Keeping the Lights On: Battery Storage, Operating Reserves, and Electricity Scarcity Pricing *

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Abstract

Prior economic studies of grid-scale energy storage have focused on using storage for arbitrage, but grid-scale storage is also used to provide ancillary services such as operating reserves. Operating reserves are essential for "keeping the lights on," particularly in electricity systems with high penetration of intermittent renewables. This paper develops a model in which a market for operating reserves runs alongside a wholesale electricity market over time. Storage may be used either for arbitrage or to provide operating reserves. Many U.S. electricity systems employ an operating reserve demand curve (ORDC) to allocate reserves and to enable electricity scarcity pricing. I show how the ORDC emerges from the solution to a planner's problem. Model parameters are estimated using data from the Electric Reliability Council of Texas. Counterfactual simulations illustrate the impact of increasing amounts of battery storage capacity. The results indicate that the majority of storage earnings are from operating reserves rather than arbitrage, even as storage capacity is scaled up. Wholesale prices and generator profits fall as storage capacity increases. This analysis yields substantially different results than an "arbitrage-only" analysis that abstracts from operating reserves.

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1 Introduction

Electricity grids across the U.S. are experiencing rapid growth in large-scale energy storage. Most of this growth is in lithium-ion battery systems. Storage investment has been particularly high in states with high renewable energy penetration, such as California and Texas. As of November, 2023, for example, California had 7.3 GW of battery storage and the Electric Reliability Council of Texas (ERCOT) had 3.2 GW of storage while in contrast all the remaining U.S. states had 3.5 GW of storage combined; [1] Storage capacity in California and Texas increased more than 10-fold from four years earlier.[2] Continued storage growth is expected in the U.S., spurred by rising renewable penetration, falling storage investment costs, and investment tax credits authorized by the federal Inflation Reduction Act.

Expansion of battery storage may have significant effects on efficiency, electricity market prices, and profits for generation sources such as natural gas, wind turbines, and solar photovoltaic (PV). Prior economic analyses of storage impacts have focused on using storage for arbitrage; see for example, Carson and Novan [2013], Guilietti et al. [2018], Schmalensee [2022], Andres-Cerezo and Fabra [2022], Karaduman [2023], and Butters et al. [2024]. The idea is that batteries would charge during off-peak net demand periods, when marginal generation cost is low, and discharge during peak periods, when marginal generation cost is high. For example, in a system with high solar PV penetration, batteries would charge mid-day when solar radiation is high and the energy price is low, and discharge in the evening as solar radiation wanes and the energy price rises.

While arbitrage is an important use of battery storage, significant amounts of storage are in fact used to provide ancillary services rather than arbitrage. Ancillary services such as operating reserves become more important as penetration of intermittent renewables rise.[3]

[1] ERCOT battery data may be found in Resource Capacity Trend Charts, at: https://www.ercot.com/gridinfo/resource/2023 California battery data may be found at a California Energy Commission site: https://www.energy.ca.gov/news/2023-10/california-sees-unprecedented-growth-energy-storage-key-component-states-clean

[2] Ibid.

[3] Operating reserves are backup resources that can be used to balance supply and demand in the event of a disruption such as a spike in demand, generation failure, or sudden drop in renewable output. Ancillary services are a broader category of support services used to ensure reliable grid operation.

Lamp and Samano [2022] report on how batteries were used in the California Independent System Operator (CAISO) grid in 2019. They find that 66% of storage capacity was labeled as arbitrage and 44% was labeled as ancillary services; the 10% overlap suggests storage capacity that could be used for either purpose. Miller et al. [2023] report that 10 percent of battery net revenue in ERCOT was from the energy market while 90 percent was from a variety of ancillary services. They project that the bulk of battery net revenue in ERCOT will continue to be from ancillary services for the next few years.

This paper extends the economic analysis of battery storage on electricity grids to allow storage to be used for either operating reserves or energy market arbitrage. There are three reasons for incorporating operating reserves into the analysis. First, battery storage growth is most prominent in areas with high penetration of renewables. Operating reserves play an increasingly important role in electric grids as intermittent renewable penetration grows; see for example, Gowrisankaran et al. [2016]. Second, there is evidence that an important use of battery grid storage is to provide a variety of ancillary services that support electric grids; see Lamp and Samano [2022] and Miller et al. [2023]. Third, markets for operating reserves are linked to wholesale electricity markets for all major U.S. independent system operators (ISO's); see Mehrtash et al. [2023] and Buchsbaum et al. [2024]. In particular, when available generation resources are scarce relative to electricity demand, a market for operating reserves may provide a mechanism for *energy scarcity pricing* that raises the wholesale energy price above marginal generation cost; see Hogan [2013]. As a consequence, incorporating operating reserves into the analysis is important for understanding episodes of high wholesale electricity prices that influence storage operating decisions and profits.

I develop a dynamic model in which a wholesale energy market and a market for operating reserves operate over time. A dynamic framework is essential for modeling storage decisions. Energy supply is provided by fossil fuel generators, renewable resources, and storage. Fossil fuel generators also provide operating reserves. Storage may be used either for operating reserves or energy arbitrage. Available storage capacity that is not scheduled to provide operating reserves in a period may be used for arbitrage. Energy demand is assumed to be perfectly inelastic up to the value of lost load (VoLL). The model allows for uncertainty regarding loads, renewable outputs, and generator capacity availability. The solution to a planner's surplus maximization problem is used to derive generation and storage allocations. Shadow prices for the planner's solution correspond to market prices for operating reserves and wholesale electricity.

The planner's optimization problem embeds the concept of an operating reserve demand curve (ORDC), which was proposed by Hogan [2013]. This is a price-sensitive demand curve that a system operator could use as an alternative to procurement of a fixed quantity of reserves. The ORDC provides a way to incentivize provision of operating reserves, since during periods of resource scarcity the price for operating reserves would be high, possibly very high. I show how an ORDC emerges from the solution of the planner's dynamic optimization problem. This problem balances the expected benefit of additional reserves for avoiding loss-of-load events against the cost of providing reserves. I also show how the wholesale energy price is linked to the reserve price during periods of resource scarcity. When the constraints of total available generation and storage resources bind, both the energy price and operating reserves price include a scarcity component based on constraint multipliers.

The ERCOT system is used as a test bed for the analysis.[4] ERCOT operates a self-contained grid that serves most of the state of Texas. Strong wind resources and favorable public policies have resulted in Texas having the highest wind turbine capacity of all U.S. states; LaRiviere and Lu [2020]. Texas has also experienced rapid growth in solar PV capacity and battery storage capacity in recent years. The analysis uses ERCOT data on loads, generation, generator outages, energy and ancillary service prices, and battery storage. This data is used to estimate and calibrate model parameters for the baseline year of 2022. Fossil fuel generation supply curves are estimated using data on wholesale prices, generation output, and generation capacity availability. The estimated model is used to run a series of counterfactual experiments that examine the impact of progressively higher exogenous levels of energy storage capacity. These experiments provide predictions about how storage growth

[4] A number of other studies have used CAISO data to study storage issues; see Yu and Foggo [2017], Lamp and Samano [2022], and Butters et al. [2024]. The choice of ERCOT as a test bed for this analysis is significant as renewables in ERCOT are wind dominant, rather than solar dominant as in CAISO. The uses and impact of battery storage are likely to be different in ERCOT compared to CAISO due to this difference in dominant renewable type.

impacts wholesale energy prices, battery usage, operating profits from storage and various generation sources, welfare, and grid reliability. The analysis then compares results from counterfactual experiments with results from a parallel analysis that excludes consideration of operating reserves and allows storage to be used only for arbitrage.

There are two main contributions of this paper. The first is to extend economic analysis of grid-scale battery storage to include both arbitrage and operating reserves. With the exception of two studies cited below, prior studies have considered only the use of storage for arbitrage. As argued above, there is evidence that operating reserves is an important use of battery storage. The second contribution is to include operating reserves in the analysis in a way that captures how the reserves market interacts with the energy market and that takes the analysis to the data. Including operating reserves is potentially important for understanding price formation and market efficiency. Mehrtash et al. [2023] explain how operating reserve markets and prices and linked to wholesale electricity markets and prices for major U.S. independent system operators.

I note some limitations of the analysis before summarizing the main results. First, the analysis assumes a single market area with a common wholesale price in each period. ERCOT and many other systems utilize a nodal network with locational marginal pricing for energy. This assumption rules out strategically locating storage facilities to alleviate transmission constraints; see Neetzow et al. [2018]. Second, the estimated generation cost functions do not take ramping costs into account. Ramping costs are potentially important for understanding high-price episodes; see Butters et al. [2024]. Third, the empirical analysis uses data at an hourly frequency. Storage studies such as Butters et al. [2024] use higher frequency price data that may better capture arbitrage payoffs to storage. Fourth, operating reserves in this study roughly correspond to Regulation Up and Responsive Reserve Service in ERCOT. Storage may be used for purposes not considered here, such as for other ancillary services (like Regulation Down) and in other markets, such as a capacity market. These limitations may bias some of the results. The assumptions of a single market area, hourly data frequency, and no ramping costs may bias storage arbitrage earnings downward. The way the operating reserve market is formulated may bias potential total storage earnings downward, as this formulation excludes some potentially profitable storage uses. Nonetheless, this analysis captures key features of the interplay between an energy market and an operating reserves market when grid-scale storage is present, and highlights the impact of increases in storage capacity when operating reserves are taken into account.

Summary of Results: I take ERCOT battery capacity in summer 2022 as the baseline amount and examine the impact of exogenous changes that double and quadruple capacity. One finding is in regard to storage operations. I find that the mean percentage of battery power capacity used for operating reserves across all hours is 79 percent for the baseline case, falling to 78 percent and 67 percent for a doubling and quadrupling of battery capacity, respectively. Battery usage varies over different time periods. Usage for reserves is lowest during summer peak net demand hours, and highest for spring and fall periods. The proportion of battery net revenue from providing operating reserves is 57 percent in the baseline case. Somewhat surprisingly, this proportion rises as battery storage capacity rises. Total battery net revenue per unit of capacity falls as battery penetration rises. However, battery net revenue is sufficient to justify battery investment cost in all cases, after taking the U.S. federal investment tax credit into account.

Increasing energy storage capacity from 7,200 MWh (baseline case) to 28,800 MWh decreases the average hourly energy price by 7 percent, and decreases average afternoon hourly energy prices by 25 percent. There are small increases in mean wholesale prices for nighttime hours. The largest impact of a storage increase is on afternoon hours of peak summer demand. The (proportional) impact of storage increases on operating reserve prices is larger than the impact on energy prices.

Increases in storage capacity yield higher social surplus. These gains come from more efficient use of fossil fuel generators, lower cost of providing operating reserves, and reduced likelihood of load shedding events. Doubling storage capacity yields an estimated mean annual social surplus increase of $204 million; quadrupling storage capacity yields an estimated mean annual social surplus increase of $434 million. There are large reductions in buyer expenditures on electricity as storage capacity rises, due to price reductions for energy and operating reserves. Operating profits of fossil fuel, wind and solar generators fall as battery capacity rises. The percentage reductions in operating profit for fossil fuel and solar generators are larger than those for wind turbines.

I also report results for a parallel analysis in which there is a sequence of wholesale electricity markets but no markets for operating reserves. Battery storage can be used only for arbitrage in this analysis. This analysis is similar to the approach taken in most prior economic analyses of storage. There are two main differences between results for this analysis and results from the full model. Social surplus rises for both models as storage capacity increases. However, the social surplus gains for the arbitrage-only model are about half those for the main model. Battery net revenue for the arbitrage-only model is lower and rises much less as storage capacity increases, compared to results for the main model. These results suggest that incorporating operating reserves into the analysis is important and useful for understanding the impact of grid-scale battery expansion.

Relation to Literature: This paper contributes to the growing literature analyzing the incentives driving storage decisions and the impact of bulk energy storage on electricity markets. Most papers in this literature focus on using storage for arbitrage. Carson and Novan [2013] and Guilietti et al. [2018] use historical wholesale electricity price data to evaluate potential private and social benefits of arbitrage via storage. These papers take prices as exogenous in their analysis. Schmalensee [2022] formulates a dynamic competition model with alternating day-time and night-time periods that allows for investment in generation and storage. He provides conditions under which a long run competitive equilibrium minimizes system cost.

Butters et al. [2024] formulate a dynamic equilibrium model of utility-scale battery adoption and operation, estimate parts of the model using CAISO data, and use the estimated model to run counterfactual simulations of the impact of exogenous storage increases on wholesale market outcomes.[5]

Two prior studies analyze joint arbitrage and operating reserve decisions for storage.

[5]Butters et al. [2024] address several issues not considered here, including storage degradation over time, endogenous storage adoption, and incentives for delayed storage investment. There are other important differences between my analysis and the analysis in Butters et al. [2024], including the fact that solar PV is the dominant renewable source in California, while wind is the dominant renewable source in Texas.

In Yu and Foggo [2017] a system operator jointly optimizes energy market dispatch and operating reserves for storage (as well as for generation). This is the approach taken in my paper as well. In contrast to Yu and Foggo [2017], my approach allows for endogenous market price formation and counterfactual experiments in which battery storage capacity varies.[6] Gowrisankaran et al. [2024] formulate a dynamic model with thermal, wind, and hydro-electric generation and apply the model to analyze Finland's electricity system. Hydro storage is used both for energy dispatch and provision of operating reserves. In contrast to Gowrisankaran et al. [2024], my analysis allows for a scarcity pricing linkage between markets for energy and operating reserves.

Lamp and Samano [2022] analyze large-scale battery charging and discharging decisions from the California Independent System Operator (CAISO). They find that charging/discharging decisions for batteries during 2018-2019 were partially consistent with an optimal arbitrage model. However, the observed data indicates smaller responses to wholesale price changes than an optimal arbitrage model would predict.

Market power is a concern for wholesale electricity markets. Andres-Cerezo and Fabra [2022] analyze a wholesale market model that allows for market power in generation, storage, and both generation and storage. They find that the source of market power affects efficiency and whether there is over- or under-investment in storage. Karaduman [2023] analyzes the impact of introducing battery storage into the South Australia electricity market using a supply function model. Estimated supply functions of individual thermal generators capture their market power in the wholesale market. Butters et al. [2024] take market power of thermal generators into account via estimation of aggregate thermal supply functions. Market power would be reflected in markups over marginal generation cost in estimated supply functions. They assume that the estimated supply functions (and embedded market power) do not change as storage is added. I use a similar approach for estimation of aggregate thermal generation supply functions.

This paper also contributes to the economics literature examining how ancillary services interact with wholesale electricity markets. Buchsbaum et al. [2024] provide evidence that

[6] Yu and Foggo [2017] analyze optimal storage decisions in response to exogenous market price processes.

changes in ancillary service markets impact generator decisions in the energy market. Joskow and Tirole [2007] model optimal scheduling of generation and operating reserves, where reserves are available to replace lost output due to an outage. A generation outage may precipitate a system collapse as the blackout cascades through the system. Gowrisankaran et al. [2016] build on Joskow and Tirole [2007] to quantify the impact of a renewable portfolio standard on welfare and grid reliability. Using data from an Arizona utility, they find that it is optimal to add operating reserves as solar penetration increases, and that these extra reserves contribute to the cost of grid integration of solar.

Electric utilities and independent system operators have traditionally set a fixed amount of operating reserves – e.g., 10% of peak load – and then allocated or procured generation capacity to provide these reserves. Hogan [2013] proposed creating an operating reserve demand curve (ORDC) for which the demand for reserve quantities would be price sensitive, with higher quantities demanded for lower reserve prices. A higher reserve quantity reduces the likelihood of a loss of load event in which available resources are insufficient to serve all customers. Hogan [2013] shows that the marginal value of reserves on the ORDC is the loss-of-load probability at the reserve quantity times the marginal net benefit of providing one more unit to customers (VoLL minus marginal generation cost). He also shows how the ORDC yields energy scarcity pricing; when resources are scarce the wholesale energy price is linked to the reserve price and includes a scarcity component that raises the wholesale energy price above marginal generation cost.[7] I show how this scarcity component of the wholesale energy price emerges from the planner's solution. Some version of the ORDC has been implemented in ERCOT and all other major U.S. ISO's; see Mehrtash et al. [2023] for an excellent survey of how the ORDC is used in ISO's.

The rest of the paper proceeds as follows: Section 2 describes the data used. The model is described in section 3. Section 4 develops the planner's solution and provides results on market prices. Section 5 reports estimation results, explains the computation approach, and reports results for the ERCOT application. Section 6 concludes.

[7]Of course scarcity pricing could also emerge from demand-side responses such as those induced by real-time pricing. However, demand-side responses are limited in most U.S. systems.

2 Data and Market Environment

ERCOT is an independent system operator that operates a wholesale electricity market covering much of the territory and most of the population of Texas. ERCOT's responsibilities include ensuring open access to transmission and maintaining system reliability. Within ERCOT there is a diversified supply portfolio that includes coal, natural gas, nuclear, wind, solar PV, and battery storage. Texas has the largest amount of wind turbine capacity of any state in the U.S. I use the year 2022 as a baseline year for the analysis. There is detailed generator data available for this year from the EPA Emissions Generation Resource Integrated Database (eGRID) report. ERCOT also has data on electricity generation by supply source, generator outages, loads, and prices for wholesale electricity and ancillary services. The rest of this section describes the data and ERCOT markets.

2.1 Generation Supply

Several sources of data are used to estimate fossil fuel generation supply functions. The ERCOT Fuel Mix Report provides total generation output at 15 minute intervals for each fuel source (coal, natural gas, nuclear, wind, etc.); see ERCOT [2022a]. I sum coal and natural gas generation output to create an hourly time series of fossil fuel output. The generation supply function depends on available capacity as well as output. Total capacity by generation type is available at the EPA eGRID report with 2022 data.[8] I supplement this with information in the Report on the Capacity, Demand and Reserves in the ERCOT Region, 2022-2031; see ERCOT [2021]. This report provides a forecast of the amount of thermal capacity available to meet peak summer demand. Table 1 summarizes generation resources in ERCOT as of 2022. Natural gas is the dominant generation type, with a little less than one-half of total generation capacity and total output. Wind turbines have the second highest capacity and output. ERCOT also has hydro and biomass generators. I omit these from the analysis as their total capacity is small and capacity factors are low.

The analysis incorporates data on generator outages. There are two reasons for using this

[8] Available at, https://www.epa.gov/egrid/download-data

Table 1: **ERCOT Generation Capacities, 2022**

Type	Total Capacity (MW)	Capacity Factor (%)
Coal	14,300	57.1
Natural Gas	56,200	38.8
Nuclear	5,000	93.2
Solar PV	11,200	24.2
Wind	31,400	38.2
Battery Storage	1,800	-
Other	600	-

Notes: Capacity factor equals average output per hour divided by capacity. Battery storage capacity is in MW of power capacity. Other capacity includes hydro and biomass.

data. First, generation supply may be viewed as being driven by marginal cost. The marginal cost of generation depends on how much capacity is available at a given time. Second, one of the purposes of operating reserves is to replace unexpected losses in generation due to outages. The outage data is used to characterize the distribution of fossil fuel generation outages.

Data on generator outages in ERCOT are reported in Unplanned Resource Outage Reports.[9] These reports provide unit name, fuel type, unit capacity, MW of outage (many outages are partial), type of outage (forced, maintenance, etc.), outage start time, and outage end time. I combined available reports to create a file with over 24,000 outage observations that covers 2022 and days preceding and following the 2022 calendar year. I focus on data for maintenance outages and forced outages for coal and natural gas units.[10]

The hourly outage data are depicted in Figures 1 and 2. There is a strong seasonal pattern for maintenance outages. These are concentrated in spring and fall periods when

[9] https://www.ercot.com/mp/data-products/data-product-details?id=NP1-346-ER

[10] The ERCOT resource outage reports also include outage information for wind and solar generation. In the next sub-section I describe the data on wind and solar generation. I model renewable generation as a random process that incorporates the effects of both weather conditions and outages. This model does not require information about renewable generation outages.

loads are relatively low. As much as 28% of capacity may be unavailable in a given hour due to maintenance outages in fall and spring. Maintenance outages tend to be very low during the summer, falling to nearly zero for many parts of the summer for coal generators. There is substantial variability in forced outages. Forced outages do not appear to have a seasonal pattern. Summary statistics for generation outages are reported in Table 2.

ERCOT has four roughly equal sized nuclear units with total capacity of approximately 5,000 MW. Nuclear power is treated as must-run capacity. It is common for maintenance outages to occur during spring and fall periods. The analysis assumes that one nuclear unit is unavailable during weeks 15 - 19 and 41 - 45. Nuclear generation output is set equal to 75 percent of total capacity during these weeks and to 100 percent of total capacity during other weeks. This yields an implied annual nuclear capacity factor of 95.6 percent, slightly higher than the observed 2022 capacity factor. Forced outages for nuclear plants are rare and are omitted from the analysis.[11]

2.2 Electricity Demand and Renewable Generation

I use hourly 2022 data on loads, wind generation, and solar generation for ERCOT. Data on hourly loads are available at ERCOT [2022b]. Total wind turbine and (utility scale) solar PV generation output are drawn from the ERCOT Fuel Mix Report. I do not observe distributed solar PV output. This output is behind the meter. Reported load data is net of distributed solar PV output.

Hourly average load and hourly average wind and solar generation capacity factors are depicted in Figure 3. Average load is highest in late afternoon and early evening. Solar peaks mid-day and wind generation is lowest on average mid-day. Loads and renewable generation are highly variable over time. Some of the variation is predictable based on hour-of-day and month-of-year. However there is also significant variation driven mainly by weather conditions.

The ERCOT wholesale electricity market operates with a price cap of $5,000/MWh. The

[11] Inclusion of forced outages, even those with a very low probability, would raise the value of operating reserves and likely yield higher predicted operating reserve prices than those reported below.

Figure 1: Coal Generation Outages, 2022

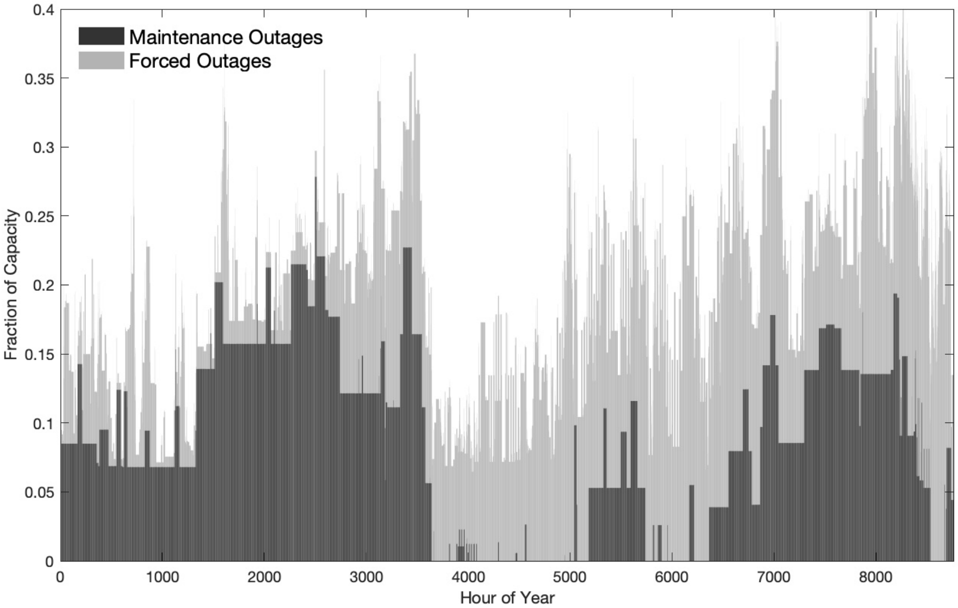


Figure 2: Natural Gas Generation Outages, 2022

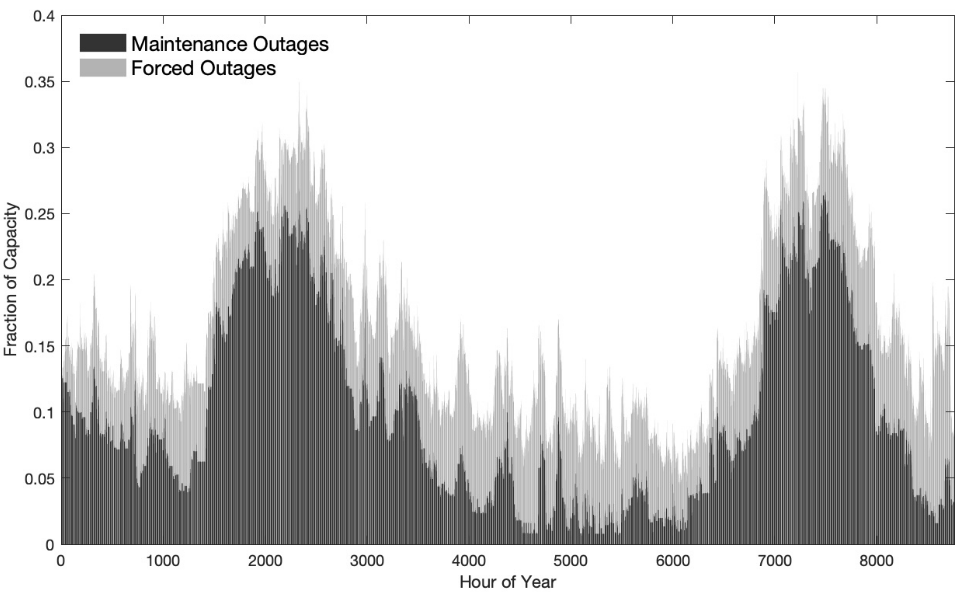
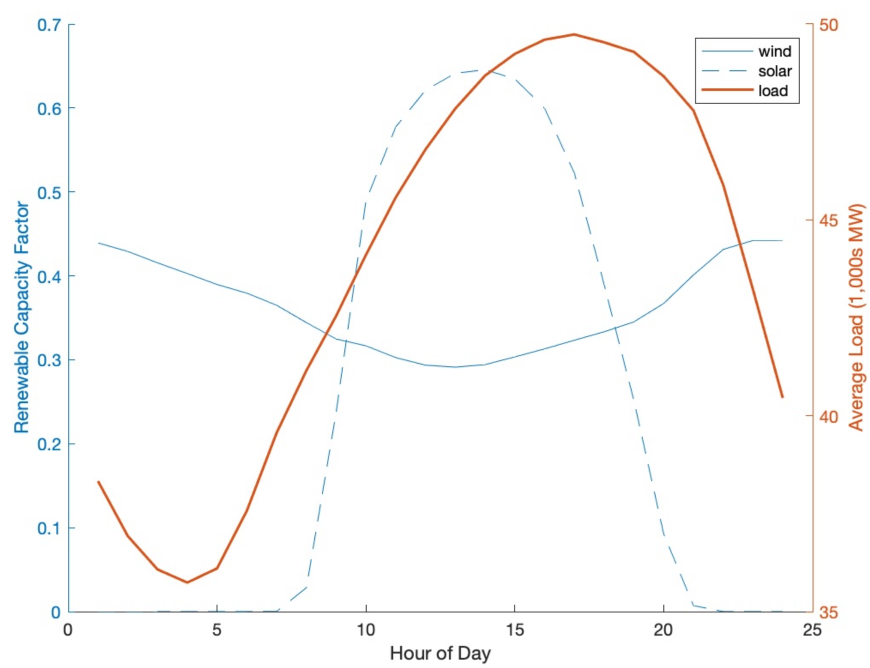


Table 2: **Outage Summary Statistics (Percent of Capacity Unavailable)**

	Natural Gas	Coal
Average maintenance	9.9	8.9
Minimum maintennce	0.6	0.0
Maximum maintenance	28.0	28.0
Average forced	6.3	10.8
Minimum forced	0.4	0.2
Maximum forced	17.0	33.0

Figure 3: Hourly Load and Renewable Capacity Factors



system operator sets VoLL equal to the price cap when constructing the ORDC. I do this as well when solving the planner's optimization problem and computing energy and operating reserve prices. If scheduled generation plus reserves for an hour is less than load then I assume that the system operator orders distributors to shed load, with the amount shed equal to the generation short-fall.[12]

I also report on welfare changes for counterfactual changes in storage. I set VoLL to $9,000/MWh when estimating welfare changes. This is the median value of VoLL estimates from Gorman [2022].

2.3 Energy Storage

A variety of energy storage technologies have been used in electricity markets. Pumped hydro storage has been in use for decades. Other technologies such as compressed air energy storage, flywheels, and batteries are also in use. Lithium-ion batteries are now the most common kind of storage in U.S. electricity markets, accounting for over 90% of battery storage capacity; see EIA [2021]. This analysis will focus on lithium-ion batteries.

Energy Information Administration form 860 provides data on energy storage facilities.[13] Virtually all bulk storage in ERCOT is lithium ion 4-hour battery type. There was significant battery expansion during 2022. Battery power capacity began at about 1,000 MW and ended at 2,683 MW. In the middle of 2022 battery power capacity was approximately 1,800 MW. I take this to be the baseline level of battery power capacity for the analysis. I assume all batteries have a four hour duration and 85% round-trip efficiency in the analysis of sections 5 and 6. This is the most common type of battery being added in U.S. markets; see Cole and Karmakar [2023]. Given the four hour duration, baseline energy storage capacity is 7,200 MWh.

EIA form 860 indicates how storage was used during the 2022 reporting year. Most storage is listed for both arbitrage and frequency regulation usage.[14] Most storage capacity also

[12]Information about load shedding protocols for ERCOT may be found at: https://www.puc.texas.gov/agency/resources/reports/leg/PUC_Load_Shed_Protocols_Study.pdf

[13]https://www.eia.gov/electricity/data/eia860/

[14]The language in the EIA form is, for example: "Indicates if this energy storage device served frequency

indicated ramping/spinning reserve usage. Specifically, 87% of capacity is listed for arbitrage use, 97% is listed for frequency regulation use, and 83% is listed for ramping/spinning reserve use. This mixed usage of battery storage is similar to what Lamp and Samano [2022] report for battery use in CAISO in 2019.

Almost all storage capacity in ERCOT is owned and operated by independent power producers. The 4 largest storage owning firms have a combined 38% of storage capacity.

2.4 Markets and Prices

The ERCOT system establishes wholesale energy prices in a day-ahead market (DAM) and a real-time market (RTM). Prices are established at multiple nodes in each market. Nodal prices are aggregated up to hub prices for several hubs. An ERCOT web site provides hourly hub DAM settlement point prices for 2022.[15] I take the average of hub DAM prices to compute a single DAM wholesale energy price for each hour. DAM prices are used to estimate generation supply functions.

ERCOT also provides 15-minute RTM hub settlement point prices.[16] I average these prices to derive an hourly average system-wide RTM wholesale energy price. Summary statistics for wholesale energy prices appear in Table 3. Ninety percent of DAM and RTM energy prices are between $10/MWh and $150/MWh. RTM energy prices are below zero for some hours. DAM and RTM energy prices are over $1,000/MWh for a few hours, mainly during hot summer periods.

The system operator coordinates multiple ancillary service markets in addition to the wholesale energy markets. Ancillary services help to maintain grid stability and reliability. These services include Regulation Up, Regulation Down, Responsive Reserve Service (RRS), Non-spin Reserve Service, and Contingency Reserve Service; see ERCOT [2024] for a description of these services. Summary statistics for ancillary service prices are in Table 3. Day-ahead prices for Regulation Up, RRS, and Non-spin are very similar, averaging about

regulation applications during the reporting year".

[15]See, https://www.ercot.com/mp/data-products/data-product-details?id=NP4-180-ER

[16]https://www.ercot.com/mp/data-products/data-product-details?id=NP6-785-ER

Table 3: **Hourly Prices, 2022**

	Average	5^{th} Percentile	95^{th} Percentile
Day Ahead Market			
Wholesale energy price ($/MWh)	64.31	17.18	141.40
Regulation Up ($/MW)	21.67	1.50	60.60
Responsive Reserve Service ($/MW)	20.31	1.15	57.70
Non-spin Reserve Service ($/MW)	22.49	0.92	77.96
Real Time Market			
Wholesale energy price ($/MWh)	62.30	10.50	111.38
RTRSVPOR* ($/MW)	5.18	0.00	3.15

* RTRSVPOR = real-time reserve price for on-line reserves.

$21.50/MW. These prices are fairly low in most hours. However during periods of resource scarcity in 2022 these prices rose to almost $3,000/MW. The real-time reserve price is quite low for most hours; it was below $0.10/MW for 90 percent of hours in 2022. However, as with day-ahead prices, the real-time reserve price was very high during periods of resource scarcity, rising to a peak of $2,545/MW in 2022. These peak real-time reserve prices are significant both as a signal of the value of operating reserves and for their impact on energy prices. Wholesale energy prices in ERCOT are constructed with the real-time reserve price serving as a price adder on top of a base price, where the base price is an average of locational marginal prices across the grid; see Mehrtash et al. [2023]. This is how the ORDC mechanism contributes to scarcity pricing in ERCOT.

The system operator procures ancillary services from generators and storage operators. Procurement amounts vary somewhat across months of year and hours of day. Table 4 reports average hourly procurement amounts for key ancillary services for 2022. Most of this is procured in the day-ahead market. For the day-ahead market the system operator chooses a fixed amount of each type of service to procure for each hour and solicits offers from generator owners and storage owners. Prices are established via procurement auctions. The system operator may decide that insufficient ancillary services have been procured in the day-ahead market as the hour of operation approaches. In this event additional reserves will be procured in a real-time market. This is where the ORDC enters. The system operator will set the ORDC based on their estimation of loss-of-load probabilities for different reserve quantities. A real-time price for reserves is set based on the intersection of the ORDC and the reserves offer curve.

Table 4: **Average Hourly Ancillary Service Procurement**

Type	Amount
Regulation Up	390 MW
Responsive Reserve Service	2,900 MW
Non-spin	3,400 MW

Notes: This data is from page 47 of Potomac-Economics [2023].

3 Wholesale Electricity Market Model

A dynamic electricity market model is developed in this section. Firms make decisions about operation of battery storage and electricity generators. Dynamics come into play since storage operators take future market conditions into account when deciding how to use batteries in the current period. Market operations take place over a sequence of time periods, $t = 1, 2, ...$ Activity takes place within two markets in each time period: a wholesale energy market and a market for operating reserves. This is a short run model in the sense that storage and generation capacities are fixed.

Another potential mechanism for dynamics involves ramping costs for generators. Ramping costs are not considered in the current version of this paper, but could be incorporated in a sequel.[17]

3.1 Demand

I assume energy demand is perfectly inelastic in each period for prices up to v, the value of lost load. The quantity demanded (load) varies across time periods according to a vector, $\boldsymbol{z}_t$, of exogenous state variables, which is assumed to follow a Markov process. The set of feasible values of $\boldsymbol{z}_t$ is restricted to a set, $\boldsymbol{Z}$. The demand function is given by:

$$D(p_t, \boldsymbol{z}_t) = \begin{cases} 0, & p_t > v \\ L(\boldsymbol{z}_t), & p_t \leq v \end{cases} \tag{1}$$

where p_t and $\boldsymbol{z}_t$ are the price and state vector in period t and $L(\boldsymbol{z}_t)$ is a function that specifies the load for each state vector $\boldsymbol{z}_t$.

Many wholesale electricity markets, including the ERCOT market, operate with a price cap. If there is a price cap, $\overline{p}$, less than the value of lost load then v in equation (1) is replaced by $\overline{p}$.

There is also a demand for operating reserves, which will be described via an operating

[17]See Butters et al. [2024] and Cullen and Reynolds [2023] for examples of dynamic wholesale market models that allow for generator ramping costs.

reserve demand curve (ORDC). In Section 4 below I show how the ORDC is derived from a planner's optimization problem.

3.2 Energy Storage

I assume a single type of battery storage is available. Let k_0 be exogenous total storage capacity. Let $\gamma \in (0,1)$ be the roundtrip efficiency. This is the fraction of energy that is not lost during the charging and discharging process. Let η be the battery's duration; the amount of time the battery is able to discharge at its rated power capacity. Then k_0/η is the battery's rated power capacity. For example, if η equals four hours then a fully charged battery can discharge at full power capacity for four hours and the battery's power capacity per hour is 1/4 of its storage capacity. I assume that all batteries have the same duration and efficiency so that the allocation across all battery capacity is equal to the allocation at the margin.

The total amount of storage capacity available at the end of period t, $s_t \in [0, k_0]$, is a state variable in the analysis. Net output from storage in t is x_{0t}. Batteries discharge when net output is positive; batteries charge when net output is negative. Discharge per period cannot exceed the minimum of rated power capacity and available storage:

$$x_{0t} \leq min\{k_0/\eta, s_{t-1}\} \tag{2}$$

The magnitude of charging per period cannot exceed the minimum of rated power capacity and unused storage capacity, adjusted for roundtrip efficiency:

$$x_{0t} \geq max\{-k_0/\eta\gamma, -(k_0 - s_{t-1})/\gamma\} \tag{3}$$

The storage transition equation is:

$$s_t = s_{t-1} - \mathbb{1}_{\{x_{0t} \geq 0\}} x_{0t} - \gamma \mathbb{1}_{\{x_{0t} < 0\}} x_{0t} \tag{4}$$

Net load and available generation capacity are uncertain at the start of each time period

t. Storage capacity available at the start of time period t must be allocated between the wholesale energy market and the operating reserves market. Let q_{0t} be scheduled net output from storage for the energy market and let r_{0t} be operating reserves from storage. The sum of scheduled net output and operating reserves cannot exceed the discharge limit:

$$q_{0t} + r_{0t} \leq min\{k_0/\eta, s_{t-1}\} \tag{5}$$

Following the realization of load and available generation capacity within period t, the planner chooses storage net output adjustment, Δq_{0t}. Storage net output adjustment may not exceed storage reserves; that is,

$$\Delta q_{0t} \leq r_{0t} \tag{6}$$

Scheduled storage net output plus adjustment yields storage net output; that is:

$$q_{0t} + \Delta q_{0t} = x_{0t} \tag{7}$$

Choices of scheduled storage net output, operating reserves, and net output adjustment must satisfy constraints (3) and (5) - (7).

3.3 Production

There are multiple types of generation, indexed by $j \in \{1, 2, ..., J\}$. The following notation is used:

x_{jt} = type-j generation output in period t

k_j = type-j generation capacity

$\lambda_j(\boldsymbol{z}_t)$ = type-j capacity availability factor $\in [0, 1]$

Capacity availability is dependent on the state vector, $\boldsymbol{z}_t$.

Conventional (fossil fuel) generation is aggregated into a single type, labeled type 1. Capacity availability for conventional generation varies over time due to forced outages and scheduled maintenance outages. Fossil fuel generation satisfies the following constraint in each period t:

$$x_{1t} \leq \lambda_1(\boldsymbol{z}_t)k_1 \tag{8}$$

The cost of fossil fuel generation is given by a function that depends on output rate and available capacity. Period t aggregate type 1 generation cost is given by function, $C(x_{1t}, \lambda_1(\boldsymbol{z}_t)k_1)$, which is increasing and strictly convex in its output argument.

Conventional generation scheduled output, q_{1t}, and operating reserves, r_{1t}, for period t are chosen at the beginning of the period, prior to the realizations of load and capacity availability. The sum of scheduled output and reserves cannot exceed expected available capacity:

$$q_{1t} + r_{1t} \leq \mathrm{E}[\lambda_1(\boldsymbol{z}_t)|\boldsymbol{z}_{t-1})]k_1 \tag{9}$$

Following the realization of load and available generation capacity within period t, the planner chooses output adjustment, Δq_{1t}. Output adjustment may not exceed reserves; that is,

$$\Delta q_{1t} \leq r_{1t} \tag{10}$$

Some scheduled output may not be available for generation due to outages. Specifically, if realized capacity availability is less than expected availability, then there is a reduction in output relative to scheduled output. Let $\epsilon_{1t} = \lambda_1(\boldsymbol{z}_t) - \mathrm{E}[\lambda_1(\boldsymbol{z}_t)|\boldsymbol{z}_{t-1})]$ be the availability forecast error. An output reduction occurs when this forecast error is negative. Final conventional generation output in t is scheduled output less output reduction (due to outages) plus output adjustment.

$$q_{1t}(1 + min\{0, \epsilon_{1t}\}) + \Delta q_{1t} = x_{1t} \tag{11}$$

There is typically a cost of providing reserves from conventional generation capacity. These costs come from some combination of startup costs for additional spinning generators, additional ramping costs, and extra costs associated with operating some units at sub-optimal generation levels. I use a reduced form representation of reserve costs as an abstraction from a more complicated generator allocation problem.[18] Reserve cost is specified as a fraction

[18] Including generator ramping costs in the analysis would account for some reserve costs. A unit commit-

$\alpha \in (0,1)$ of the incremental cost of increasing generation from q_{1t} to $q_{1t}+r_{1t}$, given expected capacity availability, $\mathrm{E}(\lambda_1) = \mathrm{E}[\lambda_1(\boldsymbol{z_t})|\boldsymbol{z_{t-1}}]$.

$$C^R(q_{1t}, r_{1t}, \mathrm{E}(\lambda_1)k_1) = \alpha(C(q_{1t}+r_{1t}, \mathrm{E}(\lambda_1)k_1) - C(q_{1t}, \mathrm{E}(\lambda_1)k_1)) \tag{12}$$

I allow for multiple types of renewable generation, such as generation from wind turbines and solar PV panels. Renewable technologies are indexed by $j \in \{2, ..., J\}$. Marginal cost is assumed to be zero for all renewable technologies. Renewable generation varies according to time of year, hour of day, and weather conditions. Capacity availability captures both deterministic and stochastic factors in this model. Renewable generation is assumed to equal the product of capacity availability and capacity in each period, for each type of renewable technology. That is, I assume no renewable curtailment.[19] This yields, $x_{jt} = \lambda_j(\boldsymbol{z}_t)k_j$, for $j \geq 2$.

Given the no renewable curtailment assumption, net load is defined as follows:.

$$NL(\boldsymbol{z}_t) = L(\boldsymbol{z}_t) - \sum_{j\geq 2} \lambda_j(\boldsymbol{z}_t)k_j \tag{13}$$

Net load is supplied by conventional generation and generation from storage.

3.4 Markets and Uncertainty

Two markets operate in each period: a real-time wholesale energy market and a real-time market for operating reserves. When these markets open in period t the state $\boldsymbol{z}_t$ is unknown. Period t net load and fossil fuel capacity availability are forecasted based on the realization of $\boldsymbol{z}_{t-1}$. Generation suppliers and suppliers of energy from storage decide how much to allocate to the energy market and how much to allocate to the reserves market in each period.

A competitive, price-taking framework is assumed for these markets. However the application to ERCOT involves estimation of generation supply curves based on observed generator

ment model from the power systems engineering literature would provide a more complete model of reserve cost.

[19] A more general model would set available capacity as an upper bound for renewable generation as in constraint (8), so that curtailment is possible.

decisions. Thus the application captures generator market power to the extent that these decisions reflect markups of price over marginal generation cost.

Below I formulate a welfare maximization problem for a system planner and characterize features of its solution. I characterize the solution first for a model in which storage capacity is zero and all energy supply is from generators. This allows me to highlight the role played by the reserves market and the derivation of an ORDC. Shadow prices from the solution to the planner's problem correspond to equilibrium energy and reserve prices.

When energy storage is included the planner's problem is an intrinsically dynamic problem. Decisions about storage use must balance the net benefit of current storage use against the expected opportunity cost of future storage availability. As with the simpler no-storage model, shadow prices from the solution to the planner's problem correspond to equilibrium energy and reserve prices.

Collapsing load and renewable generation into a single net load quantity simplifies the analysis. After adjusting for expected renewable generation, the quantity demanded in the energy market in period t will equal expected net load, conditional on $\boldsymbol{z}_{t-1}$. The price in the energy market equals the marginal opportunity cost of conventional generation in each period. This price is consistent with profit maximization by conventional generation suppliers under the perfect competition assumption. The opportunity cost terminology is important here. The marginal opportunity cost of conventional generation is the sum of two components: marginal generation cost and the opportunity cost of using generators for scheduled output rather than for reserves. When the constraint from available generation capacity binds, the opportunity cost of using generators for scheduled output rather than for reserves is positive, yielding an energy price that exceeds the marginal cost of generation. Put somewhat differently, when conventional generation capacity is scarce, the supply of one additional unit of conventional generation entails foregoing the opportunity of providing the unit for (potentially very valuable) operating reserves.

There are two stages of activity for each period t. In the first stage prices of energy and reserves are set and supply quantities for reserves and scheduled generation are allocated from conventional generators and storage. First stage decisions are based on load and generator availability forecasts using $\boldsymbol{z}_{t-1}$. The second stage occurs after load and availability realizations, which depend on $\boldsymbol{z}_t$. In this stage the system operator directs conventional generators and storage providers to adjust output up or down in response to load and resource availability outcomes. Upward adjustments are limited by the quantity of reserves set in stage one. If reserves are not sufficient to serve realized net load in stage two then there is a loss-of-load event and the system operator randomly allocates total available energy to customers.

4 Optimum and Market Equilibrium

This section describes the problem of a social planner that maximizes expected total surplus arising from a wholesale electricity market and a market for operating reserves. The planner co-optimizes for these two markets and the optimal solution links allocations across the two markets. The optimal solution also yields an operating reserve demand curve. I take shadow values from the optimal solution to the planner's problem as equilibrium market prices for energy and operating reserves. I use the planner's problem as a vehicle for computation of competitive equilibria for counterfactual experiments with varying amounts of battery storage.

4.1 The Planner's Problem

Each time period t is divided into two stages. In stage one the planner observes state $(s_{t-1}, \boldsymbol{z_{t-1}})$ and chooses $(q_{0t}, r_{0t}, q_{1t}, r_{1t})$. These choices are subject to constraints (5) and (9) and an expected net load constraint:

$$q_{0t} + q_{1t} \leq \mathrm{E}[NL(\boldsymbol{z}_t)|\boldsymbol{z}_{t-1}] \tag{14}$$

In stage two the planner chooses net output adjustment for storage (Δq_{0t}) and output adjustment for conventional generation (Δq_{1t}) after observing $\boldsymbol{z_t}$. Output adjustments are constrained by stage one reserves choices.

The planner is assumed to make choices to maximize the expected discounted present value of the stream of total (consumer plus producer) surplus. The value function $V(s_{t-1}, \boldsymbol{z_{t-1}})$ captures the planner's value at the start of period t. This value equals stage one net benefit plus stage two net benefit from output adjustments plus a continuation value. I introduce a second value function, $W(\cdot)$, to capture the planner's value at the start of stage two after the realization of state vector $\boldsymbol{z_t}$.

$$V(s_{t-1}, \boldsymbol{z_{t-1}}) = \max_{\{q_{0t}, r_{0t}, q_{1t}, r_{1t}\}} \{(q_{0t} + q_{1t})v - \mathrm{E}[C(x_{1t}, \lambda_1(\boldsymbol{z_t})k_1)|\boldsymbol{z_{t-1}}] - C^R(q_{1t}, r_{1t}, \mathrm{E}(\lambda_1)k_1) + \mathrm{E}[W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})|\boldsymbol{z_{t-1}}]\} \tag{15}$$

$$W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t}) = \max_{\{\Delta q_{0t}, \Delta q_{1t}\}} \{(\Delta q_{0t} + \Delta q_{1t} + \min\{0, \epsilon_{1t}\}q_{1t})v - \Delta C(q_{1t}, \Delta q_{1t}, \epsilon_{1t}, \lambda_1(\boldsymbol{z_t})k_1) + \delta V(s_t, \boldsymbol{z_t})\} \tag{16}$$

The function $\Delta C(\cdot)$ in (16) specifies the change in generation cost for stage two generation output adjustments. The stage one maximization in (15) is subject to constraints (5), (9), and net load constraint (14). Stage two output adjustments in (16) are subject to reserves limits and the following disturbance constraint.

$$\Delta q_{0t} + \Delta q_{1t} \leq NL(\boldsymbol{z_t}) - \mathrm{E}[NL(\boldsymbol{z_t})|\boldsymbol{z_{t-1}}] - \min\{0, \epsilon_{1t}\}q_{1t} = \epsilon_t^{NL} - \min\{0, \epsilon_{1t}\}q_{1t} \tag{17}$$

The RHS of inequality (17) is the net load forecast error (ϵ_t^{NL}) plus the magnitude of the output reduction from unexpected outages of scheduled generation. I refer to the RHS of (17) as the disturbance.

Optimality conditions for the planner's problem are explained in the Appendix. The next sub-section examines the special case of no battery storage.

4.2 Results with No Storage

If there is no storage in the system then the planner's problem collapses to a two stage optimization problem within each period. In the first stage the planner chooses scheduled generation output and reserves from generation. In the second stage the planner chooses an output adjustment from available generation in response to the realization of net load and generator availability.

With no storage the solution to the second stage is quite simple, as long as the value of lost load (v) is large relative to marginal generation cost. If the disturbance is less than or equal to reserves then the output adjustment is equal to the disturbance. Otherwise, the output adjustment is equal to reserves and there is a loss of load event, with the amount of lost load equal to the disturbance minus reserves. My analysis abstracts from externalities associated with loss-of-load events. I follow Schmalensee [2022] in assuming that all consumers have a common marginal value of electricity service equal to value of lost load (VoLL) and that when there is a resource shortfall, the amount of curtailment to consumers is limited to the loss of load.

The marginal value of reserves in stage two is zero if the reserves constraint does not bind. If the reserves constraint binds then the marginal value of reserves in stage two is:

$$\partial W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})/\partial r_{1t} = v - \partial C(q_{1t}(1 + \min\{0, \epsilon_{1t}\}) + r_{1t}, \lambda_t(\boldsymbol{z_t})k_1)\partial q \qquad (18)$$

The marginal value of reserves in period t for stage one is the expected value of (18) conditional on $\boldsymbol{z_{t-1}}$. Let $\mathrm{E}[\partial C(\cdot)/\partial q|LOL]$ be expected marginal generation cost conditional on a loss of load event. The marginal value of reserves for stage one may be expressed as:

$$\partial \mathrm{E}[W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})|\boldsymbol{z_{t-1}}]/\partial r_{1t} = (v - \mathrm{E}[\partial C(\cdot)/\partial q|LOL])LOLP(r_{1t}, q_{1t}, \boldsymbol{z_{t-1}}) \qquad (19)$$

where $LOLP$ is the loss of load probability. This marginal benefit is the net value of satisfying one more unit of load, times the probability that resources are not sufficient to serve all load. The RHS of (19) corresponds to the operating reserve demand curve described in Hogan [2013] and Liu et al. [2018]. Specifically, the RHS of (19) yields an inverse demand function for reserves that is decreasing in the amount of reserves since $LOLP$ is decreasing in reserves.

Optimal choices of scheduled generation and reserves for stage one are subject to expected capacity availability and expected net load constraints; let μ_{1t} and μ_{2t} be the (non-negative) Lagrange multipliers for these constraints, respectively. Then the necessary conditions for scheduled generation and reserves are as follows:

$$v - \mathrm{E}[\partial C(\cdot)/\partial q_{1t}|\boldsymbol{z_{t-1}}] - \mu_{1t} - \mu_{2t} = 0 \tag{20}$$

$$\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]/\partial r_{1t} - \partial C^R/\partial r_{1t} - \mu_{1t} = 0 \tag{21}$$

Marginal generation cost is uncertain in stage one. Realized marginal generation cost depends on the capacity availability outcome, the effect of scheduled output on reserve cost, and stage two output adjustment.

The nature of stage one outcomes depends on the expected capacity availability constraint. If this constraint is slack then multiplier μ_{1t} is zero and the marginal benefit of reserves in (21) is equal to the marginal cost of reserves. In this case the price of reserves is equal to the marginal cost of reserves and the price of energy is equal to expected marginal generation cost. The multiplier μ_{2t} is equal to the gap between VoLL and expected marginal generation cost.

If the expected capacity availability constraint binds then multiplier μ_{1t} is positive. In this case, the price of reserves is equal to the marginal benefit of reserves ($\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]/\partial r_{1t}$), which is equal to marginal reserve cost plus μ_{1t}. Note that the necessary condition for optimal scheduled generation also includes multiplier μ_{1t}. When capacity availability binds, scheduling one more unit of capacity to generate energy forgoes the opportunity to use the unit for reserves. As a result, the marginal opportunity cost of scheduled generation includes multiplier μ_{1t}. This multiplier is a scarcity premium that is added to marginal generation cost to yield the price of energy. This is the mechanism through which the ORDC contributes to scarcity pricing and influences energy prices; see Hogan [2013], Liu et al. [2018], and Mehrtash et al. [2023] for more on this point.

4.3 Results with Storage

Results for the model with storage are more complex, but share the spirit of the no-storage results. There is an expected capacity availability constraint for scheduled generation output plus reserves. In addition, there is a storage constraint on storage net output plus storage reserves; the upper bound is the smaller of storage power capacity and remaining available storage. If neither of these constraints bind then energy and reserves prices are driven by generation costs. The energy price is equal to marginal generation cost and the reserves prices is equal to the marginal cost of reserves from generation. If both constraints bind then both types of reserves are scarce and there is a scarcity premium that reflects the difference between the marginal value of reserves and the marginal cost of providing reserves (from either generation or storage). In this event the price of reserves is equal to the expected marginal value of reserves and the energy price is equal to the marginal cost of generation plus the scarcity premium.

There are also "in-between" cases in which either the expected capacity availability constraint or the storage constraint binds. The key point for these cases is that there is no scarcity premium coming out of the ORDC. The more common of these two cases in the ERCOT application is for storage to bind and generation capacity availability to not bind. In this case the price of energy equals marginal generation cost and the price of reserves equals marginal generation reserves cost. For the case in which expected capacity availability binds and storage does not bind, prices are driven by the marginal opportunity cost of dispatching storage. This cost depends on $\delta \partial V(s_t, \boldsymbol{z_t})/\partial s_t$, where $V(\cdot)$ is the value function defined in (15) and (16).

Profit maximizing decisions by storage operators would depend on current and future energy and reserves prices. The planner's solution yields an allocation of scheduled generation output and reserves and storage net output and reserves over time, plus an implied stochastic process for prices. My working hypothesis is that the allocation and prices coming from the planner's solution correspond to a dynamic competitive equilibrium with price-taking generation and storage operators. Cullen and Reynolds [2023] prove this equivalence for a dynamic model without operating reserves or storage. I believe a similar proof can be developed for the model with operating reserves, but do not pursue this in this paper.

5 Main Results

5.1 Estimation and Computation

The data described in Section 2 are used to estimate three different parts of the model. Data on DAM energy prices, fossil fuel generation output, and fossil fuel generation capacity outages are used to estimate generation supply functions. Data on loads, wind generation, and solar generation are used to estimate a net load process. Data on fossil fuel generation capacity outages are used to estimate a capacity availability process. These three estimated relationships are inputs into the planner's optimization problem.

5.1.1 Generation Supply

I use a simple specification of a generation supply function. For each week of the year I estimate an inverse generation supply function of the following form:

$$p^D_{dh} = \theta_1 + \theta_2 (\tfrac{x_{dh}}{\kappa_d})^{\theta_3} + \epsilon^S_{dh} \tag{21}$$

The day-ahead price for hour h of day d is p^D_{dh}. Total generation output for hour h of day d is x_{dh}. Expected available capacity for day d is κ_d. Estimation error is ϵ^S_{dh}. The form of (21) can capture a supply function that is increasing and convex in output. This allows me to capture the effect of marginal cost that increases sharply as output approaches available capacity. If firms are price-takers then this supply function is the aggregate marginal generation cost.

This approach for estimating marginal cost based on day-ahead prices is similar to the approach used in Butters et al. [2024] in their analysis of battery storage in CAISO. They use a different functional form and also include ramping costs in their analysis.[20]

[20] There are several other differences. Butters et al. [2024] estimate available capacity as a function of lagged output in order to capture the effect of ramping costs on current marginal cost. They estimate a

Generation supply functions are estimated by minimizing the sum of squared errors. The values of expected available capacity (κ_d) are set equal to the average of actual available capacity during the hours of day d. This can be rationalized based on the view that suppliers anticipate next-day available capacity accurately on average. Estimation results are summarized in Table 5. The estimated supply function is increasing and strictly convex in output for each week of the year.

I assume that the estimated generation supply functions are invariant across counterfactual experiments on the level of battery storage. Changes in battery storage charging and discharging affect supply decisions via their impact on energy prices. Estimated supply functions are used in solving the planner's optimization problems. I use estimated θ parameters and replace expected available capacity for day d (κ_d) with realized available capacity for hour h of day d for the planner's problems.

5.1.2 Net Load

Hourly values of load and renewable output exhibit significant intra-day and seasonal variability. I construct a time series of hourly net load for 2022. Load, wind output, and solar output exhibit a high degree of persistence. I estimate a simple regression model of net load for each week of the year that can capture this persistence.

$$NL_t = \textstyle\sum_{h=1}^{24}(\alpha_h^{NL} D_t^h) + \beta^{NL} NL_{t-1} + \gamma^{NL}(t - \bar{t}) + \epsilon_t^{NL} \tag{22}$$

Net load in hour t is NL_t. D_t^h is a dummy variable equal to one if hour t occurs in hour-of-day h. Variable $\bar{t}$ is the middle time period for the week. Coefficient γ^{NL} captures a within-week time trend. The estimated net load process is highly persistent. The average estimated β^{NL} coefficient across all weekly regressions is 0.97. The estimated model captures most of the variation in net load. The average adjusted R^2 across weekly estimates is 0.98. The α_h^{NL}

separate supply function for each day of the year. They do not include observations of available capacity in their estimation. They apply their estimated supply functions to real-time data on prices and infer that deviations of real-time prices from their expected value are driven by fluctuations in fuel prices and capacity availability.

Table 5: **Summary Statistics for Estimated Supply Parameters**

Parameter	
θ_1	
Mean	27.2
Std. Dev.	20.9
25th-percentile	12.5
75th-percentile	43.7
θ_2	
Mean	66.9
Std. Dev.	44.2
25th-percentile	39.0
75th-percentile	68.7
θ_3	
Mean	5.5
Std. Dev.	3.1
25th-percentile	3.2
75th-percentile	7.2

Notes: Adjusted R^2 values for weekly estimates range from 0.19 to 0.83, with an average of 0.57.

and β^{NL} coefficients are used to forecast net load in the optimization problem. The γ^{NL} coefficient is not used in forecasts in order to eliminate a possible within-week time trend. The estimated standard deviations of the error terms play an important role in formulating the operating reserve demand curve.

5.1.3 Capacity Availability

Data on outages of coal and natural gas generators are used to construct an hourly time series of total available fossil fuel capacity. In constructing this time series I fix maintenance outages during each week equal to their average value for the week. Available capacity for an hour of a week is equal to total capacity minus the fixed maintenance outage amount minus forced outage amount for the hour. The capacity availability factor for hour t, λ_t, is equal to available capacity for the hour divided by total capacity.

The hourly capacity availability factor is highly persistent. I estimate a very simple regression model for each week of the year that captures this persistence.

$$\lambda_t = \alpha^{AV} + \beta^{AV}\lambda_{t-1} + \epsilon_t^{AV} \tag{23}$$

The constant term is not hour-dependent, as hour-of-day was not found to add explanatory power. The average of estimated β^{AV} parameters is 0.92. The average adjusted R^2 across weekly estimates is 0.83. The error terms capture unexpected capacity outages. The error distributions are an important input into operating reserve demand curves.

5.1.4 Computation

I solve the planner's problem for each week of the year. The estimated relationships for generation supply, net load, and capacity availability are inputs into the planner's problem. The baseline case assumes total storage power capacity of 1,800 MW, corresponding to 7,200 MWh of energy storage capacity. For each hour the planner chooses 4 variables in stage one: scheduled thermal generation, thermal operating reserves, scheduled storage net output, and storage operating reserves. These choices are made conditional on the state at the start of the hour: available storage, previous hour net load, previous hour available capacity, and hour-of-day. After observing net load and available capacity the planner chooses output adjustments from operating reserves in stage two.

I discretize the net load and capacity availability processes in order to use discrete state dynamic programming. I use a grid of 25 net load points for each hour, with the minimum and maximum grid points set equal to observed hourly minimum and maximum net loads, respectively. I use a grid of 5 available capacity points with minimum and maximum grid points set equal to observed minimum and maximum available capacities, respectively. I compute the probability transition matrices for net load and available capacity using the estimated stochastic processes.

The level of energy storage is another state variable for the planner's problem. I solve the planner's problem for storage capacity levels of 7,200 MWh, 14,400 MWh, and 28,800 MWh. I also discretize energy storage, using between 6 and 12 grid points, depending on storage capacity. I use linear interpolation of the value function between storage grid points to allow battery charging and discharging choices that yield storage between grid points.

A finite horizon value function for stage two of the model is computed by using backward induction. This value function is used to approximate the planner's policy function for optimal generation and battery storage decisions. A 3 day (72 hour) time horizon was found to provide an excellent approximation to the planner's policy function. Once the policy function is computed for a week, a stationary probability distribution over hourly transitions between states for the week is calculated. These distributions for all weeks of the year are the basis for reported results.

I report on a parallel set of computations for a wholesale market model that abstracts from operating reserves. For this model the planner chooses generator output and battery charging or discharging in each hour, conditional on the state. The planner is assumed to know current hour net load and capacity availability at the time generator and storage decisions are made. This information assumption is in contrast to the assumption for the primary model, in which the planner's chooses scheduled output and charging/discharging prior to observing net load and capacity availability.

5.2 Baseline Results

I first compare predicted baseline hourly prices for wholesale energy and operating reserves to observed RTM and DAM prices. Figure 4 shows predicted equilibrium and observed hourly prices averaged over one year for the wholesale market and operating reserves market. Observed RTM and DAM hourly average energy prices are very similar. The intra-day pattern of average equilibrium energy prices is similar to the patterns for observed prices. However, average equilibrium prices are about 20 percent higher than average observed prices. Possible explanations for over-prediction of equilibrium prices include exclusion of ramping costs in cost estimation and continued expansion of storage capacity during 2022.[21]

I compute the DAM price for the operating reserves market as the average of the RegUp price and the Responsive Reserves price. Average DAM prices exceed average RTM reserve prices for all hours. The RTM operating reserves market does not operate for all hours; the

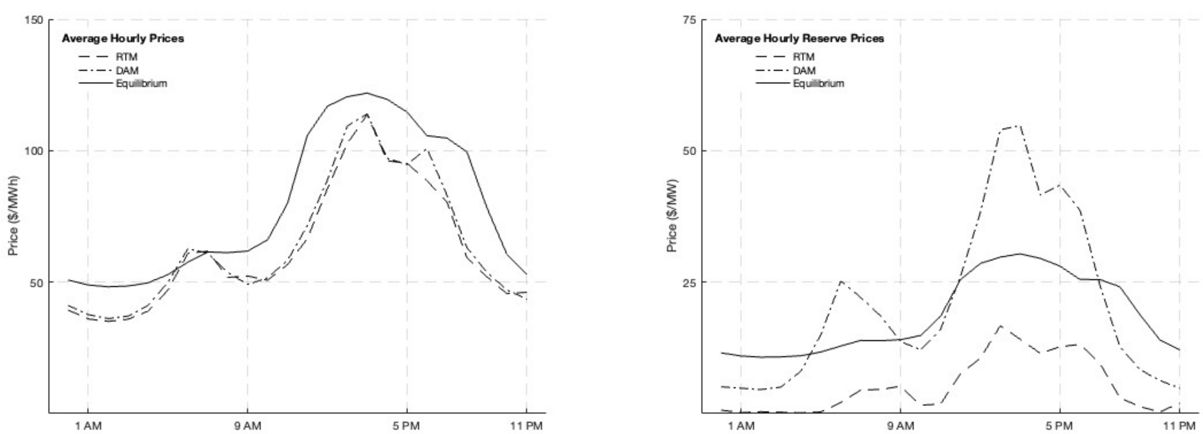
[21]Exclusion of ramping costs in estimation may bias estimated marginal cost during non-ramp hours upward.

system operator procures these reserves only if DAM reserves are projected to be insufficient to meet contingencies. DAM prices are more relevant than RTM prices for storage revenues from operating reserves, since storage owners can lock-in the higher day-ahead prices. There is no day-ahead market in my model; all operating reserves are procured in the real-time market. Overall, average predicted operating reserve prices are about 10 percent less than average DAM operating reserve prices. The under-prediction is most pronounced during peak afternoon hours. Possible explanations for under-prediction of equilibrium prices relative to DAM prices include exclusion of ramping costs in cost estimation and underestimation of likelihood of loss-of-load events for peak demand hours.

Figure 4: Actual vs. Predicted Average Hourly Prices

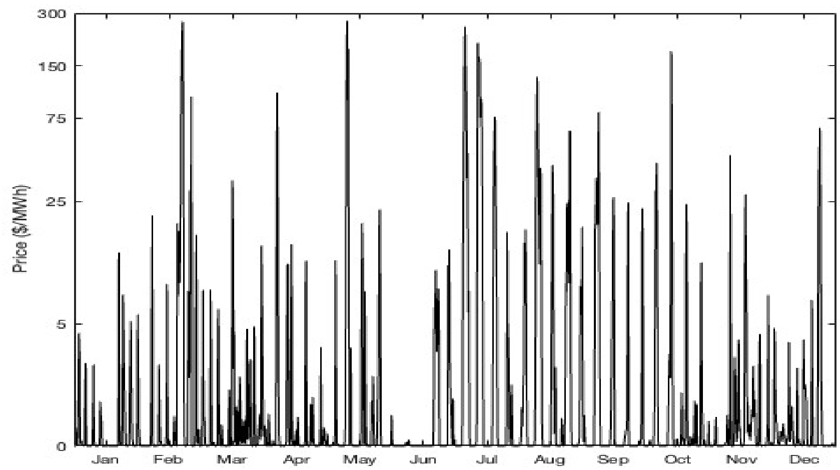
(a) Wholesale Electricity Market

(b) Operating Reserve Market



There is a great deal of variability of observed energy and operating reserve prices. Scarcity pricing contributes to some of the observed variation in prices. Recall that the real-time reserve price for on-line reserves (RTRSVPOR) serves as a price component added to LMP's to arrive at wholesale energy prices. Observed price adders for 2022 are illustrated in Figure 5. The vertical axis uses a log-scale.. The graph shows the hour-of-day average for each week of the year, across the entire year. The price adder is zero or close to zero for most hours. However, there are numerous spikes in the price adders that raise the wholesale energy price by a large amount. Figure 6 shows expected price adders for hour-of-day for each week of the year for the baseline case of the model.[22] This figure shows large spikes in price adders, especially for some summer hours. However, the frequency and size of price adders are less than those for observed price adders. The lower frequency and size of simulated price adders relative to observed adders contribute to lower variation of simulated energy and operating reserve prices compared to observed energy and operating reserve prices.

Figure 5: Real-Time Price Adders

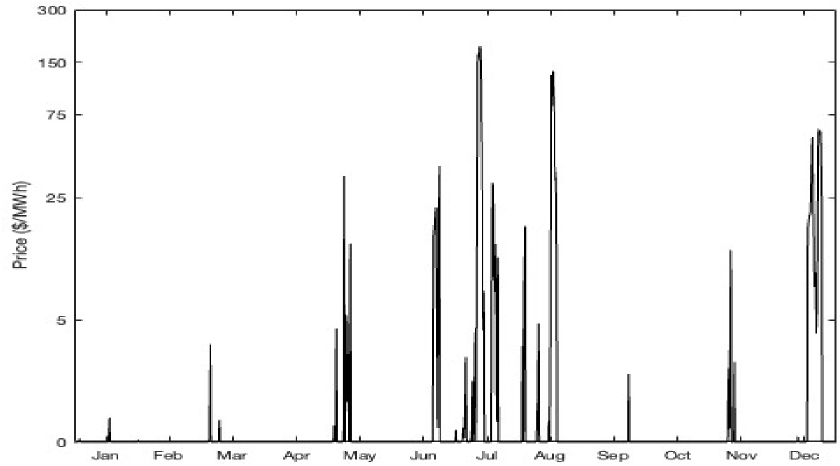


The model provides predictions of operating reserves from generators and from storage over time. Average hourly total operating reserves across the year are predicted to be 3,335 MW. This is quite close to the sum of average hourly Regulation Up and Responsive Reserve Service of 3,290 MW; see Table 4 above. The system operator procures additional reserves for the Non-Spin category; see Table 4. Additional reserves would be required for events like a nuclear generator failure and transmission outages. My model does not allow for these events. Operating reserves from storage account for 43 percent of total reserves in the baseline prediction. The overall predicted baseline loss-of-load probability is 0.18 percent. This corresponds to expected loss of load events in 16 hours per year. This is higher than the U.S. average of 5.5 hours of power interruptions in 2022.[23]

[22]A price adder is generated only for states in which the constraints for available capacity and storage both bind.

[23]EIA In-Brief Analysis, January 25, 2024; https://www.eia.gov/todayinenergy/archive.php?my=2024

Figure 6: Simulated Price Adders



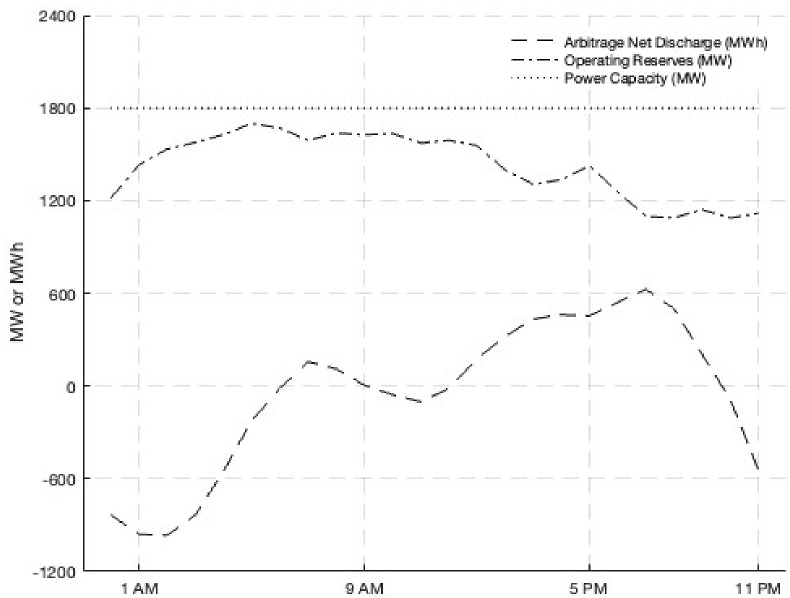
Aggregate battery power capacity is an upper bound on the amount of storage that can be used for reserves or arbitrage in an hour. Across all hours of the year, the model predicts average operating reserves from storage equal to 79 percent of power capacity. This is broadly consistent with ERCOT observed battery use reported in Miller et al. [2023]. Battery's are shifted somewhat away from operating reserves toward arbitrage net discharging during peak afternoon/evening hours, particularly so during hot summer weeks.

Optimal battery discharge does not distinguish between discharge for arbitrage and discharge required to support storage for operating reserves. I adjust optimal stage one net discharge by an amount equal to expected stage two deployment of battery operating reserves to arrive at net discharge for arbitrage.[24] The resulting hourly averages for storage operating reserves and arbitrage net discharge are displayed in Figure 7. Most charging for arbitrage is at night, with a small amount of charging mid-day. Most discharging for arbitrage is during afternoon and evening, with a small amount of discharging in early morning hours. Operating reserves from storage are highest during morning and early afternoon hours. Op-

[24] Yu and Foggo [2017] note that an electricity system operator would co-optimize the dispatch of battery storage for energy and ancillary service awards. Some of the energy dispatch will be for arbitrage and some will be in support of maintaining storage to provide operating reserves. My method for defining arbitrage net discharging assumes that providers of storage operating reserve choose energy net discharge to offset expected deployment from reserves (in stage two). This yields zero expected net energy discharge associated with operating reserves each hour.

erating reserves from storage are lower during late afternoon and evening hours when most arbitrage discharging is occurring.

Figure 7: Uses of Storage: Hourly Averages



Baseline battery net revenue is reported in Table 6. 57 percent of net revenue is from operating reserves. Arbitrage net revenue is highly skewed across hours; 50 percent of arbitrage net revenue is earned in 1.25 percent of hours. Baseline results yield projected lifetime battery net revenue of just over \$400/kWh. Estimates of battery investment cost appear in Cole and Karmakar [2023]. They report investment cost for four hour lithium ion batteries of \$482/kWh in 2022. Based on multiple independent studies they project investment cost to fall to \$386/kWh in 2025 and \$326/kWh in 2030. Baseline battery net revenue is more than sufficient to cover projected 2025 battery investment cost. Private net investment cost was further reduced by the 2022 U.S. Inflation Reduction Act, which provides a 30 percent investment tax credit for energy storage systems.

Table 6: **Baseline Battery Net Revenue**

Annual Operating Reserves (millions $)	Annual Arbitrage (millions $)	Total Annual (millions $)	Total Annual ($/kWh)	Total Lifetime ($/kWh)
184.8	141.0	325.8	45.25	401.06

Notes: Baseline results are for 7,200 MWh of storage capacity. Lifetime $/kWh assumes 12 year life and 5% annual interest rate.

5.3 Exogenous Changes in Storage Capacity

This section reports on counterfactual simulations for two exogenous changes in storage capacity: two-fold and four-fold increases in capacity relative to baseline storage capacity. These exogenous changes yield new equilibrium distributions of energy and operating reserve prices and of generator and storage dispatch allocations.

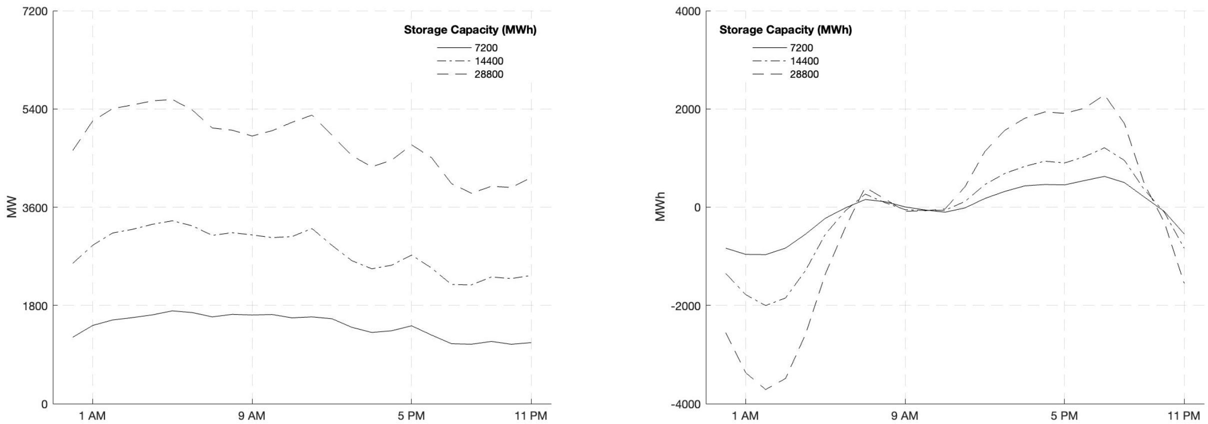
I first describe how battery use and profits change as capacity changes. Figure 8 depicts average battery use by hour of day. Panel (a) shows operating reserves from batteries for three levels of storage capacity. The pattern of average use for operating reserves by hour-of-day is similar as capacity changes. Use for operating reserves is highest in morning and mid-day hours, tapering off in late afternoon and evening hours. The percentage of capacity used for operating reserves declines as storage capacity increases. A four-fold increase in storage capacity to 28,800 MWh reduces the average percentage of power capacity used for operating reserves from 79 percent to 67 percent. The increase in operating reserves from storage displaces operating reserves from generators. A four-fold increase in storage capacity raises the provision of operating reserves from 43 percent to 90 percent of total operating reserves.[25] Panel (b) shows arbitrage net output from batteries for different storage capacities. Net output is negative for charging and positive for discharging. The pattern of average use for arbitrage by hour-of-day is similar as capacity changes. Most charging for arbitrage occurs in night-time hours; most discharging occurs in afternoon and evening hours.

There are diminishing returns to storage capacity as capacity rises. Net revenue per kWh

[25] As noted in Section 5.2, operating reserves in my model roughly correspond to Regulation Up and Responsive Reserve Service, and do not include Non-Spin Reserves. As storage capacity rises there would likely still be significant Non-Spin Reserves from generation units.

Figure 8: Average Hourly Battery Use

(a) Operating Reserves (b) Arbitrage Net Output



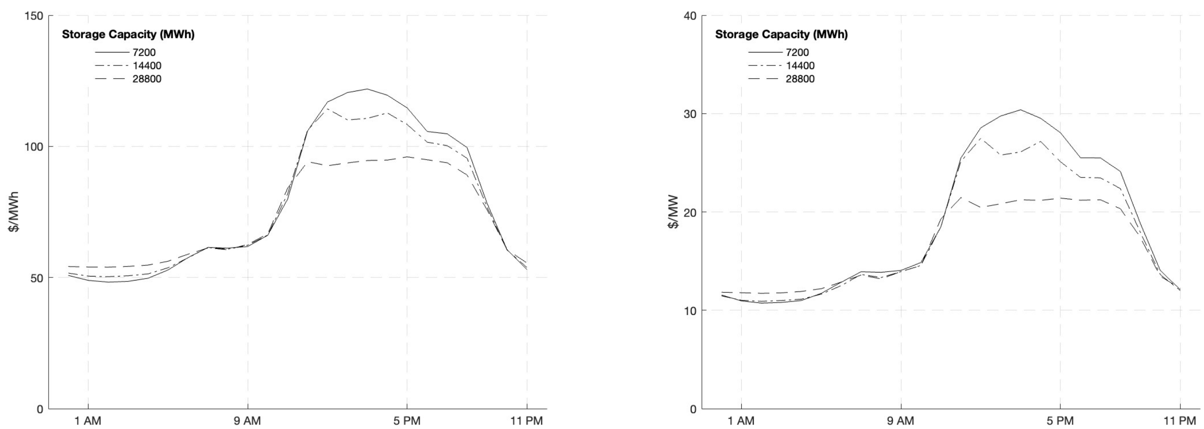
goes from \$45.25 to \$40.42 to \$30.28 as storage capacity changes from 7,200 to 14,400 to 28,800 MWh, respectively. Net revenue per kWh for the highest capacity case is just high enough to cover projected 2025 battery investment cost when the U.S. federal tax credit is taken into account. The proportion of net revenue coming from provision of operating reserves rises as storage capacity rises, in spite of the result that operating reserves as a fraction of power capacity fall with higher capacity. 57 percent of storage net revenue is from operating reserves in the baseline. After a four-fold increase in capacity, 66 percent of storage net revenue is from operating reserves. Larger amounts of storage capacity lead to higher arbitrage discharging during peak net load hours, which reduces peak energy prices and payoffs from storage arbitrage.

Figure 9 depicts average hourly equilibrium prices for different storage capacities. Wholesale energy prices are shown in panel (a) and operating reserve prices are shown in panel (b). Panel (a) illustrates that a two-fold increase in storage capacity has a modest impact on energy prices. A four-fold capacity increase has a larger effect, reducing the average peak vs. off-peak hourly price differential by about half. The largest impact of storage changes on energy prices is for afternoon hours of peak summer demand days. There are small increases in average energy prices during night-time hours as storage capacity rises.

Panel (b) graph of average hourly operating reserve prices is almost a mirror image of the panel (a) graph of energy prices (although, note the difference in vertical axis scales). This is not surprising. For non-scarcity hours the operating reserve price is driven by the marginal cost of fossil fuel operating reserves and this marginal cost is modeled as a fraction of marginal generation cost. For scarcity hours the operating reserve price is a component of the energy price, so a high operating reserve price will correspond to a high energy price. Adding storage capacity has a somewhat larger proportional effect on operating reserve prices than on energy prices. In particular, operating reserve prices are driven almost completely by marginal generation cost with a four-fold increase in storage capacity since scarcity pricing becomes rare.

Figure 9: Average Hourly Prices

(a) Wholesale Energy | (b) Operating Reserves



The first two rows of figures in Table 7 report changes in annual values of several market outcome measures as storage capacity increases. Net revenue for storage from arbitrage and from operating reserves both rise by a large amount. It's noteworthy that the gain in net revenue from operating reserves for a four-fold increase in capacity is more than double the gain in net revenue from arbitrage. While the increases in storage net revenue are large in absolute terms, the payoff per unit of storage capacity declines, as noted earlier.

Table 7 also reports changes in social surplus, buyer expenditures, and profits for solar

Table 7: **Impact of Changes in Storage Capacity**

Δ Storage Capacity	Δ Arbitrage Net Revenue	Δ Op Res Net Revenue	Δ Social Surplus	Δ Buyer Expenditures	Δ Solar Profit	Δ Wind Profit
Main Model						
7,200	95	161	204	-1,036	-107	-132
21,600	159	387	434	-3,446	-392	-372
Arb-Only Model						
7,200	35	-	113	-1,455	-151	-130
21,600	-18	-	223	-2,989	-326	-279

Notes: Results reported as changes in annual averages relative to baseline in millions of dollars.

and wind. There are large increases in social surplus and very large decreases in buyer expenditures as storage capacity rises.[26] Profit reductions for wind and solar are similar. However, baseline wind profit is more than twice as high as baseline solar profit, so the proportional changes in profit for wind are much smaller than those for solar.

5.4 Comparisons with an "Arbitrage-Only" Model

Prior economic analyses of grid-scale battery storage abstracted from operating reserves and focused on the use of storage for arbitrage in a wholesale electricity market. I apply the estimated cost functions, net load processes, and capacity availability processes used above to a model with a sequence of wholesale markets operating over time. Operating reserves are not considered in this comparison model. Storage charging and discharging decisions are made in each hour, subject to power capacity and storage capacity constraints. Information conditions are altered to account for the lack of an operating reserves market. Instead of net load and capacity availability being uncertain at the start of an hour I assume both are known. Future net loads and capacity availabilities remain uncertain. Hourly wholesale

[26]Part of the gain in social surplus is from reductions in the loss of load probability (LOLP). Doubling storage capacity reduces LOLP by almost half and quadrupling storage capacity eliminates over 80 percent of LOLP.

electricity prices are endogenous, driven by net load and capacity availability realizations coupled with generator output and storage net output decisions.

I report results for the same set of storage capacity levels reported on in section 5.3. The main results are reported in the last two rows of Table 7. One key difference is for changes in social surplus. The gains in social surplus as storage grows are only about half as large for the arbitrage-only model as they are for the main model. The most striking difference between the arbitrage-only model results and the main model results is the difference in predicted storage net revenue changes. Part of the difference is because the main model allows storage earnings from operating reserves, while this channel is absent in the arbitrage-only model. However, there are also very large differences in predicted earnings from arbitrage as storage capacity increases.[27] The increase in arbitrage net revenue for the arbitrage-only model is only about 1/3 of the increase for the main model for a doubling of storage capacity. Quadrupling storage capacity is predicted to reduce arbitrage net revenue compared to the baseline for the arbitrage-only mode, compared to a large predicted increase in arbitrage net revenue for the main model.

The large difference in storage arbitrage earnings appears to be driven by differences in energy price formation for the two models. There is more charging and discharging for arbitrage in the arbitrage-only model than in the main model. This leads to differences in peak versus off-peak price differentials for the two models. To illustrate these differentials I examined hourly average energy prices for each week for each storage capacity level for each model. For each week I took the average of the four lowest hourly energy prices to be the off-peak price for the week, and the average of the four highest hourly energy prices to be the peak price for the week. I defined the price differential for the week to be the peak price minus the off-peak price for the week. The average price differentials across all weeks of the year are reported in Table 8. Average peak vs. off-peak price differentials are 15 - 29 percent lower for the arbitrage-only model than for the main model. The significant use of storage for operating reserves in the main model yields lower charging and discharging for arbitrage,

[27]Expected annual net revenue from arbitrage for baseline capacity of 7,200 MWh is similar for the main model and the "Arbitrage-Only" model, at about $140 million.

which in turn does not depress price differentials as much as in the arbitrage-only model. The larger price differentials in the main model allows arbitrage earnings to be higher overall compared to arbitrage earnings in the arbitrage-only model.

Table 8: **Average Peak vs. Off-Peak Price Differentials ($/MWh)**

Storage Capacity (MWh)	7,200	14,400	28,800
Main Model	$83.21	$70.92	$46.58
Arbitrage-Only Model	$65.45	$50.25	$39.51

Notes: Each price differential in the table is the average of all weekly price differentials.

6 Conclusion

The current energy transition away from fossil fuels toward intermittent renewable sources presents serious challenges for electric grid management and reliability. Large scale battery storage has emerged as an important way to address these challenges. Prior economic analyses of battery storage have focused on using storage for wholesale price arbitrage. This paper develops a framework that includes a market for operating reserves, so that storage may be used to contribute to grid stability as well as used for arbitrage. This framework allows for linkages between a wholesale electricity market and a market for operating reserves. These linkages capture a form of electricity scarcity pricing used in major U.S. electricity markets. In addition, this approach allows me to capture the effects on storage additions on grid reliability as well as on market efficiency and generator profits. I estimate the model using data from the Texas ERCOT system, a system with high wind penetration and substantial solar power. Quantitative results are specific to ERCOT, but I note that the approach taken here may be applied to other markets.

I find that exogenous increases in battery storage capacity have large effects on equilibrium prices and generator profits. The largest effects are for an increase from the 2022 baseline case of 7,200 MWh of storage to 28,800 MWh. Average wholesale electricity prices fall significantly for this storage increase, particularly for summer afternoon hours. There are also decreases in operating profits for all generator types, with thermal and solar having the largest proportional operating profit reduction and wind having the smallest proportional reduction. An important finding is that a majority of storage power capacity is used for operating reserves and a majority of storage net revenue is from operating reserves, even as storage capacity rises.

I report on a parallel set of results from a model without an operating reserves market. Storage may only be used for arbitrage in this model. The quantitative results for this analysis are quite different from results from the full model. The gains in social surplus from storage expansion are smaller in the "arbitrage-only" model. Predicted battery net revenue is smaller and rises more slowly with capacity expansion for the "arbitrage-only" model.

Appendix

A Optimality Conditions

In stage one the planner chooses scheduled storage net output (q_{0t}), operating reserves from storage (r_{0t}), scheduled generation (q_{1t}), and operating reserves from generation (r_{1t}). These choices must satisfy the following constraints:

$$q_{0t} + r_{0t} \leq min\{k_0/\eta, s_{t-1}\} \tag{A1}$$

$$q_{1t} + r_{1t} \leq \mathrm{E}[\lambda_1(\boldsymbol{z_t})k_1|\boldsymbol{z_{t-1}}] \tag{A2}$$

$$q_{0t} + q_{1t} \leq \mathrm{E}[NL(\boldsymbol{z_t})|\boldsymbol{z_{t-1}}] \tag{A3}$$

Constraint (A1) limits scheduled net output plus operating reserves from storage. Constraint (A2) limits scheduled generation plus operating reserves from generation. Constraint (A3) limits scheduled storage net output plus generation to be no more than expected net load. The planner's stage one choices are set to maximize the RHS of Bellman equation (15), subject to (A1) - (A3). Let μ_{0t}, μ_{1t}, and μ_{2t} be the multipliers associated with constraints (A1) - (A3). The necessary conditions for stage one are the complementary slackness conditions associated with inequality constraints plus the following four conditions (I assume value function $W(\cdot)$ is differentiable for ease of exposition):

$$v + \frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial q_{0t}} - \mu_{0t} - \mu_{2t} = 0 \tag{A4}$$

$$\frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial r_{0t}} - \mu_{0t} = 0 \tag{A5}$$

$$v - \{(1-\alpha)\frac{\partial C(q_{1t}, \mathrm{E}(\lambda_1)k_1)}{\partial q_{1t}} + \alpha\frac{\partial C(q_{1t} + r_{1t}, \mathrm{E}(\lambda_1)k_1)}{\partial q_{1t}} - \frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial q_{1t}}\} - \mu_{1t} - \mu_{2t} = 0 \tag{A6}$$

$$-\alpha\frac{\partial C(q_{1t} + r_{1t}, \mathrm{E}(\lambda_1)k_1)}{\partial r_{1t}} + \frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial r_{1t}} - \mu_{1t} = 0 \tag{A7}$$

Conditions (A4) and (A5) are necessary conditions for optimal scheduled net output from storage and operating reserves from storage. Conditions (A6) and (A7) are necessary conditions for optimal scheduled generation and operating reserves from generation, respectively. The expression in curly brackets in (A6) is expected marginal cost of scheduled generation, taking into account the impact on the cost of reserves and on stage two output adjustments.

A.1 Special Case - No Battery Storage

In this case conditions (A4) and (A5) are eliminated. (A6) and (A7) correspond to the necessary conditions for the no-storage case in Section 4.2. The partial derivative $\frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial r_{1t}}$ represents the marginal benefit of operating reserves from generators. This marginal benefit is driven by stage two outcomes. If the net load error realization and the capacity availability error realization are such that the optimal output adjustment (Δq_{1t}) is less than reserves then the marginal value of reserves is zero. If the error realizations are such that the reserves constraint binds in stage two then the marginal value of reserves is:

$$\partial W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})/\partial r_{1t} = v - \partial C(q_{1t}(1 + \min\{0, \epsilon_{1t}\}) + r_{1t}, \lambda_1(\boldsymbol{z_t})k_1)\partial q \tag{A8}$$

ϵ_{1t} is the capacity availability factor forecast error for period t. Let $f(\cdot)$ be the joint distribution of net load forecast errors and capacity availability factor forecast errors. Let H_1 be the set of these forecast errors that causes the reserves constraint to bind in stage two, conditional on scheduled generation and reserves and $\boldsymbol{z_{t-1}}$. Errors in this set yield a loss of load event. Let $LOLP(q_{1t}, r_{1t}, \boldsymbol{z_{t-1}})$ be the probability of a loss of load event. Then the expected marginal value of operating reserves is the partial derivative in (A8) integrated over set H_1.

$$\partial \mathrm{E}[W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})|\boldsymbol{z_{t-1}}]/\partial r_{1t} = \int_{H_1}(v - \partial C(\cdot)/\partial q)f(\epsilon)d\epsilon$$

$$= (v - \mathrm{E}[\partial C(\cdot)/\partial q|H_1])LOLP(q_{1t}, r_{1t}, \boldsymbol{z_{t-1}}) \tag{A9}$$

This marginal benefit is the net value (VoLL minus marginal cost) of satisfying one more unit of load, times the probability that resources are not sufficient to serve all load.

Equilibrium prices depend on whether the capacity availability constraint (A2) binds. If (A2) is slack then multiplier μ_{1t} is zero. In this case the expected marginal benefit of reserves is equal to the marginal cost of reserves (see (A7)) and the price of operating reserves is equal to the marginal cost of reserves. The wholesale energy price equals expected marginal cost of generation. The gap between VoLL and price is equal to the net load constraint multiplier, $\mu_2 t$.

If capacity availability constraint (A2) binds then multiplier μ_{1t} is positive. In this case the price of operating reserves equals the expected marginal value of reserves, which equals marginal cost of reserves plus μ_{1t}. Wholesale energy price is expected marginal generation cost plus multiplier μ_{1t}. This constraint multiplier yields energy scarcity pricing, as described in Hogan [2013] and Liu et al. [2018].

A.2 Results for Full Model

The partial derivative $\frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial r_{0t}}$ represents expected marginal benefit of operating reserves from storage. This marginal benefit is driven by stage two outcomes. If the net load error realization and the capacity availability error realization are such that the optimal net output adjustment (Δq_{0t}) is less than reserves then the marginal value of storage reserves is zero. If the error realizations are such that the reserves constraint binds in stage two then the marginal value of storage reserves is:

$$\partial W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})/\partial r_{0t} = v - \delta \partial V(s_t, \boldsymbol{z_t})/\partial s_t \tag{A10}$$

where $s_t = s_{t-1} - \mathbb{1}_{\{q_{0t} \geq 0\}} q_{0t} - \gamma \mathbb{1}_{\{q_{0t} < 0\}} q_{0t} - r_{0t}$. The RHS of (A10) is the net value of increasing storage reserves for disturbance outcomes such that the reserves constraint binds. The partial derivative of the value function on the RHS of (A10) captures the opportunity cost of reducing storage.

Let H_0 be the set of these forecast errors that causes the storage reserves constraint to bind in stage two, conditional on stage one choices and $\boldsymbol{z_{t-1}}$. Then the expected marginal value of operating reserves from storage is the partial derivative in (A10) integrated over set H_0.

$$\partial \mathrm{E}[W(s_{t-1}, \boldsymbol{z_t}, q_{0t}, r_{0t}, q_{1t}, r_{1t})|\boldsymbol{z_{t-1}}]/\partial r_{0t} = \int_{H_0}(v - \delta \partial V(\cdot)/\partial s_t) f(\epsilon) d\epsilon$$

$$= (v - \delta \mathrm{E}[\partial V(\cdot)/\partial s_t | H_0]) Pr(H_0 | q_{0t}, r_{0t}, q_{1t}, r_{1t}, \boldsymbol{z_{t-1}}) \qquad \text{(A11)}$$

There are four cases to consider, based on whether or not the storage constraint (A1) and/or capacity constraint (A2) bind.

Case 1 - (A1) and (A2) are slack: Multipliers μ_{0t} and μ_{1t} are zero. Condition (A7) implies that the marginal benefit of generation reserves is equal to the marginal cost of generation reserves. Condition (A5) yields the marginal benefit of storage reserves is zero; I interpret this as a net marginal benefit, with the cost of providing storage reserves embedded in the value function derivative. In case 1, storage reserves would be reduced to the largest level such that the probability that reserves bind in stage two is zero (see (A11)). The price of reserves is equal to the marginal cost of reserves from generation. The wholesale price of electricity is equal to the marginal cost of generation (in curly brackets in (A6)). Note that (A4) and (A6) imply that the marginal opportunity cost of net output from storage is equal to marginal generation cost.

Case 2 - (A1) and (A2) bind: Multipliers μ_{0t} and μ_{1t} are positive. A loss of load occurs if the disturbance in stage two exceeds the sum of reserves from storage and generation. Suppose the cost of adjusting output from storage in stage two is less than the cost of adjusting generation output. Set H_1 is a subset of H_0 and H_1 is the set of errors that yield a loss of load. In this case the marginal value of reserves is given by the RHS of (A9), which by (A7) equals μ_{1t} plus the marginal cost of generation reserves. The price of reserves is equal to the marginal value of reserves from generation. The wholesale price of electricity is equal to the marginal cost of generation plus μ_{1t}. Multiplier μ_{1t} is the scarcity price adder.

Case 3 - (A1) binds and (A2) is slack: Scheduled generation and reserves are interior in this case, and constraint multiplier μ_{1t} is zero. Results are driven by necessary conditions (A6) and (A7). The price of reserves is equal to the marginal cost of generation reserves and the wholesale price of electricity is equal to marginal generation cost.

Case 4 - (A1) is slack and (A2) binds: Storage net output and reserves are interior and the generation capacity constraint limits generation schedule output and reserves in this case. Constraint multiplier μ_{0t} is zero and μ_{1t} is positive. The wholesale electricity price is driven by the marginal opportunity cost of storage ($\frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial q_{0t}}$), which exceeds the marginal cost of generation. The price of reserves is $\frac{\partial \mathrm{E}[W(\cdot)|\boldsymbol{z_{t-1}}]}{\partial r_{1t}}$, which by (A7) is equal to the marginal cost of generation reserves plus μ_{1t}.

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