(Lambert, 2019)

POLICY DRIVERS FOR BATTERY STORAGE DEPLOYMENT

ABSTRACT

Battery storage supports grid stability and the success of variable renewable energy generation. While prior literature has addressed the political economics of lithium-ion battery storage, this thesis represents one of the earliest empirical contributions on policy drivers for the technology's deployment. Through thirteen regressions, this work assesses supportive regulations from FERC and the state of California. Confirming previous academic theories, policies establishing wholesale market access and fair compensation for battery storage were shown to strongly determine its deployment (FERC Order 841 and 825). For California, renewable energy and energy storage targets also contributed significantly. These findings reinforce preceding literature while also informing energy regions looking to stimulate maximal lithium-ion battery storage development.

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Policy Drivers for Battery Storage Deployment

1. Introduction

Signs of anthropogenic climate change are evident currently, with wildfires raging in California and global temperatures surpassing record highs (Vachula, 2019; Freedman, 2019). Greenhouse gas emissions perpetuate many symptoms of climate change, already undermining global wellbeing (Mora et al., 2018). Many economic participants emit heat-trapping greenhouse gasses, but electricity producers remain the largest offenders. For context, 30% of the United States' carbon footprint is linked to electricity generation (Sources of…, 2019; Cramton, 2017). Economic reliance on electricity may only grow as global economies transition away from fossil energy (Winfield et al., 2018). The increasing prevalence of electric automobiles reflects this trend (Pereirinha et al., 2018). Supporting the continued transition away from fossil fuels, utility-scale wind and solar may dramatically reduce the environmental impact of electricity generation. However, concerns persist around on-grid variability (Sakti et al., 2018). To address the intermittent nature of renewable energy generation, this thesis will empirically assess the capacity of Federal and State policy to drive the deployment of lithium-ion battery storage in the United States.

Wind and solar power remain crucial components of any emissions reduction strategy (Egrerer et al., 2015). However, these variable renewable energy (VRE) resources generate electricity intermittently, depending upon weather and time of day. Thus, renewable energy alone in insufficient for meeting total electricity demand (Sakti et al., 2018; Rintamäki et al.,

2017). This technological limitation also results in more variability in wholesale electricity prices (Powers et al., 2020).

As an enabler of grid efficiency and stability, lithium-ion battery storage (LBS) may catalyze the maximal impact of existing and future VRE (Winfield et al., 2018; Nelson, 2017). LBS can achieve this by charging during low-demand hours and discharging during periods of high demand, preventing the waste of excess VRE generation (Nelson, 2017). Potential arbitrage profit from such activity increases with more variability in wholesale electricity markets, precipitated by VRE deployment (Powers et al., 2020). Consequently, the LBS industry has seen tremendous growth over the last two decades, amid increasing economies of scale, technological progress, VRE proliferation, and policy support (Sakti et al., 2018; Few et al., 2018; DOESD). As a measure of expansion, global LBS installation rose by nearly 177% in 2015, with US capacity growing 243% that same year (Sakti et al., 2018; Munsell, 2016).

As LBS deployment may enable both the environmental success and economic dominance of VRE, this thesis empirically investigates domestic policies from the Federal Energy Regulatory Commission (FERC) and within California. Thirteen related regressions indicate that LBS-targeted policies enabling fair compensation and participation in wholesale energy markets may be most conducive to deployment. At the federal level, these include FERC Order 841 and 825 (Appendix, Policy List 1). Additionally, California's state targets for VRE and energy storage are shown to substantially drive LBS installation (Appendix, Policy List 2). These policy levers might inform future legislation, including that of less mature global energy markets aiming to promote LBS development.

2. The US Energy System

The US power grid spans numerous regulated and deregulated utility regions, largely governed by FERC (Electric Power Markets, 2020). For simplicity, the terms energy, electricity, grid, and power will be used interchangeably to describe dynamics within the electric/utility sector. In deregulated energy systems, electricity is traded in wholesale markets managed by controlling entities known as Regional Transmission Operators (RTOs) or Independent System Operators (ISOs) (Wholesale Elec…, 2019). RTO/ISOs control the trading of energy, while power plants generate electricity, utilities transmit it, and retailers sell it on open markets (Regulated &…, 2018; Cramton, 2017; Winfield et al., 2018). Deregulated markets originated from a drive to increase competition domestically, whereupon monopoly utility companies were forced to sell their power plant assets (Wholesale Elec…, 2019). Conversely, in monopoly utility regions, single providers control the entire electricity value chain from generation to distribution (Winfield et al., 2018).

Figure 1: Map of US Wholesale Energy Markets

Sources: Electric Power Markets, 2020

Monopoly regions pictured above include the Northwest, Southwest, and Southeast (Electric Power Markets, 2020; Figure 1). Deregulated energy markets are overseen by the

California Independent System Operator (CAISO), the Electric Reliability Council of Texas (ERCOT), ISO New England (ISO-NE), the Midcontinent Independent System Operator (MISO), the New York Independent System Operator (NYISO), PJM Interconnection (PJM), and the Southwest Power Pool (SPP) (Sakti et al., 2018; DOESD; Electric Power Markets, 2020). FERC holds tremendous influence over these ISO/RTOs, with the exception of ERCOT (Sakti et al., 2018; Greenfield, 2018). Importantly, ISO/RTOs must approve mandates in compliance with FERC orders (Sakti et al., 2018). Significant interplay does exist between State, FERC, and ISO/RTO-level policy making. In addition, ISO/RTO's often enact regulations arising from stakeholder involvement which must comply with State-level policy (Sakti et al., 2018). It should be noted that, since FERC regulates interstate wholesale electricity trading, it does retain some influence over regulated monopoly regions (Federal Regulation, 2015).

Specific to deregulated regions, RTO/ISOs determine energy prices. These entities govern real-time and day-ahead wholesale electricity markets. Sellers and/or generators submit bids to RTO/ISOs which influence the determination of new wholesale prices at 5-minute increments (Wholesale Elec…, 2019). Additionally, many RTO/ISOs have capacity markets which reward excess generation above customer load to ensure that potential demand spikes can be met (Capacity Mar…, 2019). Relevant to LBS economics, ancillary services comprise grid and market mechanisms that help stabilize real-time energy supply and demand (Zhou et al., 2016; Cramton, 2017). Many FERC orders interact with wholesale, capacity and ancillary market dynamics (Sakti et al., 2018).

3. Literature Review

Electricity sector decarbonization remains a powerful mechanism for climate change mitigation (Cramton, 2017). Toward this end, VRE can reduce the environmental impact of electricity generation (Hartley, 2018). Furthermore, LBS complements VRE by storing and efficiently discharging excess renewable generation (Nelson, 2017). Accounting for intermittency, battery storage technology can also stabilize energy grids - especially those with strong VRE penetration (Winfield et al., 2018). Specific policies may drive the financial success of LBS, thereby improving the environmental and technological impact of VRE. Consequently, this thesis seeks to determine which FERC and California state policies and regulations have significantly driven battery storage deployment.

Supported by recent literature, LBS remains a viable complement to VRE in mitigating climate change. Several sources recommend market design features to spur battery storage success, including competitive neutrality, fair compensation for services, and unrestricted energy market participation. That said, some objections do persist on the immediate financial feasibility of LBS. Most pertinent economic research on LBS was published in the last five years, rendering this topic prime for additional exploration.

Scholars disagree over this thesis' stance that LBS, under ideal circumstances, can serve the grid and enable VRE's success. Several key sources concur that storage technology is essential for combating the variability and intermittency of VRE generation (Cramton, 2017; Winfield et al., 2018; Arciniegas and Hittinger, 2012; Sakti et al., 2018). In his 2017 paper, Cramton cites intermittency as a serious limitation of VRE, presenting LBS as a feasible solution (Cramton, 2017). Another study emphasizes the rapid growth of VRE which may necessitate the increased deployment of LBS (Sakti et al., 2018). This body of research supports the assumption

that VRE and LBS deployment are positively correlated and complementary due to considerable technological synergism (Cramton, 2017; Sakti et al, 2018). As more VRE on-grid can improve potential arbitrage profits for LBS, economic harmony also persists, especially in deregulated energy markets (Powers et al., 2020). Related literature substantiates the potential of LBS as a climate change mitigation technology, but there remains disagreement concerning the extent of its applicability, and whether battery deployment is always environmentally optimal (Arciniegas and Hittinger, 2012; Few et al., 2018).

In concert with this thesis and economic intuition, industrial and technological progress contributes heavily to the financial viability of battery storage. According to one source, economies of scale and ongoing research will spur lower LBS prices in the future (Few et al., 2018). Additional sources support the inevitability of falling LBS costs (Nelson, 2017; Winfield et al., 2018). Technological innovation may also lead to better performing and more robust batteries with greater storage capacity (Winfield et al., 2018; Few et al., 2018). In conjunction, one source argues that the profitability of LBS might improve as its grid balancing capabilities appreciate amid heightened intermittency from more VRE (Nelson, 2017). Thus, lower costs, improved performance, and VRE penetration may strengthen the financial prospects of LBS. The analytical portion of this Thesis leverages this literary foundation by incorporating control variables for the price of lithium-ion batteries and VRE generation.

Important literature also analyzes alternatives to LBS. Newbery (2018) compares LBS to pumped hydroelectric storage. While the properties of these technologies remain similar, as they both store power from the grid and release it opportunely, he criticizes LBS for its high relative cost, short lifespan, and temporal limitations (Newbery, 2018). Newbery (2018) asserts that batteries may not be profitable from energy arbitrage alone, but they might be more viable in

niche settings where alternatives are infeasible. Conversely, this thesis' analysis suggests wholesale market access and arbitrage may be quite lucrative for LBS. Newbery's study does focus on the United Kingdom deregulated energy system, which is structurally distinct from US markets (2018). While this thesis does not consider alternative storage technologies, it confounds detractive findings from Newbery (2018).

In a similar analysis inspecting ERCOT, Hartley considers the cost of two competing systems: VRE (wind) and LBS versus nuclear and LBS (2018). He asserts that nuclear power paired with LBS may be more cost effective. Implementing a linear programming model, Hartley discerns empirically that LBS may be expensive when paired with VRE (2018). Citing the high cost of LBS, he argues that paired fossil fuel generation might better compliment VRE economically (Hartley, 2018). Hartley's perspective remains valuable as it indicates additional limitations for LBS (Hartley, 2018). Speculatively, given the rapid decline in battery prices, recent data might be more favorable to LBS if applied to Hartley's model (Goldie-Scot, 2019).

The empirical findings of this thesis align with prior policy arguments, which widely advocate for loosening participatory restrictions on LBS in deregulated markets. In line with this stance, three studies recommend that batteries should have full exposure to the market prices for power they store and discharge, enabling maximum arbitrage potential (Li et al, 2018; Sakti et al., 2018; Winfield et al., 2018). Two of these sources also recommend that LBS should receive exposure to both capacity markets and traditional wholesale prices (Winfield et al., 2018; Sakti et al., 2018). Several authors agree that, in United States Markets, battery size minimums and other restrictions only limit the financial viability of LBS. Affirmed by the analytics in this thesis, Sakti and his co-authors praise FERC Order 841 which supports unrestricted electricity market participation (2018).

Competitive neutrality remains a central theme in academic literature. Two studies agree that policies should avoid showing favoritism to specific technologies or businesses within energy systems (Sakti et al., 2018; Nelson, 2017). In a related sentiment, several authors urge regulators to fully compensate LBS operators for additional systemic benefits (Sakti et al., 2018; Newbery, 2018; Nelson, 2017). For batteries, such strengths include response speed, grid services, and unmatched proximity to load centers (Newbery, 2018). Nelson echoed this perspective, recommending that batteries' financial, systemic, and environmental benefits be factored into energy prices (Nelson, 2017). Accordingly, this thesis identifies a significant deployment impact for FERC Order 825, which aims to fairly compensate LBS for its value on-grid (Appendix, Policy List 1).

Further informing the empirical efforts of this thesis, Polzin and co-authors shed light on a viable statistical approach for studying energy policy (2015). They model numerous mandates targeting VRE deployment, including Feed-in Tariffs and Renewable Portfolio Standards. While their core findings are tangential, their methodology for policy analysis heavily informs that of this thesis. To assess policies supporting VRE, they employ a panel data regression (Polzin et al., 2015, p. 102). Due to data availability constraints, the authors focus on the period from 2000 to 2011. Their dependent variable is newly installed VRE capacity, which they view as an accurate proxy for technology deployment (Polzin et al., 2015). They incorporate specific policy classifications to derive independent variables. These categories include incentives, market instruments, direct investment, strategic planning, and regulatory instruments, among others (Polzin et al., 2015). Polzin and his co-authors also control for technological improvement, economies of scale, and GDP (2015). They do stipulate that "determining the influence of policy measures on investments in" VRE "capacity is challenging since spatial and temporal effects

could overlap" (2015, p. 102). Referenced later, the concept of overlapping effects does represent a limitation for this thesis' model.

As support by the literature, LBS packs the necessary features to combat VRE intermittency within domestic energy regions. Such arguments coincide with this thesis' mission to inform optimal policies for LBS deployment, towards the end goal of climate change mitigation. Falling costs and innovation may drive increasingly economical solutions, but as previously noted, there do exist challenges to the financial viability of LBS. Ultimately, regulatory features including unrestricted market participation and fair compensation may improve the profitability of LBS and accelerate its deployment. These policy recommendations are inspected and ultimately substantiated in later regression analyses.

4. Methodology

The goal of this statistical analysis is to determine the extent to which specific policies, particularly those at the Federal and California State levels, have played a significant role in LBS deployment. Inspecting LBS projects in the US, this thesis will employ a model to compare policies from FERC and California. At the FERC level, regressions will be run annually from 2002 to 2019. For California, regressions will employ a quarterly frequency from Q1 2002 to Q4 2016. This approach is inspired by Polzin and his co-authors (2015), who employed a related framework to asses renewable energy deployment. The aim is to determine which policies significantly benefit LBS deployment.

The dependent variable *CD (cumulative_deployment*) is derived from the Department of Energy Global Energy Storage Database (DOESD) and Wood Mackenzie, representing aggregated new battery storage capacity/rated power (U.S. Energy Storage, 2020). Deployment

is measured in kilowatts of installed capacity, which Polzin and his co-authors (2015) argue is an "accurate proxy for the deployment of a technology" (p. 101). Methodologically, the time component of the DOESD data is hybridized between the date announced, date contracted, and date operationalized for all sampled projects. This is then combined with the Wood Mackenzie dataset to maximize accuracy and completeness from 2013 onward (U.S. Energy Storage, 2020).

Table 1. Policy Categorization for Indicator Variables

Variable	**Policy Category**	**Definition**
BS_Partic	Battery Storage Wholesale Market Participation	ANBSP; full Battery Storage participation in wholesale energy markets
BS_Comp	Improved Compensation of Battery Storage	ANBSP; improved compensation for Battery Storage
BS	Improved Wholesale Market Participation and/or Compensation	Combines *BS_Parti* and *BS_Comp* for California Analysis
Secondary_Markt	Ancillary and Capacity Market Participation	ANBSP; existence of capacity or ancillary market/battery storage participation in said market
REDR_Partic	Renewable Energy/Demand Response Participation	ANBSP; improve participation and remuneration for distributed energy resources and demand response
CA_BS_Targ	California State Battery Storage Target	ANBSP; CA state target mandating a certain level of battery storage deployment/procurement
CA_RE_Targ	California State Renewable Energy Target	ANBSP; CA state target mandating a certain level of renewable energy deployment/procurement

Sources: Sakti et al, 2018; Polzin et al., 2015; DOESD; Notes: Demand Response and Renewable Energy policies are less focused on battery storage but still impact the technology's viability. This categorization uses a similar format to that of "Table A2" from Polzin and his co-authors' paper (2015, p. 107)

Policy variables are compiled from several sources (Appendix, Policy List 1; 2). These independent variables are expressed as policy indices, indicating the number of active FERC or California mandates in any given year or quarter (Table 1). This process reflects that of Polzin and his co-authors (2015). The term accumulated number of battery storage policies (ANBSP) is

employed to inform the construction of indicator independent variables (Table 1). The utilization of an ANBSP index assumes that more policies within any given category may strengthen battery storage deployment (Polzin et al., 2015). To clarify, the terms *policy*, *regulation*, *mandate* and *legislation* are used interchangeably. It must also be mentioned that the categorization of California regulation R.15-03-011 uniquely represents a proceeding in progress. The reasoning for this inclusion is outlined in the Appendix (Policy List 2).

Time lags are also crucial in this model, as independent policy variables might affect *cumulative deployment* immediately or across several time periods (Polzin et al., 2015). This approach assumes that some LBS developers may respond very quickly to specific policies and that there might also be lags between policy approval, policy implementation, and industry response. Moreover, this modeling component aims to account for the lag between FERC orders and ISO/RTO regulatory compliance. ISO/RTOs must pass their own regulations to align with FERC, and this process can take upwards of a year (Orrick, 2020). The lag structure proposed by Polzin and his co-authors partially transfers to that used in this model (2015). For FERC, only $t\text{-}1$ is considered as an annual lag. On a quarterly basis, lags $t\text{-}2$ and $t\text{-}4$ are included for the California-level analysis. In both analyses, data and temporal limitations lead to the omission of some policy indicators when longer lags are employed. Thus, only the aforementioned structure of lags is used to prevent omitted-variable bias.

For FERC and CA, analyses use basic panel data regressions to compare the effectiveness of policy types in spurring battery storage deployment. Regressions are specified:

Estimations without time lags for FERC and CA

$$\mathrm{CD}_t = const + \sum_{i=1}^{k} ß_i SP_{it} + \gamma C_t + \mathcal{E}_t$$

Estimations with time lags for FERC and CA

$$\mathrm{CD}_t = const + \sum_{i=1}^{k} ß_i SP_{i,t\text{-}l} + \gamma C + \mathcal{E}_t$$

In the above specifications, CD_t represents cumulative LBS deployment and t stands for a specific year or quarter. Following the approach of Polzin and his co-authors (2015), *SP* (supportive policy) refers to ANBSP explanatory variables reflecting active FERC and/or California-level policies (Table 4). Both analyses incorporate k policy indicators (FERC-level k=4; California-level k=5). To account for temporal phenomena, the second specification includes l for the length of annual or quarterly time lags. C represents control variables for energy load, battery prices, GDP, and renewable energy generation (Polzin et al., 2015). Lastly, the random-error term is represented by $\mathcal{E}_t$.

For FERC and CA, this model indicates the effectiveness of specific policy categorizations in driving LBS deployment (Polzin et al., 2015). Here, “effectiveness” is tied to the significance and magnitude of policy index variable coefficients, across several lagged and unlagged augmentations. For hypothesis testing, analyses incorporate the universal null that coefficients on policy indicators are equal to zero. This strategy employs two-tailed t-testing. Additionally, threshold t-values are higher for the FERC-level analysis, given fewer degrees of freedom annually.

Table 2. Control Variables Across FERC and California-level Analyses

Control	**Unit**	**FERC-Level**	**CA-Level**
Energy Demand	MWh; Million KWh (standardized)	*ferc_cov_load*	*ca_ret_sales*
Battery Price	Dollars/kWh (log)	*bat_price*	*bat_price*
GDP	Millions of Chained 2012 Dollars (log)	*us_gdp_ferc*	*gdp_ca*
RE Generation	Net generation in thousand MWh, renewable energy (standardized)	*re_gen_ferc*	*re_gen_ca*

Sources: EIA - Independent Statistics, 2020; Goldie-Scot, 2019; Federal Reserve, 2020

Several exogenous factors might drive battery storage deployment (Table 2). Lithium-ion battery prices, often trimmed by technological improvements and economies of scale, are a crucial control (Few et al., 2018). Intuitively, more affordable batteries improve project viability and financial return. Within this model, the adoption of batteries is linked to the rate of decline in battery prices. Thus, the *battery price* control variable is run logarithmically. As regions with higher VRE penetration may benefit disproportionately from LBS deployment, the model also incorporates a control for renewable energy generation (Newbery, 2018). This inclusion accounts for the theoretical positive relationship between VRE and LBS deployment, catalyzed by technological, environmental and financial synergies (Cramton, 2017; Sakti et al, 2018; Powers et al., 2020). To reflect macroeconomic cycles, models include a control variable for GDP. Given the potential positive impact of GPD growth rate, this too is run as a logarithm. Lastly, total energy demand will be controlled for because battery storage deployment might track broader grid expansion.

5. Data

5.1 National Dependent Variable

The dependent variable dataset was acquired from DOESD and Wood Mackenzie (U.S. Energy Storage, 2020; DOESD). The first database includes 1,686 total energy storage projects from 82 countries around the world. DOESD partnered with several entities for data collection and analytics. Domestically, these entities include The California Energy Storage Alliance, The New York Battery and Energy Storage Technology Consortium, and Strategen Consulting. There is one observation for each storage project in the DOESD, and it appears these are updated intermittently (DOESD). It remains unclear how often observations are updated, and this process appears to be temporally fragmented. The data derived from DOESD may be best characterized as cross-sectional time series data. Information of interest includes operating status, rated power (in kilowatts[kWs]), location (latitude and longitude), country, date (announced, commissioned; constructed), and ISO/RTO.

This analysis is primarily concerned with the date and rated power, which both inform the *cumulative deployment* dependent variable. The total quantity of rated power announced, constructed, or commissioned in any given year or quarter will represent levels of battery storage deployment. As constraints around database use persisted due to issues with the Department of Energy's website, this complete raw dataset was the only feasible starting point.

For the first portion of this dependent variable data (2002 to 2012), observations from states not within FERC jurisdiction were dropped (Greenfield, 2018). Data for Texas, Hawaii, and Alaska was saved for the second portion of data construction. Unfortunately, not every observation from the DOESD listed a date of announcement. To account for gaps in date information, without sacrificing a significant number of variables, a new variable labelled *Hybrid Date* was created. This *Hybrid Date* variable prioritized the date of project construction. If a

"constructed" date was not provided, the "announced" date was substituted. If this too was not available, the "commissioned" date was substituted. Any observations that were entirely missing date information were eliminated, and kilowatt capacity information was converted to megawatts. Observations after 2012 were omitted as Wood Mackenzie's dataset offers a more accurate substitute (U.S. Energy Storage, 2020).

For the second portion of dataset amalgamation (20013 to 2019), data was mined directly from a Wood Mackenzie graphic (U.S. Energy Storage, 2020). This substitution enables the most accurate analysis of current policies governing the battery storage space, leveraging a reliable and lauded dataset. Contrastingly, more recent project entries appear incomplete for DOESD (U.S. Energy Storage, 2020). Using the program *GetData Graph Digitizer*, data was extracted from a Wood Mackenzie graphic (Digitize graphs, 2020; Figure 2). During this process, data for non-residential and front-of-the-meter battery storage projects was isolated. This implies that most representative projects are active on-grid or at least larger in scale. It also ensures continuity with the previous DEOSD dataset which seemingly excluded residential projects. For context, residential battery storage is generally installed behind the meter where individual batteries are negligible in size. Such batteries do not generally participate in wholesale or secondary markets (Leadbetter and Swan, 2012).

This Wood Mackenzie dataset did not include full 2019 data. To account for this shortcoming, deployment for Q4 2019 was estimated. Methodologically, an annualized growth rate for the previous Q4 data from 2016, 2017 and 2018 was calculated. This yielded the growth rate from Q4 2015 to Q4 2016, Q4 2016 to Q4 2017, and Q4 2017 to Q4 2018. The mean of these historical growth rates fed into an estimate for Q4 2019. This yielded a full Wood Mackenzie dataset from Q1 2013 to Q4 2019. After collapsing these observations annually,

corresponding deployment data for Texas, Hawaii and Alaska was subtracted, in alignment with the first portion of dataset construction (Greenfield, 2018). Once combined, the Wood Mackenzie and DOESD datasets spanned FERC governed deployment in the United States up to 2019.

5.2 National Control Variables

Battery pricing control data was acquired from Bloomberg New Energy Finance (Goldie-Scot, 2019). The annual dataset spanned the years 2010 to 2018. Citing a Credit Suisse report, the 2019 figure was calculated using a 15% annual price deflation estimate (Kukhnin et al, 2019). Next, incorporating an exponential regression model, the years from 2002 to 2009 were estimated from the most recent real data. Jointly, this historical estimation, the real data from 2010 to 2018, and the 2019 deflation estimate, yielded a complete annual dataset for battery prices ($/kWh) from 2002 to 2019.

Real US GDP under FERC jurisdiction was sourced from Federal Reserve Economic Data (Federal Reserve, 2020). This approach levered the FRED data sorting features to annualize GDP data in chained 2012 dollars for the entire US. Next, the same annual GDP data for Texas, Hawaii and Alaska was acquired and subtracted from national GDP data (Federal Reserve, 2020). GDP for 2019, as omitted from the annual dataset, was estimated assuming a standard 2% growth rate. This was consistent with growth over the preceding 5 years. This process yielded a real GDP dataset to control for fluctuations in the macroeconomy, for areas under FERC jurisdiction. Controlling for GDP might help capture the impacts of macroeconomic cycles on battery storage deployment. (Federal Reserve, 2020).

Data on renewable energy generation under FERC jurisdiction was pulled from the US Energy Information Administration’s database browser (EIA - Independent Statistics, 2020).

Navigating the database, national utility-scale solar and wind generation was collected for the entire United States. As with prior control data sets, the same information for Texas, Hawaii and Alaska was subtracted annually to account for FERC coverage (Greenfield, 2018). This amalgamation only focused on utility-scale generation, as residential and commercial datasets appeared temporally incomplete. This being a control variable, utility-scale renewable energy generation, on its own, serves as an excellent proxy for the penetration of renewable energy. Per available data, the growth of utility-scale renewables was also highly correlated with the datapoints available for residential and commercial solar. The data is presented in net generation in thousands of megawatt hours (EIA - Independent Statistics, 2020). Ultimately, as this thesis aims to isolate the true policy impact on battery storage deployment, renewable energy generation remains a crucial control.

FERC covered load in the United States represented a final control. Data on this variable was collected from the U.S. Energy Information Administration's website (Electricity Data, 2020). The dataset was augmented to reflect yearly totals for the entire energy sector nationally. After this procedure, annual totals for Texas, Alaska, and Hawaii were subtracted. This yielded an annualized dataset for energy load under FERC jurisdiction, accounting for the assumption that battery storage deployment might be impacted by more overall load on-grid. As data was unavailable for 2019, this annual total was estimated by averaging *FERC covered load* over the preceding 5 years.

5.3 California Dependent Variable

Leveraging the raw DOESD, all energy storage projects from California will be isolated. Across all states, the DOESD database appears inconsistent with strong upward trends evident in the Wood Mackenzie dataset (U.S. Energy Storage, 2020). Per these completeness concerns, the date range for this California-specific dataset was limited from 2002 to 2016. Once data from California was isolated, quarterly totals from Q1 2002 to Q4 2016 were aggregated.

5.4 California Control Variables

Per the assumption that battery storage deployment could scale with a states' energy needs, this analysis will control for energy consumption within California. Data was sourced from the US Energy Information Administration's electricity data browser (EIA - Independent Statistics, 2020). From this database, information on California retail sales of electricity (in millions KWh) was exported.

For the California analysis, it was crucial to have quarterly lithium-ion battery pricing data. To estimate this analytical component, the Bloomberg New Energy Finance annual dataset was incorporated once more (Goldie-Scot, 2019). As outlined previously, this battery pricing data spanned 2010 to 2018. Using the same exponential estimation method, all real data (Goldie-Scot, 2019) was positioned in its respective year on a quarterly time series. While the quarter of approximation was somewhat arbitrary, the 2nd or 3rd quarter appeared optimal for placing the real price, for each respective year. Because the annual data is representative of average battery pricing for each year, this mid-year approximation approach was reasonable. In turn, all real battery pricing annual data points were positioned in the second quarter of each respective year. Before running a regression, an exponential variable was generated for that original dataset. Next, the variable "projected price" was constructed. This variable represented the datapoints of

best fit for the previously run exponential regression. Unique to this approach, real annual battery prices were not substituted back into the quarterly dataset. Lastly, all quarters after Q4 2016 were dropped to align with the time span of the California-focused analysis.

Total Real Gross Domestic Product by Industry for California was extracted from Federal Reserve Economic Data (Federal Reserve, 2020). This dataset, in millions of chained 2012 dollars, was available from Q1 2005 to Q4 2016 (Federal Reserve, 2020). Next, quarterly GDP data from 2002 to 2004 was estimated using a simple linear regression model. After estimating real quarterly state GDP from 2002 to 2004, actual GDP data was substituted for the remainder of the analytical timespan. This data aggregation methodology resulted in a complete quarterly GDP dataset from 2002 to 2016, acting as a valuable macroeconomic control.

As with the FERC-level dataset, net generation from renewable energy in California was sourced from the US Energy Information Administration's database browser (EIA - Independent Statistics, 2020). The same collection process, outlined in section 5.2, was transferred to this California-specific control variable.

6. Results

Two types of regression were conducted at each of the FERC and California levels, for a total of thirteen separate regressions. The first type of regression simply searched for contemporaneous relationships between the dependent and explanatory variables. The second type of regression allows the explanatory variables to have lagged effects on the dependent variable. Across FERC and CA, these models yield large and significant results for LBS-specific policies as well as VRE and energy storage targets.

6.1 FERC-level Analysis

For the FERC-level component of this analysis, unlagged panel data regression yields compelling insight on wholesale market participatory policy (Appendix, Policy List 1). Firstly, the coefficient on battery storage participation is significant and quite sizeable (Table 3; 1). This suggests that FERC Order 841, associated with the *battery storage participation* variable, has a dominant unlagged impact on LBS. The insignificance of other indicator variable coefficients (Table 3; 1) suggests that policies directly targeting the participation of battery storage in wholesale energy markets may dominantly drive LBS deployment. Thus, the first regression aligns with Sakti, Botterud, and O'Sullivan's prediction that Order 841 would be the most impactful FERC mandate in spurring battery storage deployment (2018). This finding reflects additional perspectives regarding the benefit of unrestricted market access for LBS technology (Li et al, 2018; Winfield et al., 2018).

The second FERC-level regression was run with a 1-year time lag on policy indicator variables (Table 3, 2). In this model, the coefficient on *battery storage participation* is significant and large. This result suggests policies enabling LBS wholesale market participation retain a substantial impact on deployment, one year following implementation (Table 4). Such a finding may coincide with the lengthy period between FERC orders and eventual ISO/RSO compliance (Orrick, 2020). Interestingly, the coefficient on FERC renewable energy generation is large and significant (Table 3, 2). This output empirically affirms the presupposed positive relationship between VRE and LBS deployment, driven by numerous synergies (Sakti et al., 2018; Cramton, 2017). In agreement with this finding, the dependent variable *cumulative deployment* is also strongly correlated with *FERC renewable energy generation*.

Table 3. FERC-Level Regressions

cum_deployment	(1)	(2)	(3)	(4)	(5)	(6)	(7)
bs_partic	**294.148****		136.806	**239.466***	**197.566***	**364.875****	
	(108.106)		(76.953)	(100.467)	(90.961)	(128.065)	
L1. bs_partic		**219.758****	23.170	**290.120***	**359.946*****	186.768	
		(94.366)	(124.919)	(114.547)	(90.098)	(138.410)	
bs_comp	88.779		-126.516	**222.407***	**268.785****		
	(118.028)		(145.607)	(100.512)	(88.774)		
L1. bs_comp		19.534	-204.193	105.397	164.835		
		(116.243)	(136.314)	(110.537)	(92.649)		
secondary_markt	-65.731		-109.831	39.073	48.987		
	(62.820)		(63.025)	(45.720)	(44.535)		
L1. secondary_markt		-51.063	-96.408	36.035	65.089		
		(58.236)	(60.720)	(53.683)	(44.872)		
redr_partic	-41.449		24.288	-70.861	-87.555		-59.972
	(65.986)		(53.301)	(60.031)	(57.517)		(62.247)
L1. redr_partic		**-138.048***	**-118.285***	-44.502	-37.936		**-182.195****
		(62.666)	(54.396)	(70.629)	(70.198)		(62.837)
ferc_cov_load	-67.371	-51.561	**-97.940***	-55.892		-108.108	-40.664
	(48.227)	(43.892)	(40.695)	(56.464)		(64.189)	(52.151)
log_bat_price	48.292	46.028	60.117	-118.996	-120.124	203.244	-91.853
	(146.189)	(125.528)	(117.401)	(145.441)	(145.192)	(131.307)	(155.466)
log_us_gdp_ferc	1828.947	1041.910	1653.715	1462.694	130.729	**4406.908****	49.382
	(1526.209)	(1624.860)	(1198.254)	(1796.638)	(1188.497)	(1890.760)	(1849.903)
re_gen_ferc	390.154	**649.695*****	**932.324***			203.596	**669.360*****
	(209.681)	(170.197)	(345.541)			(211.053)	(164.717)
_cons	-30072.190	-16885.310	-26803.240	-23045.610	-1133.637	**-73912.220****	603.269
	(25728.000)	(27266.740)	(20160.460)	(30208.740)	(20521.650)	(31171.710)	(30998.170)
Observations	18	17	17	17	17	17	17
Degrees of Freed.	9	8	4	5	6	10	10
R^2	0.9845	0.9888	0.9975	0.993	0.9917	0.9701	0.9773

1%, 5%, 10% denoted: ***, **, *

Regression (3) includes all lagged and unlagged policy indicators. Here, the lagged coefficient on *renewable energy/demand response participation* is significant at a reasonable level (Table 3, 3). For context, categorized policies support the success of a broader array of distributed energy technologies. This large and negative coefficient, also present for regression (2), could imply that other technologies dominated the policy niches instituted by FERC Orders 890, 719, 745, and 765, outcompeting battery storage (Appendix, Policy List 1). Thus, the presence of less targeted policies might negatively impact LBS deployment. Perhaps the time-consuming deployment of other technologies could also lead to a significant lagged coefficient

on *renewable energy/demand response participation* (Table 3, 3). In turn, regressions (6) and (7) will further analyze lagged and unlagged results (Table 3, 2;3).

Per the strong correlation between *renewable energy generation* and *renewable energy/demand response participation*, multicollinearity concerns persist. In turn, regression (3) was executed excluding *renewable energy generation* (Table 3, 4). This exercise resulted in significant lagged and unlagged coefficients for *battery storage participation*, in line with expectations. Notably, the unlagged coefficient on *battery storage compensation* was also large and significant. This indicator variable, associated with FERC Order 825, suggests a substantial and immediate deployment response. For context, FERC Order 825 required fair remuneration for LBS services on-grid, improving potential revenues (Sakti et al., 2018). In contrast to regression (3), coefficients on *renewable energy/demand response participation* are insignificant, even amid relaxed hypothesis testing parameters (Table 3, 4). Possibly reflecting a more accurate model, regression (4) indicates that FERC Orders 841 and 825 may dominantly drive LBS deployment. These results support prior recommendations towards policy that fully rewards LBS' on-grid capabilities (Sakti et al., 2018; Newbery, 2018; Nelson, 2017).

In regression (3), the significant negative coefficient on *FERC covered load* is unexpected per the hypothesized positive relationship between total energy demand and LBS deployment (Table 3; 1). Upon testing, FERC covered energy load was correlated with *US GPD* and *renewable energy generation* (Table 3, 1). These dynamics suggest some degree of multicollinearity. Regression (5) iterates on regression (4) while addressing correlations for *FERC covered energy load* with *US GPD* and *renewable energy generation* (Table 5). This is accomplished by excluding *FERC covered energy load*. Results from regression (5) broadly mirror those of regression (4) and yield higher significance for lagged *battery storage*

participation and unlagged *battery storage compensation*. These outputs challenge the significant negative coefficient on *FERC covered load* in regression (3). Admittedly, an optimal approach might incorporate instruments for *renewable energy generation* and/or *FERC covered energy load*.

Additional regressions were conducted to analyze only *battery storage participation* and *renewable energy/demand response participation* policy indicators (Table 3, 6;7). For the first of these regressions, only the unlagged coefficient on *battery storage participation* is significant, among policy indicators (Table 3, 6). For the regression isolating *renewable energy/demand response participation*, only the lagged coefficient is significant. Interestingly, a high Pearson correlation coefficient indicates the possibility of serial correlation for both variables, with the strongest correlation between lagged and unlagged *renewable energy/demand response participation*. For *battery storage participation*, the standard errors for lagged and unlagged coefficients also increase from regressions (1) and (2). These dynamics suggest multicollinearity may be obfuscating results in regressions (6) and (7). Thus, for both *battery storage participation* and *renewable energy/demand response participation*, it remains difficult to deduce whether lagged or unlagged variables dominantly impact LBS deployment. Moreover, given only three significant results across all regressions, the importance of *renewable energy/demand response participation* is questionable (Table 3, 1-7)

6.2 California-level Analysis

Unlagged, the California-specific model yields significant coefficients for several policy indicator variables (Table 4, 1). Echoing results from the FERC-level analyses (Table 3, 4), the unlagged coefficient on *battery storage* is large and significant (Table 4, 1). Notably, due to data constraints, this California-level analysis excludes FERC Order 841. Thus, the coefficient on

battery storage suggests that any policy directly targeting the financial success or participation of LBS may drive substantial deployment. Per the California policy R.15-03-011, this dynamic is probably state-specific while predominantly capturing the effect of FERC Order 825 (Appendix, Policy List 1;2).

The unlagged California model also exhibits a significant coefficient for the *secondary market* variable (Table 4, 1). With less significance and size, this result implies a somewhat muted immediate effect for policies mandating ancillary and capacity markets. Surprisingly, this regression yields the largest coefficient for the *CA renewable energy targe*t indicator (Table 4, 1). The income tax credit for paired renewable energy and battery storage might drive this significant result, whereby LBS is deployed alongside VRE (Deloitte, 2018). Moreover, as stipulated previously, battery storage offers an excellent solution for VRE intermittency. Thus, state renewable energy targets may have the most pronounced immediate impact on LBS deployment, even compared to quotas specifically mandating energy storage. Contextually, California targets do not mandate LBS alone, although it remains the most ubiquitous modular energy storage technology (DOESD).

Looking to the lagged results for California, the coefficient on *battery storage* remains large and significant, up to a year after initial policy implementation (Table 4, 2;3). The coefficient also grows across the first three regressions, suggesting that the impact of *battery storage* policy may continue to expand with longer lags (Table 4, 1-3). *CA renewable energy target* also displays large and significant coefficients for lagged and unlagged variable iterations (Table 4, 1-3). While data restrictions prevent longer lags, state VRE targets might also drive battery storage deployment well into the future. This yield suggests that state renewable energy

Table 4. California-Level Regressions

cum_deployment	(1)	(2)	(3)	(4)	(5)	(6)
bs	**17.908*** **			4.369	**7.718** **	**8.645** **
	(4.039)			(3.534)	(3.367)	(4.001)
L2. bs		**31.071*** **		**18.146*** **		5.529
		(3.295)		(3.733)		(4.773)
L4. bs			**38.448*** **		-6.729	-2.683
			(5.553)		(5.466)	(6.012)
secondary_markt	**4.766***			-0.249	0.808	-0.044
	(2.730)			(2.386)	(2.604)	(2.505)
L2. secondary_markt		**4.320***		3.290		2.629
		(2.383)		(2.280)		(2.546)
L4. secondary_markt			3.628		1.681	-0.094
			(3.674)		(2.064)	(2.229)
redr_partic	-2.314			-2.540	-2.847	-2.480
	(3.129)			(2.271)	(2.155)	(2.092)
L2. redr_partic		-1.746		0.074		-0.816
		(2.674)		(2.293)		(2.190)
L4. redr_partic			-2.718		-0.112	2.523
			(4.050)		(2.313)	(2.376)
ca_bs_targ	5.761			1.458	**6.233** **	2.063
	(3.578)			(2.593)	(2.731)	(2.986)
L2. ca_bs_targ		**9.800*** **		**10.387*** **		**8.350*** **
		(3.014)		(2.684)		(2.848)
L4. ca_bs_targ			**10.362** **		3.917	-1.167
			(4.614)		(3.388)	(3.839)
ca_re_targ	**33.025*** **			**20.293*** **	**37.926*** **	**31.629*** **
	(5.969)			(4.730)	(4.631)	(5.780)
L2. ca_re_targ		**21.880*** **		**11.286** **		1.878
		(5.157)		(5.132)		(5.974)
L4. ca_re_targ			**45.393*** **		**43.298*** **	**27.777*** **
			(8.594)		(4.993)	(8.167)
ca_ret_sales	0.399	-0.568	0.083	-0.066	0.911	0.415
	(0.880)	(0.725)	(1.088)	(0.609)	(0.600)	(0.599)
log_bat_price	2.923	4.269	1.538	0.374	-1.345	2.297
	(5.920)	(4.497)	(6.175)	(4.752)	(5.369)	(5.597)
log_us_gdp_ferc	49.056	**72.368** **	59.980	34.392	7.162	39.056
	(41.514)	(32.561)	(48.205)	(31.294)	(35.118)	(37.257)
re_gen_ca	-0.391	-1.143	3.979	-1.515	3.133	0.137
	(1.858)	(1.641)	(2.155)	(1.408)	(1.356)	(1.657)
_cons	-734.999	-1084.903	-879.838	-501.900	-89.888	-584.544
	(643.509)	(502.234)	(739.053)	(486.578)	(546.811)	(580.253)
Observations	60	58	56	58	56	56
Degrees of Freedom	50	48	46	43	41	36
R^2	0.9566	0.9706	0.9427	0.9825	0.9850	0.9882

1%, 5%, 10% denoted: ***, **, *

targets may be a crucial policy lever for LBS deployment, especially when combined with LBS-specific participatory and compensatory policies.

For regressions (2) and (3), the coefficients on *CA battery storage target* are significant for two and four-quarter lags, although they remained small. While *CA renewable energy target* maintains tremendous impact, results for these regressions also support the effectiveness of California storage-specific targets (Table 4, 2;3). It must be noted that the scale of California's VRE target far exceeds that of its energy storage targets (Appendix, Policy List 2). Energy storage procurement targets have been far smaller, relatively. In turn, this model fails to clearly determine dominance for either state target category (Table 4, 2;3).

Regressions (4-6) were employed to better compare coefficient significance across various quarterly lag structures. These analyses indicate that the deployment impact of *battery storage* policy may be more concentrated around unlagged coefficients. While regression (4) suggests otherwise, both (5) and (6) echo this takeaway. Additionally, *CA battery storage targets* may carry the most sizeable impact on LBS deployment, two quarters after introduction. Such is evidenced by the significant coefficient on the two-quarter lagged variable (Table 4, 4;6).

The temporal dominance of *CA renewable energy target* remains more difficult to isolate. In regressions (4) an (5), both lagged and unlagged coefficients on the variable were significant. While the final regression suggests otherwise, prior results counteract the notion that state renewable energy targets have a nonexistent impact two quarters after policy implementation. However, given lower relative significance and size for the two-quarter lagged coefficient, California renewable energy targets may yield a lessened impact two quarters after enactment (Table 4, 4-6). Drivers for this finding are unclear. Speculatively, long development periods for paired LBS and VRE projects might perpetuate this impact distribution (Mcinerney and Bunn, 2019).

Although coefficients for the *secondary market* variable exhibited some significance in regressions (1) and (2), their relative size was minuscule. Furthermore, the lack of coefficient significance in later regressions suggests less deployment potential for ancillary and capacity markets in isolation (Table 4, 1-6). Categorized ancillary and capacity market policies do create compelling revenue opportunities, but regression results suggest that wholesale market access more effectively encourages mass LBS deployment. Ultimately, California-level analyses demonstrate the power of storage-specific policies and various state targets to drive the deployment of LBS technology. While results are state-specific, locally tailored policies and deployment goals may have a comparable impact within other energy market regions.

7. Conclusion

Lithium-ion Battery Storage (LBS) holds tremendous economic and environmental potential. Crucially, it can stabilize modern grids with increasing shares of variable renewable energy (VRE) generation (Cramton, 2017). LBS technology retains numerous applications on-grid, but its scope for revenue potential depends on energy market policy. A body of literature on LBS does exist, however, no known author has empirically studied policy drivers for the technology's deployment. Thus, this thesis analyzes multiple policy levers impacting the viability of LBS nationally and in California.

Through thirteen permutations of the same model, regression analysis yields insights regarding the policies best equipped to influence LBS development. National regressions, focused on FERC orders, demonstrate the relative power of Order 841 and 825. Analyses for California largely reflect these findings. This supports prior academic sentiment that LBS' economic viability largely rests on wholesale energy market access, relating to FERC Order 841

(Li et al, 2018; Sakti et al., 2018; Winfield et al., 2018). The power of Order 825 also promotes ideas around fair compensation for provision of grid services (Newbery, 2018; Nelson, 2017). California-level analyses reveals the potential of renewable energy targets to influence LBS deployment, in tandem with state goals directly prioritizing energy storage. Meanwhile, policies mandating capacity and ancillary market access may be less effective at promoting development. These quantitative findings confirm the previously theorized necessity of LBS-specific policies at the federal and state level (Sakti et al., 2018).

It should be pointed out that some methodological concerns and limitations do persist. First, a significant number of projects incorporated into both FERC and California dependent variable datasets exist outside of deregulated energy markets. This decision was made entirely due to concerns over data availability and completeness. An ideal dependent variable dataset for LBS deployment would leverage only projects within ISO/RTOs, using a similar FERC policy index. Indexed FERC orders exclusively target these deregulated markets, while the participation of LBS in regulated regions relies more on monopoly utility preference (Sakti et al., 2018). Although datasets for this thesis are dominated by deregulated market projects, added specificity in further research would better isolate the impact of FERC policies. As CAISO projects constitute most state-level observations, regression results for the California analyses may be most representative of wholesale market dynamics.

FERC-level analyses were also challenged by data limitations (elected annual time horizon). Thus, results at the national level may be less accurate than those centered on California. Future studies on LBS deployment should seek updated and more granular datasets, which may be costly and challenging to acquire. A subsequent study might incorporate quarterly regressions nationally. Such models could subdivide across specific LBS types and use cases.

New analyses could also investigate the policy-driven deployment differential between standalone and VRE-paired LBS.

While California-specific analyses shed light on localized policies, future studies could isolate additional states and energy regions. This approach might highlight deployment differences across areas with less VRE penetration and divergent political preferences. As CAISO includes just one state, regressions on multi-state ISO/RTO regions such as PJM or NE-ISO might yield useful results. An independent study on Texas might also prove valuable in this regard, as ERCOT remains outside of FERC jurisdiction and has yet to implement a capacity market (Sakti et al., 2018).

As alluded to previously, the complex temporal and geographic interplay among federal, regional, and local policy renders the isolation of deployment impacts exceedingly difficult (Polzin et al., 2015). This thesis' policy index approach also relies on some degree of subjectivity; other authors might elect different categorizations. State regulations from California's Public Utilities Commission might also suffer from redundancy and suboptimal temporal categorization. Specifically, regulation R.15-03-011 could be categorized later in future studies, as discussed in the Appendix (Appendix, Policy List 2). More broadly, localized policies could be factored into the FERC-level analysis for added analytical specificity. The inclusion of regional policies outside of California might better capture the complexity of FERC orders and ISO/RTO compliance (Orrick, 2020). The practice of assigning new policies an index value of 1 may be limiting as well, since not all policies target the same relative impact. Iterative models should aim to better represent the intended scale of individual policies.

This thesis did not empirically address the direct carbon impact of LBS. Previous literature has modeled the environmental ramifications of standalone LBS, on grid, although the

topic remains academically novel. Theoretically, carbon pricing baked into energy markets might ensure a positive environmental contribution for LBS (Nelson, 2017; Arciniegas and Hittinger, 2012). Future works could attempt to analyze true environmental impacts, amid broader policy modeling considerations.

In conclusion, LBS remains a major component of climate change mitigation through energy decarbonization, when combined with VRE. LBS can actualize a more stable, flexible and efficient grid capable of accommodating a VRE-dominated energy mix. Ultimately, policies granting unrestricted access to wholesale energy markets and additional compensation for grid services may strongly influence LBS deployment, especially within less developed global energy markets. Procurement goals for VRE and energy storage also represent effective deployment drivers.

8. Appendix

Table 5. Summary Statistics for FERC-Level Analysis (2002-2019)

Variable	Obs	Mean	Std. Dev.	Min	Max
cum_deployment	**18**	**287.0631**	**425.6449**	**0**	**1437.819**
bs_partic	18	0.111111	0.323381	0	1
bs_comp	18	0.222222	0.427793	0	1
secondary_markt	18	2.055556	1.830211	0	4
redr_partic	18	2.333333	1.748949	0	4
ferc_cov_load	18	3.31E+09	8.04E+07	3.13E+09	3.42E+09
bat_price	18	2058.511	2285.645	149.6	7865.779
us_gdp_ferc	18	1.46E+07	1341081	1.24E+07	1.71E+07
re_gen_ferc	18	105824.9	93108.18	8251.39	282538.1

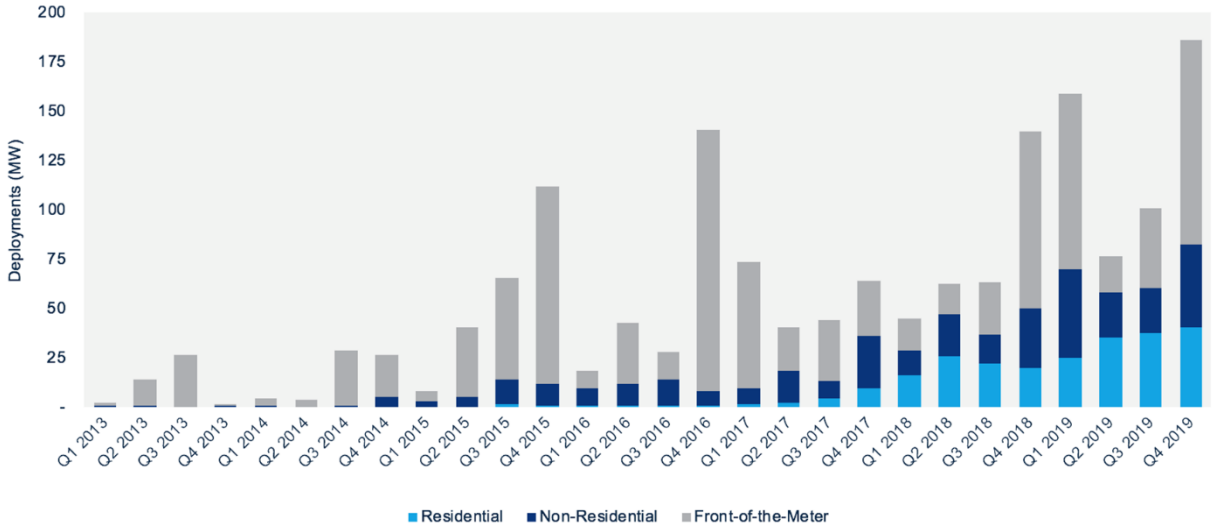
Sources: DOE Storage Database, 2020; U.S. Energy Storage, 2020; Sakti et al., 2018; EIA - Independent Statistics, 2020; Goldie-Scot, 2019; Federal Reserve, 2020

Table 6. Summary Statistics for California-Level Analysis (Q1 2002-Q4 2016)

Variable	Obs	Mean	Std. Dev.	Min	Max
cum_deployment	**60**	**13.5050**	**26.7158**	**0**	**126.788**
bs	60	0.183333	0.503939	0	2
secondary_markt	60	1.533333	1.682076	0	4
redr_partic	60	1.933333	1.686101	0	4
ca_bs_targ	60	0.7	0.96199	0	3
ca_re_targ	60	0.083333	0.278718	0	1
ca_ret_sales	60	919054.1	74677.77	815947.9	1090117
bat_price	60	2404.851	2274.294	260.0892	8534.844
gdp_ca	60	2112730	185613.5	1822762	2530175
re_gen_ca	60	2801.15	2470.9	587	10389

Sources: DOE Storage Database, 2020; Sakti et al., 2020; EIA - Independent Statistics, 2020; Goldie-Scot, 2019; Federal Reserve, 2020

Figure 2. U.S. Quarterly Energy Storage Deployments by Segment (MW)



Sources: U.S. Energy Storage, 2020

Policy List 1. Relevant FERC Orders

1. Order 890 (February 16, 2007)

   This order required that all energy technologies, regardless of whether they generate electricity, should be accounted for similarly to "generation resources in the areas of reliability standards, ancillary services, and transmission expansion planning" (Sakti et al., 2018, p. 570).

2. Order 719 (October 17, 2008)

   This next order primarily improved energy market pricing. In this vein, it was mandated that ancillary prices should be calculated 5 minutes apart (much shorter than intervals used previously). This mechanic led to more variability in the short-term ancillary market which especially benefitted battery storage (Sakti et al., 2018). Order 719 also bolstered demand response and longer-term power contracts, and it strengthened the responsiveness of ISO/RTOs to stakeholder demand. It is crucial to note that energy storage can function as demand response (Sakti et al., 2018).

3. Amendment 745 (March 15, 2011)
   This amendment required that demand response be compensated fairly when rendered cost-competitive compared to more traditional generation sources, within liberalized market environments. This amendment also mandated compensation "based on the locational marginal price (LMP)" (Sakti et al., 2018, p. 571). LMP results in wholesale energy prices that are location dependent and variable. Such reflects the geographic differences in the value of energy due to system constraints (ISO New England, 2019).

4. Order 755 (October 20, 2011)
   This order required that any provision of frequency regulation be compensated fairly, encompassing payments for capacity services and performance. For context, frequency regulation is the active bounding of alternating current frequency on the grid. A variety of assets can provide this service. Ramping up or ramping down individual power plants was traditionally employed to regulate frequency, but battery storage can perform this same grid service more quickly (Frequency Reg…, 2019) Additionally, "Within ancillary services markets, frequency regulation services typically offer the greatest economic opportunity to the owners of energy storage assets, however, the size of the market is very limited" (Sakti et al., 2018, p. 576).

5. Order 764 (June 22, 2012)
   Order 764 required transmission entities to offer scheduling within a smaller window of time (intra-hourly). It also improved energy forecasting standards by requiring data transparency around weather and outages. While this order mainly targeted variable generation (wind and solar), its features benefitted battery storage as well (Sakti et al., 2018)

6. Order 784 (July 18, 2013)
   This order required increased disclosure and transparency in markets for ancillary services. This primarily led to more sophisticated accounting for energy storage operations (Sakti et al., 2018).

7. Order 825 (June 16, 2016)
   Order 825 required fair compensation for the services provided by batteries. Without too much specificity on some of its highly technical features, this order had the potential to double energy storage profitability in some regions due to more frequent short-term price calculations.

8. Order 841 (February 15, 2018)
   This order broadly required that energy storage resources receive more open access to wholesale energy markets. All ISO/RTOs were tasked with building independent models to comply with Order 841. (Sakti et al., 2018) considers this "the most important regulatory change for energy storage resources…" (Sakti et al., 2018, p. 578).

Policy List 2. Relevant California Legislations and Regulations

1. CA AB 2514 (2010)
   This California State Assembly bill mandated the installation of energy storage systems. It required the procurement of 1.3 GW of new energy storage by the year 2020. This target was directed primarily at the State's three major utility companies (DOESD).

2. D.13-10-040 (2013)
   Technically a decision on the implementation of AB 2514, this California Public Utilities Commission regulation established procurement accountability for participating utility companies. It also solidified the goals of AB 2514, enacting an application framework for energy storage procurement (CPUC, 2020; DOESD).

3. R.15-03-011 (opened 2015)
   This second regulation from the California Public Utilities Commission was also put forth in response to AB 2514. Among more granular considerations, it suggested that utility companies should allocatively account for the services provided on-grid by battery storage. Unlike D.13-10-040, the data under which this regulation is categorized did not represent a formal decision. It is, thusly, included and categorized to capture state-level *battery storage participation* policy proceedings within the analytical timeframe of California regressions. Technically, this regulatory aspect was finalized in January of 2018, but public discussions around such a decision likely persisted from 2015 onward. Again, this policy consideration is unique and could be categorized differently if a more up to date dependent variable dataset was available. (CPUC, 2020; DOESD). California-specific analyses only spanned 2002 to 2016.

4. CA SB 350 (2015)
   This California Senate bill set an ambitious 2030 target of 50% renewable energy procurement statewide by 2030. The bill, imparted through a Renewable Portfolio Standard, was enacted on utility companies and retail energy sellers (DOESD).

5. CA AB 2868 (2016)
   As a second storage target, this Assembly bill required California's three large utilities to collectively install an additional 500 MW of energy storage. Notably, the bill is distinct from AB 2514 and prioritizes smaller scale behind the meter storage. Such may be less relevant to this thesis which focuses on large-scale battery storage. Regardless, CA AB 2868 is still included in the California policy index (DOESD).

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