Low" cost assessments on a functional form of a linear trend. The parameter assessments from these separate regressions yield the following: $\hat{C}_{2018} = 380, \hat{\delta} = -0.034, \hat{\sigma} = 0.0569$.

Optimal (dynamic) operations policy

Next, to estimate the gross value of a battery investment, we need to first determine the charge-discharge operations that the battery would undertake and the associated revenues obtained through those operations. To facilitate the computation of the optimal charge and discharge policy decision we require several inputs including the key parameters of the evolution of prices, the battery operator's technology parameters, and then a procedure for using these inputs to compute the optimal charge/discharge decision given our description of the state. We now briefly describe each of these components of estimation/computation. Broadly speaking, the steps taken in estimation/computation are specifically designed to ensure the parameters used in computing the value or optimal policy would have been known by hypothetical battery operator at that point in time (i.e., preserve the real-time information set of a battery operating in this market), as well as ensure that our estimates provide a lower bound valuation of the value of storage.

First, we describe the estimation steps for the parameters governing the process for net load. The process for net load (X_t^L) in period t is given by the following equation:

$$X_t^L = \tau_{s(t)}^L + \rho^L \left[X_{t-1}^L - \tau_{s(t-1)}^L \right] + \eta_t^L \tag{10}$$

where η_t^L is a mean zero serially uncorrelated shock with variance σ_L^2, and ρ^L governs the persistence of deviations of net load from its interval-of-day fixed effect ($\tau_{s(t)}^L$). This formulation for the process maps directly to the framework provided in the previous section with $X_s^L \equiv \tau_{s(t)}^L$, and $\varepsilon^L \equiv X_t^L - \tau_{s(t)}^L$.

Under this formulation for the process of netload to compute the optimal policy functions, we require forecasts for the full set of interval-of-day fixed effects (τ_s^L), and the parameters governing the serial correlation of the net load deviations (ρ^L, σ_L^2). For the interval-of-day fixed effects, we use a temporally disaggregated version of the day-ahead forecasts for net load from the the first day of the month. For the parameters governing the serial correlation of the net load deviations, we estimate a AR(1) model using OLS of the deviations of net load from the day-ahead forecasts (also temporally disaggregated) over the year 2015. In both cases, the approach taken for estimating the parameters that are used to solve for the optimal policies (each month) ensure that only information available to market participants at that particular date. Next, we describe the structural time series model for how market prices relate to net load. We assume that the real-time market prices, P_t, in period t are determined by the following supply curve for electricity:

$$P_t = \tau_{s(t)}^P + \delta_1 X_t^L + \delta_2 \left(X_t^L \right)^2 + \varepsilon_t^P \tag{11}$$

where $\tau_{s(t)}^P$ are interval-of-day fixed effects, and δ_1, δ_2 are the parameters of the structural supply curve that captures the possible non-linear influence of net load (X_t^L) on the real-time market

price.

Due to the high-frequency (5-minute) nature of our application, we allow for the possibility of serial correlation in ε_t^P. In particular, we assume this process is a first order auto-regressive process given by the following equation:

$$\varepsilon_t^P = \rho^P \varepsilon_{t-1}^P + \sigma_t^P \eta_t^P$$

where ρ^P controls the degree of persistence of the price deviations from the supply curve, and η_t^P is a mean zero serially uncorrelated shock with unit variance, and σ_t^P accomodates for possible heteroskedasticity.

This formulation of the real-time market prices maps directly to the framework provided in the previous section by noting that $\overline{MC}(Z) \equiv \delta_1 X_t^L + \delta_2 \left(X_t^L\right)^2$, and $X_s^P \equiv \tau_{s(t)}^P$.

Under this formulation for the structural relationship between net load and real-time prices to compute the optimal policy functions, we require estimates of the parameters governing the supply curve δ_1, δ_2, as well as estimates for the full set of interval-of-day fixed effects (τ_s^P), and the parameters governing the serial correlation of the net load deviations (ρ^P, σ_t^P).

Importantly, in contrast to the parameters governing the process for net load, described above, the parameters of the supply curve and interval-of-day fixed effects (and, the ultimate residuals) have a structural interpretation. Furthermore, while the parameters governing of the net load process influence our estimate of the value of storage *only indirectly* through their influence on the optimal policies that we compute using our dynamic framework, the parameters (and, residuals) governing the supply curve directly influence our estimates of the arbitrage value of storage that a battery would be able to recover. Moreover, these structural parameters also facilitate our estimates of what the equilibrium effects of an increasing fleet of batteries serving this market.

These considerations have the most dramatic implications for the supply curve parameters, δ_1 and δ_2, as they govern the degree to which batteries in equilibrium will dissipate the potential value they can capture through arbitrage activities through their own charging/discharging decisions. Furthermore, given that these parameters govern the relationship between net load and market prices they are also the most sensitive to the ever evolving demand and supply conditions in the California electricity market. In effect, these parameters–and possible movements in them–represent the agglomeration of shifts in natural gas prices, changes in the availability of low cost generation coming from nuclear power plants and hydroelectric sources, as well as temporary generator outages and changes in import and exports from other electricity markets. While a richer model used to model the optimal dispatch across a range of generators would model these characteristics of the market directly, to do so in our dynamic framework would be computationally infeasible. Consequently, to capture these changes we must allow for a modest degree of time variation in the δ_1 and δ_2.

Our approach to estimating the time series of δ_1 and δ_2 is motivated by three goals: (i) for the

parameters to be identified off variation in net load that provides for a transparent identification argument, (ii) to remain feasible in a psuedo real-time forecasting environment, and (iii) to be scalable both on a high frequency but also multiple year dataset.

Towards those ends, we estimate the time series of δ_1 and δ_2 by running separate OLS regressions for each day of the *day-ahead* market prices on the *day-ahead* forecast of net load (and, net load squared).[28] Given the set up of the day-ahead market in the California electricity market, these (daily) regressions constitute hourly frequency time series regressions (with 24 observations each).

This approach achieves each of our three objectives. First, the variation in net load that is used to estimate the supply curve parameters primarily comes from the plausibly exogenous variation in the final demand of electricity as well as the environmental conditions that determine the available generation that is likely to come from solar and wind. The variation across hours within the day of solar generation or for that matter how much electricity demand is driven by air conditioning needs should be uncorrelated with the supply conditions that will contribute to idiosyncratic deviations in the market clearing price.

Second, because the supply curve parameters are estimated using the *day-ahead* market prices and the *day-ahead forecast* of net load, these supply curve parameters are available to all market participants when they have to make their decisions for the real-time market. This feature of the estimation approach is critical, as it ensures that our estimate of the value of storage uses a model of the evolution of prices that would have been feasible in real-time. Finally, this approach towards estimation is computationally cheap enough to be implemented even in our high frequency and multiple year setting. In estimating the optimal policy, we use the supply curve parameters estimated from the first day of that month.[29] In our assessments of the value of storage, we use the full time series of estimates of δ_1 and δ_2, and the implied residuals from those estimates.

The remaining parameters required to estimate the battery's charge/discharge policy are the interval-of-day fixed effects ($\tau^P_{s(t)}$), and the parameters governing the serial correlation and possible heteroskedasticity of the price residual (ρ^P, σ^P_t). Here as well, it is critical that the parameters that are used to estimate the optimal policy functions could have been estimated (forecasted) in real-time.

Towards those ends, we estimate two separate regressions using the deviations of the real-time market prices from the day-ahead market prices ($\Delta_t = P_t - D_t$) and net load, only for the year 2015. The first regression is estimated at the 5-minute frequency, and includes a set of day-hour fixed effects. Thus, the estimated coefficient on net load represents the relevant

[28] To ensure the assumptions of modeling framework hold, we restrict the constant in these regressions to be zero.

[29] This approach still ensures that the policy estimated for each month uses only information that would have been available to the battery operators at that current period. To the extent that trends in demand and supply conditions lead to extensive movements in the δ_1 and δ_2 supply curve parameters, it is possible that our policy function is sub-optimal as it is estimated off a "stale" estimate of the supply curve. In this regard, one can view our estimates of the value of storage as a conservative estimate that could be increased to the extent that the battery operator could re-estimate its policy function at a finer frequency than once a month.

parameter for forecasting how the real-time market price systematically deviates from the day-ahead market price as a function of the *within* hour fluctuations in net load. The second regression is estimated at the hourly frequency, and includes individual day fixed effects. Thus, the estimated coefficient on net load represents the relevant parameter for forecasting the forward premium and how it relates to the share of net load over the day. Combining these coefficient estimates (based off only data from 2015), together with a temporally disaggregated day-ahead forecast for net load for any particular day allows us to construct forecasts for $\tau^P_{s(t)}$. To be consistent with the approach taken for δ_1 and δ_2, we use the forecasts for the first day of the month in computing our policy functions for each month.

For the parameters governing serial correlation and possible heteroskedasticity of the price residual (ρ^P, σ^P_t), we estimate an AR(1) model using OLS of the real-time market price deviations from the day-ahead market prices net of a hour-of-day and interval-of-day fixed effect.[30] To capture the possibility of heteroskedasticity, separate estimates of the variation of the resulting residuals from the above mentioned OLS regression are estimated for the late afternoon hours (5pm-9pm) and remaining hours, respectively.[31] To ensure feasibility of the policies being applied to market outcomes from 2016–2019, we estimate these parameters using only 2015 data.

Given the parameter estimates of the evolution of net load and supply curve parameters determining prices, the charge/discharge decision is a single agent dynamic problem. We discretize the problem in order to be able to compute it. In our base computation, we discretize ε^P and ε^L into a 100 dimensional grid, and we discretize the number of potential charge states into 50 levels. As was described above, our model for prices is a function of the 5-minute interval of a day, implying that $S = 288$. These dimensions result in an overall size of the state that is $100 \times 50 \times 288 = 1,440,000$ states.

Probably the most common computational method for single agent dynamic problems is Bellman recursion, which involves recursing (8) until approximate convergence. Many single agent problems with this order of magnitude of states are computable using Bellman recursion. However, Bellman recursion is a contraction mapping with modulus of the discount factor. An important complication in our model is that we are modelling the decision process at the 5 minute interval. Under a conventional annual discount factor of $\beta = 0.95$, $\beta^{\frac{1}{DI}} \approx 0.99999951$. Thus, while a Bellman recursion in our model would be a contraction mapping, the modulus would be very close to 1, making computational time infeasibly long.

A popular alternative to Bellman recursion, is policy function iteration. In our context, this method implements the following recursive algorithm. First, it defines an initial policy function vector, $\vec{P}^0$, which is a value of c for every state. This function implies a vector of static payoffs for each state, $\vec{\pi}^0$. Together with the (exogenously determined) transitions for t and $\varepsilon^P, \varepsilon^L$, the policy function defines an initial transition matrix as $\mathbf{Q}_0$. A typical element, $\mathbf{q}_{ij}$ of transition

[30] Due to the kurtosis exhibited in the real-time market prices, both the hour-of-day and interval-of-day fixed effects are estimated by taking within cell *medians* as opposed to means.

[31] Due to the kurtosis exhibited in the real-time market prices, both variance estimates are constructed using the median absolute deviation and scaling it by 1.4826.

matrix $\mathbf{Q}_0$ indicates the probability of going to state j from state i. Using this notation, we can express the vector of values for every state as:

$$\vec{V}_0 = \beta^{\frac{1}{DS}} \mathbf{Q}_0' \vec{V}_0 + \vec{\pi}_0 \Rightarrow \vec{V}_0 = (I - \beta^{\frac{1}{DS}} \mathbf{Q}_0')^{-1} \vec{\pi}_0. \tag{12}$$

Thus, (12) provides a solution to $\vec{V}_0$. Policy iteration then proceeds by solving $\vec{P}_1$ as the optimal policies given V_0, then solving $\vec{\pi}_1$, $\mathbf{Q}_1$, and V_1 analogously, and then repeating this entire process until approximate convergence. A central problem with policy iteration in our context is that a matrix inverse with as many states as we have is computationally infeasible, due to computational time, storage space, and numerical precision.

We develop a variant of policy iteration that exploits the fact that our transition matrix is sparse, since i advances deterministically, and that the state space repeats every I periods. In particular, we modify the step that solves for V in (12) and instead solve for V by performing policy iteration S (instead of 1) periods ahead.

Specifically, define $\vec{V}_s$ to be the subvector of V for all states at interval s. Define also $\mathbf{Q}_s$ to be the submatrix of transitions from interval s to the following interval (either $s+1$ or 1). Finally, define

$$\vec{\Pi}_1 = \vec{\pi}_1 + \beta^{\frac{1}{DS}} \mathbf{Q}_1' \vec{\pi}_2 + \ldots + \beta^{\frac{S-1}{DS}} \mathbf{Q}_{S-1}' \cdots \mathbf{Q}_1' \vec{\pi}_S$$

Then,

$$\vec{V}_1 = \vec{\Pi}_1 + \beta^{\frac{1}{D}} \mathbf{Q}_I' \cdots \mathbf{Q}_1' \vec{V}_1 \Rightarrow \vec{V}_1 = (I - \beta^{\frac{1}{D}} \mathbf{Q}_I' \cdots \mathbf{Q}_1')^{-1} \Pi_1. \tag{13}$$

Equation (13) allows us to express $\vec{V}_1$ with a matrix inverse that is of dimension 5,000 in our baseline setting. Using $\vec{V}_1$, we then solve $\vec{V}_I, \vec{V}_{I-1}, \ldots, \vec{V}_2$ quickly, with one-step backward recursion This results in a computational process where the computation time is linear in the number of intervals. For some of the counterfactual simulations, we calculate the value of storage under an assumption of perfect foresight. This counterfactual is meant to provide an assessment of the upper bound of the value of more informed forecasts. Under this counterfactual, we subsume the observed prices of any month within the interval-of-day fixed effects, and collapse the entire Markov transition matrix for the evolution of prices to the identity matrix. Evaluating the perfect foresight model in this way, which maintains the infinite horizon framework, is further facilitated by our novel approach to leveraging the sparsity of the transition matrix given the deterministic transition of a large share of the states.

Implementation of operations model output into adoption model

Having outlined the approach towards estimation of each component of the model that feeds into the ultimate adoption model of battery technology, we now briefly summarize the steps taken to combine these inputs into the adoption model.

First, for each month in our estimation sample (2016–2019) we estimate the optimal dynamic policy for charging/discharging decisions using the Bellman equation (e.g, see equation 8). These policies are computed using forecasts of the trajectory of net load and real-time market prices,

and an estimate of the supply curve that ties them together of that particular month. Using the supply curve of each month, we compute the optimal battery policy function for a range of different values of the total battery fleet ($K^{\star}$).

In principle, solving for the optimal policy could also be used to compute the expected gross value of batteries at varying levels of $K^{\star}$, and how this have evolved over time. A concern with this approach, however, stems from the fact that our discretization of the price process, as well as the supply curve estimates used to estimate the policies are at best approximations–and, lack capturing the volatility of demand and supply conditions that occur even *within the month* for this market. Another concern with this approach would be that it would fail to account for the amount of battery capacity that effectively "fades" away through use.

We overcome both of these issues through a set of heuristics. To ensure we capture the role of the volatility in demand and supply conditions in the market we compute the gross value of batteries from the observed time series of prices and net load as opposed to the Bellman equations assessment of the expected value. More explicitly, we continually update (at the daily frequency) the supply curve parameters (δ_1, δ_2) throughout our estimation sample. By continually updating the supply curve parameters, we better capture the likely equilibrium effects on price that would have occurred with a significant battery presence. The full time series of the supply curve parameters together with the day-ahead forecasts of net load and the day-ahead market prices lead to full time series of implied net load ($\hat{\varepsilon}_t^L$) and price residuals ($\hat{\varepsilon}_t^P$). Thus, to compute the gross value of batteries we apply our estimated policy functions to the full time series of price and net load residuals, as well as the continually updated time series of the supply curve. This approach is computationally less demanding, as we do not re-compute what the optimal policy decision for every updated value of the supply curve parameters. We view this approach as conservative its assessment of the gross value of batteries to the extent the a more finely updated policy function could achieve higher values.

In order to account for capacity fading we leverage data from the year (2015) prior to our sample period (2016–2019) as training sample. Using the pre-period training data, we solve the model using a sparse grid of different candidate round-trip efficiency levels $\sqrt{\upsilon}$. The idea is that a battery operator may be able to improve their payoff by acting as if the battery has a lower-than-actual round-trip efficiency. A battery with lower round-trip efficiency will be more reluctant to arbitrage prices unless the payoff is sufficiently high. Batteries that arbitrage less will also endure less capacity fading and thus could potentially earn a higher payoff, after considering the costs of capacity fading.

After solving for optimal policies for each of the candidate round-trip efficiency values, we simulate the evolution of the state-of-charge, f, using the actual demand and price data from the training data set for each of the candidate policies (i.e., for each candidate round-trip efficiency). We then feed the simulate series into a capacity degradation model. The capacity degradation model is based off a rainflow cylce counting algorithm developed by Xu et al. (2016).

The above procedure provides two important outputs that we use for the operations model. First, it provides an estimate of how much capacity degradation will occur on average in each

month. We use this value to adjust the discount factor β in equation 4 to account for degradation over time due to standard operations. Second, we compare realize payoffs from storage for each of the candidate round-trip efficiency values after accounting for capacity degradation and find the round-trip efficiency value that leads to the highest payoff. We then use the best performing round-trip efficiency value as $\sqrt{v}$ when we solve the model on the full data sample.[32] The outcome of this procedure is that we account for capacity degradation without adding a state variable to the operator problem. Our approach is both computational feasible and also ensures that we do not overstate the value of storage by ignoring capacity fading. The approach also allow storage operations to acknowledge the costs of capacity fading using a "rule-of-thumb" when making dispatch decisions.

Per-unit value of storage

Using our approach to account for capacity fading we simulate the policy functions on the realized sequence of price and load data. We simulate separate policies for different candidate values K^* and across each sample month. That is, we solve for how different capacity battery fleets would be dispatched and the corresponding equilibrium effects on prices for each month. Therefore, we can also calculate the discounted sum of electricity cost reductions—the value of storage—for each candidate K^* across our sample months.

Estimating the storage value for varying sized battery fleets is critical to determining optimal investment in storage capacity. Recall that the capacity adoption decision depends on two factors: (1) c the capital cost of storage, and (2) $\pi(t, K^*)$, the expected revenues per unit of capacity. Thus, we use the simulated battery operations to determine $\pi(t, K^*)$.

Solving the storage operations problem for each value of K^* informs how per-unit expected revenues π change as more storage capacity is added to the grid. Consequently, we rely on our battery operations model to identify how changes in K^* affect changes in π. In contrast, we utilize variation in renewable energy capacity over time to estimate how changes in t affect expected revenues, π. Recall that expected battery revenue can change over time, t, due to changes in renewable energy generation capacity. The enormous expansion of intermittent renewable generation over sample, namely, solar PV, has led to unprecedented changes in the dispatch patterns of fossil fuel generators and therefore the marginal cost of electricity. Thus, by solving the operations model for each month, we can evaluate how expected revenues, π change over time as the renewable portfolio standard has ramped up.

Due to the computational burden of the solving the operations model, it isn't feasible to solve the operations model for all possible battery capacity levels K^*. Instead, we solve the operations model for each month of our 48-month sample and across a grid of six candidate values of K^* ranging from 1000 MWh to 50,000 MWh. Thus, we evaluate the per-unit value of storage, $\pi(t, K^*)$ at $6 \times 48 = 288$ points. We then obtain an approximation $\pi(t, K^*)$ by estimating

[32] We also allow the optimal round-trip efficiency value to depend on the capacity of the battery fleet. Therefore we repeat this procedure separately for each level of aggregate capacity of the battery fleet.

the following regression:

$$\pi_{tk} = \gamma_0 + \gamma_1 log(K^*_{tk}) + \gamma_2 RenewableShare_{tk} + \gamma_3 X_{tk} + \nu_t + \varepsilon_{tk} \tag{14}$$

The outcome of variable, π_{tk}, is the present value of battery capacity (per unit) in month t with aggregate battery capacity k.[33] The key explanatory variables are the natural log of aggregate battery capacity and the proportion of total electricity generation that came from renewable energy sources in month t. The same set of candidate of battery capacity values are used to solve the model in every distinct month of the sample, so $log(K^*_{tk})$ will not be correlated with any omitted variables that may affect per-unit storage value. On the other hand, the renewable generation share fluctuates seasonally and is increasing systematically over time. As a consequence, the renewable share variable could be correlated with other factors that are changing over time that are also correlated with the value of storage. To address these endogeneity concerns, we include month-of-year fixed effects, ν_t, in the regression to control for seasonal factors that could be correlated with renewable generation. We also control for the average price of natural gas in month t, the average electricity load (demand) in month t, and the amount of hydroelectric resources available in month t.

4 Results

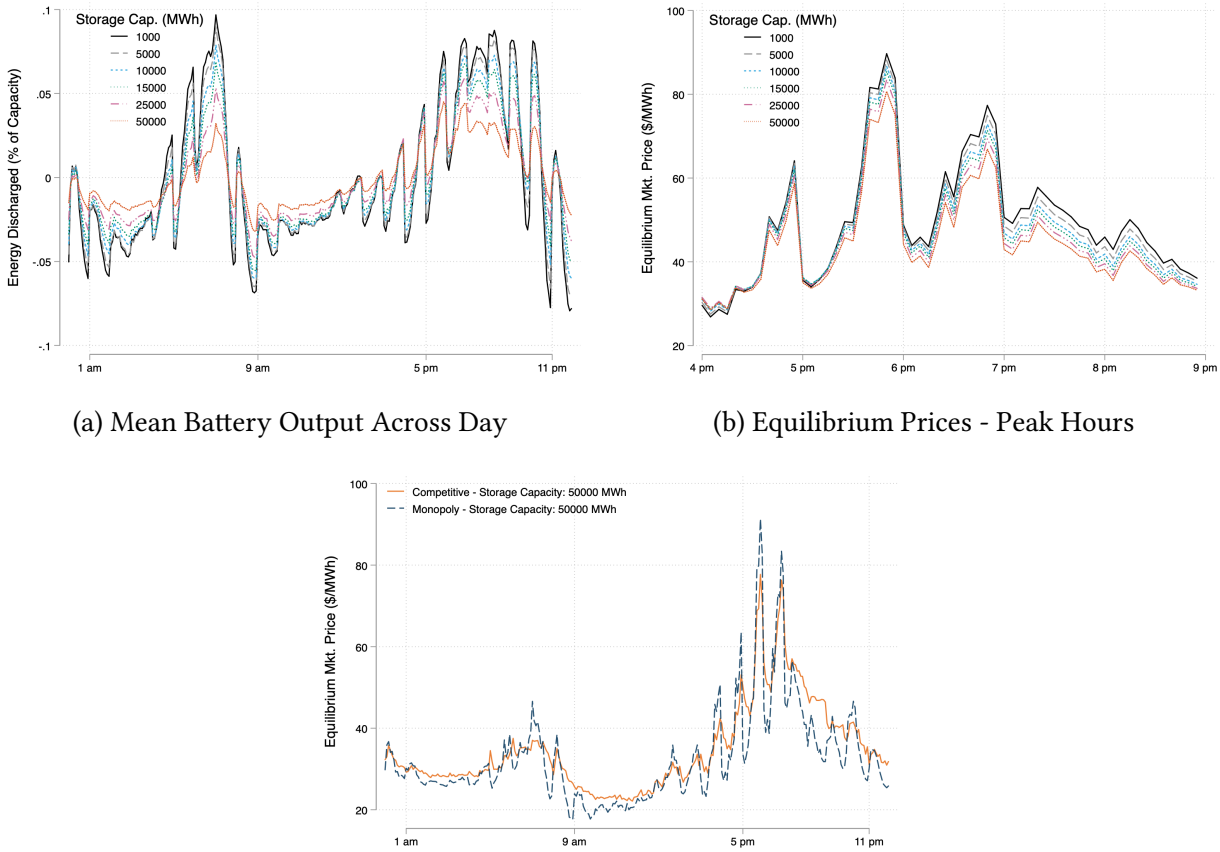
Having discussed our modelling approach, we now turn to highlighting the key results from both the operations and adoption models. We begin by discussing several findings from our operations model. In particular, we discuss temporal patterns in equilibrium battery output and how these battery outputs affect equilibrium market prices. We then report our estimated value of battery operations and show how the value of batteries changes with the share of renewable generation and the total amount of battery capacity in the market. Finally, we review our set of results pertaining to battery adoption over time. Namely, we show battery adoption trajectories under several counterfactual policy and competitive environments.

4.1 Operations Model Results

Figure 6a illustrates the mean battery discharge quantity (as percentage of total capacity) for each 5-minute interval of the day between January 2016 and December 2019. Each line in the figure shows differences in battery output across different aggregate battery fleet capacities. Batteries discharge the most during the hours that net load is the highest— 6-8 am in the morning as well as the evening peak hours of 5-8 pm. We also see that as aggregate battery capacity grows, each battery utilizes a smaller share of capacity during the morning and even peaks. As the fleet expands, Figure 6b shows that batteries operations exert a stronger effect on equilibrium prices.

[33] More concretely, π_{tk} is the lifetime value of a 1 MWh battery operating in a scenario where month t grid conditions occur in perpetuity.

Figure 6: Battery Output and Equilibrium Prices Effects



(a) Mean Battery Output Across Day

(b) Equilibrium Prices - Peak Hours

(c) Monopoly vs. Competitive Storage Operations

Notes: Each line plots the mean outcome between 2016-2019.

We see that in the 6-7 pm hours—the hours with the highest average net load—a 50,000 MWh battery fleet would reduces average prices by as much as $15/MWh.

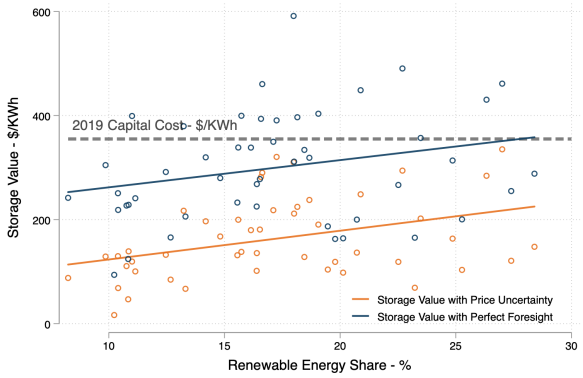
Figure 6c highlights differences in the battery output between a competitive battery market and battery fleet operated by a monopolist. A monopolist battery owners' discharge quantities are substantially than the competitive battery output during the evening peak hours. The monopolist withholds output below the socially-optimal level in order to earn higher revenue on infra-marginal outputs.

Measuring Solar and Storage Complementary

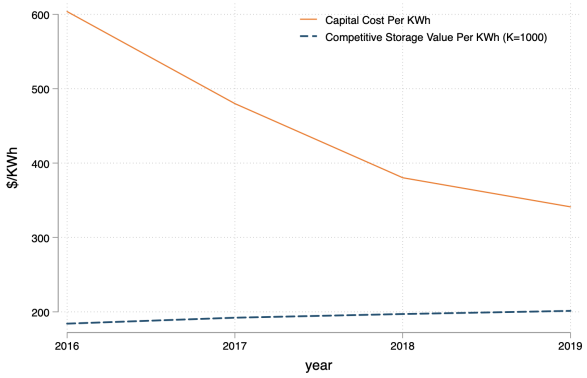
We next use the outputs from the operations model to calculate the discounted value of battery storage. In reporting our results, we first discuss how the value of storage estimated over the 2015–2019 period relates to the share of generation coming from solar—a set of results that speak directly to the complementarity of storage and renewable sourced generation.

Figure 7 provides an illustrative visualization of some key associations. The left panel of Figure 7b plots the value of battery storage for each month in our four-year sample. The orange line plots a simple linear fit of the relationship between storage value and the share of electricity

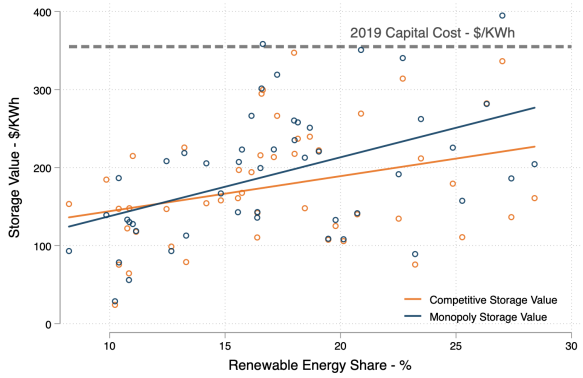
Figure 7: Implied Value of Battery Investment



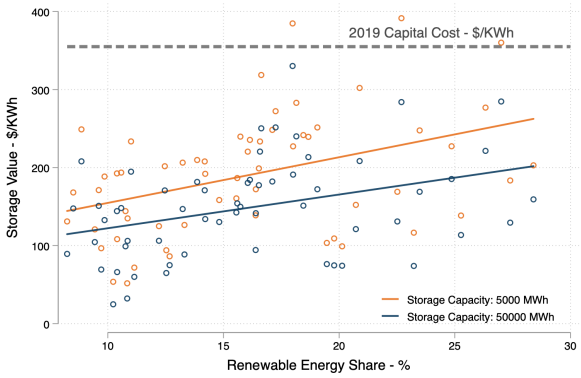
(a) Complementarities between Batteries and Solar



(b) Battery Value and Capital Cost Over Time



(c) Monopoly vs. Competitive Battery Values



(d) Battery Capacity - Returns-to-Scale

Notes: Each point in the scatter plots (b-d) represents the implied value of storage for a single month during the sample (2016-2019). The solid lines in (b-d) plot the linear trend for each group.

generated with solar PV. The dashed-grey line shows estimated break-even capital cost for a 1 MWh of storage in 2019 from Cole and Frazier (2019). In this panel, the strong positive association between the prevalence of solar generation and the value of storage is clear. Additionally, by comparing the current assessment of the capital costs to the relationship between solar generation share and the value of storage–it is evident that even modest increases in the share of solar would be associated with increases in the profitability of storage that would cover current assessments of capital costs.

As we described in earlier sections, battery capital costs have consistently fallen over the last several years. To provide a sense of how this trend relates to the future economic viability of batteries, in Figure 7b we report the simple linear trend in the per-unit-value of storage between 2016-2019, and the trend in the estimated capital cost of storage reported in Cole and Frazier (2019). For this figure we consider the case of a small storage fleet (1000 MWh) that would not have substantial effects on equilibrium prices. This graphic makes apparent that through the joint dynamics occurring both in terms of the increasing presence of solar generation, as well as the fall in battery capital costs implies the break-even point within the next several years.

Figure 7c compares the private value of storage under monopoly ownership relative to competitive ownership. At lower levels of renewable energy penetration, the value of storage is very similar across ownership regimes. However, as renewable generation increases, the monopolist is able to capture relatively more rents by withholding some output during time periods with high marginal costs.

In the bottom-left panel, Figure 7d contrasts the average per-unit value of storage for a smaller battery fleet (5000 MWh) and a larger battery fleet (50,000 MWh) under perfect competition. We see that the per-unit value of storage declines between by as much as 20% for the larger storage fleet. This pattern highlights the decrease in returns-to-scale from storage investment. As more batteries enter the market, battery operations will eventually reduce prices in peak periods and moderately increase prices in off-peak periods. By mitigating price fluctuations, batteries reduce the total cost of electricity generation but also reduces the value of subsequent battery investment.

To provide a more systematic evaluation of the relationship between renewable energy penetration and per-unit storage value, as well as storage fleet size and per-unit storage value, we estimate regression equation 14. Recall that this equation feeds into our model of battery capacity adoption.

We report the regression results in Table 1. Each specification controls for the mean daily quantity of load in month i, the average price of natural gas during month i, and the amount of hydro-electric resource available in month i. We show the results both with and without month-of-year fixed effects. We report our regression results for both the competitive market case and the monopoly market case.

Table 1: The Value of Storage as a Function of Storage Capacity and Renewable Penetration

	Dependent variable: Storage value ($ per MWh)			
	Competitive		Monopoly	
Log(K^*)	-39,847***	-39,847***	-52,826***	-52,826***
	(4,835)	(5,596)	(4,276)	(4,879)
Renewable Share [0,1]	1,202,550***	881,671***	1,085,637***	1,058,949***
	(382,205)	(165,782)	(338,036)	(144,532)
Month of Year FE	Y	N	Y	N
Load, NG Price, Hydro Controls	Y	Y	Y	Y
Observations	288	288	288	288
R^2	0.24	0.29	0.38	0.41

The results paint a clear picture of a close connection between the growth in solar generation and the value of storage. By leveraging the extended time series variation during a stretch of considerable growth in solar generation, we estimate that each percentage point increase in renewable energy market share corresponds $12 per kWH increase in the value of a storage investment in a competitive storage market. Similarly, each percentage point increase in renewable

energy share is associated with a $10 per kWH increase in the value of a monopolist's storage investment. The results also show that each 1% in battery capacity decrease the per-unit value of storage by $40 per KWh and $53 per KWh for the competitive case and the monopoly case respectively.

4.2 Battery Adoption Results

We next turn to discussing the results from our battery adoption model. We first use our adoption model to solve for the equilibrium adoption path under a competitive battery market and under a monopoly battery market. Recall that the agents' adoption decisions depend on the future trajectory of battery costs and the future path of battery values. Therefore, the adoption choice is a function of our estimates of the cost process (equation 9) and predictions of future battery values from regression equation 14. In particular, we use regression equation 14 to predict the value of a battery investment as function of the renewable generation share and the amount of battery capacity in the market in each year. We take the level of renewable generation in each future year as exogenously determined by California's renewable portfolio standard (RPS). The California RPS requires an incrementally higher share of renewable generation each year before reaching 60% in 2030.[34] To predict future battery value for adoption model, we also assume that batteries have rational expectations about the path of battery investment by other market participants.

Figure 8a depicts the mean battery capacity over time for the competitive and monopoly markets, respectively.[35] We see that for the competitive battery market, battery capacity reaches about 40,000 MWh by 2035, with almost all investment coming after 2027. The Figure also reveals that a monopolist would invest in substantially less storage capacity relative to the competitive investment level. In particular, the monopoly investment in 2035 is less than 20,000 MWh.

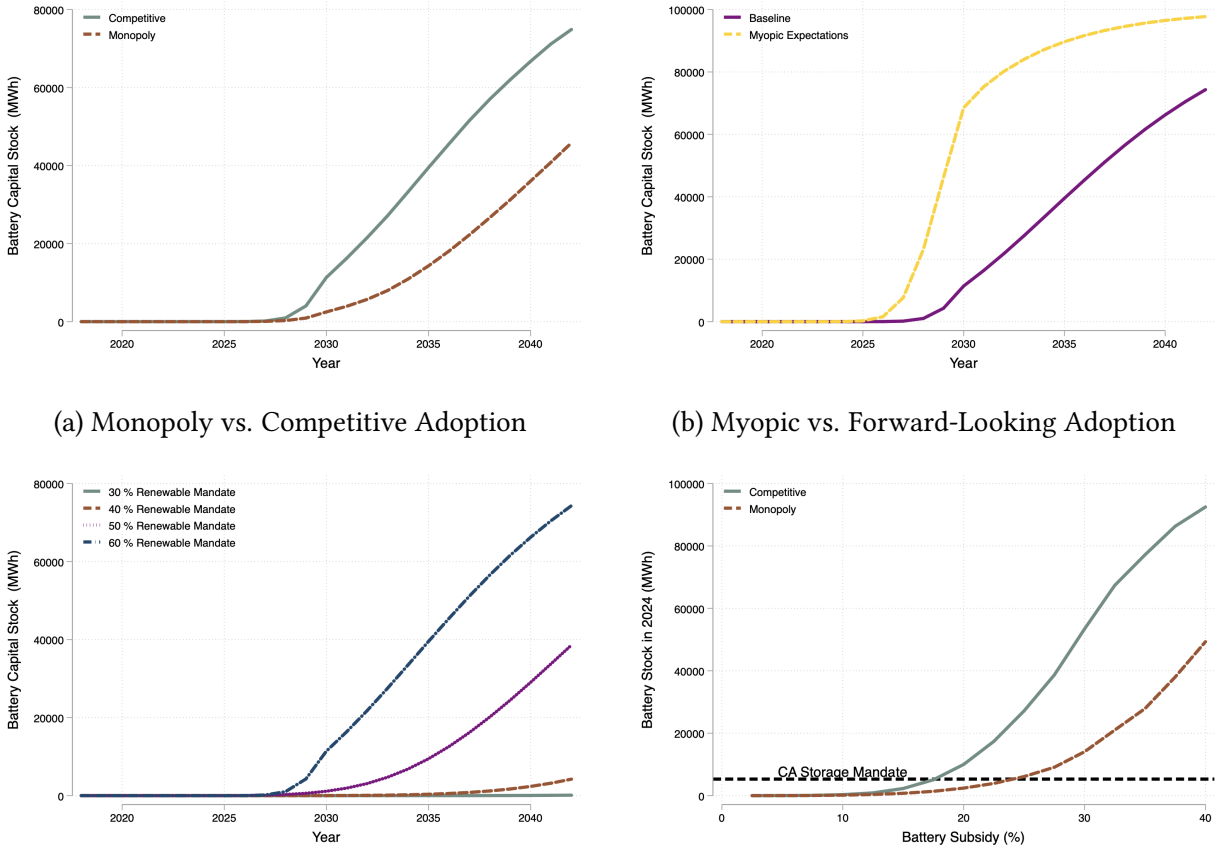
Figure 8b shows the difference in the competitive adoption path between the cases of forward-looking agents and myopic agents. Myopic agents adopt storage as soon as the current value of storage exceeds the capital cost, while myopic agents consider the potential benefit of waiting longer to invest after further capital cost declines. We see that myopic agents invest heavily in storage between the years of 2025 and 2030, reaching over 60,000 MWh by 2030. The large differences between the myopic and forward-looking investment paths demonstrates the strong option value of delaying investment due to future expectations regarding the rapidly falling capital cost of storage.

We next consider how the competitive adoption path would change in response to changes in renewable energy policy—the California RPS. Figure 8c shows the competitive market's investment in battery capacity for a 30% RPS by 2030, a 40% RPS by 2030, a 50% RPS by 2030, and a 60% RPS by 2030 (the current policy). The result indicate that almost no storage investment would

[34] We assume that renewable share remains at 60% in the years following 2030.

[35] The exact adoption path will depend on the realizations of the cost process, we therefore report the mean capacity level for each year implied by by taking the average outcome across many simulated realizations of the cost process.

Figure 8: Battery Adoption Paths



(a) Monopoly vs. Competitive Adoption

(b) Myopic vs. Forward-Looking Adoption

(c) Renewable Mandates and Battery Adoption

(d) Battery Subsidies and Battery Adoption

Notes: Figure (a) figure plots the competitive equilibrium investment

occur under an RPS below 40%. With the more aggressive renewable energy mandates, storage investment greatly increases. The 50% RPS would result in 10,000 MWh of expected storage capacity by 2035, and the 60% RPS would result in 40,000 MWh. These results suggest that battery storage investments are not likely to be economically viable unless intermittent renewable penetration is relatively high.

In Figure 8d, we investigate how government subsidies for battery storage can steer the battery adoption path for both the competitive and monopoly cases. We find that relatively modest subsidies can speed the rate of adoption. In particular, we find that with a 17% subsidy for batteries, California could achieve 5,200 GWh (1300 GW) of batteries by 2024— the amount required under California's AB 2514 battery mandate. In contrast, a relatively larger subsidy of 25% would be be need for a monopolist storage operator to invest in sufficient storage to achieve 5,200 GWh (1300 GW) of storage by 2024.

Finally, we use the adoption model to evaluate the present discounted value of batteries investment in the California. Our welfare analysis indicates that storage investments will be a highly valuable tool for California to meet its ambitious renewable energy goals. In particular, we find the total expected discounted surplus from the battery market is $6.5 billion as of 2018.

To put in other terms, the presence of battery storage increases the average value of renewable generation by $4.36/MWh.[36]

5 Conclusion

A significant challenge to meeting the world's growing demand for energy is that utilities cannot typically store electricity for later use.[37] As the majority of renewable generation come from intermittent resources, the interest and potential role for battery storage technology has grown substantially. This paper develops a dynamic, competitive equilibrium model of battery adoption and operations. The model includes a number of key features that we believe are critical for understanding the battery adoption capacity and value created by batteries under different policies. This includes modeling the equilibrium effects of large-scale battery adoption smoothing out price peaks and valleys, ramping costs, depreciation from battery use, and uncertainty as faced by agents in the market. We evaluate the predictions of our model using data on the California electricity market. We develop frontier time-series forecasting algorithm to model future marginal cost curves for electricity.

Our results indicate that complementarity between solar and battery technology is economically large. We are also currently not very far from a point where a small amount of battery storage could break even. Utility-scale battery storage would contribute significantly to the social welfare of the California electricity market, adding $4.36 per discounted MWh of renewable energy generated, as of 2018, of $6.5 billion in total. In the absence of battery subsidies or mandates, we would likely see large-scale battery adoption by about 2030, spurred by declining capital costs and increasing renewable energy penetration. Installation subsidies of 17% of $47/KWh would be necessary to meet California's battery storage mandate by 2024. If the battery storage were owned by a monopolist rather than a competitive market, more adoption would occur earlier but the adoption would create less social surplus.

[36] In present value terms, the California is expected to generate 1.5 billion MWh from renewable energy sources.

[37] The Energy Information Administration (EIA) projects world energy consumption will increase by an average of 1.4% per year through 2040 (Conti et al., 2016). As of 2011, less than 3% of all delivered electricity used storage (Dunn et al., 2011).

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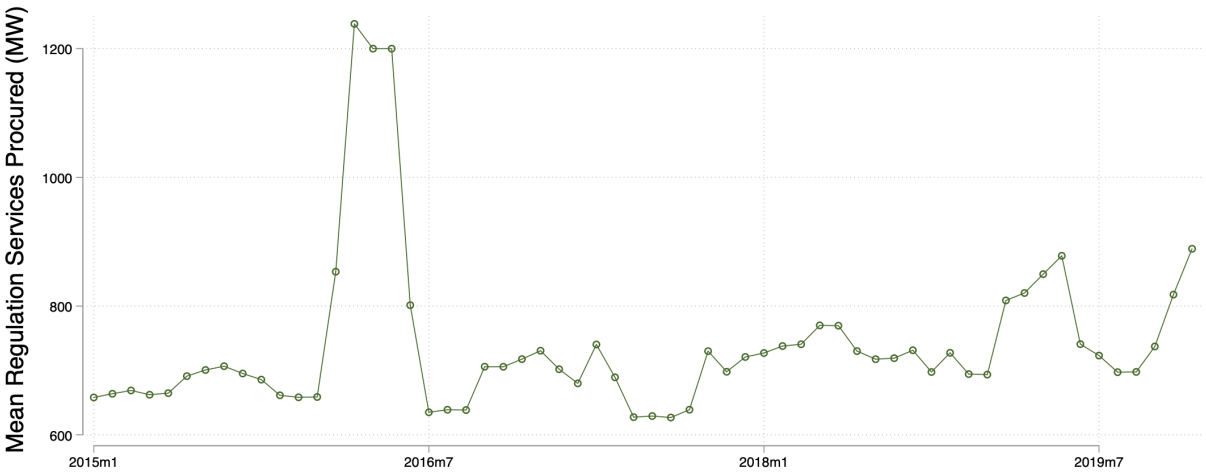
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Appendix

Figure 9: Regulation Service Quantity Procured in CAISO



Note: The figure plots the mean hourly quantity of regulation services procured by CAISO each month. Regulation quantity is calcualted the sum of "regulation up" and "regulation down" quantities in the day-ahead market.

Figure 10: Storage Applications in Day-Ahead Market

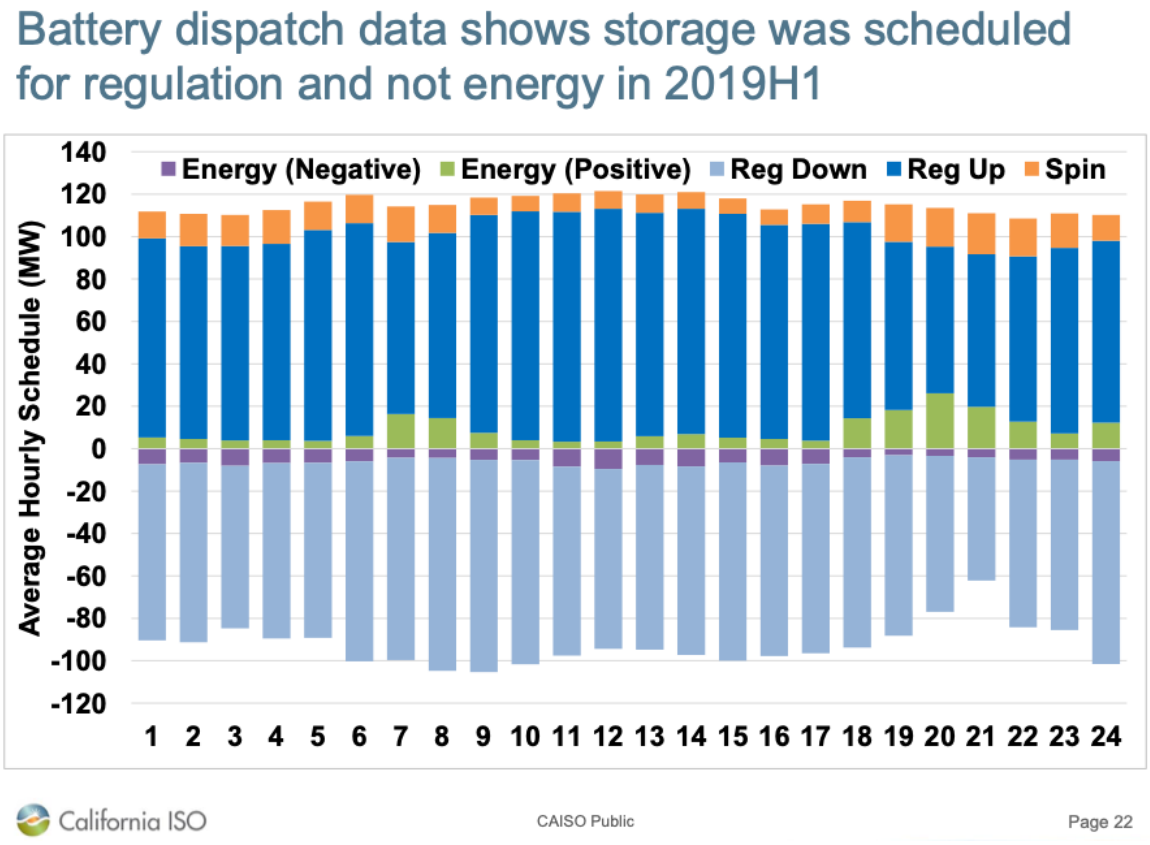


Table 2: Summary Statistics

Daytime 10 AM - 3 PM

	2015	2016	2017	2018	2019	Total
Real-Time Price ($/MWh)	25.57	24.45	23.49	27.20	25.54	25.25
	(67.06)	(80.68)	(69.44)	(61.27)	(54.62)	(67.20)
Day-Ahead Price ($/MWh)	27.80	22.47	24.14	32.13	23.75	26.06
	(8.848)	(11.10)	(15.73)	(32.32)	(14.67)	(18.82)
Battery Discharge (MW)	.	.	.	-2.908	-5.038	-4.146
	(.)	(.)	(.)	(25.65)	(35.34)	(31.66)
Solar Generation (MW)	4373.3	5634.9	7264.2	7802.7	8219.6	6658.4
	(1033.5)	(1480.1)	(1949.3)	(1939.2)	(2406.1)	(2323.1)
Imports (MW)	6659.8	6246.6	5182.9	4742.0	3295.4	5314.3
	(1106.2)	(1266.2)	(1494.9)	(1811.8)	(2068.9)	(1934.4)
Hydro Generation (MW)	1306.1	2324.4	3272.6	2114.7	2886.3	2357.6
	(568.3)	(843.3)	(932.1)	(569.6)	(809.8)	(1018.5)
Net Load (MW)	22442.0	19760.4	17745.0	16452.8	14698.5	18220.6
	(4840.2)	(4440.3)	(5368.5)	(5223.0)	(5152.0)	(5686.9)

Evening Peak 4 PM - 8 PM

	2015	2016	2017	2018	2019	Total
Real-Time Price ($/MWh)	44.14	42.59	54.51	58.90	51.58	50.34
	(95.11)	(100.4)	(135.3)	(129.1)	(105.9)	(114.5)
Day-Ahead Price ($/MWh)	41.63	40.03	56.13	67.30	52.38	51.49
	(9.889)	(13.47)	(46.49)	(70.53)	(27.94)	(41.70)
Battery Discharge (MW)	.	.	.	9.239	3.436	5.866
	(.)	(.)	(.)	(27.98)	(34.18)	(31.86)
Solar Generation (MW)	1070.7	1442.9	1882.7	2078.6	2229.8	1740.8
	(1475.2)	(1997.0)	(2679.7)	(2896.0)	(3149.8)	(2551.7)
Imports (MW)	7838.8	8296.1	7981.6	8126.7	6969.8	7882.9
	(1290.2)	(1406.6)	(1583.5)	(2079.5)	(2444.5)	(1831.1)
Hydro Generation (MW)	2190.5	3422.3	4222.8	3128.0	3930.9	3353.6
	(724.2)	(948.9)	(898.3)	(714.6)	(807.9)	(1089.5)
Net Load (MW)	27659.4	26383.9	25983.7	25285.4	24180.3	25898.8
	(4796.5)	(4823.0)	(5666.0)	(5477.4)	(5782.1)	(5449.0)

Figure 11: Day-Ahead and Real-Time Market Prices and Net load for Two Days in February 2015

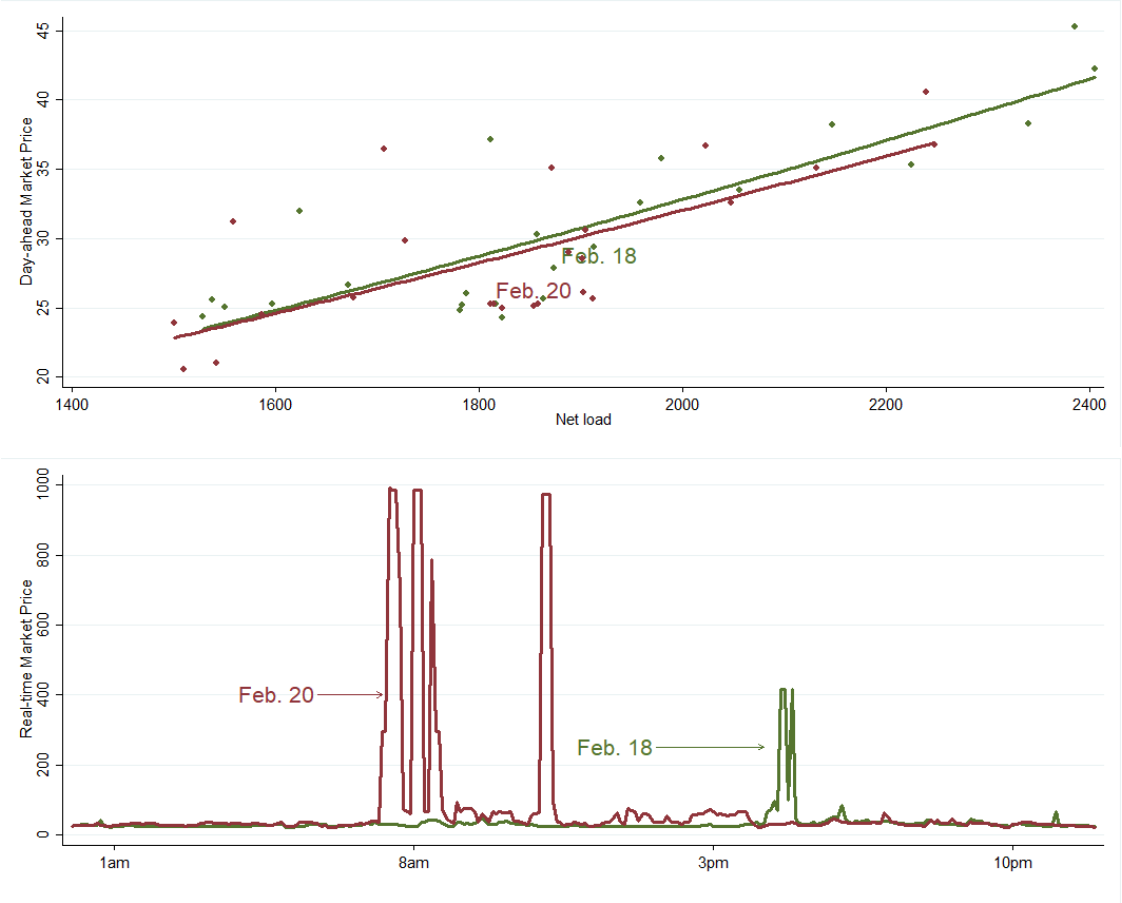


Figure 12: Day-Ahead and Real-Time Market Prices and Net load for Two Days in August 2015

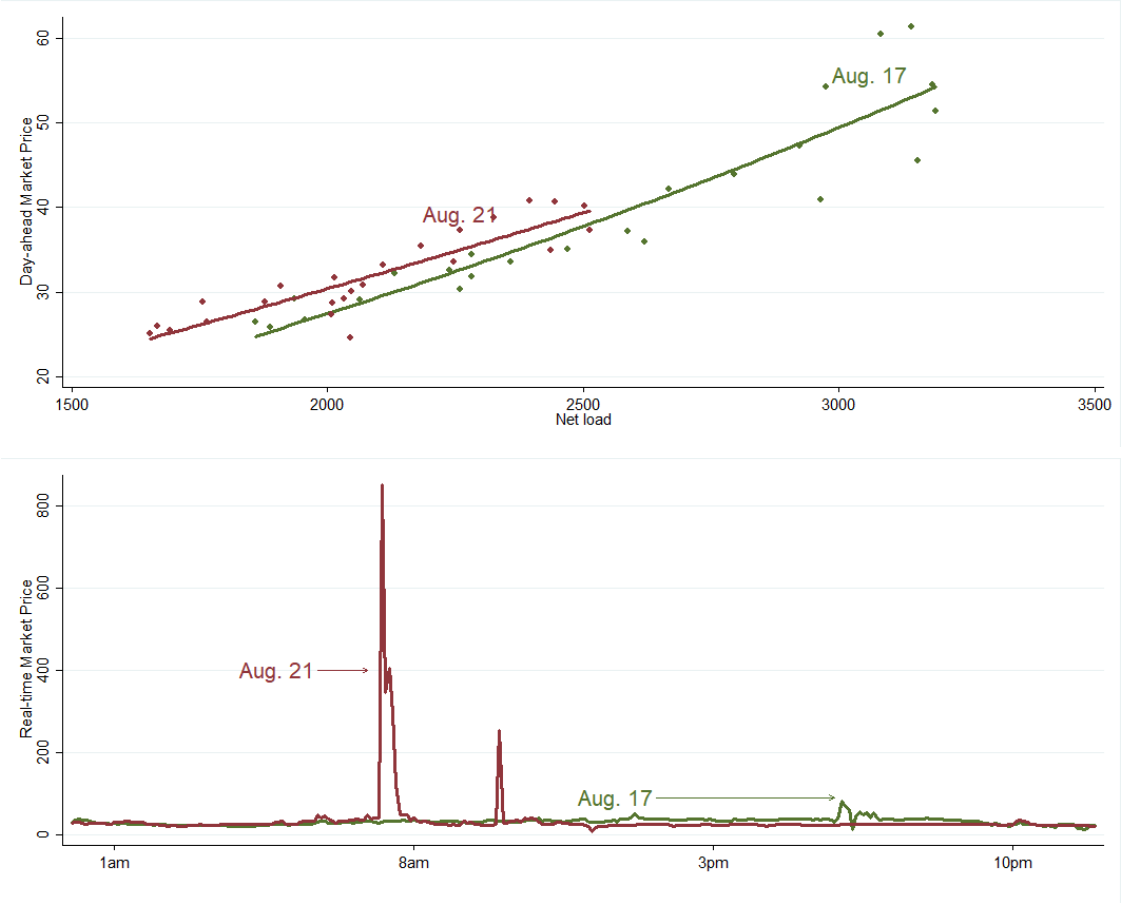


Figure 13: Day-Ahead and Real-Time Market Prices and Net load for Two Days one in August and one in May 2015

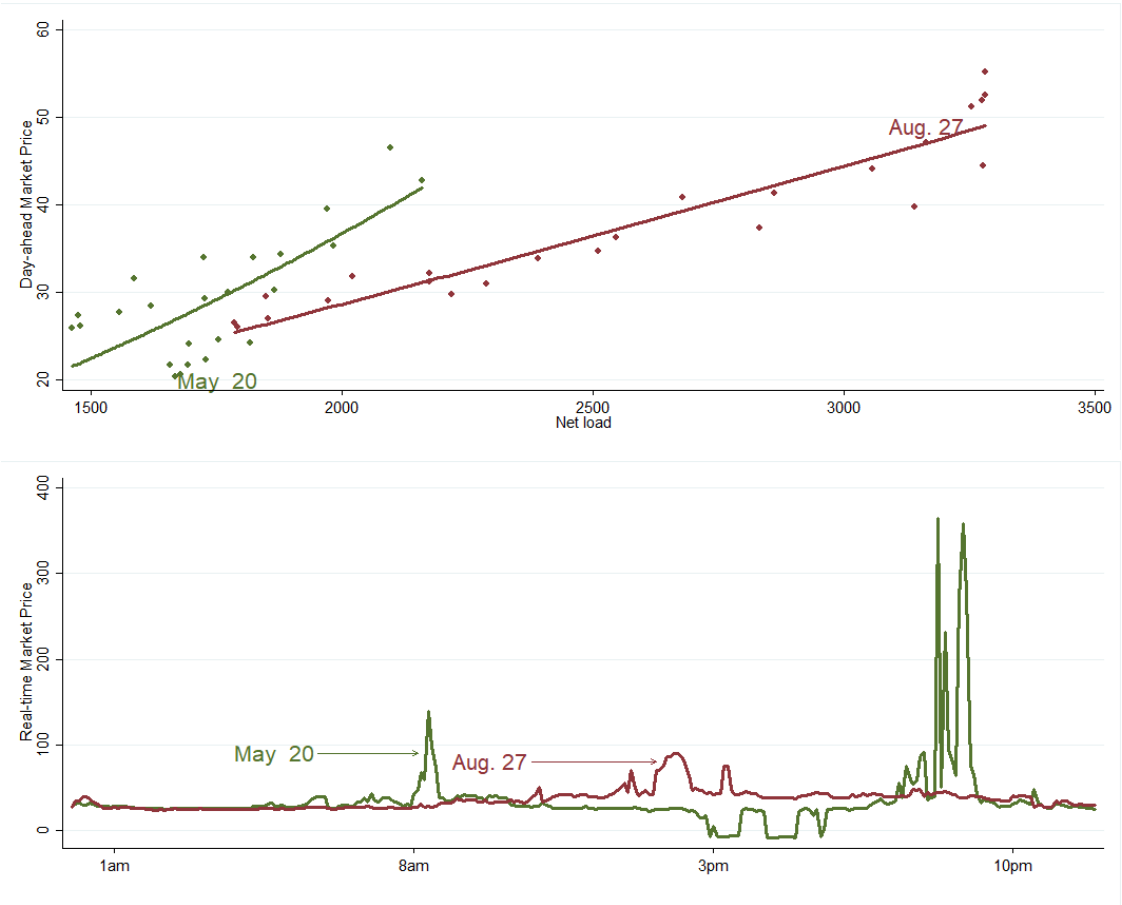


Figure 14: Day-Ahead and Real-Time Market Prices and Net load for Two Days one in August 2015 and the same day in 2016



Figure 15: Median Interval-of-day Within Hour Deviations of Real-Time Market Prices and Net load for 2015

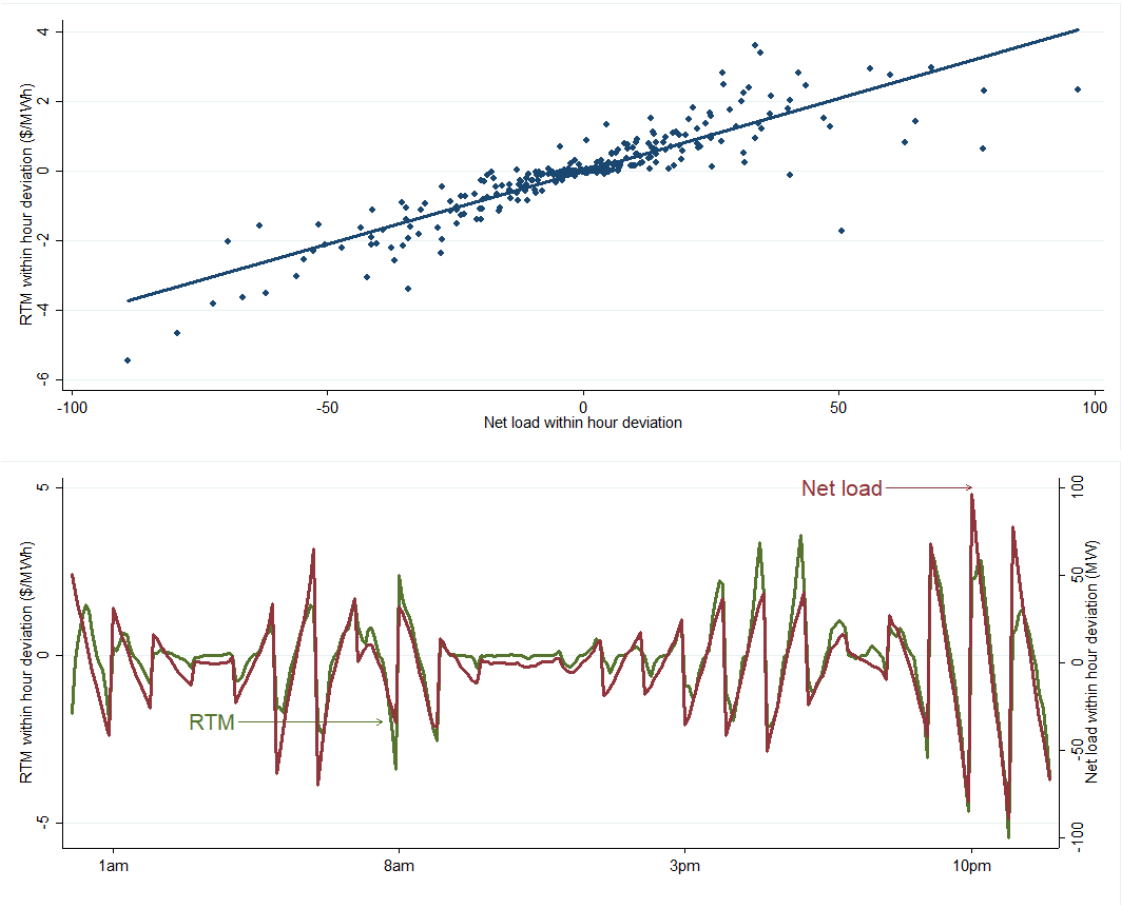


Figure 16: Median Hour-of-day Within Day Deviations of Real-Time Market Prices and Net load for 2015

