Economics of Grid-Scale Energy Storage in Wholesale Electricity Markets

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Abstract

I investigate the incentives for investing and operating grid-scale energy storage in electricity markets and the need for policies to complement investments with renewables. I develop a new dynamic-equilibrium framework that allows for storage's price impact and incumbent best responses to storage's production and apply it to study the South Australian Electricity Market. Results indicate ignoring storage's price impact leads to biased estimates; although privately operated storage entry is not profitable, it increases consumer surplus and reduces emissions, ownership has a significant effect on storage's impact, and storage substitutes or complements renewables under different generation mixes.

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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 precise matching of electricity supply and demand at every moment. In case of short-run changes on either side, a centralized entity called the System Operator (SO) calls up flexible electricity generators to balance the power grid. These units, called peakers, generally respond quickly, but they have to use more fuel, leading to inefficiencies and higher levels of carbon emissions.

The transition to a low-carbon electricity system is a critical challenge that requires renewable energy sources. However, the availability of Variable Renewable Energy (VRE) resources, such as wind and solar energy, depends on external factors that cannot be controlled, such as wind and sun. This exogenous intermittency exacerbates the gap between demand and supply due to short-run variability in their output. One solution to this challenge is grid-scale energy storage, which can smooth out fluctuations and present a more efficient and emission-friendly alternative to peakers.

A grid-scale energy storage firm participates in the wholesale electricity market by buying and selling electricity while creating private (profit) and social (consumer surplus, total welfare, and CO_2 emissions[1]) returns. Storage generates revenue by arbitraging on inter-temporal electricity price differences, buying low and selling high. If storage is small, its production may not affect prices. However, when storage is large enough, it may increase prices when it buys and decrease prices when it sells.

The price impact of grid-scale energy storage has both real and pecuniary effects on welfare. The production of energy 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. The price arbitrage also induces a transfer between producer and consumer surplus. Moreover, storing energy allows increased utilization of available capacity for VRE when electricity supply exceeds demand. Without storage, generation from these sources has to be wasted (curtailment).

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 equilibrium framework to quantify the potential effects of energy storage in the wholesale electricity market. Unlike previous literature on electricity markets, my framework considers the price impact of a new entrant and enables incumbent firms to respond consequent price changes.

My model uses data from an electricity market without energy storage to simulate the equi-

[1] The welfare analysis in this paper can be adjusted to include the costs associated with emissions. However, in this paper, I refrain from taking a stance on the social cost of emissions. Instead, I explore the impact of emissions on welfare in Section 6.

librium 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 are usually computationally intractable and not unique (Klemperer and Meyer (1989), Green and Newbery (1992)). I solve this challenge with an algorithm that models incumbent firms' best responses to the new entry by treating storage production as a particular shock to the distribution of residual demand conditional on a public signal. Thus, to solve for a new equilibrium, I compute a supply function equilibrium by iterating estimated best responses to observed variation in demand volatility in a market without energy storage.

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 a private signal such as their fuel cost. They then bid into the electricity market a day ahead of the actual production. Given incumbent firms ' strategies, I solve the storage operator's dynamic optimization problem using discrete-time finite-state value function iteration methods. Then, I model storage's production as a shift to net demand, which is the difference between demand and renewable production. 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, then thermal generators update their production based on the updated storage production, and so on. The fixed point of this process gives a new market equilibrium.

Although my framework is flexible enough to incorporate other storage technologies, in this paper I focus on batteries. 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; between 2010 to 2020 there has been 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 the 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, unlike technologies like pump hydro. Third, batteries are scalable: they use a similar type of technology regardless of their size.

In this research, I use South Australia Electricity Market data from July 2016 – December 2017.[2] In the observed period, generation in South Australia 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 equilibrium 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 electricity production capacity. Both the private and social returns are sensitive to this calculation. Previous methods that ignore the price effect 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 having grid-scale storage is socially efficient at current costs. I find that due to high investment costs in 2018, entering the electricity market is not profitable for privately operated storage. However, a such entry would increase consumer surplus and could increase 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 South Australia. 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 can 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

[2] In 2018, the world's largest lithium-ion battery at the time, Hornsdale Power Reserve (HPR), came online in South Australia.

capacity of storage; in contrast, Texas utilities are not permitted to own storage, and 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 load-owned storage. In this case, profit and consumer surplus increases are closer to the monopoly storage case than the load-owned case. This difference 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.

Then, I focus on the impact of grid-scale storage on incumbent generators' production and revenue. Storage while engaging in arbitrage affects existing generators in several ways: either by changing the marginal unit or changing the inframarginal unit's price. Storage mainly decreases the production of high-cost flexible generators and increases low-cost inflexible generators. On the revenue aspect, even though storage increases the production of low-cost generators, it still hurts their revenue due to the price impact.

Finally, I quantify the complementarity between VREs and grid-scale storage. 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. 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 several 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))[3].

The main novelty of my approach relative to previous research on electricity markets is modeling storage-induced price effects explicitly and allowing incumbent generators to respond to resulting price changes due to entry. Much of the previous literature ignores these channels and makes price-taker assumptions for storage. For small-scale storage, the assumption in the previous literature may be fine. However, as storage gets larger, this assumption overestimates 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), Jha and Leslie (2021)) 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 South Australia, energy storage decreases emissions in most scenarios, even in the absence of carbon pricing. South Australia'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. A recent working paper, Kirkpatrick (2018), empirically estimates the congestion benefits of utility-scale battery installations in California. Another recent working paper, Butters et al. (2020), focuses on the interaction between energy storage and substantial renewable penetration. Like our paper, Butters et al. (2020) models a dynamic optimization process for battery holders but discards the price impact of utility-scale batteries.

Overview In Section 2, I present graphical illustrations of the private and social returns to storage in an electricity market, explain the fundamental factors driving these returns, and discuss my

[3] 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)).

empirical approach. Section 3 outlines the data from the South Australian electricity market used in my analysis. In Section 4, I develop a model of strategic behavior in the electricity market that accounts for the dynamic profit maximization decision of the storage operator. Section 5 explains the empirical strategies employed in this study. The results of my analysis on the private and social returns to storage are discussed in Section 6. Lastly, Section 7 presents the conclusion.

2 Economics of Energy Storage in Wholesale Electricity Markets

In this section, I present various graphical representations of different aspects of my model. Firstly, I depict how electricity production and prices shift in the wholesale electricity market with a fixed level of storage production. Subsequently, I demonstrate the uncertainties and parameters involved in the storage operator's problem.

2.1 Storage's Price Effect

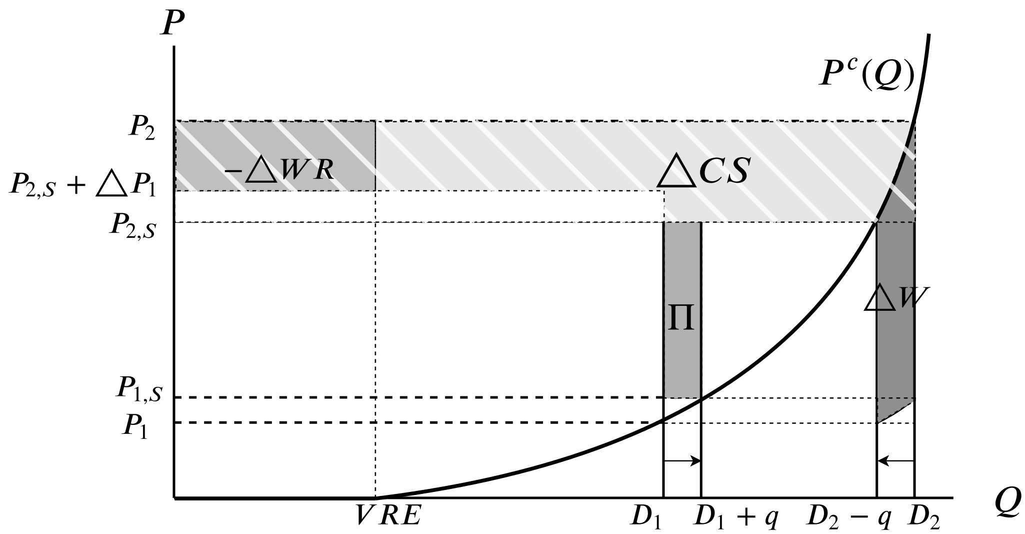
In this section, I aim to demonstrate the private and social returns of storage in a simple electricity market to provide a clear understanding of the underlying forces and justify my empirical approach. I utilize a "merit-order" curve to depict the supply of the electricity market, which orders generation sources based on their marginal cost or willingness to produce. The System Operator (SO) dispatches generation in this order to meet market demand at the lowest cost, resulting in cleared market prices. To simplify the analysis, I assume that the merit-order curve is convex.

Figure 1 shows how storage's price arbitrage affects its profits, welfare, consumer surplus, and VRE generation revenue in the context of a perfectly competitive electricity market. The merit order curve $P^C(Q)$ in this case represents the schedule of marginal costs of each generator. Figure 2 extends this analysis to markets with imperfect competition, where a market power supply relation $P^m(Q)$ deviates from the competitive cost curve $P^C(Q)$. These graphs assume perfectly inelastic demand, which is typical of electricity markets without demand-side price responsiveness, and neglect any externalities related to emissions.

2.1.1 Perfectly Competitive Electricity Markets

In a perfectly competitive electricity market, the price is a perfect indicator of marginal cost as each producer bids at their marginal cost. Let $P^C(Q)$ be the aggregated marginal cost function of generators in the market, which is the inverse of the supply function. The market operates in two periods: off-peak with low demand D_1 and peak with high demand D_2, where the prices are $P_1 = P^C(D_1) < P_2 = P^C(D_2)$, respectively. The same amount of VRE production, measured in units of VRE, is available at zero cost in both periods. When the amount of VRE production

Figure 1: Perfectly Competitive Electricity Market



If storage is large, private incentives may not be socially optimal.

increases, it shifts the $P^C(Q)$ curve to the right. The System Operator (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 price arbitrage, the energy storage operator purchases q units of electricity in the off-peak period 1, where demand is low (D_1), and sells it in peak period 2, where demand is high (D_2), with the assumption of 100% efficiency and no operational cost. Due to the inelasticity of demand, the impact of storage's production (q) is equivalent to a shift of q units in demand: storage increases D_1 by q and decreases D_2 by q. The effect of storage's production is to smooth the prices, resulting in new prices for both periods, where $P_{1,S} > P_1$ and $P_{2,S} < P_2$. Let $\triangle P_1 = P_{1,S} - P_1$ and $\triangle P_2 = P_2 - P_{2,S}$. As the marginal cost function $P^C(Q)$ is convex, the average price for the two periods decreases in Q, such that $\triangle P_2 > \triangle P_1$.

The storage operator benefits from the price difference between the two periods and creates both pecuniary and non-pecuniary effects. The change in prices for inframarginal units generates a pecuniary externality. As q increases, inframarginal units become more expensive in period 1 and less expensive in period 2, causing a shift in the cost of electricity acquisition. This shift 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. The revenue of VRE generators remains unaffected, but the decrease in average price reduces its revenue.

The production efficiency differences give rise to a non-pecuniary externality. The production of storage, q, causes a shift in the marginal generator between the two periods, thereby altering production allocation. The extra q units produced in period 1 replace the last q units produced in period 2. Since the inframarginal units produce the same amount and the demand is not flexible, the total welfare change is the difference in the cost of electricity production for an additional q units in period 1 and the last q units in period 2. The merit order, $P^C(Q)$, increases with Q; hence, this production shift decreases the total cost of production and increases total welfare. Figure 1 shows the effects of storage's profits, Π, changes in welfare, $\triangle W$, consumer surplus, $\triangle CS$, and the VRE generator's revenue, $\triangle WR$, due to these changes.

The production incentives of storage may not align with social incentives. The increase in consumer surplus depends on the price effects of storage's production, whereas the profit of storage depends on the price differences between periods. When the merit-order curve $P^C(Q)$ is steeper, the price effect $\triangle P_1$ and $\triangle P_2$ is larger, and thus, the increase in consumer surplus $\triangle CS$ is greater. However, storage's profit Π decreases since the price difference between periods is smaller. It is important to note that the welfare change $\triangle W$ is larger than storage's profit Π, indicating that subsidies for energy storage may enhance overall welfare in wholesale electricity markets. This conclusion is mainly due to the perfect competition assumption, and it may not hold in imperfectly competitive markets (refer to Figure 2.1.2).

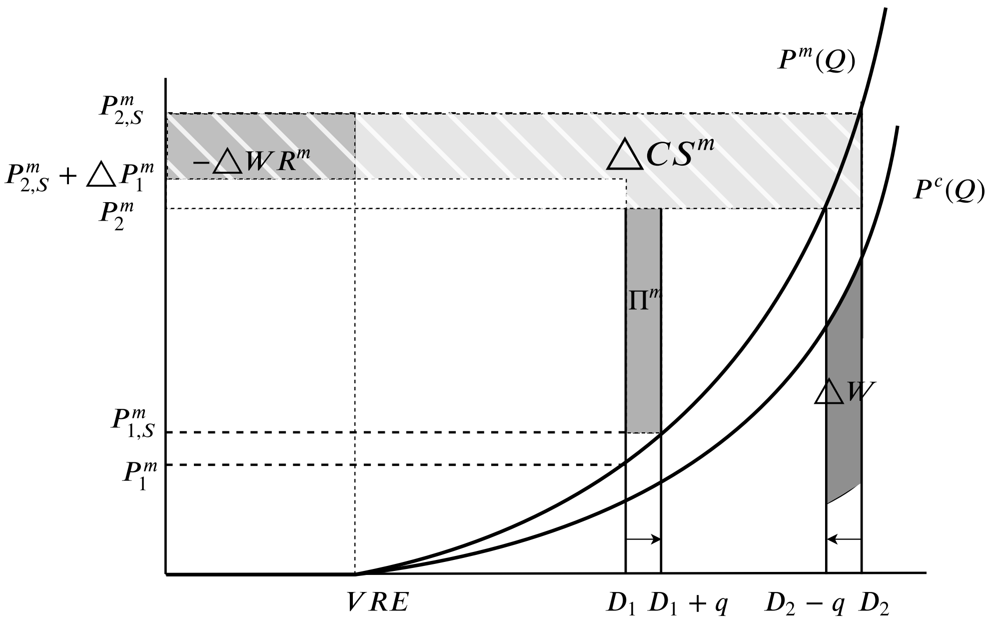
The impact of storage's production on VRE revenue depends on the correlation between VRE production and prices. If the correlation is high, then storage's higher price effects during peak periods, $\triangle P_2$, will decrease prices more than it increases prices during off-peak periods, $\triangle P_1$. As a result, the change in average prices caused by storage will decrease VRE revenue more. However, the magnitude of this effect also depends on the VRE production profile. In Section 6.5, I will discuss the relationship between storage and VRE in more detail.

As storage's production, q, increases, its price effect becomes more significant, causing private and social incentives to diverge. Although a higher q increases consumer surplus and decreases VRE revenue, it can also decrease storage operator profits, Π. As storage deployment increases, welfare, and consumer surplus rise, but thermal and VRE revenues decrease until quantities sold in both periods equalize. Larger q gives more market power to storage, smoothing prices and reducing arbitrage opportunities, which incentivizes under-production. The impact of a change in q on Π is ambiguous, and Section 2.2 delves into how storage determines the optimal q.

2.1.2 Imperfectly Competitive Electricity Markets

This behavior can be observed in the inverse of the aggregated supply function, where $P^m(Q) > P^C(Q), \forall Q$. However, assuming the same merit-order is maintained and that the markup between marginal cost and the firm's supply function increases in quantity, $\frac{\partial P^m(Q)}{\partial Q} > \frac{\partial P^C(Q)}{\partial Q}, \forall Q$, the

Figure 2: Imperfectly Competitive Electricity Market



difference between marginal cost and the firm's supply function, the markup, distorts the price signal. This results in higher prices than in the perfectly competitive case and more price variation between the two periods, $P_2^m - P_1^m > P_2 - P_1$.

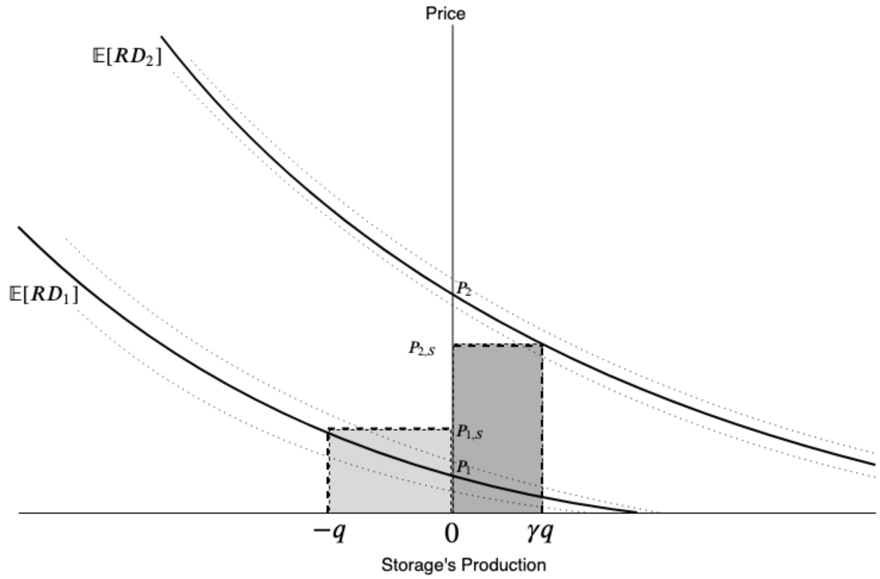
In most electricity markets, generators have market power and do not necessarily bid the short-run marginal cost of their units (Wolfram (1999), Joskow and Kahn (2001), Borenstein et al. (2002)), resulting in bids higher than their marginal cost, especially during peak demand periods. Figure 2 illustrates an inverse of the aggregated supply function where firms bid more than their marginal cost, $P^m(Q) > P^C(Q), \forall Q$. 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 in quantity, $\frac{\partial P^m(Q)}{\partial Q} > \frac{\partial P^C(Q)}{\partial Q}, \forall Q$.[4]

The presence of market power among electricity generators causes distortions in the price signal, resulting in higher prices in imperfectly competitive markets compared to perfectly competitive ones. Specifically, the firms' supply functions are above their marginal costs, resulting in a markup that increases with quantity. This leads to higher prices in both periods, $P_1^m > P_1$ and $P_2^m > P_2$, and also increases the 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

[4] A more detailed argument can be found in Klemperer and Meyer (1989).

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



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

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

In this section, the focus is on how the storage operator exploits inter-temporal price differences through arbitrage. Unlike thermal generators, the cost of storage production is dynamic, which poses a unique challenge. To begin, the technological constraints of storage are described, including power capacity, energy capacity, and round-trip efficiency. These attributes vary depending on the technology and application, such as lithium-ion or pumped hydro and energy arbitrage, residential, or ancillary services. A two-period model is then used to illustrate the storage operator's arbitrage problem.

Energy storage systems are characterized by their power capacity (K_{CH}), energy capacity (K_E), energy-to-power ratio (E/CH), and round-trip efficiency (γ). K_{CH} is the maximum rate at which storage can sell energy and determines the limit of the energy flow of storage and how quickly it can take advantage of arbitrage opportunities. K_E is the maximum level of energy that storage can hold and limits the time extent of storage's ability to engage in arbitrage. The energy-to-power ratio (E/CH) determines how quickly storage can take advantage of arbitrage up to its capacity. Lower E/CH ratios allow for faster charging/discharging, enabling storage to profit from arbitrage on smaller price fluctuations. The net ratio of power retention is called round-trip efficiency (γ), 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 round-trip efficiency describes the overall effectiveness of the energy storage system, as the process of charging and discharging expends some energy.

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, the storage 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. Given technological constraints, storage considers residual demands going forward and decides how much to buy or sell.

Let us study a two-period electricity market where 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' bids 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, 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 uses 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.

Optimal production of storage is influenced by the difference in expected prices. When the gap between the prices of the two periods increases, the arbitrage opportunity also increases, leading to a higher optimal production level, q^*. Another factor affecting the arbitrage problem is the derivative of inverse residual demands. An increase in the expected derivative of either period results in a decrease in q^*. This effect is due to the increased price effect of storage, leading to greater market power and causing private and social incentives to diverge. If the residual demands are elastic, storage produces less to maintain the price difference. In Section 4, a fully dynamic model is presented with an equilibrium analysis to explore this intuition.

3 Institutions and Data

In this section, I analyze the private and social returns of energy storage using data from Australia's National Electricity Market (NEM) spanning from July 2016 to December 2017. Firstly, I provide an overview of the institutional details and the generation mix of NEM. Next, I present statistics related to the demand, renewable production, and prices in the market. Finally, I showcase the actual energy storage production in 2018.

3.1 National Electricity Market

Australia's National Electricity Market (NEM) is operated by the Australian Energy Market Operator (AEMO) and connects five regional market jurisdictions, including Queensland, New South Wales, Victoria, South Australia, and Tasmania. AEMO's energy market has an installed capacity of around 85,000 MW and produces between 15,000 and 65,000 MW. The market serves more than 22 million people and generates over AU$16 billion in gross charges annually.

The NEM in Australia is an energy-only pool that compensates only the power that has been produced, without any capacity market.[5] All generators larger than 30MW must submit bids to the NEM to sell all their output. The NEM matches supply schedules with demand every 5 minutes in the most cost-efficient way and posts spot prices every 30 minutes for each of the five trading regions. In 2018 the maximum and minimum market prices in the NEM are AU$14,500/MWh and -AU$1,000/MWh, respectively. AEMO settles financial transactions for all energy traded in the NEM using the spot price.

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

Data The dataset used in this study was constructed using publicly available data from the Australian Energy Market Operator (AEMO). The data covers the period from July 2016 to December 2017 and pertains to the National Electricity Market (NEM), which includes South Australia and is connected only with the Victoria region. The decision to use this specific time period is based on two primary factors. Firstly, in January 2018, the world's largest lithium-ion battery (at the time) was commissioned in South Australia. Secondly, there was no entry or exit in South Australia during the selected period.

The dataset contains several variables, including daily bids, production, demand data, and forecasts for demand and renewable production. The daily bids can be mapped to the generation units in Victoria and South Australia, and the production data includes actual quantities generated from all units in the market for each 5-minute period. The demand data includes realized demand

[5] A high price ceiling intends to provide adequate incentives to stimulate generation investment.

Table 1: Generation Mix for South Australia

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.

and a proxy for residential solar production for each 30-minute period. Additionally, the dataset contains information on generator characteristics, such as the type of fuel used, thermal rates, age, location, emissions, and ownership.

Generation Mix During the sample period, the majority of electricity production in South Australia is attributed to two types of resources, namely gas, and renewables. This production mix is regarded as a viable option for the economically optimal low-carbon electricity portfolio (De Sisternes et al., 2016). Of the 13 thermal units in the region, two fuel types, natural gas, and diesel oil, are used. Gas-fired generators are responsible for almost all of the dispatchable electricity and have relatively low CO_2 emissions rates. On the other hand, diesel oil-fueled generators, known as peaker plants, are only operational for a few hours each month to meet peak demand and have high CO_2 emissions rates. As indicated in Table 1, wind production accounts for approximately 35%, gas generators contribute 45%, and solar PV accounts for 10% of the total electricity production. Natural gas-fueled generators exhibit a variation in CO_2 emissions rates due to differences in fuel efficiency, environmental regulation compliance, and production profiles. Imports from the Victoria region mainly originate from brown coal thermal generators. In South Australia, AGL, Pelican Energy, and Origin Energy are responsible for almost 95% of thermal generation, which has raised market power concerns in the region over the years.[6]

3.2 Variation in Demand, Renewable Production, and Prices

The seasonal average daily profiles of demand, import, wind production, solar PV production, and gas power plant production in South Australia are displayed in Figure 4. The peak-time demand in South Australia often occurs after sunset across seasons due to high solar energy production, similar to the "duck curve" observed in California. Wind production remains steady throughout the day, with a small variation between seasons on average. Although the average production and demand profiles exhibit some common patterns in power systems, there is substantial day-to-day variation. The dashed lines in Figure 4 represent one standard deviation in the daily demand and renewable production profiles. Wind production has very high volatility, regardless of the time of day, while solar has significant volatility around noon. The variability in intermittent resources and demand makes daily demand and price patterns difficult to generalize, and it aids the model in recovering firms' optimal responses to energy storage's production. Specifically, the model exploits the variation in residual demand, which comprises both renewables and demand, to estimate firms' best responses to energy storage.

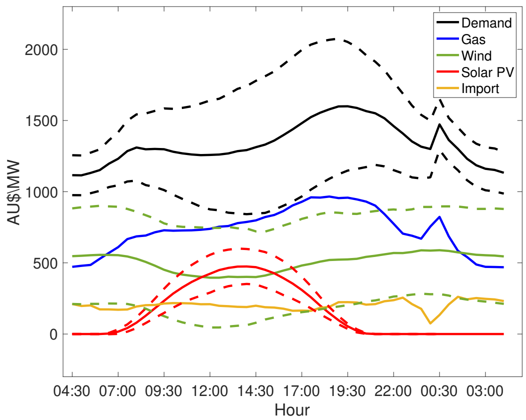
The NEM is known for its highly volatile prices, which can be attributed to the "missing money" problem in energy-only electricity markets. This problem may arise due to low price caps that do not provide adequate incentives for power plant investment. While many electricity markets address this issue through capacity markets, the lack of baseload generators and high wind generation penetration in South Australia exacerbate the problem, leading to even greater price volatility. As a result, there are increased incentives for arbitrage, making the environment more profitable for energy storage.

During the observed period, the average price per MWh is AU$100.8, and there is a high level of price volatility, as indicated by the standard deviation of AU$266. The daily price pattern shows a peak at 6 pm (AU$190) and a low at 4 am (AU$60), resulting in a price spread of approximately AU$130. However, deploying energy storage is not solely based on the price spread between high and low prices; it also depends on how long high and low prices persist. When the E/CH ratio is high (i.e., it takes longer to charge the battery), battery owners must seek more low-price periods to buy and longer high-price periods to sell.

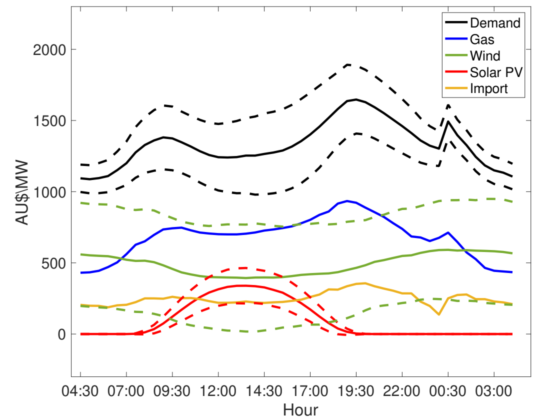
Identifying patterns in the highest and lowest price periods is crucial for storage's arbitrage strategies. While average prices may follow predictable patterns (as shown by the black line in Figure 5), they are not persistent due to high variations in demand and renewable production between days. To understand the variation in the dataset, I conducted an exercise where I picked

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

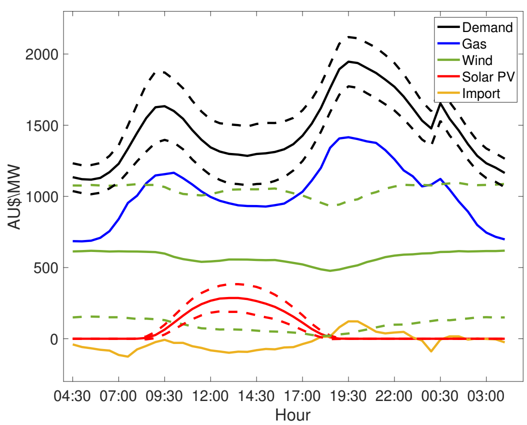
Figure 4: Daily Production and Demand Profiles in South Australia



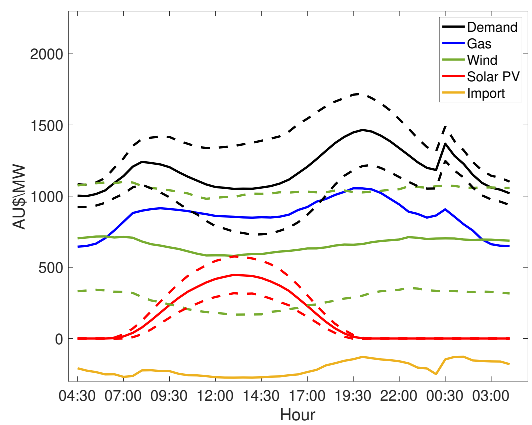
(a) Summer



(b) Fall

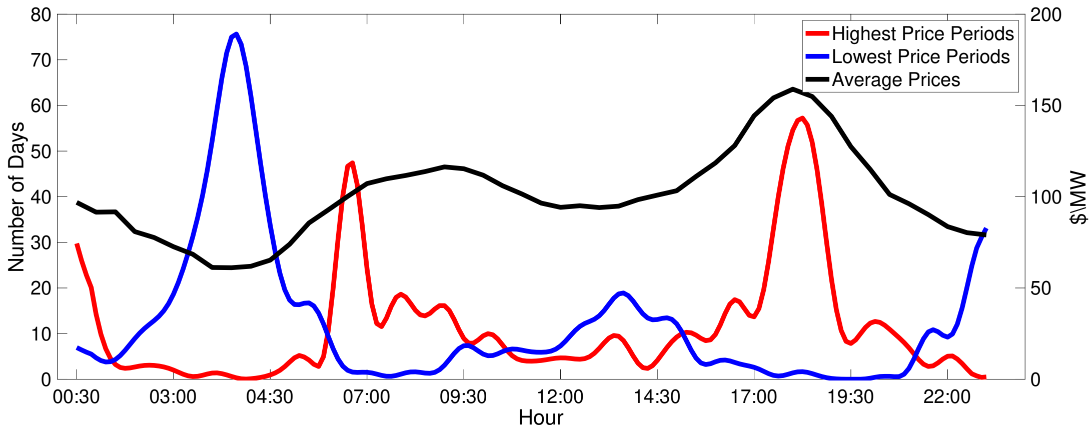


(c) Winter



(d) Spring

Figure 5: Price Patterns in South Australia July 2016 – December 2017

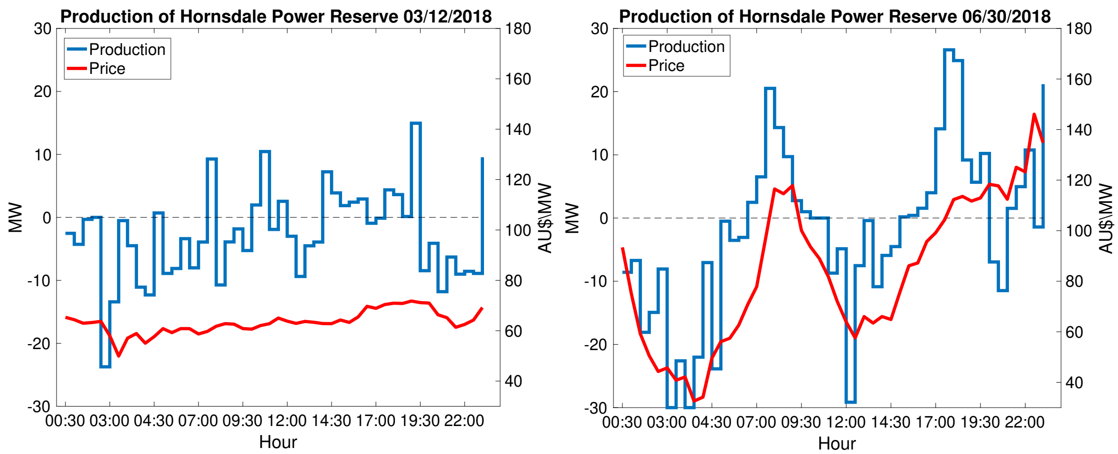


the highest and lowest price periods for each day in our dataset. As shown in Figure 5, the histogram of the highest (blue line) and lowest (red line) price periods within a day displays significant variability. Peak and off-peak price periods within a day vary significantly, making it challenging for storage to follow a simple, formulaic strategy for buying/selling power at different times throughout the day. Thus, storage needs to engage in more diversified day-to-day operations to fully exploit the arbitrage opportunity.

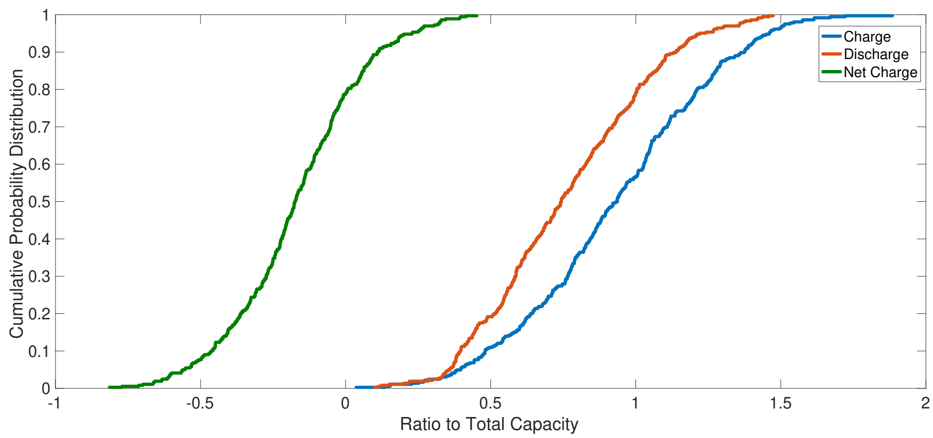
3.3 Observed Strategies of Storage Operator: The impact of electricity price's daily variation

This subsection examines the operational strategies of energy storage through a case study of the Hornsdale Power Reserve (HPR) in South Australia. HPR is a lithium-ion battery that became operational in January 2018 and was the largest of its kind in the world at that time. Tesla Inc. constructed HPR at the cost of around AU$70 million, fulfilling a wager made by CEO Elon Musk to complete the project within 100 days of the contract signature. HPR provides ancillary and energy services in the NEM and has an energy capacity of 129 MWh and a power capacity of 100 MW. The government retains the right to call on the stored power under specific circumstances, but HPR is privately operated. As per the agreement with the local government, HPR must reserve 70 MW of power and 9 MWh of energy capacity for the ancillary services market, leaving the remaining 120 MWh energy and 30 MW power capacity available for arbitrage in the NEM energy market.

The objective of the storage operator of HPR remains unclear due to unknown features of its contract with the South Australian government. Additionally, the expansion of VRE in South



(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 6: Prices and Production of Hornsdale Power Reserve in 2018

Australia by around 40% during this time poses challenges for my identification strategy. Despite not utilizing data from this period in my estimation strategy, I draw on the observed strategies of HPR to inform some of my assumptions in the model section. Specifically, I assume that energy storage owners employ diverse, dynamic charge/discharge strategies based on anticipated price fluctuations.

The fluctuation in within-day price patterns creates varying incentives for energy storage's daily operations, as illustrated by the subfigures in Figure 6a showcasing storage's behavior on two typical days. Although HPR's operations vary day-to-day, these visualizations provide insight into the assumptions made in the model section. The image on the left displays relatively stable prices, leading HPR to engage in minimal arbitrage due to the low price variation. Conversely, the image on the right shows volatile prices, causing HPR's production to closely follow short-term price changes. However, HPR's failure to utilize its full power capacity of 30 MW when producing indicates that it may be under-producing due to its market power.

HPR's operations in 2018 involved 1.12 full charge and discharge cycles per day on average but with a significant day-to-day variation. Figure 6b presents the cumulative distribution function (CDF) of its charge/discharge decisions within a day relative to its energy capacity, indicating a lack of a consistent daily production pattern. The green line in Figure 6b shows the daily change in total charge level relative to its capacity, highlighting HPR's active participation in arbitrage activities by purchasing or selling significant amounts of energy and beginning the next day with a different level of energy. The observed variability in HPR's operations indicates that dynamic considerations are crucial for effective arbitrage policies. While Appendix B examines static policies such as fixed-time or fixed-price buying and selling, the model section focuses on 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 procedure. 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.[7] 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.[8].

Each day, before the auction, nature draws a public signal $X_m \in \mathcal{X}$. Then firms observe a realization $X_d \in X_m$. The $H \times 1$ demand vector D_d has probability density function $f_D(D_d|X_d)$ conditional on X_d. The public information set in practice contains information such as publicly available demand and renewable production forecasts. 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.[9] 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. 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: storage, thermal, and renewable, for which I use i, j, and r to represent each type of firm, respectively. The model considers the bidding decisions of firms with different technologies in a daily electricity auction.

[7] A constant price elasticity conditional on signal X can be incorporated into the model.

[8] The evidence in empirical literature to support this assumption can be found(Ito (2014), and Borenstein and Bushnell (2015))

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

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.[10] By 2020, no electricity market yet has charge-level contingent 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, $\boldsymbol{Ch_d} = (Ch_{d1}, \dots, Ch_{dH})$. 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 B, 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.[11]

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

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

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,

[10] The model is flexible to incorporate any roundtrip efficiency rate. In Section 6, I specify γ to be 85%.

[11] The public charge level increases the state space that one needs to consider to solve the equilibrium.

$p^c_{dh}(a_{dh}) = S^{-1}_{idh}(D_{dh} - a_{dh})$, 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

$$\max_{\boldsymbol{Ch_d} \in \mathcal{CH}^H_i(Ch_d)} \mathbb{E}\Bigg[\sum_{h=1}^{H} a_{dh}\Big(\int\int p^c_{dh}(S_{-idh}, D_{dh}, a_{dh}) f_{D_h}(D_{dh}|X_d)\sigma_{-i}(S_{-idh}|X_d)\Big) \tag{4.2}$$

$$+ \sum_{X_{d+1}} V(X_{d+1}, Ch_{d+1}) f_X(X_{d+1}|X_d)|\sigma_{-i}, X_d, Ch_d\Bigg],$$

where $\mathcal{CH}^H_i(Ch_d)$ 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 $\mathcal{CH}^H_i(Ch_d)$ 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' bids 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 South Australia 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, $\sigma_j : \mathcal{X} \times \mathbb{R} \to \mathcal{S}^H_j$, 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

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

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

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

Trade South Australia trades electricity with its neighbor region, Victoria. To incorporate trading into the model, I model Victoria as a firm bidding in the South Australian 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 South Australia 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 South Australia. 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.

To account for electricity trading between South Australia and Victoria, I incorporate Victoria as a bidding firm in the South Australian electricity market. I model firm Victoria's bidding behavior, similar to other thermal firms, by submitting its supply schedule $S_{VIC}(p)$ into the market. However, unlike other thermal generators, I allow firm Victoria to purchase electricity, enabling South Australia to sell electricity at lower prices compared to Victoria. This flexibility also helps to alleviate some curtailment issues that may arise when renewable production exceeds demand in South Australia. To represent the capacity of firm Victoria, I use the transmission line capacity with S_{VIC} ranging from -800 to 700, accounting for potential price differences between the two regions when the transmission limit hits.

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 South Australia is lower than Victoria, firm Victoria buys, $S_{VIC,dh}(p_{VIC} - \epsilon) \leqslant 0$ ($S_{VIC,dh}(p_{VIC} + \epsilon) \geqslant 0$) for any $\epsilon > 0$.

4.2.3 Renewable Production

In order to achieve their greenhouse gas emissions reduction targets, many countries have implemented programs to encourage investment and production of renewable energy. These policies typically take the form of output-based subsidies rather than investment subsidies. Such financial incentives discourage 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) theoretically, and Bahn et al. (2019) empirically show that firms with diverse energy portfolios might have incentives to manipulate renewable production or under-produce from their thermal generators. This is a growing concern as renewable penetration levels increase. 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 not to 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^* , and the transition matrix f_X is a Markov Perfect Equilibrium if*

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

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

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

$$X \textit{ follows } f_X \tag{4.7}$$

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 A Best Response Mapping

In this section, I describe an algorithm to find an equilibrium that is equivalent to Definition 4.1 by modeling energy storage's production's impact on incumbents as a change in the public signal. This new computationally tractable algorithm uses the market equilibrium without storage as an initial step 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 the 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 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 $\sigma_i = \Lambda_i(\sigma_{-is})$.

SO starts clearing the demand by using storage's production. Thermal firm j forms an expectation on storage's production. Storage's production for period h, a_h is distributed conditional on the realization of X with probability distribution $\bar{\sigma}_{ih}(a_h|X)$. Since the 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,

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

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, $f_{D'}^{\sigma_i}(D'|X) = \int_{-\boldsymbol{K_{CH}}}^{\boldsymbol{K_{CH}}} f(D-a|X)\bar{\sigma}_i(a|X)da$, where K_{CH} is the power capacity of the storage. Now, net demand after storage, D', is the relevant demand to compete for thermal generators' residual demand. Therefore thermal generators' respond to the new distribution $f_{D'}^{\sigma_i}(D'|X)$.

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'.

Assumption 4.4. *$\forall X, \exists X^{\sigma_i}$, that $X^{\sigma_i}, X \in X_m$, in which,*

$$f_{D'}^{\sigma_i}(D'|X^{\sigma_i}) = f(D|X).$$

Notice that here I assume that the distribution of D' can be partitioned into sets conditional on a signal X^{σ_i}, $f_{D'}^{\sigma_i}(D'|X^{\sigma_i})$, 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. Failing this condition can still provide an upper boundary for storage's profitability.[12]

Now, thermal generators observe X^{σ_i} but not X. With the new signal X^{σ_i} and given other firms' strategies σ_{-ij}, the thermal generator j's problem becomes

[12] I pick the closest distribution of demand to match this new distribution. If a distribution exceeds the support of our data, then incumbent firms become less competitive, so the storage's profitability would be higher.

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

By Definition 4.4, 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*

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

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

Here the signal coordinates thermal generators' strategies conditional on signal X^{σ_i}. Since realizations X^{σ_i}, X both belong to the same set X_m, the thermal generator's expected 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, $\widehat{\sigma}_i = \Lambda_i(\widehat{\sigma}_{-is})$.

In summary, a new storage operator optimally responds to the strategies of the rest of the market conditional on the signal X. The storage production creates an updated signal X^{σ_i} for the net demand, as explained in Section 4.4.1. The thermal generators use this signal to respond to both storage and each other, as outlined in Section 4.4.2. The storage operator then updates its optimal response based on changes in the thermal generators' strategies, as discussed in Section 4.4.3. This iterative process continues until a fixed point, denoted as σ^*, is reached. The process converges when there are no further updates in any of the $w_{X^{\sigma_i},X}$ parameters.[13]

5 Empirical Strategies

This section presents the empirical strategies used in this study. First, the estimation of the public signal X and the conditional distribution of net demand $f_D(D|X)$ are demonstrated. Next, an algorithm is described to solve the infinite horizon problem of storage under different ownership structures. The algorithm for finding the equilibrium in a market with storage is also presented. Additionally, the approach to incorporating an expansion in renewable capacity into the model is discussed. Finally, the methods for calculating electricity production, CO_2 emissions, and storage investment costs are outlined.

5.1 Classifying Days: Estimating Distribution of Demand

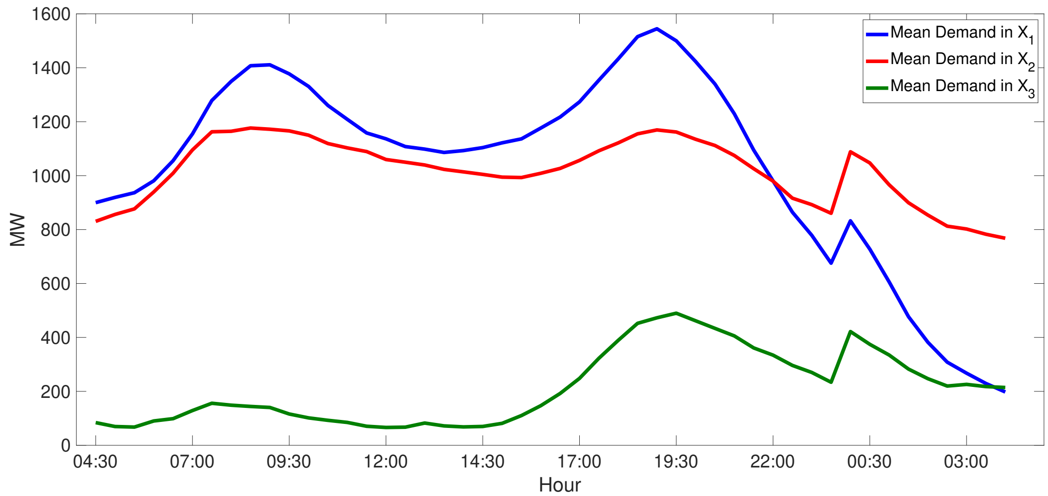
In electricity markets, renewable resources typically have a lower merit order, meaning they are dispatched before other resources. Therefore, in the South Australian electricity market, the system operator first clears demand with renewables and then calls on storage and thermal generators. To reflect this, I define a new variable called net demand, which is the difference between demand and renewable production. Net demand is a more relevant variable for the model because thermal generators and storage compete to meet net demand.

In South Australia, there are two renewable resources: solar and wind. Almost all solar generation in South Australia comes from rooftop solar PVs, which are consumed directly by customers, reducing their demand from the grid. The demand observed in the dataset is the demand after solar PV production. I calculate net demand in the data as the difference between demand and wind generation. I assume no curtailment for wind generation since the AEMO's Quarterly Energy Dynamics reports indicate that wind curtailment in South Australia during this period was less than 5%.

To generate a signal X, I begin by categorizing observed net demand vectors D_d into N_X groups $\mathcal{X} = X_1, \ldots, X_{N_X}$ based on their corresponding forecast vector FD_d. I employ the k-median clustering algorithm to form these groups. This algorithm partitions vectors into clusters with the goal of minimizing the within-cluster sum of squares. Once the grouping is done, I calculate the median of each group to obtain the signal X.

[13] Note that this algorithm does not necessarily converge. If firms respond to demand shocks in the same way, i.e., bid more competitively or less, I conjecture that the algorithm is going to result in a contraction mapping. In practice, in my dataset, the procedure converges to a fixed point with many initial starting values.

Figure 7: Mean Net Demand for 3 Clusters



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

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

I employ the elbow method to determine the optimal number of clusters, N_X. This involves analyzing the total within-cluster sum of squares as a function of the number of clusters and selecting the point at which the addition of a new cluster does not significantly improve the objective. After applying this method, I select $N_X = 16$ as the optimal number of clusters.

Figure 7 illustrates the expected net demand conditional on $X \in X_m$, $\mathbb{E}[D|X]$, for three different signal values exhibiting a wide variety of net demand patterns in South Australia. This variation in observed net demand patterns is essential for identifying the best responses of incumbent firms. The green line represents a day with almost zero net demand, providing information on how thermal generators bid on a day with abundant renewable production. The red line represents a smoother net demand profile than the blue line. Storage production on a blue line day can smooth net demand and transform it into a red line day. This richness in net demand patterns addresses out-of-sample concerns for the procedures outlined in Section 4.4.2 and Section 5.5.

To estimate the distribution of net demand conditional on signal X, I assume an AR(1) process within each cluster m. Specifically, for each hour h and cluster m, the net demand D_{dh} follows:

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

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

5.2 Solving Storage's Problem

The assumption that the charge level at the end of the day, Ch_{d+1}, is a discrete multiple of 30 MW allows for a finite number of possible charge levels. This, combined with the finite set $\mathcal{X}$ and K_{CH}, means that there are only a finite number of value functions for storage to assign a value. Specifically, there are $N_X \times \frac{K_{CH}}{30}$ value functions. It is important to note, however, that storage's charge level within the day is still continuous, and this discretization only applies to the final charge level at the end of the day.

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}.

Starting with a set of initial continuation values, I employ finite states value function iteration methods to compute the optimal bidding strategies $\sigma^*_i = \Lambda_i(\sigma_{-i})$. For each possible initial charge level Ch_d, I solve the storage operator's problem, considering all possible terminal charge levels Ch_{d+1}, and select the one that maximizes the net present value of revenue. At each iteration t, I update the continuation values by inverting the bellman equation, namely $V^{t+1} = (I - \beta F)^{-1}\Pi^t$, and then solve the storage operator's problem again to obtain the flow payoff Π^{t+1}. For further details, refer to Appendix A.

Ownership

I analyze different ownership structures for storage to investigate the difference between private and social incentives for storage. In Section 2.2, I focus on the problem of a monopoly storage operator that aims to maximize its revenue. In contrast, I consider three different ownership structures in this section: monopoly, load-owned, and competitive storage. Each ownership structure has a unique objective for the storage operator.

In the case of monopoly storage, the operator acts as a monopolist in the storage market and maximizes its revenue. On the other hand, load-owned storage aims to minimize the market electricity acquisition cost. This scenario results in the highest possible consumer surplus increase that storage can achieve, assuming demand is inelastic. In the competitive storage case, many small storage units engage in arbitrage simultaneously, maximizing individual revenues. Although individual small storages do not internalize their price effect, at the aggregate level, they affect prices. This case can be thought of as a perfectly competitive storage market.

However, as storage's production increases, the problems of monopoly and competitive storages start to differ due to market power. Monopoly storage tends to sell when the price is high, and its price effect is low to maximize its revenue. On the other hand, load-owned storage sells when the price effect and demand after storage's production are high to maximize the decrease in electricity acquisition cost. In other words, monopoly storage prefers periods with low price elasticity to buy and sell, while load-owned storage prefers high (low) price elasticity periods to sell (buy). In Section 6.3, I discuss the results of different storage ownership structures.

5.3 Simulating Thermal Generator's Best Responses and Estimating 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),

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

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 the simulated net demand after storage's production with the mean demand of the estimated demand clusters in Section 5.1. To update the thermal generators' strategies σ_{-i} in the iteration of $\Lambda_j(\sigma_i, \sigma_{-ij}|X^{\sigma_i})$, I use these weights, as described in Proposition 4.1. The weights $w_{X^{\sigma_i},X}$ are also used to update draws of $\widehat{S}_{-id}$ in the storage operator's problem in Section 4.4.3. I iterate this process until there are no further updates in the weights. While I do not provide proof of the existence or uniqueness of the fixed point, I observe that in my dataset, the procedure converges to a fixed point.

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

Changes in Welfare and Emissions The use of storage has an impact on the production of electricity by thermal generators, leading to changes in production costs and CO_2 emissions. By analyzing these changes in production, I am able to measure the impact on consumer surplus, total welfare, and CO_2 emissions in the market.

In the model, the change in total welfare is assumed to be equal to the change in the cost of electricity production, as demand is considered inelastic. To estimate the cost of electricity production, AEMO's Integrated System Plan (ACILAllen (2016)) provides data on heat rates (GJ/MWh), CO_2 emissions (ton/MWh), fuel cost (AU$/GJ), and start-up cost (AU/$MW) for each generator. These cost estimates are comparable with inflation and fuel price adjusted versions of Reguant (2014) and Wolak (2007). After adjusting for heat rates and fuel prices, I use Reguant (2014)'s estimates for ramp-up cost. Start-up and ramp-up costs are calculated in terms of fuel, and the induced emissions are added to the CO_2 emissions calculations. Table 6 in Appendix A shows industry estimates of cost parameters for each generating unit in South Australia. I use the following model to calculate the cost of producing q_{jd} by firm j in day d[14]:

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

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 the 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 charging patterns can drastically affect the level of degradation of its material (Koller et al. (2013), Abdulla et al. (2016)). In Appendix B, I include a usage cost for storage production to address these concerns.

Round-trip Efficiency I use HPR's 2018 data to estimate the round-trip efficiency, which includes information on how much HPR buys and sells in the energy market. Although several factors can affect round-trip efficiency, such as temperature and pace of usage, I assumed a uniform round-trip

[14] Note that I only specify the firm's cost function to calculate the change in the producer surplus.

efficiency. To calculate the charge levels in the data, I used the equation

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

To determine the optimal value of γ that minimizes the range of Ch_{dh}, I considered the possible charge levels of HPR, which ranged from 0 to 120. I found that $\gamma = 0.85$ provided the best fit, taking into account the fact that the dataset did not include HPR's supply to ancillary services. As a result, I assumed that HPR's supply of ancillary services accounted for 5

5.5 Higher Penetrations of Renewable Resources

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

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

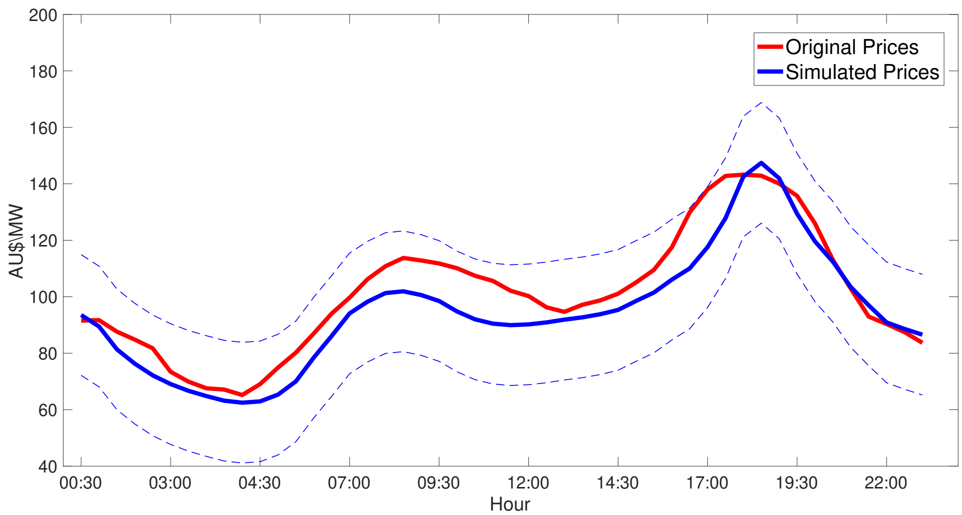
Following the same procedure as in 4.4, I define a new signal $X^r \in \mathcal{X}$, which provides information about the distribution of D^r_{dh}. Using the algorithm described in Section **??**, I estimate thermal generators' strategies based on X^r. The difference for X^r is that it is also observed by the storage, which means that storage's production does not affect the signal X^r, unlike signal X^{σ_i}. Therefore, the probability of signal X^r given signal X, denoted by $w_{X^r,X}$, needs to be calculated only once.

6 Results

In this section, I present my findings on the private and social returns to storage in the electricity market, which I estimate using a simulated 2000 consecutive day period based on calculated market equilibrium strategies σ^*. First, I examine the fit of my model in the baseline case without energy storage and compare summary statistics of my estimates with those of the Hornsdale Power Reserve (HPR) in 2018. Second, I investigate the impact of the price effect, uncertainty, and firms' responses on the storage operator's private incentives, by comparing different energy storage models. Third, I evaluate the private and social returns of storage under different ownership structures,

[15] This assumes a linear relationship between renewable capacity and renewable production. The updated formulation can be adjusted to incorporate different additional renewable production profiles.

Figure 8: Average Original vs. Simulation Prices



namely monopoly, load-owned, and competitive storage. Fourth, I explore how storage affects existing generators' production and revenues. Finally, I analyze the interaction between storage and renewables under various levels of investment in solar and wind generation as well as storage.

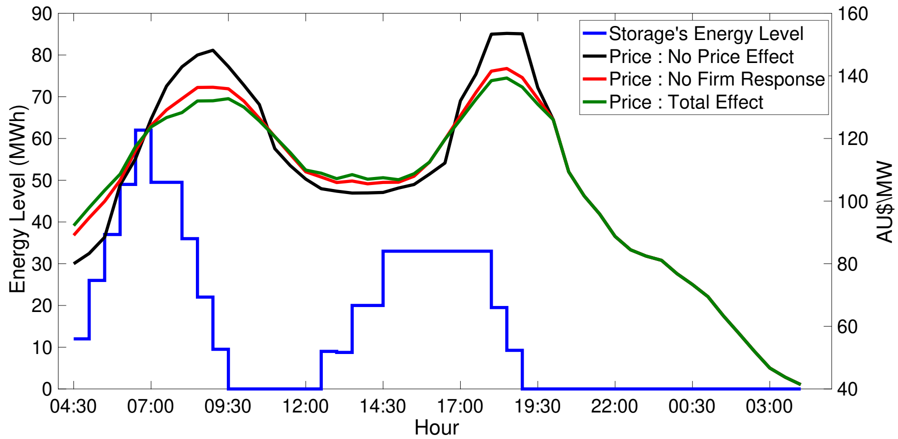
6.1 Model Assessment

To ensure the validity of the model, it is important to examine its performance in the absence of energy storage. First, the model assumes that firms condition their production on the public signal X_d. In order to assess the validity of this assumption, I calculate the variation in thermal generators' bids explained by the estimated clustering. To construct the distance measure, I use L^2 distance for each of the observed market prices and compare the resulting supply schedules, S_{jd}. The analysis reveals that the estimated clusters explain 91

Electricity price patterns are essential for evaluating the profitability of energy storage. Although the model does not use price moments, I present a comparison of simulated average daily prices against actual data in Figure 8. The dashed lines in the figure indicate one standard deviation in simulated prices. The simulated price pattern is comparable to the observed data, although it misses some price spikes. The model fails to match periods with a price above AU$1000, which occurs only 0.4% of the time in the observed period. These extreme prices arise from sudden expected changes, such as generator failures and transmission outages, which are challenging to simulate without an extensive dataset.

To further evaluate the model's accuracy, I compare summary statistics of my estimates for energy storage with observed energy storage data from the Hornsdale Power Reserve (HPR). The

Figure 9: Storage's Price Impact Under Different Models for a Representative Day



model does not use HPR's data, and I use data from July 2016–December 2016 to calibrate my model. The calibrated estimates are then compared to HPR's data from 2018. The average prices in these two periods are very similar, with HPR's profit in 2018 being AU\$1.52 million compared to my estimate of AU\$1.34 million after adjusting for the AU\$1000 price ceiling.[16] However, HPR did 616 charge/discharge cycles in 2018, whereas my estimate is 529 per year.

In reality, the storage operator adjusts storage's production during the day in response to more information about demand and other firms' bids, whereas my model does not allow for within-day adjustments. This new information leads to higher revenue and activity than my estimates. Appendix B discusses how changing the storage operator's information set affects its strategies. Additionally, HPR solves a joint profit maximization in energy and ancillary services markets and can adjust its participation accordingly, which can increase energy-only market revenue.[17]

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

The current literature on energy storage largely overlooks its price effects or fails to consider how they affect other firms' bidding practices or assumes an extreme type of competition (Cournot or Bertrand) (Sioshansi et al. (2009), De Sisternes et al. (2016), Salles et al. (2017)). While the price impact of storage is negligible when it is small, ignoring it can result in biases as storage size grows. To address this gap, this section delves into the biases that arise when storage's price effect is not taken into account.

In Figure 9, I compare the impact of storage prices on a representative day across different

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

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

Table 2: 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				
Storage's Price Uncertainty	×	✓	✓	✓
Storage's Price Effect	×	×	✓	✓
Firms' Response to Storage	×	×	×	✓

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.

models. When the price effect of storage is ignored, the storage operator has no incentive to under-produce, and the market price follows the black line. Subsequently, when I consider the storage price impact without allowing other firms to respond, the storage operator engages in arbitrage, leading to a smoother price path. The red line shows the resulting price path after the storage operator buys low and sells high based on the supply schedules submitted by other firms. However, when storage affects prices, other firms may alter their bidding strategies to maintain their market power, and the impact on prices is theoretically ambiguous (Vives (2010), Genc and Reynolds (2011)). Despite this, the blue line suggests that firms become more competitive in response to storage, as it is smoother than the red line. Therefore, the equilibrium impact amplifies storage's price effect.

Table 2 presents an evaluation of the storage operator's profits under four different models. In the first column, it is assumed that the storage operator has perfect foresight about future prices, and the storage is small, with no price effect. Going from Model 1 to 4, one simplifying model assumption is relaxed each time. In column 2, the perfect foresight assumption is relaxed, and the storage operator produces conditional on a public signal, X_d. In column 3, storage is large, so no storage-induced price effect assumption is made. In column 4, other firms can respond to storage's production, and a new equilibrium is calculated following Section 4.4.

Table 2 indicates that omitting the price effect and uncertainty of large storage overestimates its profit. Comparing columns 1 and 2 reveals that uncertainty significantly affects profitability, even when storage is small. However, the results may not be robust to the modeling of uncertainty and the storage operator's information structure. In the model, two main sources of uncertainty affect the storage operator's problem: net demand and other firms' bids. Appendix B addresses the robustness of the results for the information structure of the former. The results remain qualitatively unchanged.

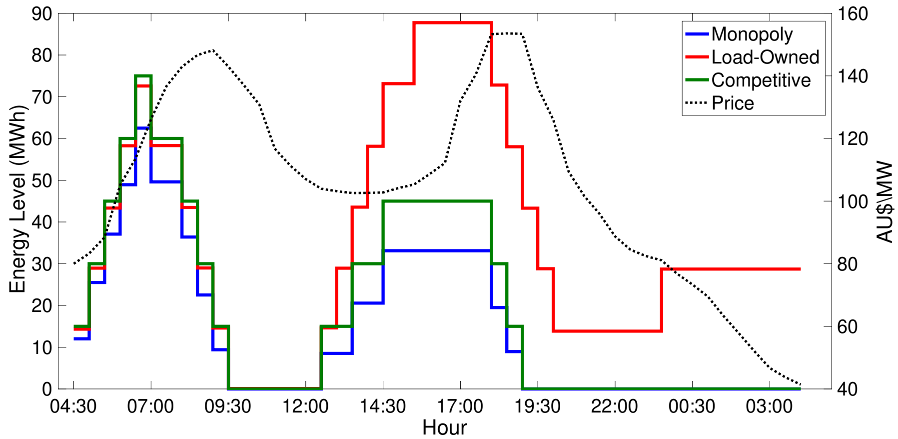
The results in column 3 of Table 2 demonstrate the significant impact of the price effect on the profitability of large storage. As electricity prices smooth out and inter-temporal price differences decrease, the storage operator's profit per unit decreases, and arbitrage opportunities shrink. Therefore, using price-taker models for large storage significantly overestimates its profit. In column 2, without the price effect, storage almost breaks even, while in column 3, substantial improvements on the cost side are necessary. Failing to account for this price effect channel in energy storage profitability calculations can lead to incorrect conclusions. These findings suggest that policymakers and market participants should consider the effects of energy storage on prices and take them into account when assessing the profitability of large-scale storage investments.

When energy storage does not have a price impact, there is no incentive for other firms to adjust their bidding strategies. However, if prices change due to storage, firms may modify their strategies to reflect changes in their market power. The impact of these adjustments on the storage operator's profit is unclear according to the literature on supply function equilibrium. Nonetheless, comparing the results in columns 3 and 4 of Table 2 reveals that firms' responses to storage will reduce the storage operator's profit. This is because firms will become more competitive in response to changes in market power, bidding more aggressively and reducing peak prices, which will decrease the storage operator's profit. However, this change suggests that energy storage can mitigate incumbent firms' market power and enhance consumer welfare. The following section will discuss the effect of increased competition on consumer welfare and surplus.

6.3 Private Incentives are not Socially Optimal

In this section, I utilize my model estimates to examine the private and social returns for energy storage with a capacity of 120 MWh and 30 MW across different ownership structures: monopoly, load (consumer) owned, and competitive. Each ownership structure has unique objectives that I formalize in 5.2. Figure 10 illustrates the differences in the optimal charge level of the storage operator under different ownership structures for a representative day. Table 3 presents the private and social returns of the storage operator under different ownership structures. To compute storage's installation and market production costs, I employ industry estimates by utilizing the models in Section 5.4. The remainder of the summary statistics is obtained from the counterfactual exer-

Figure 10: Optimal Energy Level Under Different Ownership Structures for a Representative Day



cises.[18]

Monopoly Case: Positive externalities cannot be internalized by market prices

n the monopoly case, I consider a single grid-scale energy storage that maximizes its profit. The monopoly case provides the highest private return, making it the most relevant case for understanding entry incentives for the storage operator. However, monopoly storage has incentives to under-produce due to its market power. As shown in Figure 10, the monopoly storage engages in less arbitrage compared to other ownership structures. The first row of Table 3 presents the private and social returns for the monopoly case. To maximize its profit, the storage undergoes an average of 529 full charge and discharge cycles per year, which can be interpreted as the energy storage's production or activity level. I assume that emissions costs are not considered in this analysis, but I discuss their impact separately in Section 6.5.

The negative profit (given entry) indicates that energy storage is not currently profitable. There are two factors that affect profitability: the extent of arbitrage and the investment cost. Despite the South Australian electricity market having one of the highest price spreads globally, the results suggest that the market is not lucrative enough for private storage investment solely for engaging in arbitrage. However, a substantial reduction in costs, approximately 60%, could stimulate energy storage entry. Additionally, there may be concerns regarding the information structure of the storage operator, which can impact revenue. Some of these concerns are addressed in Appendix B.

Energy storage creates positive non-pecuniary externalities by improving production efficiency and reducing emissions content of marginal units. The discrepancy between storage's revenue and

[18] In this section, I will not include the impact of emissions on welfare and will address it separately in Section 6.5. My methodology allows for emissions costs to be incorporated into the welfare analysis at any given level.

Table 3: Storage Operator's Private and Social Returns Under Different Ownership Structures

	Per Year						
	Million AU$					Thousand Ton	
	Storage's			Δ in Market's			
Ownership	Revenue	Cost	Profit	Consumer Surplus	Cost	Δ in CO_2 Emissions	Number of Cycles
Monopoly	1.34	3.03	-1.69	3.25	-1.54	-3.12	529
Load Owned	0.59	3.03	-2.44	5.45	-2.21	1.61	1120
Competitive	1.06	3.03	-1.97	3.56	-1.77	-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.

the change in market cost indicates a divergence between private and social returns. As explained in Section 2.1.2, the bids of other firms may not accurately reflect their production cost, and their market power can distort prices, leading to a misalignment of private and social incentives.

Energy storage also provides benefits to consumers by affecting the revenue of inframarginal units. The storage operator sells (buys) when prices are high (low) and decreases (increases) prices, leading to a reduction in average prices. This decrease in prices reduces the cost of acquiring electricity, resulting in an increase in consumer welfare. Since the model assumes inelastic demand, the decrease in electricity acquisition costs is equivalent to the increase in consumer welfare.

Despite being unprofitable for private investment, energy storage is socially desirable from the perspective of consumers. The increase in consumer surplus resulting from storage is greater than its cost, indicating a market failure due to underinvestment. The storage operator does not take into account the pecuniary externalities when making investment decisions.

To address this underinvestment issue, a lump-sum payment or capacity markets for storage can be implemented. In a capacity market, the storage operator is paid the difference between the change in consumer surplus and its revenue. However, some capacity markets require units to be ready to produce on demand, which poses a challenge for storage since its production is contingent on its charge level. Reserving some capacity can directly affect storage's production and profit, requiring further analysis under different regulatory constraints.

The discrepancy between the storage operator's profit and the increase in consumer surplus is driven by two factors: the market power of other firms and the storage operator's market power. Other firms' market power distorts market prices, while monopoly storage causes underproduction. In the next two cases, the effects of these two forces are analyzed separately.

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

The load-owned case incorporates inframarginal considerations into the storage operator's decision-making process and results in the most significant increase in consumer surplus induced by storage. Figure 10 illustrates that the production of load-owned storage can be substantially different from the monopoly case. Load-owned storage seeks out periods with high price effects and demand to sell and maximize the storage's price impact, while monopoly storage only looks for periods with low price effects to maintain a high price difference between periods.

Load-owned storage maximizes the transfer from the consumer side to the producer side and helps to alleviate the market power of thermal generators. Therefore, if the system operator (SO) is concerned about mitigating market power and reducing electricity acquisition costs in the electricity market, the load-owned case can be seen as storage owned by the SO. However, load-owned storage does not necessarily maximize welfare since market prices do not always reflect the marginal cost of electricity production. If the SO does not gather information about generator costs, maximizing consumer surplus can be considered a proxy for maximizing welfare.

The second row of Table 3 indicates that load-owned storage nearly doubles the increase in consumer surplus compared to the monopoly case. It does so by doubling the number of cycles of monopoly storage and sacrificing over half of its revenue. Although load-owned storage does not necessarily maximize overall welfare, it does increase welfare compared to the monopoly case. However, it also leads to increased CO_2 emissions due to higher storage activity. This effect is mainly caused by more energy being lost to round-trip efficiency with increased storage production.

The significant difference between the monopoly and load-owned cases in terms of consumer surplus increase suggests that solving the under-investment problem of the storage operator alone may not be sufficient to achieve higher social returns. One concern with the misalignment of private incentives for storage operation may be the market power of storage, as discussed in Section 2.2. The economics literature extensively discusses the market power of thermal generators (e.g., Wolfram (1999), Borenstein et al. (2002), Wolak (2003)). Sioshansi (2014) considers a case where storage reduces welfare due to its market power. To address concerns about the market power of the storage operator, a competitive storage market case is considered.

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

In the competitive case, I consider a single grid-scale energy storage with no market power that aims to maximize its profit. One could interpret this case as numerous small storage providers that do not internalize their price effect but affect prices at the aggregate level. These storage operators aim to minimize price differences. Figure 10 shows that the production of competitive storage 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

Table 4: Storage's Impact on Incumbent Generators Under Different Ownership Structures

	Per Year				
	Thousand MWh		Million AU$		
	Δ in Production of		Δ in Revenue of		
Ownership	Natural Gas Generators	Diesel-Oil Generators	Natural Gas Generators	Diesel-Oil Generators	Renewables
Monopoly	6.70	-4.31	-0.90	-1.02	-1.70
Load Owned	21.92	-8.34	-1.86	-1.55	-1.43
Competitive	14.38	-6.34	-0.93	-1.18	-1.62

Notes: This table presents storage's impact on existing generators. 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.

welfare), under the assumption of a perfectly competitive electricity market. Therefore, the market power effects of other firms can explain the difference between the competitive and load-owned cases.

The third row of Table 3 shows that competitive storage increases consumer surplus and welfare more than the monopoly case but does not reach the welfare levels of load-owned storage. Moreover, the decrease in revenue is not as significant as in the load-owned case. As Section 5.2 suggests, increasing competition decreases the distance between the load-owned and monopoly cases. While monopoly energy storage can deliver high enough social returns, load-owned storage can push it even further. The competitive case yields intermediate returns between monopoly and load-owned. However, the 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 regarding the disparity between private and social returns. Firstly, the storage operator's market power is important, but even abolishing that power is not enough to fully utilize energy storage. As discussed in Section 2.1.2, due to the market power of incumbent firms, the storage operator's profit-maximizing incentives do not align with welfare-maximizing incentives in a market with imperfect competition, even when storage is small. This 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 of not allowing SOs to use energy storage as a generating asset may lead to socially inefficient or no usage of energy storage.

6.4 Storage's Impact on Existing Generators

When energy storage engages in arbitrage, it affects existing generators in several ways. Specifically, when energy storage sells, the marginal unit is replaced by storage, causing the price to decrease. When storage buys, new units become marginal, and the price increases. As a result, energy

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				Δ in CO_2 Emissions	Curtailment
	Revenue	Cost	Profit	Consumer Surplus	Cost	Wind Revenue	Solar PV Save		
Baseline	1.34	3.03	-1.69	3.25	-1.54	-1.70	-0.44	-3.12	-
Double Wind Capacity	2.75	3.03	-0.28	6.12	-3.12	1.63	-0.38	-8.89	-18.6
Double Solar Capacity	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.

storage affects marginal generators by shifting energy production in time and inframarginal units by changing energy prices. The degree of impact on marginal and inframarginal units depends on the production and price levels. Table 4 shows the impact of storage on different fuel-type generators under different ownership structures.

In all ownership structures, energy storage mainly decreases the production of diesel-oil generators and increases that of natural gas generators. Diesel-oil generators tend to be marginal units when market prices are high due to their high fuel cost, and energy storage often replaces their production by selling during high-price periods. In contrast, natural gas generators tend to be on the margin when prices are low, so storage buys electricity and increases the production of natural gas power plants. The difference between the natural gas and diesel-oil power plants' energy production adds up to the traded energy with Victoria, along with the energy loss due to round-trip efficiency.

On the revenue side, even though storage increases the production of natural gas generators, it still hurts their revenue due to the price impact. Natural gas power plants lose money as inframarginal units even when energy storage replaces diesel-oil generators. This impact is more significant in the load-owned storage case, as the price impact is the highest. Therefore, natural gas generators lose more money than diesel oil generators. Renewables lose similar revenue because they cannot adjust their production.

6.5 Storage's Impact on Renewables and CO_2 Emissions

Investing in energy storage is motivated by the need to support the increased capacity of Variable Renewable Energy (VRE) sources. Energy storage plays a critical role in smoothing the variability and intermittency of VRE and reducing its curtailment. Moreover, VRE increases intertemporal price differences, which in turn increases the private returns of energy storage investment (Woo et al. (2011), Ketterer (2014)). Thus, it can be inferred that both VRE and energy storage should exist to promote simultaneous expansion and mutual support.

This study examines the interaction between VRE and energy storage by considering changes in VRE capacity. For each wind and solar PV generation, I double the production capacity and calculate the equilibrium without energy storage using the model in Section 5.5.[19] I then introduce energy storage in both cases to calculate its 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.

Two factors affect energy storage's effect on renewable revenue: the change in average prices and the correlation between renewable generation and prices. First, storage decreases average prices by smoothing price differences, which ultimately leads to a decrease in renewable 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' returns more by engaging in arbitrage, decreasing high prices, and increasing low prices.

First, my findings indicate that at moderate levels of renewable power, where 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, which has stable production throughout the day, as shown in Figure 4, the decrease in average prices hurts wind generators' revenue significantly. Despite wind production being negatively correlated with prices (-0.193), the average price effect dominates. On the other hand, solar generation and prices are positively correlated (0.014), so both forces hurt solar revenue.

Second, I consider the scenario where wind generation production is increased 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. Doubling wind production doubles the storage-induced consumer surplus and total welfare increase, mainly due

[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.

to a decrease in curtailment. Storage prevents a notable portion of the curtailment, increasing the return to wind production. Additionally, higher wind generation capacity leads to higher revenue for energy storage, making entering the electricity market almost profitable for privately operated storage.

Third, I consider the scenario where solar generation production is increased from 10% to 20% of the overall market production. Since solar generation is at a moderate level (no curtailment), it results in around 500 MW yearly curtailment of electricity. Doubling solar production does not lead to a significant change in private and social returns to energy storage since there is no significant curtailment. 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.

In contrast to previous studies on the CO_2 emissions effects of energy storage (Hittinger and Azevedo (2015), Lueken and Apt (2014)), my findings suggest that storage can decrease emissions. The impact of energy storage on emissions depends on two main factors: the change in emissions content of the marginal unit and the round-trip efficiency of the storage system. While changing the emissions content of the marginal units can have different implications, the results presented in Table 5 indicate that, on average, energy storage in South Australia tends to replace higher-emitting diesel-oil generators with lower-emitting natural gas generators. This shift is due to the tendency of energy storage to increase the production of low-emission natural gas generators while decreasing the production of high-emission diesel-oil generators. Additionally, although low round-trip efficiency can lead to more waste and therefore increased emissions, the decrease in emissions associated with the replacement of higher-emitting units is large enough to more than offset the losses due to round-trip inefficiency. Finally, when curtailment occurs, energy storage can further decrease emissions by preventing a significant portion of the curtailment.

7 Conclusions

Governments worldwide have implemented policies to encourage and subsidize investment in renewable energy, aiming to reduce greenhouse gas emissions from electricity production. However, renewable energy from wind and solar power can pose challenges to the stability and operation of the electricity grid due to their variability, intermittency, and non-dispatchability. Grid-scale energy storage can potentially address these challenges. Nevertheless, private incentives for investing in and operating grid-scale energy storage may not align with social incentives, leading to under-investment and under-utilization of storage capacity.

This paper presents a dynamic framework to model the effects of energy storage in wholesale electricity markets, taking into account the price effects of storage production and the responses of incumbent generating firms. The model incorporates estimates of thermal generation sources' responses to observed variation in demand volatility in a market without energy storage to recompute the new supply function equilibrium when energy storage is introduced.

The results of the model have significant policy implications for energy storage in electricity markets. The study finds that investing in energy storage may not be profitable, even if such investment would increase consumer surplus and reduce electricity production costs and emissions to the extent that it becomes socially desirable. Therefore, public policy responses such as subsidies or capacity markets for energy storage may be necessary. Additionally, changing the ownership of energy storage can improve its social returns, but these improvements cannot be achieved through a competitive storage market. Therefore, a further regulatory assessment of the ownership question of energy storage is recommended. Finally, the results indicate a non-monotonic relationship between returns for renewables and energy storage investment, suggesting a need for policies that complement investments in renewables at different penetration levels with energy storage.

This paper suggests several future lines of research. First, the revenue of storage capacity in ancillary services and capacity markets could be considered in addition to the wholesale energy market. Second, regulations in electricity markets can be updated to allow for fair and efficient energy storage entry and participation. The optimal regulatory framework for energy storage could be calculated based on storage units' responses to such changes in incentives. Finally, extending the model to nodal pricing would enable the determination of location-specific returns for energy storage investments in US electricity grids.

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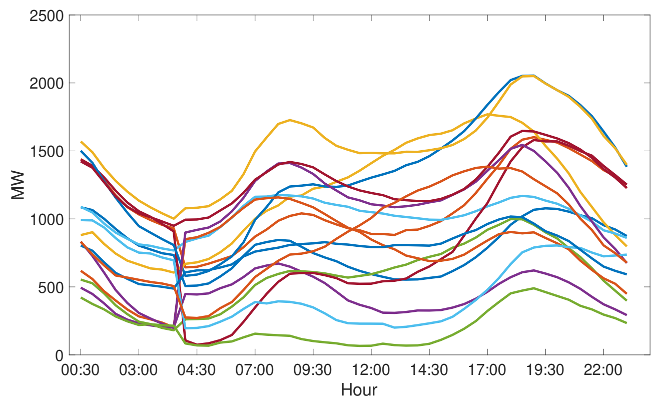
Figure 11: Mean Net Demand Clusters



Appendix

A Estimation Details

Clustering I use the k-median clustering algorithm to group days and construct $\mathcal{X}$. K-median algorithm gives a relatively more stable result then k-mean algorithm. I use the elbow method to pick the optimal number of clusters,16.

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

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

Figure 11 shows $\boldsymbol{\mu_{X_m}}$, average day net demand for all 16 day types. The observed data shows a wide variety of net demand patterns. This is helpful especially for out-of-sample concerns for large energy storage and renewable entries.

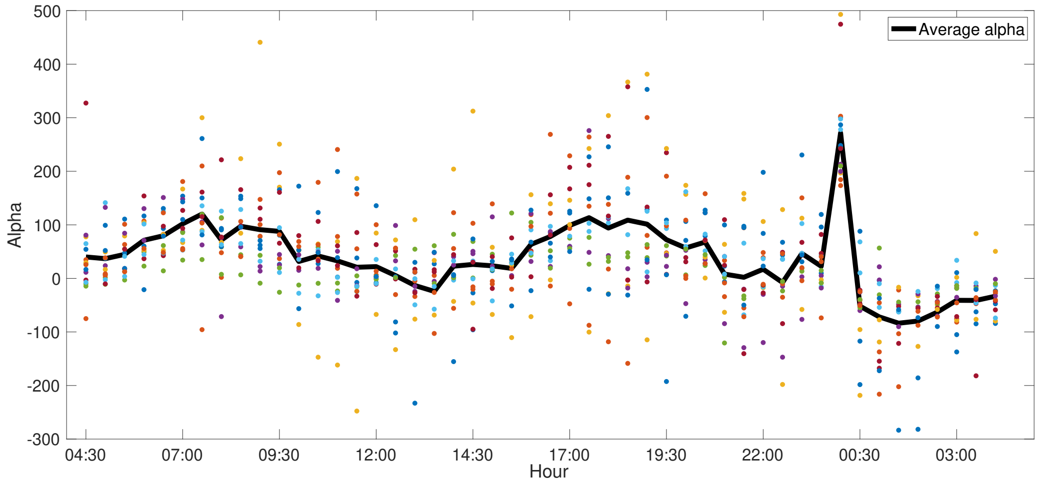
Within-day Process In order to fully characterize $f_D(D|X)$, I estimate the distribution of net demand conditional on signal X. Within the day, I assume net demand follows an AR(1) process within each cluster m,

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

Figure 12 shows set of estimates for α. Black line shows the averages. The average α coefficients, period fixed effects, show somewhat similar patterns with a significant pike at midnight. In South Australia around midnight there is a demand surge due to many coordinated boiler.

Figure 13 shows set of estimates for β. Black line shows the averages. The average β coefficients,

Figure 12: Estimated αs



persistence, are close to 1. This means that there is a significant persistence in demand, as one would expect.

B Robustness

Figure 13: Estimated βs

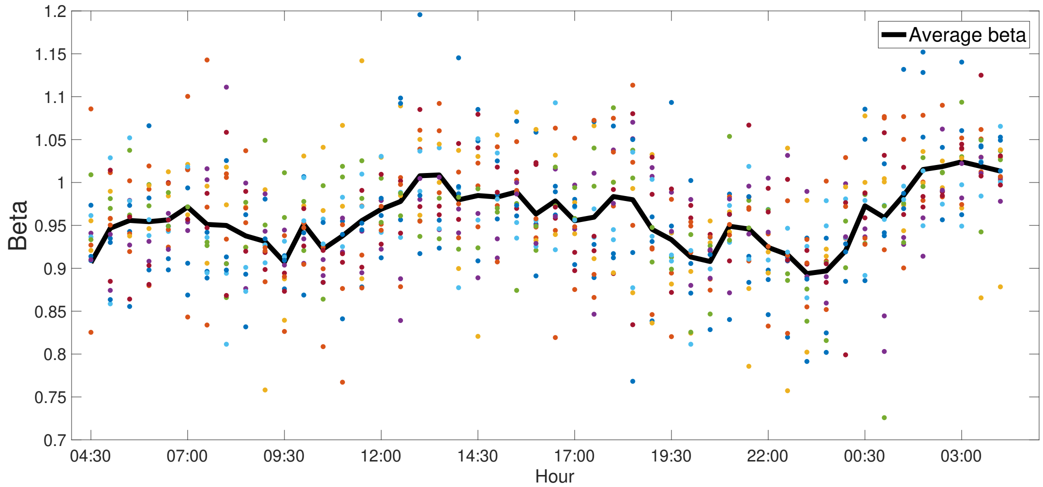


Table 6: Generation Costs for South Australia

Generator Name	Fuel 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

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.

Table 7: 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.

Table 8: 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 9: 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.