Packing Power: Electricity Storage, Renewable Energy, and Market Design

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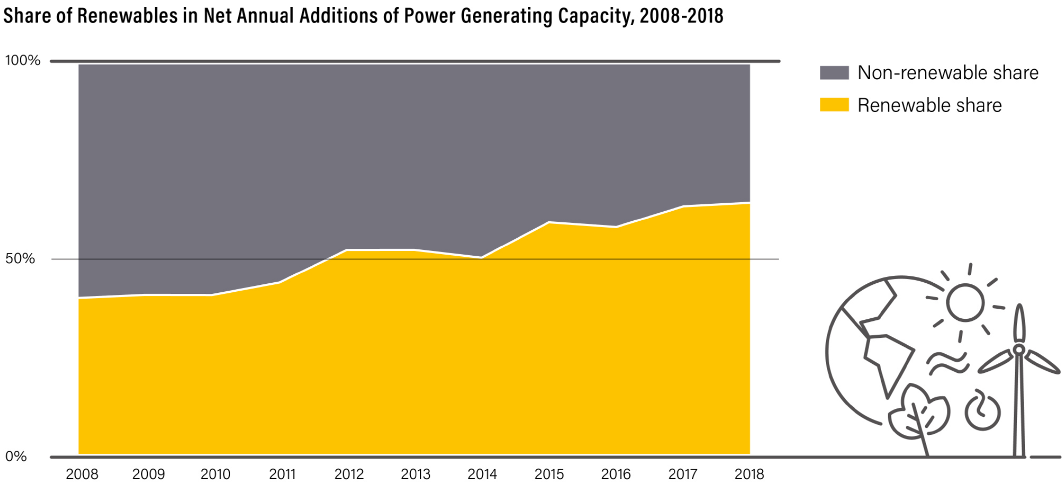
Renewables on the Rise



Source: REN21

Renewables reduce CO_2 emissions but intermittency introduces challenges

- Need to quickly switch to fossil fuel plants as the sun sets or goes behind a cloud

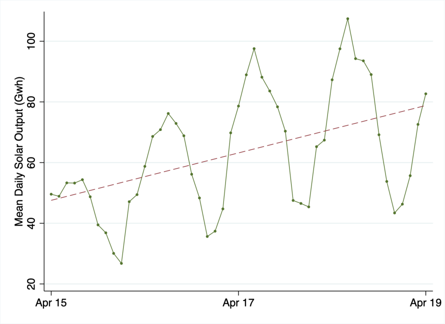
Battery storage offers a promising complement to renewable energy

- Batteries can release energy when the sun is not shining
  - Reduce costs of adjusting power plants
  - Improve grid reliability
- Utilities have long been interested in storage
  - However, relatively high capital costs have limited investment in storage to date
- Climate policy and technological advances are driving a surge in storage investment

Policy Developments

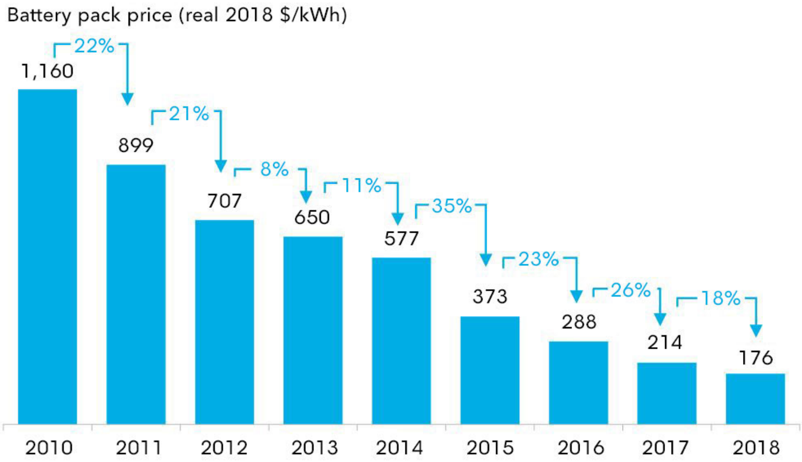
- Several states with renewable energy standards are concerned about grid reliability
- Some new policies incentivize or require battery storage procurement
  - For example:
    - CA has a 60% renewable energy mandate by 2030
    - CA passed a 1.3 GW battery storage requirement by 2024

Figure: California Electricity Generation from Solar PV



R&D Developments

- Heavy R&D in storage tech from firms and academic researchers
- The 2019 Nobel Prize in Chemistry was awarded for work on lithium-ion batteries



Source: BloombergNEF

The purpose of this paper:

- Investigate the value of battery storage as a complement to renewable energy
  - Evaluate value of storage given dynamically optimizing charging and discharging
    - Evaluate storage value over a period when solar energy penetration has grown tremendously
    - How do complementarities between renewable energy and storage affect the break even point of storage?

- Next, we quantify a key dimension that may inhibit battery operators from capturing the estimated values from our dynamic framework
  - Understand how market design affects the value of batteries
    - Current rules prevent batteries from submitting bids that condition on energy in inventory

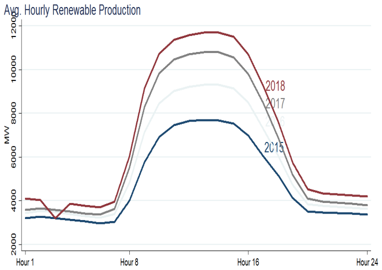
Related Literatures

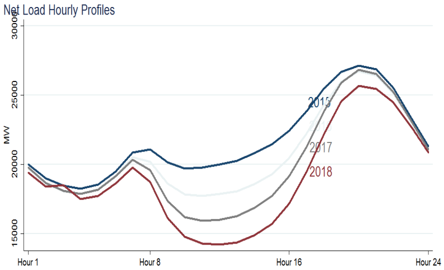
- Studies that evaluates storage value
  - Engineering papers include Mokrian and Stephen (2006), Walawalkar et al. (2007), Sioshansi et al. (2009, 2011), Xi et al. (2014), Mohsenian-Rad (2015)
  - Economics papers include Carson and Novan, (2013), Holladay and LaRiviere (2018), Kirkpatrick (2018), and Karaduman (2019)
- Forecasting and computation of dynamic models
  - Hamilton (1989), Reynolds (2019), Janczura and Weron (2010)
- Market & environmental impacts of new energy technologies
  - E.g., Cullen (2013), Novan (2015), Wolak (2018), Woo et al. (2016), Craig et al. (2018), Bushnell and Novan (2018)

The Focus of Our Study

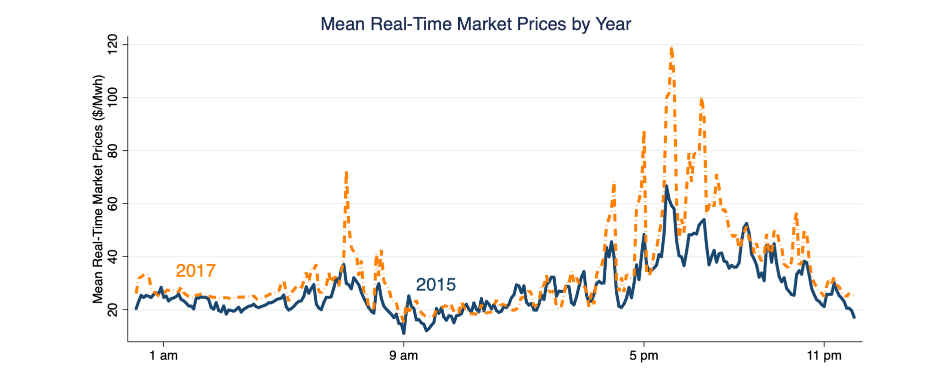
- Evaluate value of storage with California ISO (CAISO) data from 2015-2018
  - Key variables: electricity prices, solar and wind generation, demand
  - Aggregate battery charge/discharge quantities every 5 minutes in 2018
- Why California?
  - Over a third of all solar PV capacity in the entire US!
  - Huge growth over our sample period
- Innovations of our study:
  - Focus on evaluating complementarity between storage and renewables, more focus on market mechanisms, and forecasting
  - Valuations take seriously forecasting, uncertainty, and high frequency data
  - Use variation in renewable energy penetration and battery charging decisions
- Biggest limitations:
  - We do not model fact that large-scale battery installations will lower equilibrium price dispersion (and thereby lower value of battery storage)

Renewable Energy Penetration in CA Has Led to the “Duck Curve”





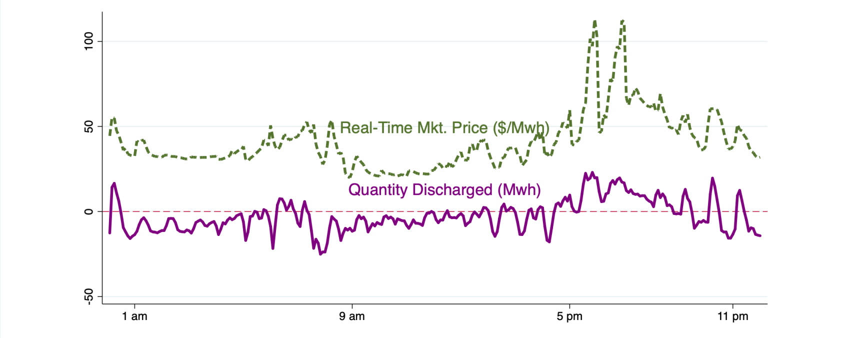
Prices Spike With the Duck Curve



Batteries Act as Arbitrageurs, Following Prices

- Batteries profit from charging when price is low and discharging when price is high
  - This reduces generation costs by allocating production to times when lower cost power plants are available
  - Reduces adjustment costs by smoothing production over time

Figure: Mean Observed Battery Output, May 2018 - April 2019



Theoretical model

- We model decisions of a battery owner
  - Normalize capacity to 1
  - Denote per-period discount factor as β
  - Assume battery owner takes prices as given
- State space:
  1. Time interval over day, i
     - $I = 288$ periods (5 minutes each) over one day
     - Easily extends to one-week problem to capture weekends
  2. Price residual, ε_j, $j = 1, \ldots J$; and "regime", R_t
  3. Amount stored, $s \in [0, 1]$
- Decision: a firm at state $(i, s, \varepsilon_j, R_t)$ chooses optimal charge/discharge amount
- Technology:
  - Some energy is lost while charging/discharging:
    - Charging c units requires purchasing c/υ units, $0 < \upsilon < 1$
    - Discharging c units generates $c\upsilon$ units
  - Batteries have a maximum charge rate F

A Model for Prices

Our model for prices attempts to incorporate much of the institutional detail of CAISO:

- Each hour maintains a real-time market at the 5 minute frequency
- High autocorrelation, abbreviated extremely high, and negative prices

Thus, prices evolve at the 5 minute frequency according to a 3-regime model:

$$p_t = \begin{cases} p_t^1 = \mu_{i(t)} + \rho\left(p_{t-1}^1 - \mu_{i(t-1)}\right) + u_t^1 & u_t^1 \sim F^1(\cdot) & \text{if } R_t = 1 \\ p_t^2 = u_t^2 & u_t^2 \sim F^2_{(100,\overline{U})}(\cdot) & \text{if } R_t = 2 \\ p_t^3 = u_t^3 & u_t^3 \sim F^3_{(\underline{U},0)} & \text{if } R_t = 3 \end{cases}$$

$$\text{Prob}\left[R_{t+1} = jj\right] = \gamma^{jj}_{h(t+1)}$$

- $\mu_{i(t)}$: interval-of-day fixed effect ($\varepsilon_t = p_t^1 - \mu_{i(t)}$).
- ρ: AR(1) process.
- $\gamma^{jj}_{h(t)}$: hour-of-day specific regime probability.

We estimate each regime with rolling 12 month windows.

Bellman equation

$$V(i, s, \varepsilon_{jt}, R_t) = \max_c \Big\{ -(\mathbb{1}_{\{c>0\}} c/\upsilon + \mathbb{1}_{\{c<0\}} c\upsilon) p_t(\varepsilon_{jt}, R_t) +$$

$$\beta \sum_{j'=1}^{J} V(i + 1 - \mathbb{1}_{\{i=I\}} I, s + c, \varepsilon_{j' t+1}, R_{t+1}) Pr(j', R_{t+1} | j, R_t) \Big\}$$

where charge amount satisfies:

1. Instantaneous charge restriction: $-F/\upsilon \leq c \leq F\upsilon$
2. Capacity restriction: $0 \leq s + c \leq 1$

Note that:

- Time loops through from 1 to I
- Conditional probabilities $Pr(j', R_{t+1} | j, R_{t+1})$ depend on our model for prices (discretized)

Computation of dynamic solution

Number of states:

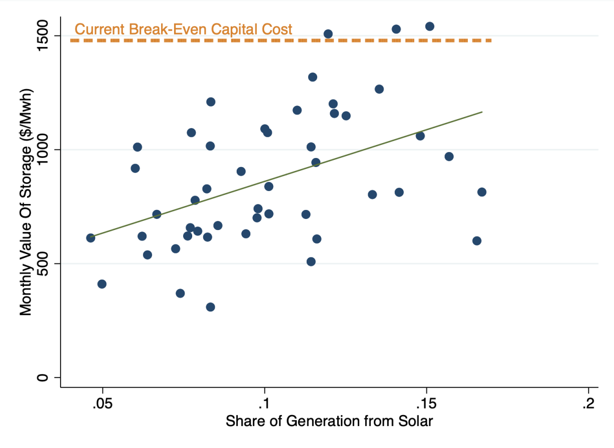
- 100 resid. price states $\times$ 40 discretized charge levels $\times$ 288 periods $=$ 1,152,000
- A lot!

Our computation method:

1. Policy iteration
    - Iterate on:
        A. Period profits π and transition matrix Q
        B. Value $V = (I - \beta Q)^{-1}\pi$
    - Works well with β close to 1
    - But requires matrix inverse, limiting to about 20,000 states
2. New methods that leverage sparseness of transitions
    - Transition always from i to $i + 1$
    - Also, deterministic transition to $s + c$

Computational Details

Results: Value of Storage vs Solar Share of Generation



- Measures realized values given policies calculated from Bellman equation

Regressions: Storage Value and Solar Generation

$$\log\left(\mathit{Storage\ Value}_i\right) = \beta_0 + \beta_1 \log\left(\mathit{Solar}_i\right) + \beta_2 \log\left(\mathit{Load}_i\right) + \beta_3 \mathbf{X_i} + \varepsilon_i.$$

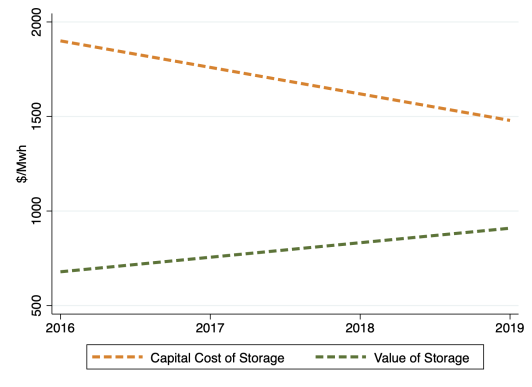
	(1)	(2)
Log(Mean Solar Generation)	0.553***	0.865**
	(0.152)	(0.320)
Month FE	No	Yes
NG Price Control	No	Yes
N	48	48

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When Does Battery Investment Break-Even?

- Each one percentage point increase in solar generation is associated with a 0.86% increase in the value of storage
- Extrapolation of this association $\Rightarrow$
  - Batteries will become cost effective if:
    - Solar generation share reaches 25% penetration with current costs
    - Or if battery costs fall by 38% at current solar generation levels

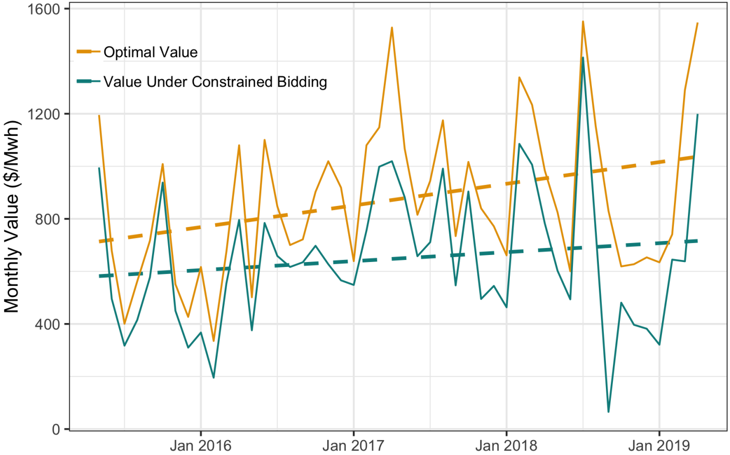


Electricity Market Design and the Value of Storage

- Batteries may not recover the value reported in the previous results due to current market rules
- Market rules do not allow batteries to condition their bids on the energy level in their inventory (i.e. how full the battery is)
  - They can only condition bids on the history of prices and the time of day
- Counterfactual Experiment:
  - Calculate profitability of battery using observed prices but where charge/discharge amount is the same across energy inventory levels, given price history and time of day

Value of Better Market Design

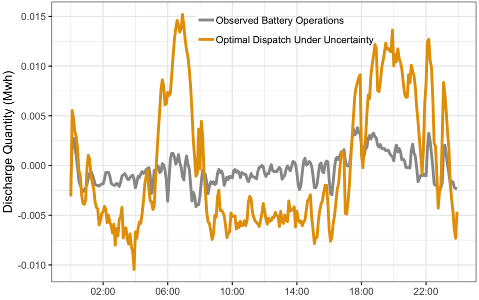
- Over our sample period, the bidding restrictions to not allow bids to depend on the stock of energy held lower the value by 26%.
- This difference in values has been growing over time.



Observed vs Optimal Battery Operations

- Results show the potential value of storage has increased substantially, but that market rules may limit the extent this value can be recovered by battery operators.
- In April 2018, CAISO began publishing aggregate battery output (charge/discharge) quantities
  - We compare optimal storage dispatch from our model with observed battery output.

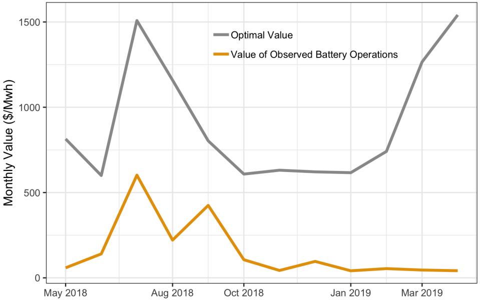
Figure: Observed vs. Optimal Storage Dispatch by Time of Day



Observed vs Optimal Battery Operations

- Optimal policy suggests that batteries should be changing output levels more frequently within hours as well as across hours
  - Our optimal policy suggests battery should be cycling 1.68 times per day on average relative to the average of 0.54 cycles per day observed in the data
  - Between May 2018 and April 2019, the observed behavior from the existing fleet of batteries recovers only 16% of the value recovered by the optimal policy.

Figure: Value of Observed vs. Optimal Storage Dispatch by Month

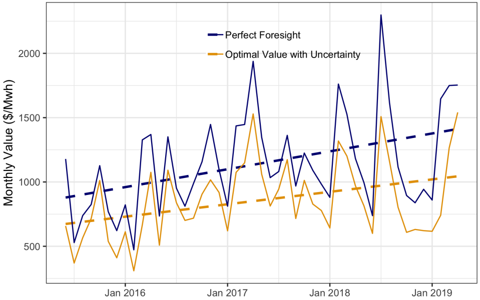


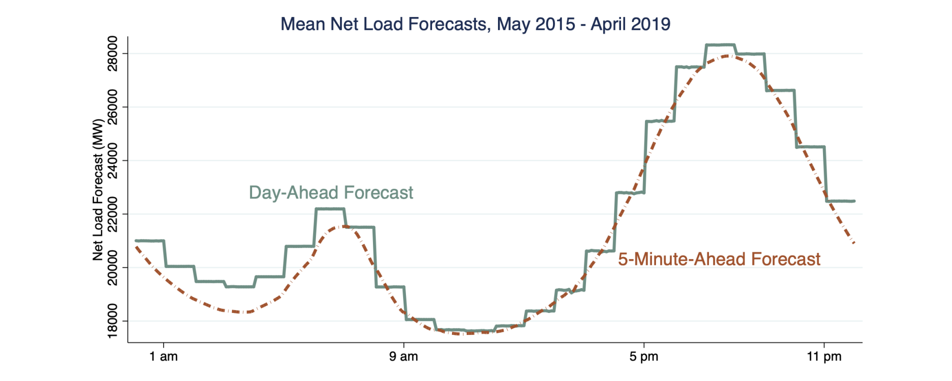
Conclusions and Next Steps

- Solar penetration is creating more price variation
  - Doubling of solar penetration greatly increased the value of battery storage
- We are quite near utility-scale batteries being break even
  - Trend lines show that this will occur in about two years
- But, value of batteries is affected by market design
  - CAISO energy market design lowers profitability of batteries by 26%
  - Appears that CAISO batteries could be dispatched efficiently
- Lots to do:
  - Improve price forecasting
    - Will only increase value of batteries
  - Understanding optimal battery adoption and policies
  - Counterfactuals with equilibrium price changes?
  - You tell us!

Additional Results: Measuring the Value of Improved Forecasts

- Prices have become more unpredictable over time
  - This could reduce the value of storage
- We obtain an upper bound on the value of improved forecasts
  - Solve the storage problem given perfect foresight about future prices
- Perfect foresight adds 33% to the value of storage,
  - Better forecasts add more value with more solar generation





Mean Net Load Forecasts, May 2015 - April 2019
Net Load Forecast (MW)
28000
26000
24000
22000
20000
18000
Day-Ahead Forecast
5-Minute-Ahead Forecast
1 am
9 am
5 pm
11 pm

RTM Prices

Details on computation

- We perform policy iteration *for one period only*
  - Value for other periods solved with backward recursion
- For a given policy:
  - Let Q_t be the transition matrix at time t to the next time ($t+1$ or 1)
  - V_t be the vector of values for all states at time t
  - π_t be the vector of per-period profits for all states at time t
- Idea is to perform policy iteration T (instead of 1) periods ahead
- Define:

$$\Pi_1 = \pi_1 + \beta Q_1 \pi_2 + \ldots + \beta^{T-1} Q_{T-1} \cdots Q_1 \pi_{T-1}$$

- Then,

$$V_1 = \Pi_1 + \beta^T Q_T \cdots Q_1 V_1 \Rightarrow V_1 = (I - \beta^T Q_T \cdots Q_1)^{-1} \Pi_1$$

  - $V_T, V_{T-1}, \ldots, V_2$ can then be quickly solved with one-step backward recursion
- Why is this method effective?
  - Matrix inverse limited to dimension 4000 (charge levels times price residuals)
  - Method results in computation time that is linear in number of periods

▸ Computation