Economics of Grid-Scale Energy Storage

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Abstract

The transition to a low-carbon electricity system is likely to require grid-scale energy storage to smooth the variability and intermittency of renewable energy. I investigate whether private incentives for operating and investing in grid-scale energy storage are optimal and the need for policies that complement investments in renewables with encouraging energy storage. In a wholesale electricity market, energy storage systems generate profit by arbitraging inter-temporal electricity price differences. In addition, storage induces non-pecuniary externalities due to production efficiency and carbon emissions. I build a new dynamic equilibrium framework to quantify the effects of grid-scale energy storage and apply it to study the South Australian Electricity Market. This equilibrium framework computes a supply function equilibrium using estimated best responses from conventional sources to observed variation in the residual demand volatility. Accounting for storage's effect on equilibrium prices is quantitatively important: previous methods that ignore this channel overestimate the profitability of operating a storage unit. The first set of results shows that although entering the electricity market is not profitable for privately operated storage, such entry would increase consumer surplus and total welfare and reduce emissions. A storage operator that minimizes the cost of acquiring electricity could further improve consumer surplus by twice as much. Importantly, a competitive storage market cannot achieve this outcome because other power plants distort prices. These results argue for a capacity market to compensate for a private firm for investing in storage. The second set of results shows that at moderate levels of renewable power, introducing grid-scale storage to the system reduces renewable generators' revenue by decreasing average prices. For high levels of renewable generation capacity, storage increases the return to renewable production and decreases CO_2 emissions by preventing curtailment during low-demand periods.

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1 Introduction

Energy storage is the capture of energy produced at one time for use at a later time. Without adequate energy storage, maintaining the stability of an electric grid requires equating electricity supply and demand at every moment. System Operators (SO) that operate deregulated electricity markets call up natural gas or oil-fired generators to balance the grid in case of short-run changes on either side. These peaker units are generally fast and flexible, but due to rapid adjustments in their heat rates, they are inefficient and emit high levels of carbon. Production of Variable Renewable Energy (VRE) resources, such as wind and solar energy, exacerbates the gap between demand and supply due to their short-run variability in output. Energy storage presents a more efficient and environment-friendly alternative.

A grid-scale energy storage firm participates in the wholesale electricity market by buying and selling electricity. Energy storage creates private (profit) and social (consumer surplus, total welfare, CO_2 emissions[1]) returns. Storage generates revenue by arbitraging inter-temporal electricity price differences. If storage is small, its production does not affect prices. However, when storage is large enough, it may increase prices when it buys and decrease prices when it sells. This has both pecuniary and real effects on welfare. The price arbitrage transfers surplus between producers and consumers. The production of storage also shifts the production of electricity from peak periods to off-peak periods. The shift in production between generating units affects production costs and CO_2 emissions. Moreover, storing energy also allows increased utilization of available capacity for VRE when supply exceeds demand. Without storage, generation from these sources has to be curtailed.

In this paper, I ask whether the private and social incentives for investing and operating energy storage in wholesale electricity markets are aligned. To answer this question, I develop a dynamic framework to quantify the potential effects of energy storage in the wholesale electricity market. My model uses data from an electricity market without energy storage to simulate the equilibrium effects of a hypothetical storage unit on electricity markets. I cast the storage operator's arbitrage problem as an infinite horizon dynamic optimization with uncertainty. The charge level of storage links one period to the next. The storage operator creates revenue by arbitraging short-run inter-temporal electricity price differences. I account for the effect of this arbitrage on prices and find a new market equilibrium in which I allow incumbent firms to respond to storage's production. An important challenge in this analysis is to obtain counterfactual supply function equilibria, which is usually computationally intractable and not unique (Klemperer and Meyer (1989), Green and Newbery (1992)). I solve this challenge by modeling incumbent firms' best responses by treating storage's production as a shock to the distribution of residual demand conditional on a public sig-

[1]In this paper, I am excluding emissions' impact on welfare. My approach can incorporate emissions costs into the welfare analysis for any given level. I discuss the extent of emissions impacts on welfare in Section 6.

nal. Thus, to solve for a new equilibrium, I compute a supply function equilibrium using estimated best responses to observed variation in demand volatility in a market without energy storage.

In my model, private returns to storage are maximized by trading on intra-day price fluctuations in the wholesale electricity market. These would be facilitated by fast response arbitrageur technologies like batteries. This focus is also motivated by the rapidly decreasing cost of grid-scale batteries; the last decade saw a 70% reduction in the price of lithium-ion battery packs. Batteries have several advantages over other available energy storage technologies. First, batteries provide faster adjustable production. High flexibility creates an advantage for batteries in responding to short-run price variations and intermittency of renewables. Second, batteries can operate across larger geographic areas. Installing a battery on any part of the power system does not require considerable further investment in the grid. Third, batteries are scalable: they use a similar type of technology regardless of their size.

To model the decision of firms, I represent the electricity market as a multi-unit uniform price auction. Each day, before the auction, firms observe a public signal that contains information such as publicly available demand and renewable production forecasts, and they then bid into the electricity market a day ahead of the actual production. I solve the storage operator's dynamic optimization problem using discrete-time finite-state value function iteration methods, given incumbent firms' strategies. Then, I model storage's production as a shift to demand. Storage decreases the demand when it is producing and increases the demand when it is charging. I estimate incumbent firms' best responses to this shift in demand by using observed variation in demand in a market without energy storage. Storage updates its best response conditional changes in thermal generators' strategy. The fixed point of this process gives new market equilibrium strategies.

In this research, I use South Australia (SA) Electricity Market data from July 2016 – December 2017.[2] In the observed period, generation in SA consists of almost 50% VRE and 50% gas-fired generators. This generation mix is a good candidate for an economically optimal low-carbon electricity production portfolio (De Sisternes et al. (2016)). It also produces some of the highest price variability among electricity markets in the world, which creates a favorable environment for energy storage. The high penetration level of VRE also creates a large variation in residual demand, which helps my model to recover firms' best responses to storage's production.

I evaluate the private and social returns of hypothetical energy storage by estimating equilib-

[2]In 2018, the world's largest lithium-ion battery at the time, Hornsdale Power Reserve (HPR), came online in SA. This also favors this market for being a test case for energy storage. Tesla Inc. built HPR for a cost of AU$70 million after its CEO Elon Musk wagered "100 days from contract signature or it is free". HPR is privately operated, with the government having the right to call on the stored power under certain, undisclosed circumstances. The unknown features of this contract make the storage operator's objective unclear. Also, around the same time, VRE capacity in SA increased by around 40%, which creates problems for identifying the observed impact of the storage addition. Therefore, I use this period's data only for comparison and illustration purposes.

rium strategies in the electricity market. I allow the decisions of grid-scale energy storage to affect prices. My results suggest that accounting for the equilibrium effects of storage is important for understanding the efficiency of the market. This result holds even for a unit that is only 5% of the average daily capacity.[3] Both the private and social returns are sensitive to this calculation. Previous methods that ignore this channel overestimate the profitability of operating a storage unit by two-fold. Incumbent firms change their bidding strategies in response to the production of energy storage. This response occurs because storage's activity changes thermal firms' residual demand, and therefore, their market power. From a theoretical perspective, it is unclear how incumbent firms update their bidding strategies in response to a change in the level of demand (Vives (2010), Genc and Reynolds (2011)). I find that in the presence of energy storage, incumbent firms bid more aggressively; in other words, energy storage helps to mitigate market power in electricity markets. Accounting for generators' best responses decreases the storage operator's profit by 10% and increases consumer welfare by 10%.

Next, I ask whether the absence of grid-scale storage is socially inefficient at current costs. I find that due to high investment costs, entering the electricity market is not profitable for privately operated storage. However, such entry would increase consumer surplus and total welfare while also reducing CO_2 emissions. The storage-induced consumer surplus change is two times as large as the storage operator's profit, and the combined benefits are higher than the investment cost. This difference in private and social returns makes investing in storage unprofitable but socially desirable, which presents an under-investment problem. Additionally, unlike the previous literature on storage's CO_2 emissions effect (Hittinger and Azevedo (2015), Lueken and Apt (2014)), I find that storage decreases emissions in a market like SA. These results argue for a capacity market to compensate a private firm for investing in storage.

This under-investment problem suggests a public policy response, including the form of regulation that should be enacted. A hotly debated area is who should be able to own and operate storage units. In 2018, California Public Utility Commission mandated utilities to invest in around 2 GW capacity of storage. In contrast, Texas utilities are not permitted to own storage. Federal Energy Regulatory Commission (FERC) does not allow SOs to use energy storage as a generating or transmission asset. I consider different ownership structures for energy storage: monopoly, load (consumer) owned, and competitive. I find that load-owned storage, which operates the unit to maximize consumer surplus, almost doubles the consumer surplus increase. To address potential market power concerns of a monopoly storage operator case, I also evaluate a perfectly competitive storage market. Importantly, a competitive storage market increases total welfare but would not yield a socially better outcome than the load-owned storage. In this case, profit and consumer surplus increases are closer to the monopoly storage case than the load-owned case. This differ-

[3] The average flexible generation in SA is around 600 MW. These results hold for 120 MWH 30 MW storage.

ence shows that the storage operator's market power is important, but price signals are not the right incentives to maximize social incentives, even when there is no market power, because other firms distort prices.

Many countries and states subsidize investment in VRE to reduce greenhouse gas emissions. Energy resources such as solar and wind power produce electricity at almost zero carbon emission but with high variability in output that depends on weather conditions rather than demand. These VRE resources are only available at certain times; it is non-dispatchable and intermittent. Solar generators produce electricity only when the sun is shining, and wind generators produce electricity only when the wind is blowing. Therefore, the expansion of VRE capacity amplifies short-run differences between demand and supply. Grid-scale energy storage can bridge this gap efficiently, making it an important complement to VRE expansion. In February 2018, FERC issued a final rule (Order 841) requiring SOs in the US to establish a participation model for energy storage in electricity markets.

Finally, I quantify the complementarity between VREs and grid-scale storage. I study the interaction between these technologies by assessing changes in their revenues as renewable generation is increased. At moderate levels of renewable power, when there is almost no curtailment for VREs, I find that introducing grid-scale storage to the system reduces renewable generators' revenue by decreasing average and peak prices. This is the current situation in South Australia, and below that, in most electricity systems worldwide. However, when VRE capacity is doubled from this base, storage increases the return to renewable production and decreases CO_2 emissions by preventing curtailment. Higher VRE capacity also leads to higher revenue for energy storage as a result of an increase in price variation. This non-monotonic relation between returns for VRE and energy storage investment leads to a need for more carefully designed policies that complement investments in renewables with encouraging energy storage.

Related Literature This paper contributes to four different literatures. First, this paper contributes to the work exploring the value of energy storage. Several engineering-oriented studies focus on energy storage's private benefits (e.g., Graves et al. (1999) McConnell et al. (2015), Salles et al. (2017)), its role in low-carbon electricity systems (De Sisternes et al. (2016)), and its effects on social welfare (e.g., Sioshansi et al. (2009) , Sioshansi (2014))[4].

The novelty of my approach relative to previous research on the value of energy storage is modeling storage-induced price effects explicitly and allowing incumbent generators to respond to resulting price changes. Much of the previous literature ignores these channels and makes price

[4]Other engineering studies include the interaction between storage and CO_2 emissions (Hittinger and Azevedo (2015), Lueken and Apt (2014)), storage and renewables (Sioshansi (2011)), and storage's ownership (Sioshansi (2010), Siddiqui et al. (2019)).

taker assumption for storage. For small-scale storage, the assumption in the previous literature may be fine. However, as storage gets larger, this assumption overestimate its profitability. Additionally, failure to model price changes and generators' responses to price effects results in large biases in estimated social returns that include consumer welfare and CO_2 emissions changes.

Second, this paper contributes to a large literature in economics on liberalized wholesale electricity markets by introducing energy storage technology. My paper studies energy storage's market power (e.g, Wolfram (1999), Borenstein et al. (2002), Wolak (2003), Mansur (2008)) and strategic behavior in multi-unit auctions (e.g., Wolak (2007), Hortacsu and Puller (2008), Reguant (2014)). In this literature, dynamic considerations of firms are usually ignored or simplified due to non-essential cost complementarities of conventional technologies. In this paper, the inherently dynamic nature of the storage operator's problem requires a more detailed dynamic approach.

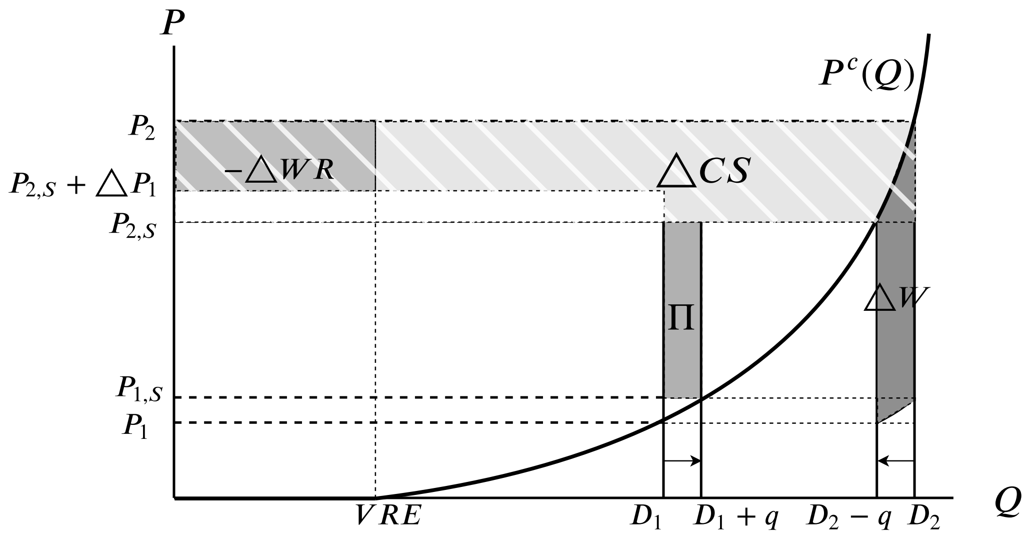
Third, this paper contributes to the small but growing literature in economics on energy storage. Carson and Novan (2013) focus on several battery storage technologies' effects on emissions by using hour-specific marginal emission rates in Texas ERCOT. They find that energy storage increases carbon emissions. However, this result depends on the generation mix in the electricity market. In general, the production of low-cost CO_2 intensive generators like coal power plants in the electricity network drives this result. I find that in SA energy storage decreases emissions in most scenarios, even in the absence of carbon pricing. SA's generation mix is a better candidate for an economically optimal low-carbon electricity production portfolio, and therefore may be a better representation of the environmental impact of energy storage on future electricity grids.

Overview The remainder of this paper is organized as follows: Section 2 illustrates the private and social returns to storage in a simple electricity market, highlights the basic forces behind these returns, and motivates my empirical strategy. Section 3 describes the SA market data I use in my analysis. Section 4 develops a model of strategic behavior in the electricity market that incorporates the storage operator's dynamic profit maximization decision. Section 5 outlines the empirical strategies I use. Section 6 discusses estimates of the private and social returns to storage. Section 7 concludes.

2 Basic Economics of Energy Storage in Wholesale Electricity Markets

This section provides several graphical illustrations of different parts of my model. First, I describe (given storage's fixed level production) how electricity production and prices change in the wholesale electricity market. Second, I demonstrate the uncertainties and parameters in the storage operator's problem. Finally, I show how other firms in the market respond to storage-induced price changes.

Figure 1: Perfectly Competitive Electricity Market



If storage is large, private incentives are not socially optimal.

2.1 Storage's Price Effect

In this section, I illustrate storage's private and social returns in a simple electricity market to highlight the basic forces behind these returns and motivate my empirical strategy. I use a "merit-order" curve as a stylized depiction of the electricity market supply. This arranges generation sources in order of increasing marginal cost or willingness to produce. The System Operator (SO) dispatches generation in this order to meet the market demand at the lowest cost, and clears the market at market prices. I assume the merit-order curve is convex.

Figure 1 illustrates the effects of storage's price arbitrage on storage's profits, welfare, consumer surplus, and VRE generation revenue. To simplify exposition, I begin by assuming that the electricity market is perfectly competitive. In this case, the merit order curve $P^C(Q)$, is simply the schedule of marginal costs of each generators. Figure 2 demonstrates the same effects by relaxing the perfect competition assumption in wholesale electricity markets, adding a market power supply realation $P^m(Q)$ that lies about the competitive $P^C(Q)$ cost curve. In both cases, I assume perfectly inelastic demand, as is the case in electricity markets with no demand-side price responsiveness (e.g., when customers do not face real time prices), and abstract away from externalities due to emissions.

2.1.1 Perfectly Competitive Electricity Markets

In a perfectly competitive electricity market, price is a perfect signal for the marginal cost because every producer bids its marginal cost. Let $P^C(Q)$, the inverse of the supply function, be the aggregated marginal cost function of generators in the market. There are two periods, off-peak with low demand D_1 and peak with high demand D_2, where prices are $P_1 = P^C(D_1) < P_2 = P^C(D_2)$, respectively. Same VRE production, VRE units, available at cost 0 in both periods. When VRE is higher, it shifts $P^C(Q)$ to the right. The SO uses multi-unit uniform price auctions, so consumers pay $P^C(Q^*)$ for each unit of their consumption of Q^* units of electricity.

To engage in arbitrage, the storage operator buys $q < \frac{D_1+D_2}{2}$ in period 1 and sells it in period 2, assuming that storage works with 100% efficiency with no operational cost. Since demand is inelastic, storage production q will have the same effect as a q shift in demand: storage increases D_1 by q and decreases D_2 by q. Storage's production smooths prices, as new prices are set for both periods, $P_{1,S} > P_1$ and $P_{2,S} < P_2$. Let $\triangle P_1 = P_{1,S} - P_1$ and $\triangle P_2 = P_2 - P_{2,S}$. Since $P^C(Q)$ is convex, in Q the average price for the two periods decreases, $\triangle P_2 > \triangle P_1$.

The storage operator profits from the inter-temporal price difference and induces pecuniary and non-pecuniary effects. A pecuniary externality arises due to the change in prices for inframarginal units. As q increases, inframarginal units become more expensive in period 1 and less expensive in period 2, which drives the change in the cost of electricity acquisition. This change is a transfer from producers to consumers. Since consumers use more energy in period 2, $D_2 > D_1$, and $P^C(Q)$ is convex, the overall consumer surplus increases. VRE generators' production does not change, but the decrease in average price decreases its revenue.

Non-pecuniary externality arises due to production efficiency differences. Storage's production, q, shifts the marginal generator in the market between periods and changes production allocation. The extra q units of production in period 1 replace the last q units of production in period 2. Since the inframarginal units produce the same amount and demand is not flexible, the total welfare change is the difference in the cost of electricity production of an extra q units in period 1 and the last q units in period 2. The merit-order, $P^C(Q)$, is increasing in Q. Therefore, this production shift lowers the total cost of production and increases total welfare. Storage's profits, the changes in welfare, consumer surplus, the VRE generator's revenue, and the thermal producer surplus are represented by:

$$
\begin{aligned}
\Pi &= \big(P^C(D_2-q) - P^C(D_1+q)\big)q, \\
\triangle W &= \int_{D_2-q}^{D_2} P^C(Q)dQ - \int_{D_1}^{D_1+q} P^C(Q)dQ, \\
\triangle CS &= \big(P^C(D_2) - P^C(D_2-q)\big)D_2 - \big(P^C(D_1+q) - P^C(D_1)\big)D_1, \\
\triangle WR &= \big(-P^C(D_2) + P^C(D_2-q) + P^C(D_1+q) - P^C(D_1)\big)VRE. \\
\triangle TPS &= \triangle W - \Pi - \triangle CS - \triangle WR.
\end{aligned}
$$

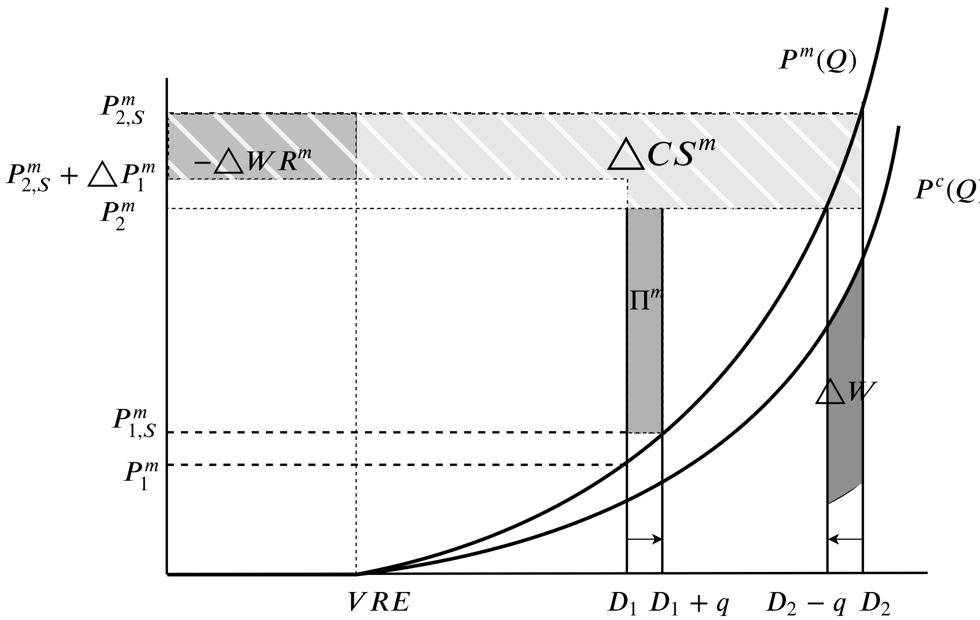
The private and social incentives for storage's production are not necessarily aligned. The change in consumer surplus is a function of the price effect of storage's production, where storage's profit is a function of price differences between periods. If $P^C(Q)$ is steeper, the price effect $\triangle P_1$ and $\triangle P_2$ is larger , and therefore $\triangle CS$ is bigger. However storage's profit, Π, decreases since the price difference between periods is smaller. Notice that here the welfare change is larger than storage's profit, $\triangle W > \Pi$. This is mostly due to the perfect competition assumption; this relationship does not necessarily hold in imperfectly competitive markets (see Figure 2.1.2).

The change in average prices decreases VRE revenue since VRE production is the same in both periods. However, this effect also depends on the VRE production profile. An important factor for the magnitude of this effect is the correlation of VRE production and prices. Storage's higher price effects during peak periods, $\triangle P_2$, decreases prices more than it increases prices during off-peak periods, $\triangle P_1$. Therefore, if the correlation between VRE production and prices is high, then storage's price effect hurts VRE revenue more. In Section 6.4, I discuss the relation between storage and VRE in more detail.

In order to check how much a change in q changes storage's profits, welfare, consumer surplus, and VRE generator's revenue, let us look at the first-order conditions w.r.t. q:

$$
\begin{aligned}
\frac{\partial \Pi}{\partial q} &= P^C(D_2-q) - P^C(D_1+q) - \Big(\frac{\partial P^C(D_2-q)}{\partial q} + \frac{\partial P^C(D_1+q)}{\partial q}\Big)q \\
\frac{\partial \triangle W}{\partial q} &= P^C(D_2-q) - P^C(D_1+q) \\
\frac{\partial \triangle CS}{\partial q} &= \frac{\partial P^C(D_2-q)}{\partial q}D_2 - \frac{\partial P^C(D_1+q)}{\partial q}D_1 \\
\frac{\partial \triangle WR}{\partial q} &= \Big(-\frac{\partial P^C(D_2-q)}{\partial q} + \frac{\partial P^C(D_1+q)}{\partial q}\Big)VRE \\
\frac{\partial \triangle TPS}{\partial q} &= -\frac{\partial P^C(D_2-q)}{\partial q}(D_2 - VRE - q) + \frac{\partial P^C(D_1+q)}{\partial q}(D_1 - VRE + q).
\end{aligned}
$$

Figure 2: Imperfectly Competitive Electricity Market



When storage's production, q, is small, the price effect is negligible. Without storage's price effect, profit and welfare maximization incentives are aligned. As storage's production, q, increases, its price effect increases, and private and social incentives diverge. A higher q, and therefore a higher price effect, increases consumer surplus and decreases VRE revenue, but the price effect can decrease Π. An increase in storage's deployment increases welfare and consumer surplus but decreases thermal and VRE revenues until the quantities sold in both periods are equal. Larger q creates more market power for storage. Its production smooths prices and decreases arbitrage opportunities. Therefore, the storage operator has incentives to under-produce. However, the effect of a change in q on Π is ambiguous. Section 2.2 shows how storage picks the optimal q.

2.1.2 Imperfectly Competitive Electricity Markets

Most electricity markets are characterized by generators with market power and firms do not necessary bid the short-run marginal cost of their units (Wolfram (1999), Joskow and Kahn (2001), Borenstein et al. (2002)).[5] Figure 2 illustrates an inverse of the aggregated supply function where firms bid more than their marginal cost, $P^m(Q) > P^C(Q), \forall Q$. WLOG, I assume the same merit-order is maintained; therefore, the marginal cost curve, $P^C(Q)$, is the same as in Figure 1. I also assume the difference between marginal cost and the firm's supply function, the markup, increases

[5]Especially around peak demand periods firms may have incentives to put higher markups on their bids. Some generators with high production adjustment cost (ramping cost), such as nuclear, may have incentives to bid lower than their marginal cost to make sure they continue to produce at low demand periods.

in quantity, $\frac{\partial P^m(Q)}{\partial Q} > \frac{\partial P^C(Q)}{\partial Q}, \forall Q$.[6] Notice that the market power of firms distorts the price signal. Therefore prices in an imperfectly competitive markets are higher than in the perfectly competitive case, $P_1^m > P_1$ and $P_2^m > P_2$. In addition, the increasing markup creates more price variation between the two periods, $P_2^m - P_1^m > P_2 - P_1$.

The higher price volatility gives more room for engaging in arbitrage; therefore, the storage's profit for a given q is higher in the imperfectly competitive case, $\Pi^m > \Pi$. The inverse of the supply curve $P^m(Q)$, is steeper than $P^C(Q)$; therefore storage's price effect is larger. Due to larger price effects, changes in consumer welfare, VRE, and the thermal generator's revenue are also larger than in the imperfectly competitive case, $\triangle CS^m > \triangle CS$, $\triangle WR^m > \triangle WR$. Since the merit-order is maintained, the change in welfare is the same as in the competitive case, $\triangle W^m = \triangle W$.

The price in the imperfectly competitive electricity market is not a perfect signal for the marginal cost of electricity production. Unlike in the perfectly competitive case, change in welfare and the storage operator's profit follows different supply curves, $P^C(Q)$ and $P^m(Q)$ respectively. Therefore even when q is small profit and welfare maximization incentives are not aligned. As q increases, the market power of storage amplifies the difference between private and social incentives. In this case, the welfare change is not necessarily larger than the profit of storage. If the merit-order is not maintained (cheaper units bid higher than more expensive units), then the misalignment of private and social incentives can increase even further.

Figures 1 and 2 show that private and social returns and their comparisons depend on a particular market structure, inverse of the aggregated firms' bids $P(Q)$, and storage's production q. This ambiguity in a simple market model suggests a data-driven model is required for more precise and accurate comparisons.

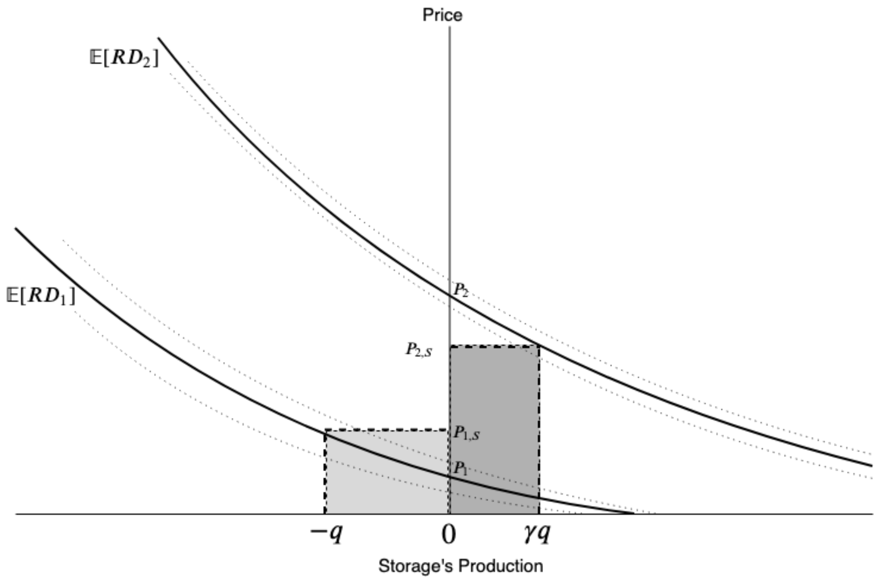
2.2 Electricity Arbitrage Problem

The storage operator engages in arbitrage by exploiting inter-temporal price differences. Unlike thermal generators, storage's production cost (the price of electricity at the time of charging) is dynamic. Hence, storage solves a dynamic problem. In this section, I first describe storage's technological constraints. Then, I study a two-period model to illustrate a storage operator's arbitrage problem.

Storage is typically characterized by its power capacity (MW), its energy capacity (MWh), and its round-trip efficiency. Depending on the technology (e.g., lithium-ion, pumped hydro) and the application (e.g., energy arbitrage, residential, ancillary services), these attributes significantly vary.

[6]See Klemperer and Meyer (1989) for a more formal argument.

Figure 3: Storage's Problem in a Two Period Model



Storage compares expected prices and elasticities of inverse residual demands of two periods.

Power Capacity K_{CH} is the maximum rate that storage can sell energy. K_{CH} dictates the limit of the energy flow of storage and how fast it can take advantage of arbitrage opportunities.

Energy Capacity MWh is a composite unit of energy equivalent to one 1 MW of power sustained for one hour. K_E is the maximum level of energy that storage can hold. K_E limits the time extent of storage's ability to engage with an arbitrage.

Energy to Power Ratio The energy to power ratio (E/CH) determines how fast storage can take advantage of arbitrage up to its capacity. Lower E/CH rates allow for faster charging/discharging; therefore, storage can profit from arbitrage on smaller price fluctuations.

Round-trip Efficiency The process of charging and discharging expends some energy. The net ratio of power retention is called round-trip efficiency, $\gamma \in (0, 1)$, expressed as a percentage. Batteries typically have higher round-trip efficiency rates, between 0.8-0.95, than other technologies such as pumped hydro and molten salt.

The charge/energy level links the storage owner's problem between days and periods. It affects storage's production in future periods. If storage sells all its energy at the end of a period, it cannot sell any electricity next period. Therefore, storage's operator solves a dynamic problem. Given other firms' bids and demand, storage faces the residual demand curve, *i.e.* total demand minus the bids of thermal firms. Storage considers residual demands going forward and decides how much to buy or sell given technological constraints.

Let us study a two-period electricity market where a monopoly storage maximizes profit and incumbent firms bid without considering storage's effect. The storage operator faces the inverse of the stochastic residual demands in two periods, RD_1^{-1} and RD_2^{-1}, where period 1 is off-peak and period 2 is the peak period. Storage has a power capacity $K_{CH} = \bar{q}$, a round-trip efficiency γ, and starts with zero energy. Figure 3 demonstrates the storage owner's problem. The residual demand, RD, has two sources of uncertainty: firms' bid and demand. The storage operator forms an expectation about inverse residual demand in both periods and decides to buy q units of energy in the first period at $P_{1,S}$. In the second period, the storage operator sells only γq due to round-trip efficiency. The rectangle on the left-hand side of Figure 3 is what the storage operator pays in the first period, and the rectangle on the right-hand side is the revenue that the storage operator gets in the second period. The storage operator's problem is expressed by:

$$\max_{q \leqslant \bar{q}} \mathbb{E}[RD_2^{-1}(\gamma q)]\gamma q - \mathbb{E}[RD_1^{-1}(-q)]q,$$

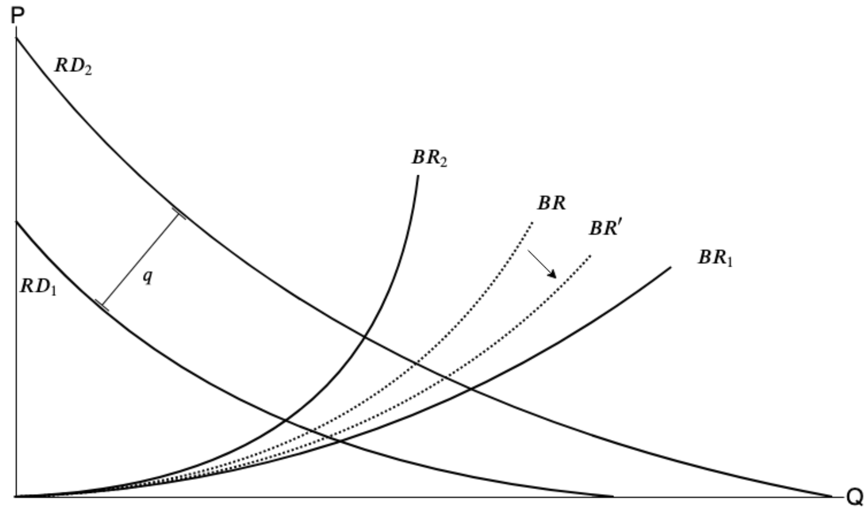
This simple formulation decomposes the storage operator's problem. In Section 4, I model each of these pieces. First, residual demand includes demand, renewables, and other firms' bids. Second, the expectation operator requires an information structure for firms and the storage operator. Last, storage's production q affects other firms' bids; therefore, it changes the residual demand. Assuming for now that storage's production does not change residual demand, first-order conditions give:

$$q^* = \begin{cases} -\dfrac{\gamma\,\mathbb{E}[RD_2^{-1}(\gamma q)] - \mathbb{E}[RD_1^{-1}(-q)]}{\gamma^2\,\mathbb{E}[\frac{\partial RD_2^{-1}(\gamma q)}{\partial q}] + \mathbb{E}[\frac{\partial RD_1^{-1}(-q)}{\partial q}]} & \text{if } q^* \leqslant \bar{q} \\ \bar{q}, & \text{if } q^* \geqslant \bar{q} \\ 0, & \text{if } q^* \leqslant 0. \end{cases}$$

If storage's power capacity, $\bar{q}$, is small storage, it either produces its full capacity or nothing depending on the sign of q^*. If the expected price in the second period is higher than in the first period, then $q^* > 0$ and storage use its full capacity. As $\bar{q}$ increases, the probability of q^* being an interior solution increases. The first-order condition, assuming q^* is an interior solution, shows several forces influencing storage's optimal production.

The difference in expected prices affects optimal production. As the gap between periods' prices increases, the arbitrage opportunity increases, and therefore q^* also increases. Inverse residual demands' derivatives are another factor in the arbitrage problem. As the expected derivative of either period increases, q^* decreases. The effect is due to increasing storage's price effect, and

Figure 4: Thermal Generator's Problem with Two Day Type



Storage's production affects thermal generator's market power.

therefore its market power. This force causes private and social incentives for storage to diverge. If the residual demands are (in)elastic (in other words, storage has higher market power), then it produces less(more) to keep the price difference high. In Section 4, I take this intuition to a fully dynamic model and an equilibrium analysis.

2.3 Firms' Response to Storage

The storage-induced price and quantity change both the profit and the market power of thermal generators. Consequently, incumbent firms may want to update their bids by responding to storage's production. In the economic theory literature, supply function equilibrium (SFE) concepts are used to solve equilibrium strategies of the players in wholesale electricity markets. However, empirically solving SFE is usually computationally intractable, and it does not yield a unique solution (Klemperer and Meyer (1989), Holmberg (2008) , Vives (2011)). Instead, I treat the production of energy storage as a shock to demand and compute a supply function equilibrium using estimated best responses to observed variation in firms' residual demand volatility. Figure 4 illustrates my estimation approach.

Let us examine a thermal generator's problem for a single day without storage. There are two possible inverse residual demand functions for the day, RD_2^{-1} (low) and RD_1^{-1} (high), where $RD_2^{-1} - RD_1^{-1} = q$. The generator observes a public signal X, which can have two values, low X^l and high X^h, with the same probability $g(X^l) = g(X^h) = \frac{1}{2}$. Conditional on signal X, inverse residual demand has a probability function $f(RD^{-1}|X)$. For simplicity, let us assume X^l

and X^h give perfect information about residual demand, $f(RD_1^{-1}|X^l) = f(RD_2^{-1}|X^h) = 1$. Next, the generator uses bids BR_1 and BR_2 with respect to signals X^l and X^h.[7] The expected bid of the generator is $BR = \frac{BR_1+BR_2}{2}$.

Consider a storage that produces q MW in a day with signal X^h with some probability $p \in (0,1)$. The production q shifts RD_2^{-1} to the left and makes it the same as RD_1^{-1}. In other words, storage's production turns the firm's high residual demand day, RD_2^{-1}, in to a low residual demand day, RD_1^{-1}. Now, assuming that signal X^h still signals a high residual demand day, the signal mapping f changes. I define an augmented mapping $\widehat{f}$ for the public signal X that includes information about storage's production, in which $\widehat{f}(RD_1^{-1}|X^l) + \widehat{f}(RD_1^{-2} + q|X^l) = \widehat{f}(RD_2^{-1}|X^h) = 1$. In this case, signal X^l also includes days with storage's production at high residual demand days. With the updated signal mapping $\widehat{f}$, the firm still uses BR_1 in days with signal X^l since either with or without storage it faces residual demand RD_1^{-1}. Also, the probability of signals needs to be updated, $\widehat{g}(X^l) = \frac{1+p}{2}, \widehat{g}(X^h) = \frac{1-p}{2}$. Now the expected firm's bid becomes $BR' = \frac{BR_1(1+p)+BR_2(1-p)}{2}$. Notice that storage's production $q > 0$ decreases the market power of the generator, as BR is steeper than BR'. From a theoretical perspective, the change in demand's effect on an incumbent firms' bidding strategies is ambiguous (Vives (2010), Genc and Reynolds (2011)).

Figure 4 illustrates my estimation approach as I model energy storage as a shock to firms' residual demands and compute firms' best responses using estimated best responses to observed variation in firms' residual demand. In Section 4.4, I take this intuition to compute a supply function equilibrium in the market with energy storage.

3 Institutions and Data

I use Australia's National Electricity Market (NEM) between July 2016 – December 2017 to study private and social returns of energy storage. In this section, I first discuss institutional details and the generation mix of NEM. Then, I show statistics about demand, renewable production, and prices. Finally, I illustrate the production of actual energy storage from January 2018 – December 2018.

3.1 National Electricity Market

In Australia, the Australian Energy Market Operator (AEMO) operates the electricity market, the National Electricity Market (NEM). The NEM connects five regional market jurisdictions: Queens-

[7] The effect of increasing residual demand on market power is ambigous in the SFE literature. Under some assumptions, Vives (2010) shows firms bid more aggressively when residual demand is lower. Genc and Reynolds (2011) show the set of possible equilibrium prices shrinks from below. I discuss the observed effect in the results section.

land, New South Wales, Victoria, South Australia (SA), and Tasmania. AEMO operates an energy market that produces between 15,000 and 65,000 MW, with around 85,000 MW of installed capacity. The market serves more than 22 million people and collects over AU$16 billion in gross charges per year.

The NEM is an energy-only pool; it only compensates power that has been produced. There is no capacity market or technical forward market.[8] All generators larger than 30MW must sell all their output by submitting bids to the NEM. The NEM matches generation's supply schedules with demand[9] in the most cost-efficient way for each 5-minute period. The NEM averages the 5-minute prices and posts spot prices every 30 minutes for each of the five trading regions. In the NEM, the minimum and maximum market prices are $AU14,500/MWh and –$AU1,000/MWh, respectively. AEMO uses the spot price as the basis for settling financial transactions for all energy traded in the NEM.

In the NEM, generating units submit their 'daily bid' before 12:30 pm on the day before the supply is required. The daily bid consists of 48 individual bids, one for each half-hour period. Each half-hourly bid is a step function with 10 different price-quantity steps. By market rules, the ten price steps for all 48 half-hour bid should be the same. These market rules imply that a firm has a 490-dimensional daily strategy set for each unit that it owns. The quantity bids must be increasing in prices and less than the generator's capacity. The NEM uses these bids to clear the market and construct a production agenda for the day. The day starts at 4:30 am. Every 5 minutes, the AEMO releases the NEM Dispatch overview, which includes prices, demand, generation, renewable production, and trade between regions for the last five minutes.

Data I construct a dataset from publicly available data from the AEMO. SA is a part of the NEM, connected only with the Victoria region. In the counterfactual analysis, I use data from July 2016 – December 2017. There are two primary motivations for using this period. First, in January 2018, the world's largest (at the time) lithium-ion battery came online. Second, there is no entry or exit in SA during this period.

The main variables in the data set are bids, production, demand data, and forecasts for demand and renewable production. The bidding data includes daily bids and can be mapped to the generation units in Victoria and SA. The production data has actual quantities generated from all units in the market for each 5 minute period. The demand data has realized demand and a proxy for residential solar production for each 30 minute period. I also have data on generator characteristics, such as the type of fuel used, thermal rates, age, location, emissions, and ownership. I provide a more detailed explanation of the data in Appendix A.

[8] A high price ceiling provides adequate incentives to stimulate generation investment.

[9] There is no bidding on the demand side in the NEM.

Table 1: Generation Mix for SA

Generator Name	Average Production (MW)	Capacity (MW)	CO2 Emission Rates (ton per MWh)	Units	Fuel Type	Technology	Owner
Torrens Island	333.1	1320	0.72	8	Natural Gas	Steam Sub-Critical	AGL
Pelican	218.0	529	0.48	1	Natural Gas	CCGT	Pelican Power
Osborne	124.9	204	0.57	1	Natural Gas	CCGT	Origin Energy
Quarantine	24.3	233	0.84	5	Natural Gas	OCGT	Origin Energy
Ladbroke	20.8	100	0.66	2	Natural Gas	OCGT	Origin Energy
Hallett	3.7	220	1.19	1	Natural Gas	OCGT	EnergyAustralia
Mintaro	3.6	105	0.96	1	Natural Gas	OCGT	Synergen
Dry Creek	1.1	171	1.36	3	Natural Gas	OCGT	Synergen
Pt Stanvac	0.8	65	1.49	1	Diesel oil	Compression	Lumo
Angaston	0.6	50	1.01	1	Diesel oil	Compression	Lumo
Lonsdale	0.4	21	1.49	1	Diesel oil	Compression	Lumo
Snuggery	0.3	69	1.49	1	Diesel oil	OCGT	Synergen
Port Lincoln	0.2	78	1.56	2	Diesel oil	OCGT	Synergen
Rooftop PV	138.7	780	0	-	Solar	Renewable	Miscellaneous
Wind	553.8	1600	0	13	Wind	Renewable	Miscellaneous
Import from VIC	141.9	800	1.12	-	Brown Coal	Steam Sub-Critical	Miscellaneous

Notes: The sample is from the South Australia Electricity Market July 2016 – December 2017. Rooftop PV is AEMO's estimation. Import from Victoria's emissions rate is the quantity-weighted region average.

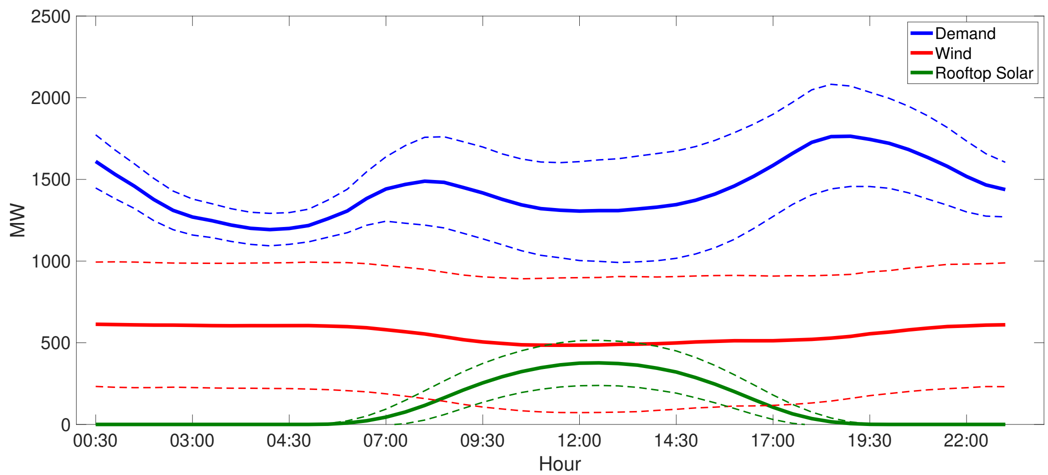
Generation Mix In the sample period, production mostly comes from two types of resources: gas and renewables. This generation mix is considered a good candidate for the economically optimal low-carbon electricity production portfolio (De Sisternes et al. (2016)). There are 13 thermal units with two fuel types: natural gas and diesel oil. Gas-fired generators generate almost all of the dispatchable electricity, with relatively low CO_2 emissions rates. Diesel oil-fueled generators, peaker plants, are only active for a few hours each month to meet peak demand, with high CO_2 emissions rates. As Table 1 shows, wind production constitutes around 35%, gas generators 45%, and Solar PV 10% of electricity production. There is a dispersion in CO_2 emissions rates within natural gas-fueled generators due to fuel efficiency, environmental regulation compliance, and production profiles. Imports from the Victoria region mostly come from brown coal thermal generators. In SA three firms, AGL, Pelican Energy, and Origin Energy, produce almost 95% of thermal generation.[10]

3.2 Variation in Demand, Renewable Production, and Prices

Figure 5 displays the average daily profile of demand, import, wind production, Solar PV production, and gas power plant production in SA. SA's peak-time demand is after sunset, due to high solar energy production, similar to the ”duck curve” in California. Wind production is, on aver-

[10]The high market shares of these firms raised a lot of market power concerns in SA over the years.

Figure 5: Daily Renewable Production and Demand Profiles in SA July 2016 – December 2017

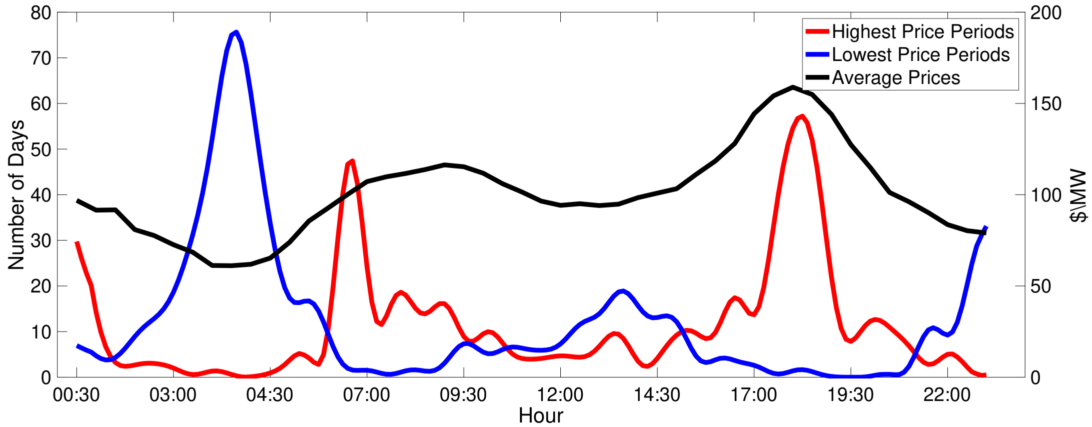


age, steady throughout the day. Even though these average production and demand profiles show some familiar patterns in power systems, the variation from day to day is very high. Dashed lines in Figure 5 show one standard deviation in the daily profile of demand and renewable production. Regardless of the time of day, wind production has very high volatility, and solar has considerable volatility around noon. The variability in intermittent resources and demand makes daily demand and price patterns hard to generalize and helps the model recover firms' best responses to storage's production. In particular, I exploit variation in residual demand (which includes both renewables and demand) to estimate firms' best responses to energy storage.

Highly volatile prices characterize the NEM. The high price periods help to solve the well-known ”missing money” problem in energy-only electricity markets. This problem occurs because marginal cost pricing with binding low price caps usually cannot provide sufficient incentives to invest in a power plant in the first place. Many electricity markets address this problem via the capacity market. The lack of baseload generators and the high penetration of wind generation in SA further amplify price volatility. These features create even higher incentives for arbitrage, which in turn creates a more profitable environment for energy storage.

In the observed period, the average price per MWh is AU$100.8, with a standard deviation of AU$266. Daily prices peak at 6 pm (AU$190) and are lowest at 4 am (AU$60). This gives a ballpark price spread of AU$130. However, deploying storage does not just depend on the difference between high and low prices; it also depends on the persistence of high and low prices. If the E/CH ratio is high (i.e., it takes a long time to charge the battery), battery owners must find more periods with low prices to buy and longer periods with high prices to sell.

Figure 6: Price Patterns in SA July 2016 – December 2017

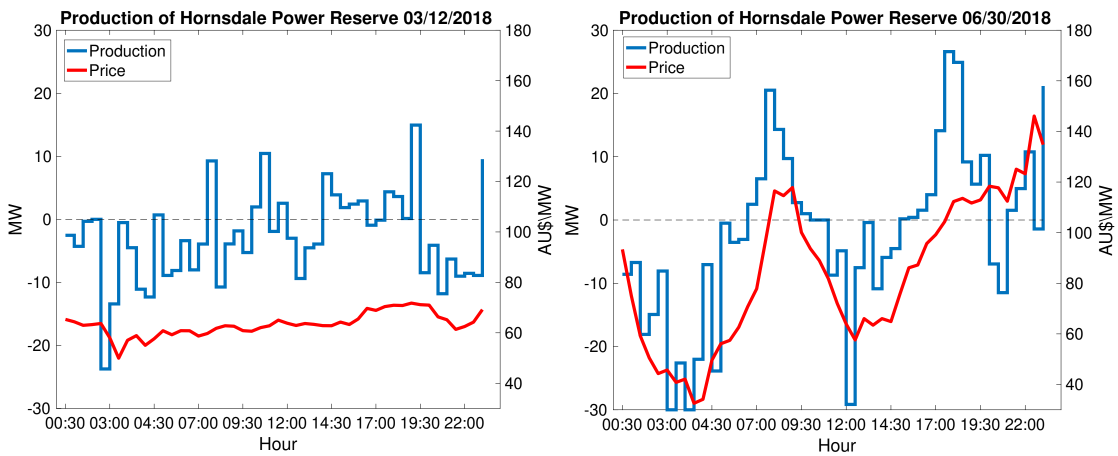


Average prices (the black line in Figure 6) appear to follow predictable patterns. However, they are not persistent due to high differences between days. Figure 6 also shows a histogram of the highest (blue line) and lowest (red line) price periods within a day. Peak and off-peak price periods within a day vary quite a bit. Because of this variation, storage cannot follow a simple, formulaic strategy for buying/selling power at different times throughout the day. It needs a more diversified day-to-day operations to utilize the arbitrage opportunity fully.

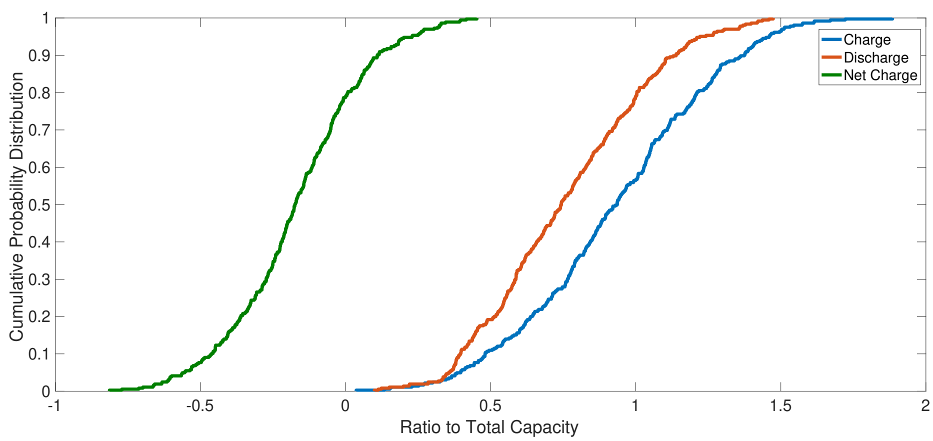
3.3 Strategies of Storage Operator: The impact of electricity price's daily variation

Hornsdale Power Reserve (HPR) was the largest lithium-ion battery in the world in 2018. HPR is located in SA, where it officially came online in January 2018. Tesla Inc. built HPR for a cost of about AU$70 million, after it's CEO, Elon Musk, wagered that it would be complete "100 days from contract signature.". HPR provides ancillary and energy services in the NEM, with 129 MWh energy capacity and 100MW power capacity. HPR is privately operated, with the government having the right to call on the stored power under certain circumstances. According to the HPR's agreement with SA's local government, HPR must reserve 70 MW power and 9 MWh energy capacity for the ancillary services market. The remaining 120 MWh energy and 30MW power capacity can be used to engage in arbitrage in the NEM energy market.

The unknown features of HPR's contract with the SA government make the storage operator's objective unclear. Also, around this time, VRE in SA expanded around 40%, which creates problems for my identification strategy. Although my estimation strategy does not use data from this time period, I use data on HPR's observed strategies to motivate some of my assumptions in the model section. Specifically, I assume that the owners of energy storage use various dynamic



(a) Storage's Behavior on a typical Stable Prices and Volatile Prices Day



(b) CDF of Total Charge/Discharge/Net Charge in a day Relative to Capacity

Figure 7: Prices and Production of Hornsdale Power Reserve in 2018

charge/discharge strategies conditional on the expected price variations.

The variation in within-day price paths creates different incentives for storage's daily operations. Subfigures in Figure 7a illustrate storage's behavior on two typical days. While HPR's operations fluctuate day-to-day, these illustrations help motivate my assumptions in the model section. The figure on the right has relatively stable prices. HPR does not engage in much arbitrage due to low price variation. The figure on the right, on the other hand, has volatile prices. HPR's production closely follows short-run price changes. However, HPR does not always use its full power capacity, 30 MW, when it is producing, suggesting that HPR could be under-producing due to its market power.

HPR engaged in 1.12 full charge and discharge cycles per day in 2018. However, this average obscures lots of day-to-day variation. Figure 7b shows CDF of storage's total charge/discharge/net charge decisions for each day in 2018. The high variation in both figures suggests that HPR does not follow the same production pattern every day. Figure 7b also suggests that some days HPR buys (sells) a lot and starts the next day with a fully charged (discharged) battery to engage in arbitrage.

These different observed deployment policies suggest that the optimal arbitrage policy involves dynamic considerations. In Appendix C, I consider static policies for energy storage such as buying/selling at the same hours, buying/selling at some certain prices, etc. In the model section, I study a dynamic infinite horizon problem for the storage operator.

4 Model

In this section, I build a model of strategic behavior in the electricity market that incorporates the storage operator's dynamic profit maximization decision. In order to formalize firms' decisions, I represent the electricity market as a uniform price multi-unit auction.

I first describe the electricity demand and market-clearing prices. Next, I lay out payoffs and strategies for firms with different production technologies and model trade between regions. With this information, I derive equilibrium conditions for my model. Finally, I show an alternative best response mapping and computationally tractable re-formulation of the equilibrium analysis.

4.1 Electricity Demand and Market Clearing

The System Operator (SO) runs a daily individual multi-unit uniform price auction for each of the H periods of the following day. I take electricity demand for each period h of the day d, D_{dh}, to be inelastic. In electricity markets, the bulk of demand is from utilities. The end consumer usually pays a fixed price per MWh, which makes the demand very inelastic in the short run.[11].

Each day, before the auction, firms observe a public signal $X_d \in \mathcal{X}$. The public information set contains information such as publicly available demand and renewable production forecasts. The $H \times 1$ demand vector D_d has probability density function $f_D(D_d|X_d)$ conditional on X_d. The signal X_d and the publicly known function f_D inform firms about the distribution of the daily electricity demand for the next day. Conditional on X_d, the signal X_{d+1} has the probability density function $f_X(X_{d+1}|X_d)$. This Markovian structure links demand profiles across days.

Each firm k submits a bid to the market each day for the following day. These bids are supply schedules $S_{kd}(p) = \big(S_{kd1}(p), \dots, S_{kdH}(p)\big)$, where $S_{kdh} : \mathbb{R} \to \mathbb{R}$ for the period h of the day d. The bid, S_{kdh}, should be increasing in p. For each period h, the market clearing price p^c_{dh} satisfies the condition $\sum_k S_{kdh}(p^c_{dh}) = D_{dh}$. I assume there is no transmission constraint within the market.[12] The vector p^c_d represents the price vector for the day d. Firm k gets paid $\sum_{h=1}^{H} S_{kdh}(p^c_{dh})p^c_{dh}$ for the day d.

4.2 Payoffs and Strategies

There are $k = 1, \dots, N$ firms that maximize their profit. Each firm owns $u = 1, \dots, U_k$ generators to produce electricity with some technological capacity, e.g., a maximum/minimum level of production. For ease of exposition, I assume each firm owns one generator. After deriving the model, I explain how I incorporate firms' portfolio decisions into their problems. I denote firm k's bidding strategy σ_k, and the market strategy $\sigma = (\sigma_1, \dots, \sigma_N)$. There are three types of firms in the electricity market, sorted according to their electricity production technology: storage, thermal, and renewable, for which I use i, j, r to represent each type of firm, respectively. The model considers the bidding decisions of firms with different technologies in a daily electricity auction.

4.2.1 Storage Operator's Problem

The storage operator's problem is linked between days and periods through a charge level $Ch \in \mathcal{CH}$. The charge level at the beginning of the day constrains the set of strategies storage can use within that day. If the storage operator expects high (low) prices at the beginning of the next day, it might decide to end today with a high (low) energy level to sell (buy) electricity at the beginning of the next day. Hence storage solves an infinite horizon problem. To simplify exposition, I assume storage's round-trip efficiency γ is 1.[13] No electricity market yet has charge-level contingent

[11]There is evidence in empirical literature to support this assumption (Ito (2014) and Borenstein and Bushnell (2015))

[12]In the NEM, transmission constraints within regions are rarely binding. My trade formulation allows for transmission constraint between regions.

[13]In Section 6, I specify γ to be 85%.

bidding available for storage technologies. Therefore the model assumes that the storage operator only picks quantities to produce, $S_{idh} = Ch_{dh} - Ch_{dh+1} = a_{idh}$, rather than supply schedules.

The storage operator starts day d with charge level Ch_d and picks a set of charge levels, $\boldsymbol{Ch_d} = (Ch_{d1}, \ldots, Ch_{dH})$. The storage operator's expected daily payoff is $\mathbb{E}[\pi_{id}] = \mathbb{E}\left[(Ch_d - Ch_{d1})p^c_{d1} + \sum_{h=2}^{H}(Ch_{dh-1} - Ch_{dh})p^c_{dh}\right]$. The charge level at the end of the day carries over to the next day, $Ch_{dH} = Ch_{d+1}$.

Assumption 4.1. *The charge level at the beginning of the day, Ch_d, is private information.*

Thermal generators can only infer the distribution of Ch_d conditional on the public signal X. This assumption rules out any inference on Ch_d conditional on the history of public signals X, and it keeps thermal generators' problem Markovian. In Appendix C, I consider the case in which Ch_d is public information, assuming that thermal generators perfectly infer to actual Ch_d conditional on the history of public signals X.

I focus on Markov strategies for the storage operator. The bidding strategy of the storage operator is a mapping from the public signal and charge level at the beginning of the day to the vector of charge levels, $\sigma_i : \mathcal{X} \times \mathcal{CH} \to \mathcal{CH}_i^H$, where $\mathcal{CH}_i$ represents the sets of bids that satisfy technological constraints such as power and energy capacity. Given the Markov strategy profile σ for the market, the storage operator's expected value function is

$$
\begin{aligned}
V(X_d, Ch_d, \sigma_{\mathbf{i}}, \sigma_{-\mathbf{i}}) = \mathbb{E}\,\Big[\sum_{h=1}^{H} \pi_{idh}(\boldsymbol{Ch_d}, p^c_{dh}, Ch_d) \\
+ \beta \int V(X_{d+1}, Ch_{d+1}, \sigma_{\mathbf{i}}, \sigma_{-\mathbf{i}}) f_X(X_{d+1}|X_d)\big|\sigma_{-i}, X_d, Ch_d\Big],
\end{aligned}
\tag{4.1}
$$

where σ_{-i} is the strategy of thermal generators.

As Figure 3 represents, the storage operator considers inverse residual demands p^c_{dh} to maximize its daily revenue. At the beginning of the day d, storage faces H expected residual demands. I calculate the inverse residual demand function for storage by inverting the market clearing condition, $p^c_{dh}(a_{dh}) = S^{-1}_{idh}(D_{dh} - a_{dh})$, where S^{-1}_{idh} is the inverse of the aggregated bids of thermal firms and storage's production is $a_{dh} = Ch_{dh-1} - Ch_{dh}$. The problem of the storage operator, maximizing its net present value of revenue, at the beginning of the day d can be rewritten as

$$
\begin{aligned}
\max_{\boldsymbol{Ch_d} \in \mathcal{CH}_i^H(Ch_d)} \mathbb{E}\Bigg[\sum_{h=1}^{H} a_{dh}\Big(\int\int p^c_{dh}(S_{-idh}, D_{dh}, a_{dh}) f_{D_h}(D_{dh}|X_d)\sigma_{-i}(S_{-idh}|X_d)\Big) \\
+ \sum_{X_{d+1}} V(X_{d+1}, Ch_{d+1}) f_X(X_{d+1}|X_d)|\sigma_{-i}, X_d, Ch_d\Bigg],
\end{aligned}
\tag{4.2}
$$

where $\mathcal{CH}_i^H(Ch_d)$ represents a set of charge levels, constrained by technological constraints and initial charge level Ch_d. The storage operator's charge level decisions within a day do not affect the continuation payoff unless they affect the terminal charge level Ch_{d+1}. If storage's energy to power ratio (E/CH) is high, the set $\mathcal{CH}_i^H(Ch_d)$ is smaller. In Section 5.2, I discuss how power and energy capacity constraints interact.

4.2.2 Thermal Generators

Thermal firm j submits daily bids to maximize their expected profit conditional on their information set and their beliefs about other players' strategies, given by σ_{-j}. Firm j's information set, I_{jd}, contains the public signal, X_d, and a signal $\epsilon_{jd} \in \mathbb{R}$. This private signal could be interpreted as any shocks to firm j's daily profit, such as cost shocks and information about demand or other firms. Also, it gives an explanation for variation in data in thermal firms' bid conditional on the public signal.

Assumption 4.2. *The signal ϵ_{jd} is a private signal and $\epsilon_{jd} \perp\!\!\!\perp \epsilon_{jd'} | X_d \neq X_{d'}\ \forall j$.*

This assumption allows for the correlation of private signals conditional on the demand distribution signal. For example, firms can have different hedging functions conditional on the demand. However, the model does not allow for persistent shocks across days.

The model also assumes no cost complementarities across days for thermal generators, such as start-up and ramp-up costs, but it allows for within-day cost complementarities. In the case of high start-up and ramp-up costs, these complementarities can have an impact on the generator's profit. However, Reguant (2014) shows that start-up and ramp-up costs for gas power plants are not significant. Since SA only has gas power plants as thermal generators, these low-cost links between days do not affect a firm's daily optimization decision.

The bidding strategy function of the thermal firm is a mapping from the private and public signal to supply schedule vectors, $\sigma_j : \mathcal{X} \times \mathbb{R} \to \mathcal{S}_j^H$, where $\mathcal{S}_j$ represents sets of supply schedules that satisfy the technological constraints of the firm j and the market rules. If other firms' strategies are given by a strategy profile σ_{-j}, firm j's expected daily profit given a signal X_d and bid S_{jd} is

$$\mathbb{E}[\pi_{jd}|\sigma_{-j}, X_d, \epsilon_{jd}] = \mathbb{E}\left[\sum_{h=1}^{H} \pi_{jdh}(S_{jdh}, p_{dh}^c, \epsilon_{jd})|\sigma_{-j}, X_d, \epsilon_{jd}\right] =$$

$$\sum_{h=1}^{H} \int\int \pi_{jdh}(S_{jdh}, D_h, S_{-jdh}, \epsilon_{jd}) f_D(D_h|X_d) \sigma_{-j}(S_{-jdh}|X_d) dD dS_{-jdh}. \tag{4.3}$$

The ex post profit of firm j is $\pi_{jd} = \sum_{h=1}^{H} S_{jdh}(p_{dh}^{c*})p_{dh}^{c*} - C_j(S_{jd}(p_d^{c*}), \epsilon_{jd})$, where C_j is the cost function of firm j and p_d^{c*} is a vector of market prices. The cost function for each day is a function of the production vector for the day $S_{jd}(p_d^{c*})$ and the private signal, which allows for within-day cost complementarities.

Trade SA trades electricity with its neighbor region, Victoria. To incorporate trading into the model, I model Victoria as a firm bidding in the SA electricity market. Similar to the other thermal firms, firm Victoria submits supply schedule $S_{VIC}(p)$ into the market. However, unlike other thermal generators, I allow firm Victoria to purchase electricity when $p_{VIC} > p_{SA}$. This flexibility allows SA to sell electricity when prices are lower relative to Victoria. Also, it mitigates curtailment at some capacity when renewable production is higher than demand in SA. I use transmission line capacity as the capacity of the firm Victoria, $S_{VIC} \in [-800, 700]$. This allows for differences between the two regions' prices.

I use the market-clearing condition for Victoria to calculate S_{VIC}. I assume Victoria's renewable production, demand, and trade with other regions are exogenous. Therefore, the market-clearing condition in Victoria is

$$S_{VIC,dh}(p) = Trade_{SA}(p) = \sum_{k \in VIC} S_{kdh}(p) - Export_{Others,dh} - Renewable_{VIC,dh} - Demand_{VIC,dh},$$

where $S_{VIC,dh}(p)$ is a bid of firm Victoria in day d and period h. Notice that if the price in SA is lower (higher) than Victoria, firm Victoria buys (sells), $S_{VIC,dh}(p_{VIC} - \epsilon) \leqslant 0$ ($S_{VIC,dh}(p_{VIC} + \epsilon) \geqslant 0$) for any $\epsilon > 0$.

4.2.3 Renewable Production

As a part of greenhouse-gas-emissions mitigation targets, most countries have programs to support renewable production and investment: e.g., Renewable Portfolio Standards (RPS), Renewable Energy Targets (RET), Production Tax Credits (PTC), and Feed-in Tariffs. Most of these policies are output-based subsidies rather than investment subsidies. These financial supports disincentivize a potential strategic reduction in renewable production. I assume renewable generator r with $\overline{a}_r$ capacity is non-strategic and its production is exogenous, $a_{rdh} \in [0, \overline{a}_r]$.

Assumption 4.3. *The renewable generator's bid is equal to renewable production, $S_{rdh} = a_{rdh}$.*

Acemoglu et al. (2017) and Genc and Reynolds (2019) show that firms with diverse energy portfolios might have incentives to manipulate renewable production or under-produce from their thermal generators. In my dataset, the owners of renewable generators do not have thermal generators in their portfolios. Therefore, I assume output-based subsidies are large enough for the renewable generator to not under-produce.

4.3 Equilibrium

In this section, I define equilibrium in the daily electricity market. For every day d, thermal generators and storage simultaneously bid into the electricity market ahead of actual production. For every realized demand level in every period h, the SO aggregates supply bids and clears the market at the lowest possible price.

Definition 4.1. *The strategy profile σ^* is a Markov Perfect Equilibrium if*

$$\sigma_j^*(X, \epsilon_j) = \underset{S_{jd}(p) \in \mathcal{S}_j^H}{\operatorname{argmax}} \; \mathbb{E}[\pi_{jd} | \sigma^*, X, \epsilon_j], \forall j \in N \setminus \{i\} \textit{ and } \forall X, d, \epsilon_j, \tag{4.4}$$

$$V(X, Ch, \sigma^*) \geqslant V(X, Ch, \sigma_i', \sigma_{-i}^*) \; \forall X, Ch, \sigma_i', \tag{4.5}$$

$$D_{dh} = \sum_{j=1}^{N \setminus \{i\}} S_{jdh}(p_{dh}^{c*}) + a_{idh} + a_{rdh} \; \forall d, h. \tag{4.6}$$

Equation 4.4 requires that thermal generators maximize their expected daily profits. Since the public signal is the only relevant information for demand, other firms' bids and storage's charge level, thermal generators condition their strategy only on the public signal and their private signal. Equation 4.5 guarantees that there is no profitable deviation from σ_i^*, as storage's value function is defined in Equation 4.1. Both storage and thermal generators form their expectations on demand conditional on public signal X. The SO runs a multi-unit auction, and the electricity market clears at p_{dh}^{c*}, where demand equals the sum of storage's production, renewable production, and thermal firms' supply, as Equation 4.6 shows.

Solving the thermal generator's problem, Equation 4.4, involves supply function equilibrium, which is usually computationally intractable and not unique (Klemperer and Meyer (1989), Green and Newbery (1992)). In the next subsection, I propose computationally tractable re-formulation to find σ^*.

4.4 An Equivalent Best Response Mapping

In this section, I describe an equilibrium definition that is equivalent to Definition 4.1. This new equilibrium definition suggests a computationally tractable algorithm in which the market equilibrium without storage can be used to find an equilibrium with storage. First, I show the updated market-clearing condition after storage's production and define an updated net demand. Then, I describe a firm's problem under a new signal that conveys information about updated net demand. I show how this new signal changes storage's problem. Finally, I propose a new equilibrium definition.

First, let us construct the best response function for storage, $\Lambda_i : \boldsymbol{\sigma}_{-i} \rightarrow \boldsymbol{\sigma}_i$, which is a mapping from strategies of thermal generators to sets of strategies for the storage. For any set of strategies for the rest of the market, $\sigma_i = \Lambda_i(\sigma_{-i})$ gives the set of strategies that maximizes net present value of the revenue of storage, as in Equation 4.5. Similarly, for the thermal generators, let us define the best response function $\Lambda_j : \boldsymbol{\sigma}_i \times \boldsymbol{\sigma}_{-ij} \rightarrow \boldsymbol{\sigma}_j$, where σ_{-ij} is strategies of thermal firms other than firm j, as in Equation 4.4.

4.4.1 Net Demand After Storage's Production

Let us define market equilibrium strategies in a market without a storage as σ_{-is}, in which thermal firm j's strategy is σ_{js}. The strategy σ_{-is} satisfies Definition 4.1 in a case in which storage's production is always zero, $a_{idh} = 0 \; \forall d, h$ and it can be observed in data. Storage enters the market, and its operator maximizes net present value of the revenue in response to market strategies of thermal firms, by $\sigma_i = \Lambda_i(\sigma_{-is})$.

Storage's production is inelastic, and it has a lower merit order than thermal generators. Therefore, the SO starts clearing the demand by using storage's production. Storage's production for period h, a_h is distributed conditional on X with probability distribution $\bar{\sigma}_{ih}(a_h|X)$. Thermal firm j forms an expectation about storage's production. Since charge level is private information, the only relevant information about storage's production is the signal X. The expected distribution of storage's production conditional on public signal X is $\bar{\sigma}_i(a|X) = \mathbb{E}_j[\sigma_i(X, Ch)|X]$. Recall the market clearing condition for period h after storage production a_h,

$$\sum_{j=1}^{N \setminus \{i\}} S_{jh}^{\sigma_{-is}}(p_h^c) = D_h - a_h = D'_h,$$

where $S_{jh}^{\sigma_{-is}}$ is a bid of firm j under the strategy σ_{-is}, and D'_h is the net demand after storage. Since the SO first clears storage's production, thermal generators compete to meet net demand after storage's production, D'_h, instead of D_h. Net demand after storage D'_h consists of the difference of two random variables, D_h and a_h, with distribution conditional on X, $\bar{\sigma}_{ih}(a_h|X)$ and $f_D(D_h|X)$, respectively.

Let us define the probability density function of net demand after storage conditional on signal X, $f_{D'}^{\sigma_i}(D'|X) = \int_{-\boldsymbol{K_{CH}}}^{\boldsymbol{K_{CH}}} f(D-a|X)\bar{\sigma}_i(a|X)da$. Now, net demand after storage, D', is a more relevant object for thermal generators' residual demand than demand, D. Therefore thermal generators' respond to the new distribution $f^{\sigma_i}_{D'}(D'|X)$.

4.4.2 Thermal Generators' Response to Storage's Production

Thermal generators compete to meet net demand after storage's production, D'_h, given storage's production strategies σ_i. Let us define another signal X^{σ_i} from the same set as $X \in \mathcal{X}$, which conveys information about the distribution of D'.

Definition 4.2. *If two signals X^{σ_i}, X belong to the same set $X^{\sigma_i}, X \in X_m$, then the distribution of D' conditional on X^{σ_i} is the same as the distribution of D conditional on X,*

$$f^{\sigma_i}_{D'}(D'|X^{\sigma_i}) = f(D|X),\ \forall X, X^{\sigma_i}.$$

Notice that this definition implicitly assumes that the distribution of D' can be partitioned into sets conditional on a signal X^{σ_i} , $f^{\sigma_i}_{D'}(D'|X^{\sigma_i})$, such that these new distributions can fit into partitioned distributions of D conditional on signal X, $f(D|X)$. Storage's production often smooths daily demand profiles by engaging in arbitrage. Therefore, if $\mathcal{X}$ is rich enough, such a signal can be defined. I discuss out of sample issues for D' in Section 5.3.

I assume thermal generators observe X^{σ_i} but not X. Given a day with $X_d \in X_m$, the signal $X^{\sigma_i}_d$ does not necessarily belong to set X_m. For some realization of net demand D_d, storage's production can be large enough to shift D'_d, and signal $X^{\sigma_i}_d$ can belong to a different set $X_{m'}$. Therefore, conditional on observing signal $X^{\sigma_i}_d \in X_{m'}$ a thermal generator cannot distinguish a day with public signal $X_d \in X_m$ and $X_d \in X_{m'}$. With the new signal X^{σ_i} and given other firms' strategies σ_{-ij}, the thermal generator j's problem becomes

$$\underset{S_{jd}(p)\in\mathcal{S}^H_j}{\text{argmax}} \Big[\sum_{h=1}^{H}\int\int \pi_{jdh}(S_{jdh}, D'_h, S_{-jdh}, \epsilon_{jd}) f^{\sigma_i}_{D'}(D'_h|X^{\sigma_i}_d)\sigma_{-ij}(S_{-jdh}|X^{\sigma_i}_d)dD'dS_{-jdh}\Big].$$

By Definition 4.2, conditional on two signals belonging to the same category, the distribution of net demand after storage's production is the same as the distribution of net demand. Therefore, I use the firms' strategies σ_{-is} to find a new equilibrium.

Proposition 4.1. *If two signals X^{σ_i}, X belong to the same category X_m, and a strategy set σ_{js} is a firm's equilibrium strategies in a market without storage, define*

$$\widehat{\sigma}_j(S_{jd}|X^{\sigma_i}_d) = \sigma_{js}(S_{jd}|X)\ \forall j, X_m \in \mathcal{X}.$$

Then market strategies for firms, $\widehat{\sigma}_{-is}$, is an equilibrium for firms in a market where storage uses strategy σ_i.

Proof: See Appendix 4.

Here the signal X^{σ_i} coordinates thermal generators' strategies conditional on signal X^{σ_i}. Since X^{σ_i}, X both belong to the same set X_m, the thermal generator's net demand distribution under both signals is the same. Therefore if thermal generators use their strategies under signal X^{σ_i} in the same way as under signal X, their strategies constitute an equilibrium, as they were in the market without energy storage. Notice that $\widehat{\sigma}_{-is}$ is an equilibrium given storage's strategy σ_i. Therefore thermal generator j's best response to storage's strategy is $\Lambda_j(\sigma_i, \widehat{\sigma}_{-ijs}|X^{\sigma_i}) = \widehat{\sigma}_j$.

4.4.3 Revisiting Storage's Problem

The update in firms' strategies, $\widehat{\sigma}_j$, changes storage's problem. Although storage knows its production a_{dh}, it does not know the realization of demand. Therefore, I assume that storage does not observe X^{σ_i} and cannot infer X^{σ_i}. Thermal generators update their market strategy to $\widehat{\sigma}_{-is}$. Conditional on observing X, thermal generators' strategy is

$$\widehat{\sigma}_{-is}(S_{-is}|X) = \sum_{X^{\sigma_i}} w_{X^{\sigma_i},X}\sigma_{-is}(S_{-is}|X^{\sigma_i}), \forall X,$$

where weight $w_{X^{\sigma_i},X}$ is the probability of signal X^{σ_i} conditional on signal X. With the updated firms' strategy $\widehat{\sigma}_{-is}$, storage solves its best response problem again, $\widehat{\sigma}_i = \Lambda_i(\widehat{\sigma}_{-is})$.

4.4.4 Equilibrium

Here, I define equilibrium as a fixed point of the best response functions of storage and firms.

Proposition 4.2. *The strategy profile σ^* is a Markov Perfect Equilibrium if*

$$\Lambda_i(\sigma^*_{-i}|X) = \sigma^*_i, \tag{4.7}$$

$$\Lambda_j(\sigma^*_i, \sigma^*_{-ij}|X^{\sigma^*_i}) = \sigma^*_j, \ \forall j \in N \setminus \{i\} \tag{4.8}$$

$$D_{dh} = \sum_{j=1}^{N\setminus\{i\}} S_{jdh}(p^{c*}_{dh}) + a_{idh} + a_{rdh} \ \forall d, h, \tag{4.9}$$

where strategies of thermal firms other than firm j is σ_{-ij}.

This equilibrium definition embeds an algorithm for finding an equilibrium. First, the storage operator's best responses to the rest of the market's strategies are conditional on signal X. Storage's production leads to another signal X^{σ_i} for updated net demand, as in Section 4.4.1. Thermal generators observe this signal and respond to both storage and each other, as in Section 4.4.2. Then, storage updates its best response conditional on changes in thermal generators' strategy, as in Section 4.4.3. This process can be iterated until a fixed point, σ^*, is found. The process converges when there is no update in any $w_{X^{\sigma_i},X}$s.

5 Empirical Strategy

In this section, I outline my empirical strategies. First, I show the estimation of public signal X and the conditional distribution of net demand $f_D(D|X)$. Then, I describe the algorithm I use to solve storage's infinite horizon problem under different ownership structures. I present the algorithm for finding the equilibrium in a market with storage. Then, I discuss how to incorporate an expansion in renewable capacity into my model. Finally, I discuss how I calculate CO_2 emissions, electricity production, and storage investment costs.

5.1 Classifying Days: Estimating Distribution of Demand

In electricity markets, renewable resources usually have lower merit order. Therefore, the SO first clears the demand with renewables then calls on storage and thermal generators. I define a new variable, net demand, which is the difference between demand and renewable production. Net demand is a more relevant variable for the model since thermal generators and storage compete for the net demand.

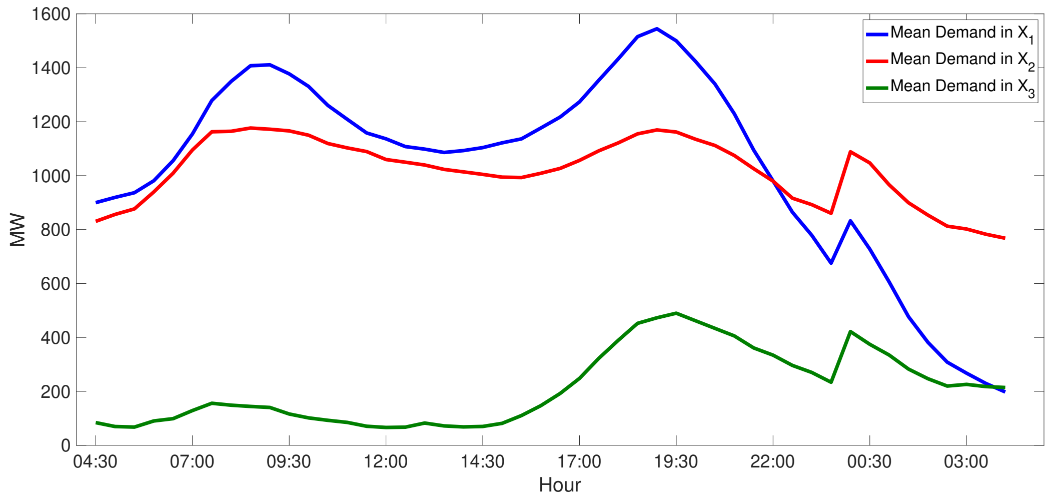
There are two renewable resources in SA; one is solar, the other is wind. All the solar generation in SA comes from rooftop solar PVs. Customers directly consume this electricity; therefore, they buy less from the grid. The demand in the dataset is demand after solar PV production. I calculate net demand in data as the difference between demand and wind generation. In the dataset, I do not observe curtailment for renewable. According to the AEMO's Quarterly Energy Dynamics reports (AEMO (2018)) , wind curtailment around this period is less than 5 % in SA; therefore, I assume there is no curtailment.

In order to define signal X, I assign observed net demand vectors D_d (size 48×1) to N_X groups $\mathcal{X} = \{X_1, \ldots, X_{N_X}\}$ by using their corresponding forecast vector FD_d. I use the k-median clustering algorithm to group days and construct $\mathcal{X}$. For given number clusters, this algorithm partitions vectors into clusters. The objective of this algorithm is to minimize within-cluster sum of squares,

$$\underset{\mathcal{X}}{\operatorname{argmin}} \sum_{m=1}^{N_X} \sum_{d \in X_m} ||FD_d - \boldsymbol{\mu_{X_m}}||^2,$$

where $\boldsymbol{\mu_{X_m}}$ is the median vector in X_m.

Figure 8: Mean Net Demand for 3 Clusters



I use the elbow method to pick the optimal number of clusters, N_X. The elbow method looks at the total within-cluster sum of squares as a function of the number of clusters and picks a point in which a new cluster does not improve the objective much. I pick the number of clusters to be $N_X = 16$. The observed data shows a wide variety of net demand patterns.

Figure 8 shows expected net demand conditional on $X \in X_m$, $\mathbb{E}[D|X]$ for 3 different signal X. The green line demonstrates a day in which net demand is almost 0. Particularly observed thermal generators' bids in this day provide information about how thermal generators bid in a day with abundant renewable production. Next, the red line displays a smoother net demand profile than the blue line. Storage production in a blue line day can smooth net demand and transform it into a red line day. These types of richness in net demand patterns addresses out-of-sample concerns for the procedure in Section 4.4.2 and in Section 5.5.

In order to fully characterize $f_D(D|X)$, I estimate the distribution of net demand conditional on signal X. Within the day, I assume net demand follows an AR(1) process within each cluster m,

$$D_{dh} = \beta_{mh} D_{dh-1} + \alpha_{mh} + \epsilon_{m_{dh}} \forall h, m,$$

where α_{mh} stands for fixed effects of period and cluster, β_{mh} is the persistence in net demand, and $\beta_{m1} = 0$ for each m. Within each cluster m, net demand D follows a distribution following the AR(1) model with parameter set $\theta_m = (\alpha_{m1}, \beta_{m1} \ldots, \alpha_{m48}, \beta_{m48})$. In Appendix B I present θ_m. I assume a Markov process for the transition of signal X, $f_X(X_{d+1}|X_d)$.

5.2 Solving Storage's Problem

In order to solve the storage operator's problem in Equation 4.2, first I assume the charge level at the end of the day, Ch_{d+1}, is a discrete multiple of 30 MW.[14] Since both $\mathcal{X}$ and K_{CH} are finite, there are only $N_X \times \frac{K_{CH}}{30}$ value functions of storage to assign a value. Notice that storage's charge level within the day is still continuous.

For the storage operator's flow payoff, I simulate the price function p^c_{dh} in Equation 4.2 by drawing 100 sets of $\widehat{S}_{-idh}$ and $\widehat{D}_{dh}$ conditional on X from σ_{-i} and f_D respectively. I estimate thermal generator j's strategies, σ_j, by using its bids in data. Then I calculate price function p^c_{dh} by inverting the market-clearing condition from Equation 4.6. The inverse of the sampled aggregate supply bid, S^{-1}_{idh}, is not smooth; therefore, I locally approximate the price function by a quadratic polynomial. I constrain the quadratic polynomial approximation to be decreasing in storage's production a_{dh}.

Given initial continuation values, I use discrete-time, finite states value function iteration methods to solve for $\sigma^*_i = \Lambda_i(\sigma_{-i})$. I solve storage's problem for every initial charge level Ch_d, conditional on ending the day with every terminal charge level Ch_{d+1}. Then, I pick the terminal charge level that gives the highest net present value of revenue. I update values for continuation values at iteration $t+1$ by inverting the bellman equation, by abuse of notation, $V^{t+1} = (I - \beta F)^{-1}\Pi^t$. Given the updated values, I solve storage's problem to find $t+1$th iteration's flow payoff, Π^{t+1}. In Appendix B, I show details of the procedure.

Ownership

I consider different storage ownership structures to examine the extent of the disparity between storage's private and social incentives. Section 2.2 considers only monopoly storage's problem, where it maximizes its revenue. In this section, I consider three different ownership structures: monopoly, load-owned, competitive.

Depending on the ownership structure, the storage operator's objective varies. Monopoly storage is essentially a monopolist in the storage market, in which it maximizes its revenue. On the other hand, a load-owned storage minimizes the market electricity acquisition cost. This case gives the highest consumer surplus increase that storage can reach since I assume demand is inelastic. The competitive storage case is the environment where many small storage units engage in arbitrage simultaneously, maximizing individual revenues. Individual small storages do not internalize their price effect, but at the aggregate level, they affect prices. This case can be thought of as a perfectly competitive storage market.

To illustrate the different objectives, similar to Section 2.1, I consider a market with two periods. Storage buys in first period and sells in second period. Price functions are P_1, P_2, with an inelastic

[14] In the NEM, all generators larger than 30MW must sell all their output by submitting bids.

demand Q_1 and Q_2. The objectives and first-order conditions are

$$\max_q -P_1^s(q)q + P_2^s(-q)q\,, \qquad \text{FOC} \ : P_2^s(-q) - P_1^s(q) - \frac{\partial P_2^s(-q)}{\partial q}q - \frac{\partial P_1^s(q)}{\partial q}q,$$

$$\max_q -P_1^s(q)(Q_1+q) - P_2^s(-q)(Q_2-q)\,, \quad \text{FOC} : P_2^s(-q) - P_1^s(q) - \frac{\partial P_2^s(-q)}{\partial q}(q-Q_2) - \frac{\partial P_1^s(q)}{\partial q}(q+Q_1),$$

$$\max_q -P_1^s(q)q + P_2^s(-q)q\,, \qquad \text{FOC} : P_2^s(-q) - P_1^s(q),$$

in which storage is monopoly, load-owned, and competitive, respectively, and $P_1^s(q) = P_1(Q_1+q)$ and $P_2^s(-q) = P_2(Q_2-q)$.

Notice that, when storage's production q is small, the price effect is negligible and all the objectives are aligned. As storage's production gets larger, monopoly and competitive storages' problem depart due to market power. Monopoly storage sells when the price is high and its price effect is low to maximize its revenue. On the contrary, load-owned storage sells when price effect and demand after storage's production are high to maximize the decrease in electricity acquisition cost. In other words, monopoly storage prefers low price elasticity periods to buy and sell.

Yet, load-owned storage prefers high (low) price elasticity periods to sell (buy). I discuss the results of different storage ownerships in Section 6.3.

5.3 Simulating Thermal Generator's Best Responses and Defining a New Signal

To solve for σ^* in Section 4.3, I start with estimated market equilibrium strategies of thermal firms, σ_{-is}. First I solve $\sigma_i = \Lambda_i(\sigma_{-is})$ by following Section 5.2. Given the storage operator's strategies σ_i, for each simulated $\widehat{D}_{dh}$ and storage's production a_{dh}, I calculate $\widehat{D}'_{dh}$. I check the distance between realized net demand after storage's production, $\widehat{D}'_{dh}$, with mean demand of the clusters $\{X_1, \ldots, X_{16}\}$. I assign day d to a cluster whose mean demand is the closest to $\widehat{D}'_h$, X_m.

I define the new signal $X_d^{\sigma_i}$ to be a member of X_m. In order to approximate weight $w_{X^{\sigma_i},X}$ (probability of signal X^{σ_i} conditional on signal X),

$$w_{X^{\sigma_i},X} \approx \sum_{\widehat{D}'_d(X)\in\widehat{\boldsymbol{D}}'_d(X)} \frac{\mathbb{1}\{\mu_{X^{\sigma_i}} = \operatorname{argmin}_{m\in\{1,\ldots,N_X\}} \|\widehat{D}'_d(X) - \boldsymbol{\mu_{X_m}}\|\}}{100},\ \forall X, X^{\sigma_i},$$

where $\widehat{\boldsymbol{D}}'_d(X)$ is the set of simulated net demand after storage's production for a day given the state X, $\boldsymbol{\mu_{X_m}}$ is the mean vector in X_m, $\sum_{X'} w_{X^{\sigma_i},X} = 1$, and $w_{X^{\sigma_i},X} \geqslant 0, \forall X, X'$.

Here, I compare simulated net demand after storage's production with mean demand of estimated demand clusters in Section 5.1. For iteration of $\Lambda_j(\sigma_i, \sigma_{-ij}|X^{\sigma_i})$, I use these weights to update thermal generators' strategies σ_{-i}, as in Proposition 4.1. I update draws of $\widehat{S}_{-id}$ according to weights $w_{X^{\sigma_i},X}$ in the storage operator's problem in Section 4.4.3. Then, I iterate this process

Table 2: Generation Costs for SA

Generator Name	Marginal Cost (AU$/MWh)	Ramping Cost (AU$/MWh)^2	Start-up Cost (AU$/MW)	Operational Cost (AU$/MWh)
Torrens Island	57.32	0.03	15	7.19
Pelican	59.56	0.03	15	7.19
Osborne	88.88	0.05	5	2.16
Quarantine	86.20	0.05	100	10.69
Ladbroke	98.59	0.05	100	10.69
Hallett	123.48	0.07	100	10.69
Mintaro	105.56	0.06	100	10.69
Dry Creek	113.61	0.06	100	10.69
Pt Stanvac	65.48	0.04	100	11.18
Angaston	106.06	0.06	100	11.18
Lonsdale	65.48	0.04	100	11.18
Snuggery	111.45	0.06	100	10.69
Port Lincoln	106.31	0.06	100	10.69
Import from VIC	-	-	-	-

Notes: The table shows AEMO's Integrated System Plan's estimates of electricity production cost for each generator in South Australia Electricity Market July 2016 – December 2017.

until there is no update in weights. Appendix B shows the details of the algorithm. I do not prove the existence or uniqueness of the fixed point. However, in my dataset, the procedure converges to a fixed point.

5.4 Welfare and Emissions changes, Storage Investment Cost and Round-trip Efficiency

Welfare and Emissions Changes Storage changes the electricity production of thermal generators. Therefore, it affects the cost of producing electricity and CO_2 emissions. By comparing these production changes, I calculate the consumer surplus, total welfare, and CO_2 emissions changes in the market.

In my model, change in total welfare is equal to change in electricity production cost, since demand is inelastic. AEMO's Integrated System Plan (ACILAllen (2016)) contains information about each generator's heat rates (GJ/MWh), CO_2 emissions (ton/MWh), fuel cost (AU$/GJ), and start-up cost (AU$/MW). These industry-estimated costs are comparable with inflation and fuel price adjusted versions of Reguant (2014) and Wolak (2007). I use Reguant (2014)'s estimates for ramp-up cost, after adjusting by heat rates and fuel prices. I also calculate start-up and ramp-up costs in terms of fuel and add the induced emissions into the CO_2 emissions calculations. Table 2 shows industry estimates of cost parameters for each generating unit in SA. I use the following model to calculate the cost of producing q_{jd} by firm j in day d:

$$C_j(q_{jd}) = \sum_{h=1}^{H} \alpha_{j1} q_{jdh} + \alpha_{j2} \mathbb{1}(q_{jdh} > q_{jdh-1})(q_{jdh} - q_{jdh-1})^2 + \alpha_{j3} \mathbb{1}(Start_{jdh}) q_{jdh}.$$

Given the calculated market equilibrium strategies σ^*, I simulate 2000 consecutive days. Then, I compare each generator's production before and after the storage's production. For each change, I calculate differences in the cost of production and CO_2 emissions.

Storage Investment I use the estimates from Fu et al. (2018) for storage investment cost. For Energy to Power ratio 8, 4, 2, 1, 0.5, I use US$320, US$380, US$454, US$601, US$895 per KWH, respectively. Similar to Lazard (2018), I assume storage has a 20-year lifetime and does not degrade over its lifetime. Some prediction models use cycle life instead of calendar life. Some studies show that storage's charging patterns can drastically affect the level of degradation of its material (Koller et al. (2013), Abdulla et al. (2016)). In Appendix C, I include a usage cost for storage's production to address these concerns.

Round-trip Efficiency I use HPR's data in 2018 to estimate round-trip efficiency. The data includes how much HPR buys and sells in the energy market. A lot of factors can effect round-trip efficiency: temperature, pace of usage, etc. I assume a uniform round-trip efficiency. I calculate charge levels in data using

$$Ch_{dh} = \sum_{d'=1}^{d} \sum_{h'=1}^{h} (1 - \gamma * \mathbb{I}(a_{dh} > 0)) a_{dh}.$$

I pick a γ that minimizes the range of Ch_{dh}, which includes possible charge levels of HPR $[0, 120]$. I find 80% to have the best fit. However, the dataset does not include HPR's supply to ancillary services. I assume HPR supply to be 5% of its production to ancillary services. Therefore I pick $\gamma = 0.85$.

5.5 Higher Penetrations of Renewable Resources

To model an increase in VRE capacity, I use the observed renewable production in the data. For an M% increase in renewable capacity, I update total renewable production a_{rdh} by $a'_{rdh} = a_{rdh} * (1 + \frac{M}{100})$.[15] If updated renewable production exceeds the total of demand trade capacity of SA with Victoria, $a'_{rdh} > D_{dh} + 700$, SO curtails the difference. Storage can decrease the curtailment by buying electricity when renewable production exceeds demand. I define updated net demand by

[15] Here, I am assuming that an increase in renewable capacity linearly increases renewable production. One can simulate the effects of different additional renewable production profiles by changing the update formulation.

$$D^r_{dh} = \begin{cases} D_{dh} - a'_{rdh}, & \text{if } D_{dh} + 700 - a'_{rdh} \geqslant 0 \\ 0, & \text{if } D_{dh} - a'_{rdh} + 700 < 0. \end{cases}$$

Similar to the procedure in 4.2, I define a new signal $X^r \in \mathcal{X}$, which conveys information about the distribution of D^r_{dh}. I follow the same procedure in Section 5.3 to estimate thermal generators' strategies. The difference for X^r is that it is also observed by the storage. Therefore, storage's production does not affect the signal X^r unlike signal X^{σ_i}. Now $w_{X^r,X}$ gives the probability of signal X^r conditional on signal X, and needs to be calculated only once.

6 Results

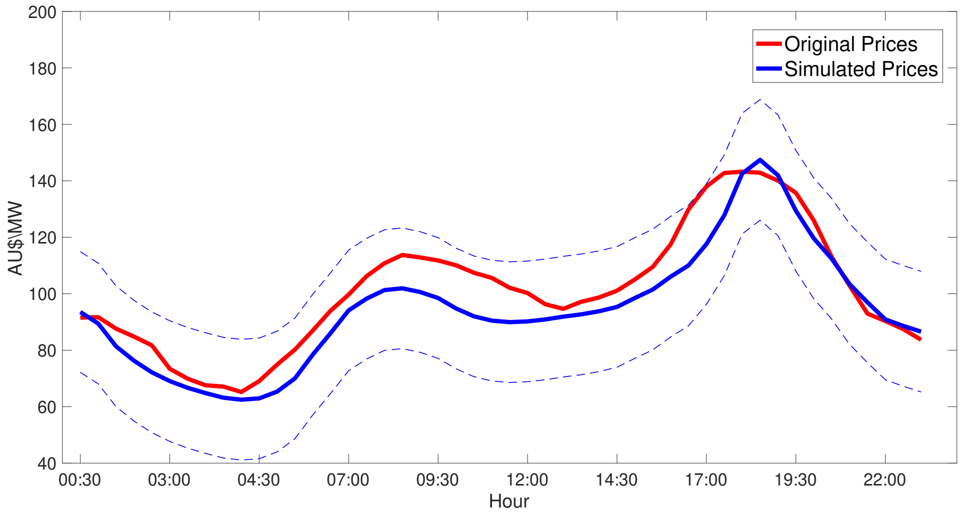
In this section, I present my estimates of the private and social returns to storage in the electricity market. Given the calculated market equilibrium strategies σ^*, I simulate 2000 consecutive days. First, I discuss the fit of my model in the baseline case without energy storage. Here, I compare summary statistics of my estimates for energy storage with Hornsdale Power Reserve (HPR) in 2018. Second, I compare models of energy storage and demonstrate how the price effect, uncertainty, and firms' responses affect the storage operator's private incentives. Third, I look at different ownership structures for storage. I assess the storage operator's private and social returns under each scenario: monopoly, load-owned, and competitive storage. Last, I discuss the interaction between storage and renewables under different levels of investment in renewables (solar and wind generation) and storage.

6.1 Model Assessment

Before turning to estimates of energy storage's effect, it is important to understand the fit of the model in the baseline case without energy storage. First, the model assumes firms condition their production on public signal X_d. In order to check the validity of the public signal, I calculate the variation explained in thermal generators' bids by the estimated clustering. The calculation includes comparing supply schedules, S_{jd}. To construct the distance measure, I use L^2 distance for each of the observed market prices. Clusters explain 91% of the variation in the firms' bids and 86% of the variation in the daily demand vector, D_d. Appendix B shows details of the k-medians algorithm and constructed L^2 distances.

Electricity price patterns are key for storage's profitability. Note that the model doesn't use price moments. It also uses observed bids and demand conditional on the public signal. Figure 9 presents the simulated average daily prices against the actual data. Dashed lines in Figure 9 show one standard deviation in simulated prices. The simulated price pattern is comparable to

Figure 9: Average Original vs. Simulation Prices



the observed data, in spite of missing some price spikes. My model fails to match periods with a price above AU$1000. These extreme prices periods only occur 0.4% of the time in the observed period.[16]

I also compare summary statistics of my estimates for energy storage with observed energy storage, HPR. Note that the model does not use HPR's data. I use data from July 2016–December 2016 to calibrate my model, and I compare the calibrated estimates to HPR's data from 2018. Average prices in these two periods are very similar, AU$100.8 and AU$99.8 with a standard deviation AU$266.2 and AU$267.6, respectively. After adjusting for the AU$1000 price ceiling, HPR's revenue in 2018 is AU$1.52 million compared to my estimate of AU$1.34 million.[17] In another aspect, HPR did 616 charge/discharge cycles in 2018, whereas my estimate is 529 per year.

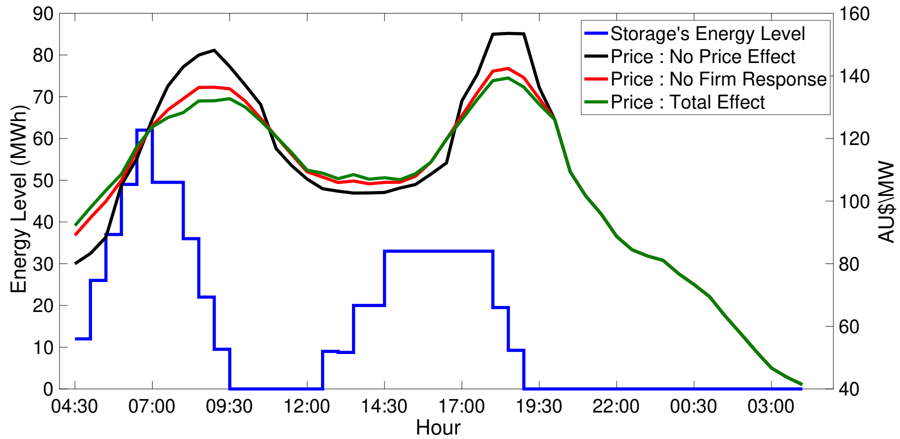
In reality, the storage operator updates storage's production during the day in response to receiving more information about demand and other firms' bids, whereas my model does not allow within day adjustments. This new information leads to higher revenue and activity than my estimates. In Appendix C, I discuss how changing the storage operator's information set effects its strategies. On top of the adjustments, HPR solves a joint profit maximization in energy and ancillary services markets and can adjust its participation accordingly, which can lead to an increase in energy-only market revenue.[18]

[16]These extreme prices occur under sudden expected changes such as a failure of a generator, transmission outages. It is very hard to simulate these prices without an extensive dataset of such changes. In Appendix C, I suggest a way to incorporate the effect of extreme prices into the storage operator's revenue.

[17]HPR made AU$2.43 million revenue from the energy-only market in 2018. Incorporating these extreme price periods to my model by following Appendix C increases my estimates to AU$1.96 million

[18]My model incorporates this effect by decreasing the round-trip efficiency rate.

Figure 10: Storage's Price Impact Under Different Models for a Representative Day



6.2 Private Returns: Market Power, Uncertainty and Firms' Best Response Effects

The energy storage literature either ignores storage's price effects or models them without considering the implications on other firms' bidding (Sioshansi et al. (2009), De Sisternes et al. (2016), Salles et al. (2017)). When storage is small, the price effect is negligible; therefore, storage does not affect other firms' revenues. However, as storage gets larger, biases from ignoring price effects might arise. In this section, I consider the biases that afflict the model without storage's price effect.

In Figure 10, I compare the storage's price impact on a representative day under different models. When storage does not have a price impact, the storage operator does not have any incentives to under-produce. The black line is the same price path as in the market without storage. Next, I consider the storage's price impact without allowing other firms to respond. As the storage operator engages in arbitrage, it smooths the price path. Since in data, other firms submit supply schedules as their willingness to produce, I can calculate new prices after storage's production. The red line is smoother than the black line, as the storage operator buys low and sells high. Last, when storage affects prices, other firms may have incentives to change their bids, since the price change affects their market power. Theoretically, the equilibrium impact on prices is ambiguous, since the effect of storage on incumbent firms' bidding strategies is ambiguous (Vives (2010), Genc and Reynolds (2011)). However the blue line suggests, as it is smoother than the red line, firms bid more aggressively as a response to storage. Therefore the equilibrium impact amplifies storage's price effect.

In Table 3, I evaluate the storage operator's profit under four different models. The first column assumes that the storage operator has perfect foresight about future prices, and the storage is small; therefore, there is no price effect. Going from Model 1 to 4, I relax one simplifying model assumption each time. In column 2, I relax the perfect foresight assumption. In this model, the storage

Table 3: Storage's Yearly Returns Per 1 MWh

	(1)	(2)	(3)	(4)
Storage's Private Returns				
Revenue (1000 AU$ per MWh)	46.66	23.31	12.38	11.18
Cost (1000 AU$ per MWh)	25.27	25.27	25.27	25.27
Profit (1000 AU$ per MWh)	21.39	-1.96	-12.89	-14.09
Number of Cycles	994	842	601	529
Model Assumptions				
Uncertainty	×	✓	✓	✓
Price Effect	×	×	✓	✓
Firms' Response	×	×	×	✓

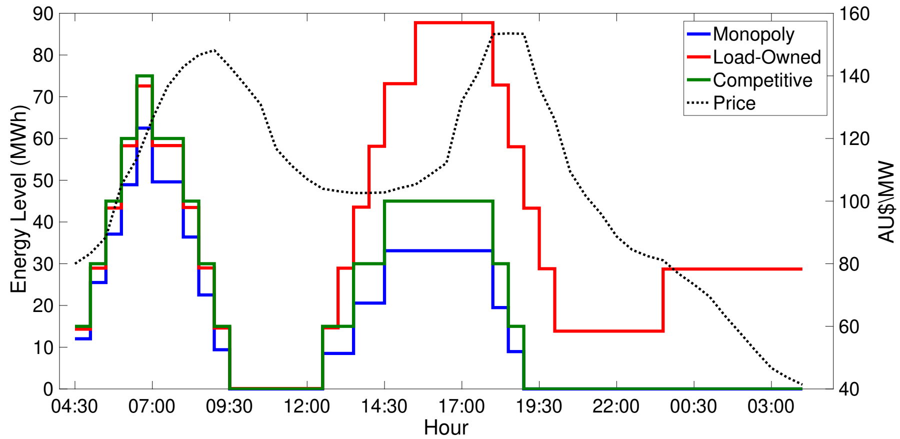
Notes: This table presents storage's simulated private returns per MWh for four different specifications. In all specifications, the Energy to Power ratio is 4 and round-trip efficiency is 85%. For specifications (3) and (4), storage has 120 MWh, 30 MW capacity. The sample is from the South Australia Electricity Market July 2016 – December 2017.

operator does not observed prices but observes a public signal, X_d, and produces conditional on that signal. I use Equation 4.1 to formulate the storage operator's uncertainty. In column 3, storage is large, so I relax no storage-induced price effect assumption. In column 4, I allow other firms to respond to storage's production and calculate a new equilibrium following Section 4.4.

Table 3 suggests that omitting the price effect and uncertainty of large storage overestimates its profit. Comparing columns 1 and 2 shows that uncertainty significantly affects profitability, even if storage is small. One concern about this comparison is that the results may not be robust to the modeling of uncertainty and the storage operator's information structure. In the model, there are two main sources of uncertainties in the storage operator's problem, net demand and other firms' bids. In Appendix C, I address the robustness of the results for information structure of the former. Results qualitatively unchanged.

Column 3 shows that when storage is large, the price effect has a significant impact on storage's profitability. Electricity prices smooth out as the storage operator buys and sells more. Intertemporal price differences decrease as storage's production increases and arbitrage opportunity shrinks. Therefore, the storage operator's profit per unit decreases. This result suggests that using price taker models for large storage significantly overestimates its profit. Without the price effect storage almost break-even, in column 2, whereas with price effect, there needs to be substantial improvements on the cost side, in column 3. Failing to address this price effect channel in energy storage profitability calculations can lead to incorrect conclusions.

Figure 11: Optimal Energy Level Under Different Ownership Structures for a Representative Day



If there is no price effect due to storage's production, other firms do not have any incentive to change their strategies. However, when there is a change in prices, firms update their strategies due to changes in their market power. The literature on supply function equilibrium suggests that the effect of this update on the storage operator's profit is ambiguous (Vives (2010), Genc and Reynolds (2011)). Comparing columns 3 and 4 shows that firms' response to storage decreases the storage operator's profit. This means firms respond to the change in market power by bidding more aggressively, thereby decreasing peak prices and the storage operator's profit. This change suggests that storage mitigates incumbent firms' market power and increase consumer welfare. In the next section, I discuss the effects of increasing competition on welfare and consumer surplus.

6.3 Private Incentives are not Socially Optimal

In this section, I use my model estimates to discuss private and social returns for energy storage with a capacity of 120 MWh and 30 MW under different ownership structures: monopoly, load (consumer) owned, and competitive. Each ownership has different objectives as I formalize in 5.2. Figure 11 displays the differences in the optimal charge level of the storage operator under different ownership structures for a representative day. Table 4 shows the private and social returns of the storage operator under different ownership structures. For calculating storage's installment and market's production cost, I use industry estimates by following the models in Section 5.4. The rest of the summary statistics comes from the counterfactual exercises.

In this section, I am excluding emissions impact on welfare and considering them separately in Section 6.4. My approach can incorporate emissions costs into the welfare analysis for any given level.

Table 4: Storage Operator's Private and Social Returns Under Different Ownership Structures

	Per Year								
	Million AU$					Thousand MWh		Thousand Ton	
	Storage's			Δ in Market's		Δ in Production of			
Ownership	Revenue	Cost	Profit	Consumer Surplus	Cost	Natural Gas Generators	Diesel-Oil Generators	Δ in CO_2 Emissions	Number of Cycles
Monopoly	1.34	3.03	-1.69	3.25	-1.54	19.70	-10.31	-3.12	529
Load Owned	0.59	3.03	-2.44	5.45	-2.21	34.42	-14.34	1.61	1120
Competitive	1.06	3.03	-1.97	3.56	-1.77	27.08	-12.34	-2.64	820

Notes: This table presents storage's simulated private and social returns. In all cases, storage has 120 MWh, 30 MW capacity, with 85% round-trip efficiency. The sample is from the South Australia Electricity Market July 2016 – December 2017.

Monopoly Case: Positive externalities cannot be internalized by market prices

In monopoly case, I use single grid-scale energy storage that maximizes its profit. Monopoly case gives the highest private return; therefore, it is the most relevant case to understand entry incentives for the storage operator. Also, monopoly storage has incentives to under-produce because of its market power. As Figure 11 presents, monopoly storage engages in less arbitrage relative to the other ownership structures. The first row of Table 4 shows private and social returns. Storage undergoes 529 full charge and discharge cycles over a year on average to maximize its profit. The number of cycles can be interpreted as the production (activity) of energy storage.

The negative profit (conditional on entry) shows energy storage is not profitable. There are two forces that affect profitability: the extent of the arbitrage and the cost of investment. Although the SA electricity market has one of the highest price spreads in the world, results show that the electricity market is not yet profitable enough for fully private investment in storage to only engage in arbitrage. However, a substantial improvement on the cost side, around 60%, can trigger entries for energy storage. Also, there might be some concerns about the robustness of the information structure of the storage operator, which can affect revenue. I address some of these concerns in Appendix C.

Storage introduces positive non-pecuniary externalities by changing the production efficiency and emissions content of marginal units. The difference between storage's revenue and change in market cost shows that there is a misalignment of private and social returns. As I discuss in Section 2.1.2, firms' bids do not necessarily reflect their production cost. The market power of other firms distorts market prices and cause misalignment of private and social incentives.

Storage also introduces positive pecuniary externalities for consumers by changing the inframarginal units' revenue. Storage operator sells (buys) when prices are high (low) and decreases (increases) prices. It decreases average prices since the energy storage price effect is higher at high time prices (due to higher residual demand elasticity, as in Section 2.1). A decrease in average prices decreases electricity acquisition costs. Since the model assumes demand to be inelastic, electricity acquisition cost decrease is equal to the consumer welfare increase.

Even though investing in storage is not privately profitable, it is socially desirable from the consumer's point of view. The storage-induced increase in consumer surplus is larger than its cost. This gap between private and social returns suggests a market failure, namely an under-investment problem. The storage operator does not internalize pecuniary externalities for its investment decision. This market failure resembles the "missing money" problem in electricity markets (e.g., Hogan et al. (2005) and Joskow (2008)).

Like the solution of the "missing money" problem, a lump-sum payment or capacity markets for storage can address this entry problem, in which the storage operator gets paid the difference between a change in consumer surplus and its revenue. Some capacity markets require units to be ready to produce on call. Since storage's production is contingent on its charge level, this requirement imposes a floor on storage's capacity at all times. Reserving some capacity directly affects storage's production and profit; therefore, it requires analysis with different regulatory constraints.

There are two factors that drive the discrepancy between the storage operator's profit and the increase in consumer surplus, the market power of other firms, and the storage operator. The market power of other firms distorts the market prices, and the market power of monopoly storage causes an under-production. In the next two cases, I disentangle the effects of these two forces.

Load-Owned Case: Ownership change can extend the social returns

Load-owned case adds the inframarginal considerations to the storage operator's problem and gives the greatest storage-induced consumer surplus change. As Figure 11 shows, load-owned storage's production could be drastically different from the monopoly case. Load-owned storage searches for periods for higher price effect and higher demand to sell to maximize the price impact of the storage, whereas monopoly storage only looks for low price effect periods to keep price difference between periods high.

Load-owned storage maximizes the transfer from the consumer side to the producer side and helps to mitigate the market power of thermal generators. Therefore, if the SO has concerns such as mitigating market power and decreasing electricity acquisition cost in the electricity market, the load-owned case can be interpreted as SO owned storage. However, load-owned storage does not necessarily maximize welfare, since market prices are not necessarily the marginal cost of electricity production. If SO does not elicit information about the generator's cost of production, consumer surplus maximization can also be interpreted as a proxy for welfare maximization.

The second row of Table 4 indicates that load-owned storage almost doubles the monopoly storage's consumer surplus increase. It does so by doubling the number of cycles of monopoly storage, losing more than half of its revenue. Although load-owned storage does not necessarily maximize the total welfare, it increases the welfare compared to the monopoly case. However, it increases CO_2 emissions. This effect is mostly due to the higher activity of storage. More production of storage leads to more energy lost to round-trip efficiency.

The significant difference between the monopoly and load-owned cases for consumer surplus increase shows that solving the under-investment problem of the storage operator is not necessarily enough to reach higher social returns. One concern with the misalignment of private incentives for operating can be the market power of storage, as I discuss in Section 2.2. The economics literature widely discusses the market power of thermal generators (e.g., Wolfram (1999), Borenstein et al. (2002), Wolak (2003)). Sioshansi (2014) considers a case in which storage decreases welfare due to its market power. To address concerns about the storage operator's market power, I consider a competitive storage market case.

Competitive Case: Highest social return cannot be achieved by increasing competition

In competitive case, I use single grid-scale energy storage with no market power that maximizes its profit. One can interpret this case as many small storage providers that do not internalize their price effect but affect prices at the aggregate level. These storage operators want to minimize price differences. As Figure 11 shows, competitive storage's production is closer to the monopoly case. Competitive storage engages in arbitrage without considering its price effect. As Section 2.1.1 suggests, this case perfectly aligns with maximizing welfare (and consumer welfare), under the assumption of a perfectly competitive electricity market. Therefore other firms' market power effects can explain the difference between competitive and load-owned cases.

Table 4's third row shows that competitive storage increases consumer surplus and welfare more than the monopoly case, but does not reach the load-owned welfare levels. Also, the decrease in revenue is not as large as in the load-owned case. As Section 5.2 suggests, increasing competition decreases the distance between the load-owned and monopoly cases. Monopoly energy storage can deliver high enough social returns, while load-owned storage pushes it even further. The competitive case yields intermediate returns between monopoly and load owned. However, results also suggest that there is still a significant gap between private and social returns in the absence of the storage operator's market power.

The comparison between these three cases suggests two conclusions for private and social returns disparity: storage operator's market power is important, but even abolishing that power is not enough to fully utilize energy storage. As I discuss in Section 2.1.2, due to the market power of incumbent firms, the storage operator profit-maximizing incentives do not align with welfare-maximizing incentives in a market with imperfect competition even when storage is small. This

Table 5: Storage Operator's Private and Social Returns Under Different Renewable Levels

	Per Year								
	Million AU$							Thousand Ton	Thousand MWH
	Storage's			Δ in Market's					
	Revenue	Cost	Profit	Consumer Surplus	Cost	Wind Revenue	Solar PV Save	Δ in CO_2 Emissions	Curtailment
Baseline	1.34	3.03	-1.69	3.25	-1.54	-1.70	-0.44	-3.12	-
Double Wind	2.75	3.03	-0.28	6.12	-3.12	1.63	-0.38	-8.89	-18.6
Double Solar	1.65	3.03	-1.38	4.30	-2.12	-1.43	-0.78	-4.15	-0.1

Notes: This table presents storage's simulated private and social returns under different renewable production capacities. In the baseline case, renewable capacities are at levels as they are currently seen in South Australia. In the double wind (solar) case, I double wind (solar) production by using observed renewable profiles in South Australia. In all cases, storage is a monopoly and has 120 MWh, 30 MW capacity, with 85% round-trip efficiency. The sample is from the South Australia Electricity Market July 2016 – December 2017.

discrepancy affects the day-to-day operations of the storage operator and cannot be fixed via competition or fixed payments. This result suggests that FERC's rule for not allowing SOs to use energy storage as a generating asset may lead to socially inefficient or no usage of energy storage.

6.4 Renewables and CO_2 Emissions

An increase in VRE capacity is one of the main motivations for investing in energy storage. Energy storage supports VRE by smoothing the variability and intermittency and decreasing the curtailment of VRE. On the other hand, VRE increases intertemporal price differences and increases private returns for energy storage investment (Woo et al. (2011), Ketterer (2014)). Therefore this leads to the intuition that should both exist in support each and promote simultaneous expansion.

I study the interaction between VRE and storage by considering changes in VRE capacity. For each wind and solar pv generations I double the production capacity and first calculate the equilibrium without energy storage by using the model in Section 5.5.[19] Then I introduce energy storage in both cases to calculate storage's impact on the doubled renewable scenarios. Table 5 shows the private and social returns of monopoly energy storage and non-strategic renewables' revenue under different generation capacities.

There are two factors that affect energy storage's effect on renewable revenue: the change in average prices and the correlation of renewable generation and prices. First, storage decreases average prices by smoothing price differences. Overall this force leads to a decrease in renewable

[19] Note that the VRE capacity expansion may lead to some thermal generator exits. My results for VRE generation expansion might not be a long-run equilibrium.

revenues since renewable production is exogenous. Second, if renewable production is negatively correlated with prices, then the storage price effect increases renewables' revenue by smoothing the prices. Depending on the magnitude of these components, energy storage can hurt or support renewables. The literature on renewables considers a high correlation between demand and renewables' production as a high value for renewables (Keane et al. (2010)). In my model, storage damages higher value renewables' return more by engaging in arbitrage, decreasing high prices, and increasing low prices.

First, I find that at moderate levels of renewable power (when there is almost no curtailment for VREs), as currently seen in South Australia, introducing grid-scale storage to the system reduces renewable generators' revenue. For wind, on average, its production is stable throughout the day, as in Figure 5, the decrease in average prices hurts wind generators' revenue a lot. Even though wind production is negatively correlated with prices, -0.193, the average price effect dominates. On the other hand, solar generation and prices are positively correlated, 0.014. Therefore for solar, both forces hurt its revenue.

Second, I increase wind generation production from 35% to 70% of the overall market production. Due to high electricity generation from VRE at times, this expansion leads to around 50 thousand MW yearly curtailment of electricity. I find that doubling wind production doubles the storage-induced consumer surplus and total welfare increase. The main factor driving this welfare change is a decrease in curtailment. Storage increases the return to wind production by preventing a notable portion of the curtailment. Additionally, higher wind generation capacity leads to higher revenue for energy storage as a result of an increase in price variation. In this case, entering the electricity market becomes almost profitable for privately operated storage.

Third, I increase solar generation production from 10% to 20% of the overall market production by following the model in Section 5.5. Since solar generation is at a moderate level (no curtailment), it results in around a 500 MW yearly curtailment of electricity. Since there is no significant curtailment, I find that doubling solar production does not lead to a significant change in private and social returns to energy storage. However, as solar production increases, storage still hurts its revenue. Although in the scenario correlation between solar production and prices becomes negative, -0.033, the average price impact still dominates.

Unlike the previous literature on storage's CO_2 emissions effects (Hittinger and Azevedo (2015), Lueken and Apt (2014)), I find that storage decreases emissions. Two main factors affect emissions: the change in emissions content of the marginal unit and storage's round-trip efficiency. Changing the emissions content of the marginal units may have different implications. The CO_2 emissions-order does not necessarily follow the merit order; therefore, this shift can increase emissions. Table 5 suggests that, on average, storage replaces units that have higher CO_2 emissions with ones that have lower CO_2 emissions in SA. This is because it tends to increase low-emission natural gas generators' production and decrease high-emission diesel-oil generators' production. On the other hand, low round-trip efficiency causes more waste, which in return increases production and emissions. The former effect in CO_2 emissions is large enough to more than offset the loss due to round-trip inefficiency. In the case of curtailment, energy storage decreases emissions even more by preventing a notable portion of the curtailment.

7 Conclusions

Many governments have adopted policies to encourage and subsidize investment in renewable energy to reduce greenhouse gas emissions from their electricity sectors. The characteristics of renewable energy from wind and solar power pose particular challenges to the operation and stability of the electricity grid. Grid-scale energy storage holds the promise of mediating the operational challenges created by their inherent variability, intermittency and non-dispatchability. However, if private incentives for operating and investing in grid-scale energy storage are not aligned with social incentives, there may be under-investment and under-utilization of storage capacity.

In this paper, I introduce a dynamic framework to model the effects of introducing energy storage into a wholesale electricity market. The model incorporates storage production's price effect and allows for a new equilibrium to arise due to incumbent generating firms' responses to storage. I use estimated responses from thermal generation sources to observed variation in demand volatility in a market without energy storage to recompute the new supply function equilibrium when storage is introduced to the market.

My results have several policy implications on energy storage in electricity markets. First, investing in storage may not profitable, even when such entry would increase consumer surplus and reduce electricity production cost and emissions to the extent that it becomes socially desirable. This result argues for public policy responses such as subsidies or capacity markets for energy storage. Second, changing the ownership (objective) of energy storage can improve its social returns. However, these improvements cannot be attained by a competitive storage market. This result suggests a further regulation assessment on the ownership question of energy storage. Third, there is a non-monotonic relation between returns for renewables and energy storage investment. For moderate levels of renewable power, storage reduces renewable generators' revenue; however, for high levels of renewable power, storage increases renewable generators' revenue. This result suggests a need for policies that complement investments in renewables at different penetration levels with energy storage.

This paper motivates several future lines of future work. First, in this paper, I only consider the revenue of storage capacity in a wholesale energy market. System Operators manage many markets to maintain grid reliability and stability, such as ancillary services and capacity markets. Although ancillary services are smaller markets compared to energy markets, the revenue stacking approach (which combines ancillary services and capacity markets as well) may give a better approximation for the profitability of energy storage. Second, regulations in electricity markets can be updated to allow for fair and efficient energy storage entry and participation. Storage units' responses to such changes in incentives can be calculated to find an optimal regulatory framework for energy storage. Third, in this paper, I use the Australian National Electricity Market, which has zonal pricing. By extending my model to nodal pricing, it would be possible to find location-specific returns for energy storage investments in the US electricity girds.

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Table 6: Storage Operator's Private Returns Under Different Specifications

	Information Structure		Storage Operator's Policy		Roundtrip Effiency		Charging Cost per MW		
	Ch is public information	Storage observes bids	Static	Strike Prices	Higher	Lower	AU$200	AU$100	AU$50
Storage's Private Returns (Per Year)									
Revenue (Million AU$)	1.32	2.10	0.87	1.01	1.61	1.20	0.67	0.88	1.09
Cost (Million AU$)	3.03	3.03	3.03	22.50	3.03	3.03	0.52	0.69	0.88
Profit (Million AU$)	-1.71	-0.93	-2.16	-21.49	-1.42	-1.83	0.15	0.19	0.21
Number of Cycles	527	551	365	467	518	601	22	58	148

Notes: This table presents storage's simulated private returns. For information structure, I consider two specifications; storage's charge level to be public and storage observes other's bids. For storage operator's policy, I consider two policies: the same charge/discharge policy every day and charge/discharge policies by using strike prices. For roundtrip efficiency, I consider two different roundtrip efficiencies: 75% and 95%. For charging costs, I assume different operating costs corresponding to cycle lifetime levels 2500, 5000, and 10000. In all cases, storage is a monopoly and has 120 MWh, 30 MW capacity. The sample is from the South Australia Electricity Market July 2016 – December 2017.

Appendix (coming soon)

A Data Appendix

B Estimation Details

C Robustness

C.1 Storage with Different Technological Constraints

C.2 Renewable and Storage with Different Technological Constraints

Table 7: Storage Operator's Private and Social Returns Under Different Power and Energy Capacities

	Per Year				
	Million AU$				
	Storage's			Δ in Market's	
	Revenue	Cost	Profit	Consumer Surplus	Cost
Panel A. Change in Power Capacity					
120 MWh, 120 MW	1.98	4.79	-2.81	4.73	-1.28
120 MWh, 60 MW	1.64	3.62	-1.98	3.91	-1.32
120 MWh, 30 MW	1.34	3.03	-1.69	3.25	-1.54
120 MWh, 15 MW	1.19	2.56	-1.37	2.79	-1.85
Panel B. Change in Energy Capacity					
240 MWh, 30 MW	1.69	5.12	-3.43	3.67	-1.61
120 MWh, 30 MW	1.34	3.03	-1.69	3.25	-1.54
60 MWh, 30 MW	1.12	1.81	-0.69	2.78	-1.42
30 MWh, 30 MW	0.87	1.12	-0.25	2.14	-1.21

Notes: This table presents storage's simulated private and social returns under different storage capacities. In all cases, storage is a monopoly with 85% round-trip efficiency. The sample is from the South Australia Electricity Market July 2016 – December 2017.

Table 8: Storage Operator's Private and Social Returns Under Different Renewable and Storage Capacities

	Per Year								
	Million AU$							Thousand Ton	Thousand MWH
	Storage's			Δ in Market's					
	Revenue	Cost	Profit	Consumer Surplus	Cost	Wind Revenue	Solar PV Save	Δ in CO_2 Emissions	Curtailment
Panel A. 60 MWh 15 MW									
Baseline	0.83	1.51	-0.68	2.02	-0.92	-1.05	-0.31	-1.43	-
Double Wind	1.82	1.51	0.31	3.88	-1.89	1.09	-0.28	-4.85	-10.2
Double Rooftop	1.17	1.51	-0.34	2.75	-1.21	-0.97	-0.50	-1.57	-0.1
Panel B. 240 MWh 60 MW									
Baseline	1.89	6.06	-4.17	5.36	-2.13	-2.34	-0.64	-6.22	-
Double Wind	4.87	6.06	-1.19	9.70	-5.14	2.60	-0.45	-13.43	-26.6
Double Rooftop	2.01	6.06	-4.05	6.02	-2.19	-2.01	-0.82	-6.87	-0.3

Notes: This table presents storage's simulated private and social returns under different renewable production capacities. In the baseline case, renewable capacities are at levels as they are currently seen in South Australia. In the double wind (solar) case, I double wind (solar) production by using observed renewable profiles in South Australia. In all cases, storage is a monopoly with 85% round-trip efficiency. The sample is from the South Australia Electricity Market July 2016 – December 2017.