The Value of Hydropower as a Grid-Scale Storage Resource: A Commodity Market Approach

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***Abstract*—Energy storage plays a crucial role in modern power systems, providing services such as grid stability, frequency regulation, and load balancing. However, as storage deployment expands, arbitrage profitability declines due to market saturation, pointing to the need for new business models that more fully compensate energy storage. This paper presents empirical research on the value of energy storage using a commodity-based framework. We examine hydropower as a proxy for grid-scale storage, using exogenous variation in reservoir storage volume to estimate causal effects of storage on (1) real-time electricity prices and (2) risk premiums, measured by the day-ahead to real-time price spread, in the Northwestern United States between May 2022 and November 2024. Employing fixed-effects and lagged dependent variable models, we find that a 10% increase in reservoir storage volume reduces real-time prices by approximately 6% and lowers risk premiums by about 5%.**

***Index Terms*—hydropower, storage, valuation**

I. Introduction

Stored energy can substantially reduce system costs and alleviate grid stress, yet most electricity markets lack mechanisms that compensate storage for these benefits. Instead, energy storage receives revenue through energy arbitrage—buying electricity when prices are low and selling when prices are high. However, as storage deployment expands, arbitrage profitability declines due to market saturation and narrowing price differentials [1]. This trend underscores the need for new business models that more fully compensate the value energy storage provides to the power system. We explore market benefits from energy storage which asset owners aren't compensated for under current market structures. Without mechanisms to reward these services, investment in energy storage may be slowed, leaving power systems to not fully realize its benefits.

We propose a commodity-market–based framework to assess the full system value of energy storage and better align compensation with system-wide benefits. Using the Northwestern United States, a hydro-rich region with substantial reservoir storage, we empirically evaluate the value of hydropower reservoir storage as a test case for long-duration energy storage. Our research is most closely related to the work of Botterud et al. [2] and Weron and Zator [3] who examine the impact of hydropower reservoir storage on convenience yield and risk premiums in the NordPool, the Norwegian electricity market. We build on the model of Botterud et al. [2], but address econometric issues noted in Weron and Zator [3] and add factors specific to the Northwestern market (natural gas storage, wind and solar production), providing unique insights into the value of reservoir energy storage. An important contribution of our work is that we also propose a methodology which bounds the impact of including or excluding a lagged-risk premium variable to capture the impact of past market outcomes which can influence current trading decisions.

We use a risk premium framework which defines futures prices as the expected future spot price plus a risk premium reflecting participants' risk aversion. If more risk-averse consumers hedge, excess demand pushes futures above expected spot prices (negative risk premium); when producers hedge, excess supply pushes futures below expected spot prices (positive risk premium) [2],[4]. Risk premium rises with volatility and captures the increased compensation needed for bearing supply or demand risk [5]. We hypothesize that demand for futures contracts is likely to be higher when hydropower reservoir levels are low, due to increased hedging pressure from demand-side risk, resulting in an inverse correlation between energy storage and risk premium. As an extension of our work, we consider the impact that increasing hydropower reservoir storage volumes has on other aspects of price formation, including the impact of hydropower reservoir storage on real-time prices.

II. Pacific Northwestern Reservoir Storage

The Northwest is a region of vertically integrated utilities with robust bilateral trading. The mid-Columbia trading hub serves as a futures market, while the Western Energy Imbalance Market (WEIM) allows for real-time electricity trading in a centralized spot market [6]. This analysis considers dams which market hydropower at the mid-Columbia trading hub [7]. These include Wells, Rocky Reach, Rock Island, Wanapum, and Priest Rapids dams. Upstream from the Wells Dam are two dams whose power is marketed by the Bonneville Power Administration (BPA): Chief Joseph Dam with 2,069 MW in nameplate capacity [8]; and further upstream, the Grand Coulee Dam with 6,809 MW of capacity [9]. Downstream from the Priest Rapids Dam are four dams whose power is marketed by BPA [10], [11], [12], [13].

This work was supported by the Dept. of Energy, Office of Electricity and by the Water Power Technologies Office. We would like to thank Jeremy Twitchell and Paul Wetherbee for their review and helpful comments during various stages of this work.

979-8-3315-8138-1

III. Data

A. Price Data

We utilize day-ahead price data for the mid-Columbia trading hub which is made available to the U.S. Energy Information Administration (EIA) from the Intercontinental Exchange (ICE) [14]. We obtain 5-minute real-time price data from the California ISO's OASIS system (CAISO OASIS) which publishes locational marginal price (LMP) data for price nodes and aggregated price nodes in the WEIM [15].[1] Real-time price data are available at aggregate price nodes for 11 balancing authorities in the Northwest which also participate in the WEIM.[2] We limit our study period to May 2022 to November 2024 for data completeness across balancing authorities.

To align with the daily availability of our day-ahead price data, we then aggregate our hourly average real-time pricing data to daily averages by using a load-weighted average of hourly prices for each balancing authority. We obtain load data from the EIA, which publishes hourly load data for each balancing authority [16].

Risk premium is defined as $\ln(E_t S_{t+T}/F_{t,T})$, consistent with Weron & Zator [3], where $F_{t,T}$ is futures price at time t for a delivery time $t+T$ and $E_t S_{t+T}$ is expected time $t+T$ spot price from time t. By using day-ahead prices as proxies for predicted spot price, we are using ex-post risk premium. This differs from ex-ante risk premium, where ex-ante forecasts of future prices are used as proxies for expected spot price. Day-ahead prices are imperfect proxies for expected real-time prices, but ex-post risk premium can serve as an unbiased proxy for ex-ante risk premium if price expectations of market participants are correct on average [3].

Hydrological data, including reservoir storage volume and inflow, is obtained from the Columbia Basin Water Management Division of the U.S. Army Corps of Engineers [17]. Reservoir storage level is published as the storage volume in a particular reservoir on an hourly basis. This differs from the total reservoir volume, as legal and practical considerations preclude using much of the available reservoir volume for hydropower reservoir storage. Daily values are summed across reservoirs and divided by the sum of maximum hydropower reservoir storage volumes at each dam to find reservoir storage volume as a percent of maximum reservoir storage capacity.

Daily inflow to a reservoir is measured in thousands of cubic feet per second and summed across all dams. We specify our inflow variable as a deviation from daily average historical inflows over 22 years between November 2003 and November 2024.

B. Data for Other Explanatory Variables

This analysis uses daily historical Henry Hub natural gas prices published by the EIA [18]. Henry Hub is a natural gas transaction hub located in Louisiana, which serves as a price benchmark for natural gas in the U.S. [19]. Weekly natural gas inventory data is obtained from EIA's weekly natural gas storage report [20]. The sum of natural gas inventory across the West and Mountain regions is used to create a natural gas inventory variable spanning the balancing authorities in the study. Hourly demand data is obtained from the EIA [16].[3] For each balancing authority, hourly demand is summed to daily granularity. Hourly wind generation and solar generation data is obtained from the EIA and summed to daily granularity.

C. Data for Extension to Real-time Price

Real-time WEIM price data from CAISO OASIS enables an analysis of the impacts of reservoir level on real-time prices. For the real-time price analysis, select variables are aggregated to hourly instead of daily granularity (prices, reservoir storage, demand levels). Solar and wind generation, which are available at hourly totals, are summed to daily totals to address heteroskedasticity in the data. All other variables are maintained at the same level of granularity as in the risk-premium analysis (daily inflow, daily natural gas prices, and weekly natural gas volumes).

IV. Empirical Approach

Our empirical framework exploits exogenous variation in hydropower reservoir levels and inflow to those reservoirs to determine the value of hydropower reservoir storage, as such, the hydropower reservoir storage for the dam system (as a proportion of max storage capacity) for the dam system is the independent variable of interest.

A. Risk Premium

Our econometric model is structural; we include variables which drive risk premiums and prices through causal economic relationships. Other than hydropower reservoir levels, several control variables are included in our models. We include electricity demand as it has been shown to have a negative and statistically significant impact on risk premium in power markets [21]. Electricity demand is largely insensitive to wholesale prices, making it plausibly exogenous. We include natural gas volume in the West and Mountain regions as natural gas volume has been shown to have a negative impact on forward premium in the PJM interconnection [22]. Natural gas volume is also plausibly exogenous as supply and demand decisions for natural gas storage are determined through other markets. We include Henry Hub natural gas prices as a proxy for natural gas fuel costs. The Henry Hub index may introduce

[1] Data for aggregate price nodes represents the weighted average LMP for multiple price nodes, with weights being distribution factors.

[2] Price Nodes: Bonneville Power, Avista, PacifiCorp West, PacifiCorp East, Idaho Power, Puget Sound Energy, Portland General Electric, Tacoma Power, Seattle City Light, Nevada Power and Northwestern Energy

[3] For demand data from the EIA, 11/04/2024 appeared to have missing data as 0 was reported as load for this date. This date was dropped from the analysis.

979-8-3315-8138-1

measurement error if weakly correlated with local natural gas prices. By using hydropower reservoir levels as a proxy for reservoir storage, we mitigate the attenuation bias potentially propagated by the fuel price index. We find model estimates insensitive to gas prices through a robustness check where natural gas price is respecified as Idaho natural gas price published by the EIA [23]. Solar and wind generation are dependent on the sun shining or wind blowing and are plausibly exogenous. To control for differences in prices and risk premiums that may vary due to demand variation by weekday [24], we include day-of-week fixed effects. Long-run trends, such as changes in the generation resource portfolio or seasonality are controlled for with month-by-year fixed effects. Because of the time-dependent nature of electricity prices where past realizations of prices can influence futures and expected spot prices [2] (and thus, the risk premium), we also included a lagged risk premium variable in some specifications of our model.

To achieve stationarity, we transform solar generation by first-differencing. Given the seasonal patterns of natural gas price and natural gas volume, we deseasonalized these variables[4], including only the stochastic portion which can't be explained by seasonality as our identifying variation.

For model 1, we utilize a fixed effects model to determine the short-term impact of reservoir energy storage on risk premiums. This model establishes the upper bound for the impact of reservoir level on risk premium as it assumes any important omitted variables are time-invariant, which tends to result in coefficient estimates that are biased upwards [25].

$$\begin{aligned} RP_{t,T,i} = {} & \alpha_0 + \alpha_1\, RESF_t + \alpha_2 INFD_t + \alpha_3 \Delta D_{t,i} + \alpha_4 GV_t \\ & + \alpha_5 GP_t + \alpha_6 \Delta S_{t,i} + \alpha_7 W_{t,i} + \alpha_8 X_t{}' \\ & + \alpha_9 BA_i + \epsilon_{t,i} \end{aligned} \tag{1}$$

Where $RP_{t,T,i}$ is the risk premium between time t and $t + T$ in balancing authority i. $RESF_t$ is the reservoir storage volume as a proportion of maximum reservoir storage capacity on day t in Wells, Rocky Reach, Rock Island, Wanapum, and Priest Rapids dams, expressed as a percent of total capacity. $INFD_t$ is the deviation from the daily historical average inflow, $\Delta D_{t,i}$ is the first-differenced electricity demand for each balancing authority, GV_t is the deseasonalized weekly gas volume, GP_t is the deseasonalized daily Henry Hub natural gas price, $\Delta S_{t,i}$ is first-differenced solar generation for each balancing authority, $W_{t,i}$ is wind generation for each balancing authority, and X_t is a set of time fixed effects which include day-of-week fixed effects and month-by-year fixed effects. In our first model, we also include a balancing-authority fixed effect, BA_i, to account for observed and unobserved differences in balancing authorities such as differences in infrastructure that may influence supply and demand. We estimate our model with Driscoll-Kraay standard errors to account for both heteroskedasticity and AR1 autocorrelation in the errors.

In model 2, we include a lagged risk premium (RP) variable:

$$\begin{aligned} RP_{t,T,i} = {} & \alpha_0 + \alpha_1\, RESF_t + \beta_1 RP_{t-1,i} + \alpha_2 INFD_t \\ & + \alpha_3 \Delta D_{t,i} + \alpha_4 GV_t + \alpha_5 GP_t + \alpha_6 \Delta S_{t,i} \\ & + \alpha_7 W_{t,i} + \alpha_8 X_t{}' + \alpha_9 BA_i + \epsilon \end{aligned} \tag{2}$$

We acknowledge that including a lagged risk premium variable with our balancing-authority level fixed effects can induce dynamic panel bias [24] but demonstrate the potential impact of that bias by providing the upper and lower bounds of reservoir storage impacts on risk premiums in models 1 and 3, respectively. By including the lagged risk premium variable but excluding the balancing authority level fixed effects, we establish the lower bound of the hydropower reservoir storage impact on risk premiums, as this model produces coefficient estimates that will tend to be the most conservative [26], [27]:

$$\begin{aligned} RP_{t,T,i} = {} & \alpha_0 + \alpha_1\, RESF_t + \beta_1 RP_{t-1,i} + \alpha_2 INFD_t \\ & + \alpha_3 \Delta D_{t,i} + \alpha_4 GV_t + \alpha_5 GP_t + \alpha_6 \Delta S_{t,i} \\ & + \alpha_7 W_{t,i} + \alpha_8 X_t{}' + \epsilon_{t,i} \end{aligned} \tag{3}$$

B. *Real-time Price Analysis*

As an extension of our work, we examine how increasing hydropower reservoir storage affects price formation, including impacts on real-time prices and their distribution. To estimate the short-term impacts of hydropower reservoir storage on real-time prices in the WEIM, our approach leverages our econometric framework formulated for the risk premium analysis but adds an important control needed for the more granular hourly data: hour fixed effects to control for hourly price variation within a day. Because of the time-dependent nature of electricity prices where past realizations of prices can influence future prices [2], we also included a lagged real-time price variable in some specifications of our model.

We found that only natural gas volume was non-stationary, and deseasonalized that variable by removing the seasonal component, including only the stochastic portion which can't be explained by seasonality as our identifying variation. Due to some high, outlying values during a January 2024 polar vortex in the Pacific Northwest, we log transformed gas prices. We also log transformed demand due to a few extreme outlier values. The dependent variable of real-time prices is log transformed to enable consistency in interpretation with the risk premium analysis.

For real-time price model 4, we propose a fixed effects model to determine an upper bound of the short-term impact of reservoir energy storage on real-time price:

[4] To deseasonalize the natural gas price and natural gas volume variables, we regressed gas price and gas volume on month and year controls and retained the residuals as the transformed values.

$$\ln(LMP_{t,i}) = \alpha_0 + \alpha_1 RESF_t + \alpha_2 INFD_t + \alpha_3 \ln(D_{t,i}) + \alpha_4 GV_t + \alpha_5 \ln(GP_t) + \alpha_6 S_{t,i} + \alpha_7 W_{t,i} + \alpha_8 X_t{}' + \alpha_9 BA_i + \epsilon_{t,i} \quad (4)$$

$LMP_{t,i}$ is the locational marginal price at time t in balancing authority i. All other variables are defined as before, except $\ln(D_{t,i})$ is the logged electricity demand for each balancing authority and $\ln(GP_t)$ is the logged daily Henry Hub natural gas price. We estimate our model with Driscoll-Kraay standard errors to account for both heteroskedasticity and AR1 autocorrelation in the errors.

In some specifications of the regression, we include a lagged real-time locational marginal price variable (LMP) with the same log transformation as the dependent variable, as shown in real-time price model 5:

$$\ln(LMP_{t,i}) = \alpha_0 + \alpha_1 RESF_t + \beta_1 \ln(LMP_{t-1,i}) + \alpha_2 INFD_t + \alpha_3 \ln(D_{t,i}) + \alpha_4 GV_t + \alpha_5 \ln(GP_t) + \alpha_6 S_{t,i} + \alpha_7 W_{t,i} + \alpha_8 X_t{}' + \alpha_9 BA_i + \epsilon_{t,i} \quad (5)$$

Similar to our approach for the risk premium models, this provides upper and lower bounds of reservoir storage impacts on real-time price in model 1 and model 3, respectively. The lower bound is provided by including the lagged real-time price variable but excluding the balancing authority level fixed effects as shown in real-time price model 6:

$$\ln(LMP_{t,i}) = \alpha_0 + \alpha_1 RESF_t + \beta_1 \ln(LMP_{t-1,i}) + \alpha_2 INFD_t + \alpha_3 \ln(D_{t,i}) + \alpha_4 GV_t + \alpha_5 \ln(GP_t) + \alpha_6 S_{t,i} + \alpha_7 W_{t,i} + \alpha_8 X_t{}' + \epsilon_{t,i} \quad (6)$$

V. RESULTS

A. Risk Premium

We find that an increase in hydropower reservoir storage volume significantly reduces risk premiums across all balancing authorities. As shown in Table I, which includes balancing authority level fixed effects but does not include the lagged risk premium variable results in an upper-bound estimate for the impact of hydropower reservoir storage volume (as a proportion of maximum storage capacity) on risk premium. The impact is significant and negative, with a coefficient of -0.66, meaning that increasing hydropower reservoir storage volume by 10% of its total storable volume results in an estimated decrease in risk premium by approximately 7%. Model 2, which includes both a balancing authority level fixed effect and a lagged risk premium variable results in a negative and statistically significant coefficient of -0.46, indicating a 10% increase in hydropower reservoir storage reduces the risk premium by 5%. Model 3, which excludes the balancing authority level fixed effect but includes a lagged risk premium variable establishes the lower bound coefficient estimate at -0.46, meaning that an increase in reservoir storage volume of 10% reduces risk premiums by about 5%.

TABLE I: BOUNDED IMPACT OF RESERVOIR LEVEL ON RISK PREMIUM

Reservoir Level Impact on Risk Premium[a]	**Models** *Model (1)* *BA-level Fixed Effects*	*Model (2)* *Fixed Effects & Lagged Risk Premium*	*Model (3)* *Lagged Risk Premium*
Reservoir Storage Volume (as a proportion of max. capacity)	-0.6608 (0.2679) **	-0.4622 (0.2313) **	-0.4589 (0.2217) **
Observations	552	552	6072
R-squared	0.266	0.320	0.321

a. Standard errors are in parentheses. Standard errors have been transformed to remove AR(1) serial correlation and heteroskedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B. Real-time Price

We find that an increase in hydropower reservoir storage volume also significantly reduces real-time prices. Real-time price model 1 finds a significant and negative impact. A coefficient of -1.53 indicates that increasing hydropower reservoir storage volume by 10% of its total storable volume results in an estimated decrease in real-time price by approximately 15%. Real-time price model 2, which includes both a balancing authority fixed effect and a lagged real-time price variable results in a negative and statistically significant coefficient of -0.51, indicating a 10% increase in hydropower reservoir storage decreases real-time price by approximately 5.2%. Real-time price model 3, which excludes the balancing authority fixed effect but includes a lagged real-time price variable establish the lower bound coefficient estimate at -0.50, meaning that an increase in reservoir storage volume of 10% decreases real-time prices by about 5%. Table II displays the bounded impacts of reservoir fraction on real-time price.

TABLE II: BOUNDED IMPACT OF RESERVOIR LEVEL ON REAL-TIME PRICE

Reservoir Level Impact on Real-Time Price[a]	**Models** *Model (1)* *BA-level Fixed Effects*	*Model (2)* *Fixed Effects & Lagged Real-time Price*	*Model (3)* *Lagged Real-time Price*
Reservoir Storage Volume (as a proportion of max. capacity)	-1.5265 (0.1456) ***	-0.5148 (0.0523) ***	-0.5033 (0.0523) ***
Observations	229505	226807	226807
R-squared	0.533	0.775	0.775

a. Standard errors are in parentheses. Standard errors have been transformed to remove AR(1) serial correlation and heteroskedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

979-8-3315-8138-1

VI. Discussion

We find that, on average, a 10% increase in hydropower reservoir storage volumes reduces risk premiums by 5%. Our results are consistent with Botterud et al (2010), who examined the relationship between reservoir level and risk premium in Nord Pool between 1996 and 2006. Intuitively, our findings indicate that higher reservoir storage volumes lower the compensation required by power purchasers for holding electricity futures contracts. In short, storage reduces market participants' risk. We posit that reservoir storage serves as a mechanism for managing short-term imbalances of supply and demand in electricity markets, leading to that reduced risk. In future work, we will continue to examine the value of hydropower reservoir storage through assessing the impact of reservoir storage during meteorologically driven grid stress events as well as examine the impact of reservoir storage on other price dynamics such as price spikes and volatility. Our findings provide empirical support for developing future market frameworks that more accurately capture the risk-reducing and reliability-enhancing contributions of grid-scale energy storage.

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