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Griffith Business School
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Caps-and Floors for Long Duration Storage and Firming: Contract Design under Risk and Price Asymmetry

Farhad Billimoria[1] and Paul Simshauser[2]
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Abstract
This article examines the design and valuation of cap-and-floor hedge contracts in hybridised electricity markets, with a focus on their interaction with merchant price risk and project finance structures. Cap-and-floor or 'collar' mechanisms have emerged as a prominent policy instrument to support long-duration storage and firming investment by enhancing project bankability. We show that when investments are financed under leveraged project finance constraints, the value of a profit-sharing collar contract is driven primarily by its ability to truncate left-tail revenue risk rather than its risk-neutral fair value. As a result, to meet financing requirements, collars are likely to be provided to investors at prices that differ materially from actuarial fair valuations. Incorporating imperfect foresight and empirically calibrated heavy-tailed price forecast errors, we demonstrate that downside dispersion plays a central role in determining debt sizing and investment incentives. Moreover, by examining re-contracting potential, we find the presence of centrally provided profit-sharing collars may materially reduce participant incentives to participate in forward derivative markets, weakening one of the commonly cited advantages of the structure. Overall, it emphasises the importance of transparent contract valuation and careful hedge market design in hybridised electricity markets.

Keywords: electricity markets, risk trading, project finance, contract design, energy storage.

JEL Codes: D52, D53, G12, L94 and Q40.

[1] Corresponding author: farhad.billimoria@oxfordenergy.org. Visiting Research Fellow, Oxford Institute for Energy Studies, Head of US West – Aurora Energy Research.
[2] Centre for Applied Energy Economics & Policy Research, Griffith University. Energy Policy Research Group, Cambridge University. This work represents the work of the authors' only and does not represent the views of any institution. Errors and omissions remain our own.

1. Introduction

Under the canonical electricity market design, full-strength price formation creates efficient short-term operational incentives, and together with liquid forward markets, guides investment commitments (Schweppe *et al.*, 1988). Active forward markets are essential for risk management in electricity markets (Deng and Oren, 2006) and indeed when combined judiciously with physical assets, have the effect of stabilising otherwise volatile and un-bankable revenue streams (Simshauser, 2020, 2026). However, in recent times, governments across multiple jurisdictions have opted for a more active role to accelerate supply-side investments in renewables, motivated by concerns of incomplete markets (Newbery, 2016), disorderly retirement (Rai and Nelson, 2020), and/or the political challenges in enacting durable price signals for environmental externalities (Crowley, 2017). In markets like Australia's National Electricity Market (NEM), but extending to many others, central hedging schemes or market hybridisation (Roques and Finon, 2017; Joskow, 2022; Keppler, Quemin and Saguan, 2022; Gohdes et al., 2023) have emerged as a primary mechanism for providing long-term contractual support to new clean investment.

A novel contract design being implemented in certain centralised schemes is the *cap and floor* or (profit-sharing) *collar* contract[3]. This form of contract has been particularly popular for programs targeted towards storage and especially short- and long-duration energy storage (LDES) but has also been adapted to firming resources (e.g. gas) and renewables. Schemes adopting variants of this form of contract include in Australia - the Capacity Investment Scheme (CIS) at the Commonwealth level, the Long-Term Energy Supply Agreement (LTESA) in New South Wales and the Firm Energy Reliability Mechanism (FERM) in South Australia; and in the UK – the LDES Cap & Floor (OFGEM, 2025). This type of contract seeks to bound the market risk of a storage or generation resource vis-à-vis cashflow support to secure debt finance on the one hand, while sacrificing equity upside returns on the other. A key issue for any centralised hedging or revenue support scheme is whether they undercut participation in existing forward markets for derivatives and PPAs.

There are two broad means by which central schemes may mitigate damage to forward markets. First, central agencies may recycle CfD collars back into the market. Second, design hedge structures that retain incentives for derivative market participation without imposing the risk of being 'double hedged'. An argued benefit of the revenue collar relates to the latter. A collar is *prima facie* believed to preserve incentives for secondary trading because the project retains spot market exposures when gross profits[4] remain with the bounds of the cap and floor. Indeed, the Australian Government's 'Capacity Investment Scheme' Design Paper argues resources are not prevented from 're-contracting' such as via derivative trades:

> "*Both the [renewable] Generation CISA and [storage] Clean Dispatchable CISA have been designed to preserve incentives for proponents to participate in contract markets. … Projects would have the full incentive to sign contracts between the floor and the ceiling.*" (Department of Climate Change Energy and the Environment, 2024).

In this article, we interrogate valuation implications and incentives for re-contracting following the award of a government-initiated CfD collar in Australia's NEM. The objective is to test the presumption that re-contracting is optimal, or indeed desirable, when uncertainty is considered along with the implied valuations of such hedges. A key focus of our analysis is asymmetric risk. It is common in the broader financial economics literature to assume that risk preferences are symmetric – both upside and downside deviations from mean returns are considered equivalent. While computationally

[3] While both these terms are interchangeable, we will preference the term *collar* for the remainder of this paper, to avoid confusion with standard call option contracts, which may also be called caps. Certain references to caps-and-floors remain where appropriate.
[4] The definition of gross profit for a resource is the difference between market revenues and market costs. A range of the alternative terms are employed in the literature including gross margin, net revenue, or net operational revenue.

convenient, this assumption is at odds with observed outcomes, investment metrics and parameters of power project financings. Financial outcomes for generators and storage *are asymmetric*. Power prices are positively skewed, margins are clustered around a low band, albeit punctuated by rare periods of extreme high price events which impact the statistical distribution of profits of generation resources trading in wholesale markets.

Our key findings are twofold. First, when asymmetric risk preferences are considered for longer duration storage, there may be disparities between contract design thresholds required to maintain bankability and central agency fair valuations of a collar contract. Second, CfD collar designs may struggle to deliver upon their key postulated advantage – the incentive for participants to continue re-trading in derivative markets.

The article is structured as follows. Section 2 reviews the literature. Section 3 develops our modelling methodology. Section 4 discusses results. Policy implications and concluding remarks follow.

2. Review of the state of the art

In this review of the state of the art, we focus upon two main areas, (1) hedging design with a focus on collar contracts, and (2) characterisation of risk in financial markets and energy markets.

2.1 Risk trading and contract design

There is a deep body of work discussing hedging and risk management in electricity markets. The suite of swaps (two-way hedges), forward and option-based derivatives that were developed based on the legacy merit-order stack of baseload, mid-merit, peaking generation are well discussed in multiple works (see Simshauser, 2020, 2021). More recently, the literature has evolved to examine hedges for renewable resources – with a strong focus upon the canonical *Contract-for-Difference* (Newbery, 2023), and variants including partially contracted financing (Gohdes et al., 2023; Gohdes, 2025). CfDs for storage are still an emerging area with no single prevalent contract design (Mastropietro et al., 2024). A set of designs exchange a fixed payment stream for payments that vary based on a storage benchmark. Yardstick contracts determine the benchmark by examining the ex-post optimal net revenues of the asset (Billimoria and Simshauser, 2023; Gabrielli et al., 2022). These contracts are also identified as the asset proxy or financial twin for storage (Soumoy, 2025). Top-bottom spread contracts, which are also common in derivative markets, set the benchmark more simply in the form of the difference between the top and bottom priced hours of the day. Certain markets expand the variable payments to reflect incremental payment streams of the market's design. e.g. capacity payments, ancillary services etc.

Net revenue collars or revenue sharing contracts are also emerging as a means of facilitating investment – including storage, renewables and firming (i.e. thermal) generation. The New South Wales government launched the LTESA for storage, structured as a series of options to access a variable payment as a top-up to net revenues with a corresponding clawback. The Australian government's flagship clean energy policy program, the CIS, adopts a collar structure targeting 14GW of storage and dispatchable resources, and 26GW of renewables. South Australia's FERM supports dispatchable and long-duration capacity, structured as a revenue sharing scheme.[5] Further, the UK government is running a series of tenders for LDES projects supported via cap-and-floor contracts. The cap-and-floor hedge contract is argued to have several desirable properties Billimoria (2024), viz. it is thought to preserve spot market incentives (subject to certain limits) along with operational flexibility because it locks the unit into charging or discharging at specific times of the day. Units are also able to participate in ancillary service and other network- or system-based revenues. Further, the design aligns with standard project financing structures to maintain revenue protection and downside

[5] All three CfDs are managed by AEMO Services, a subsidiary of AEMO, the Australian market operator.

support, while allowing central agencies to redistribute windfall gains. Finally, and importantly, the design is argued to preserve the incentive of project owners to continue to participate in forward markets – which is essential for retail suppliers and therefore consumers. We will return to this latter point below.

By contrast, bilateral storage deals have been transacted though a range of structures including virtual tolls, spread contracts, revenue-sharing and percent-of-perfect guarantee schemes (Billimoria and Simshauser, 2023), with the academic rationale developed in Anaya and Pollitt (2015) and Gabrielli et al. (2022) to swap volatile market-based cashflows for more certain cashflows.

A key issue for any hybridised market construct is the substitution of the incentives facing commercial market participants with that of a central agency. Several issues emerge including ensuring contract design is compatible with (i) maintaining incentives for spot market participation; (ii) ensuring appropriate allocation of public and private risk; and (iii) limiting distortions on existing derivative contract markets. Billimoria and Simshauser (2023) address the first problem – identifying that with a hard cap in place, units have little incentive to participate in forward markets once the cap is reached. Soft caps, which operate as a margin-sharing arrangement, were proposed.

Derivative market distortions are discussed in Simshauser (2019) and Flottmann *et al.*, (2025). The concern is that government-initiated contracts absorb generator hedging commitments, and without recycling, may adversely impact forward market liquidity and price formation in derivative markets. In contestable retail markets with customer switching, retail suppliers rely on hedge structures and derivative trading remains an fundamental aspect of retailer portfolio management, and 'portfolio tuning'. There is thus the potential for a vicious paradox where government-initiated CfD schemes, developed on the rationale of incomplete markets, may themselves impair the proper functioning of the very forward markets they are seeking to rectify (Flottmann *et al.*, 2025).

The recent 'Nelson Review' in Australia (Nelson *et al*, 2025) identified 'the tenor gap' between retailer and project financier appetite as the motive. A key research question is whether revenue collars provide incentives for resource owners to continue to manage risk by transacting in derivative markets. These volumes are material to retailer portfolio risk management, and to long-term market robustness more generally.

2.2 Risk-aware optimization and the cost of capital

The characterisation of risk is important to understanding decision making (Krokhmal et al., 2011). This section reviews literature relevant to this topic. Markowitz's seminal work led to the formalization of the view that a decision under uncertainty can be evaluated through a two-parameter model of risk and return, with an emphasis on the optimization aspect of risk management (Markowitz, 2008). That is, a theoretically efficient balance between risk and return can be found through framing the decision as a maximization of a risk-aware utility function U that integrates both measures of risk ρ and return π:

$$\max U(\pi, \rho)$$

In Markowitz's seminal mean–variance (MV) model, return is measured as the expected value of the random variable, and risk is measured as the variance. Risk-return tradeoff measures such as the Sharpe ratio flow from this setting (Markowitz, 2008). This provides the seminal portfolio optimization framework for pricing the systematic risk of capital assets. Such approaches have been applied to electricity risk management, hedging and system planning problems (Simshauser, 2020; Gohdes, 2025; Simshauser, 2026).

Despite advantages in computational tractability and parameterization, there are however challenges to using variance as a risk measure (Krokhmal et al., 2011). The key challenge is the symmetric treatment of risk – where upside and downside variations from the mean are considered risk equivalent (i.e. higher-than-average outcomes are valued similarly to lower-than-average outcomes). Empirically, this has links to long-standing discrepancies in between observed equity premia and investor risk aversion (known as the equity premium puzzle) (Benartzi and Thaler, 1995). Indeed, over time Markowitz posited the adoption of downside risk measures of semi-variance and semi-deviation as more heuristically intuitive measures of risk, as they focus on reduction losses rather than both upside and downside deviations from the mean (Markowitz, 2008). This is especially applicable to a financial hedging problem, where the focus is very much on managing downside risks.

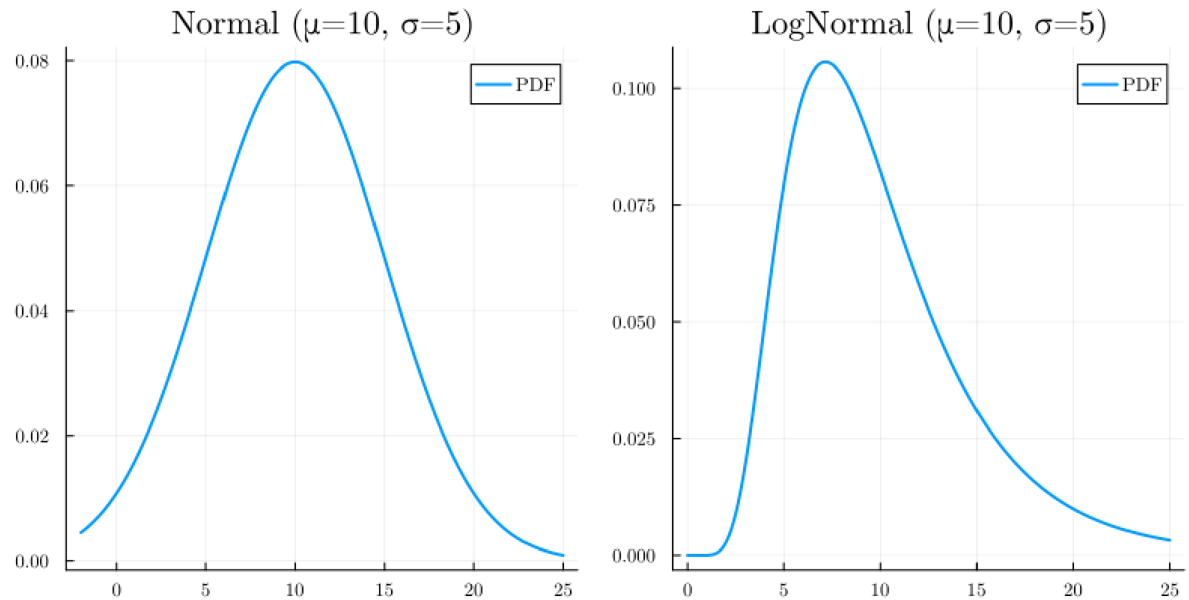
Hogan and Warren (1974) demonstrated the fundamental structure of the Sharpe-Lintner capital asset pricing model is retained when semi-deviation is substituted for standard deviation. The Sortino ratio is a corollary of the Sharpe ratio[6] where risk-return trade-offs are measured using the downside semi-deviation as opposed to the standard deviation (Sortino and Price, 1994). Empirical studies apply semi-variance measures and the Sortino ratio[7] in characterising risk perceptions across several industries, including in power and energy applications. While not addressed in the research to date, this framework is relevant to power markets as (i) both investment as well as post-operational trading decisions generally focus on the management of downside risks, and (ii) power prices in energy-only markets are highly skewed, and heavy tailed (Simshauser, 2026).

A simple illustration of the significance is shown in Figure 1. Consider the normal and lognormal probability distribution functions (PDF) (e.g. of profits or cashflows) below each with the same mean and standard deviation ($\mu = 10, \sigma = 5$, respectively). The positive skew of the lognormal distribution gives it a lower downside semi-deviation than the normal distribution. Given a risk-free rate r^f of 5, the Sharpe ratios of the distributions would both be 1.0 suggesting an equivalent risk return trade-off. Intuitively however, the lognormal distribution seems preferable if the perception of risk is focused on downside variations. The Sortino ratio, in measuring risk as the downside semi-deviation, better reflects the focus on downside risk; for the sample distributions the Sortino ratios of the normal and lognormal distributions are measured at 1.5 and 4.2 respectively. Simshauser (2020, 2026) relies on a modified Sharpe ratio that incorporates downside risk measures based on probability of exceedance (POE) to optimise electricity hedge portfolios for investment screening and bankability purposes.

[6] Underpinned by a Markowitz mean-variance approach, the Sharpe ratio measures the difference between the expected returns of the investment π and the risk-free rate of return r^f, divided by the standard deviation of the investment returns σ. $\therefore U^{sh}(\widetilde{\Phi}_{\omega}) = \frac{\pi - r^f}{\sigma}$

[7] The Sortino ratio adopts an asymmetric risk measure, the downside deviation $\underline{\sigma}$, and is calculated as the difference between the expected returns and a minimum acceptable return; divided by the downside deviation. $U^{so}(\widetilde{\Phi}_{\omega}) = \frac{\pi - r^f}{\underline{\sigma}}$,

Figure 1: PDFs of Normal and Lognormal distributions



An alternative perspective on risk perception emerges in the literature under the topic of risk-constrained optimization. Here the optimization problem is defined as the maximisation of returns subject to hard constraints on risk, mathematically formulated as:

$$\max U(\pi) \; s.t. \rho \geq \rho_0$$

In the field of financial risk management, Value-at-Risk (VaR) (for financial assets) and Earnings at Risk (EaR) (for commodities) are among the most widely known and utilized measures (Duffie and Pan, 1997), and has been adopted as the de-facto standard for measuring risk exposures of forward positions – particularly in electricity trading.

Leveraged finance, both corporate and project financing (the latter being most common for financing new capital-intensive power projects) involve tranched sources of capital with differing levels of recourse.[8] For debt capital, financial uncertainty is managed through a set of risk constraints on the sizing of debt. Similar constraints govern triggers for default, equity lockup and other stress conditions, framed by financial ratios such as debt service coverage ratios, Debt to EBITDA and so on (see for example Simshauser, 2021; Gohdes, Simshauser and Wilson, 2022). For stochastic forms of power generation, the sizing is often linked to EaR via PoE thresholds. For example, requiring debt service ratios for 95th percentile outcomes exceed particular thresholds. Equity imposes risk constraints in sizing investment too, based on PoE risk tolerances and sources of capital.

This leads to investment decisions framed as risk-constrained optimization problems, where owners seek to maximise returns subject to achieving risk constraints specified by capital sources. An important distinction on the application of risk-constrained models to power project financings is that the capital structure decision is often co-optimized with forward commitment parameters (Simshauser, 2021; Gohdes et al., 2023; Gohdes, 2025; Simshauser, 2026).

Given this research background, the focus of this article is on the impact of operational risk and the distributions of cashflows on contract optimality under different risk-aware optimization frameworks.

[8] Indeed, as noted by credit rating agency Moody's *"projects with contractual support will almost always score stronger in this sub-factor than projects with merchant exposure".*

Our contribution to the literature is the integration of price forecast uncertainty vis-à-vis the optimal hedge decision for profit-sharing collar contracts, and to demonstrate how risk characterization may affect the willingness to re-contract. Specifically, we apply an asymmetric risk measure, the Sortino ratio, in relation to hedging in electricity markets. We apply this framework to evaluate the ability of market participants to re-contract under profit-sharing collar contracts, a key postulated benefit of the design. We believe this is an important gap in the literature and the outcome is critical for policy makers as it relates to retail supplier trading, and therefore end-user pricing and consumer welfare.

3. Models for Optimal Contracting

This section sets out the methodology and modelling framework for optimal contracting. We first set out the nomenclature and subsequently set out the modelling framework.

3.1 Nomenclature

Sets

$t \in T$	Ordered set of half-hourly trading intervals over a period T
$\omega \in \Omega$	Set of scenarios
r ϵ FR	Set of frequency reserve services

Parameters

$\lambda^{e}_{t,\omega}$	Locational marginal price for energy [$/MWh]
$\lambda^{r+/-}_{t,\omega}$	Marginal price for reserves (raise +, lower -) [$/MWh]
$\hat{\lambda}^{e}_{t,\omega}$, $\hat{\lambda}^{r+/-}_{t,\omega}$	Perceived price for energy or reserves [$/MWh]
$\overline{\lambda^{e}_{d,m}}$, $\underline{\lambda^{e}_{d,m}}$	Ordered energy price of a trading day *d* by hour *m* [$/MWh]
$c^{v}_{t,\omega}$	Resource variable costs (incorporating fuel and VOM) [$/MWh]
$c^{st}_{t,\omega}$	Resource start cost ($ per start)
C^{I}	Resource investment cost ($ per MW)
$k^{r+/-}$	Reserve utilization (raise +, lower -) (%)
q^{c}, q^{d}	Storage charging and discharging efficiency (%)
ϕ, ϕ^{fl}, ϕ^{cap}	Fixed contract price general, for cap, and for floor
$\varepsilon^{e}_{t,\omega}$	Price forecast error (scaled) [$/MWh]
$\varepsilon^{e-PD}_{t,\omega}$	Price forecast error (unscaled) [$/MWh]
z^{e}	Scaling factor for price forecast error
$A_{t,\omega}$	Resource availability at time t in scenario ω [%]
e	Battery duration [hours]
P^{min}	Minimum stable generation level [MW]
R^{u} , R^{d}	Ramp-up and ramp-down rates
P	Resource capacity
$\varsigma^{r+/r-}$	Maximum upward or downward reserve dispatch as a proportion of capacity
S	Call option (cap) strike price
$\overline{S}, \underline{S}$	Collar upside and downside threshold [$/MW]

Decision variables

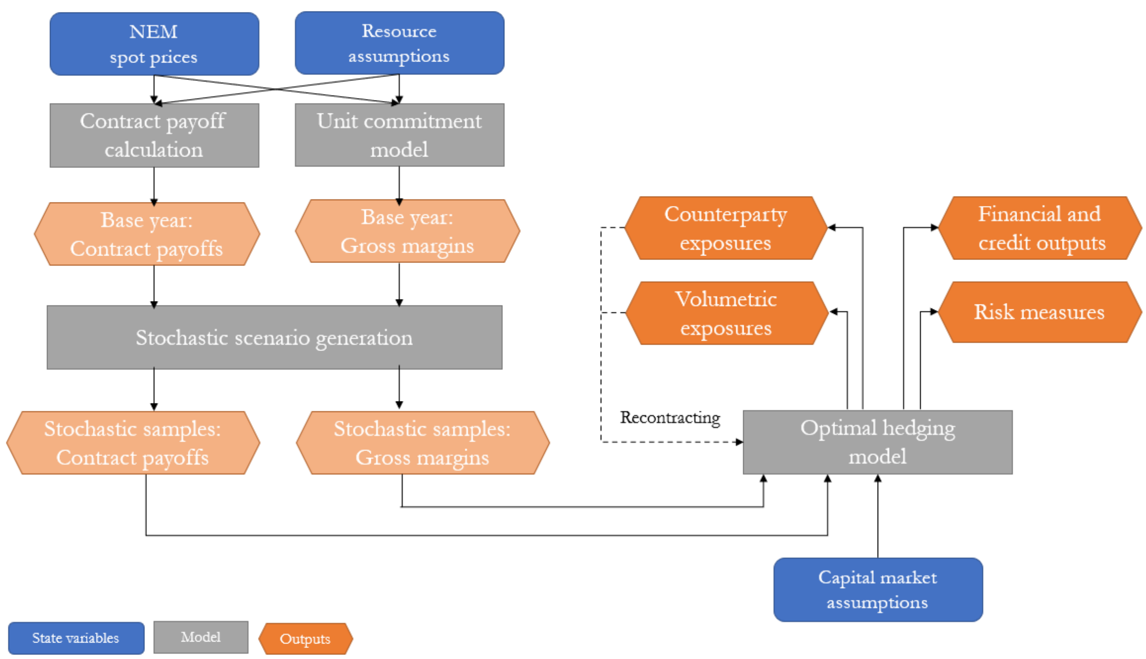
$p^{e}_{t,\omega}$	Scheduled power generation [MW]
$p^{d}_{t,\omega}$	Scheduled power discharge [MW]
$p^{c}_{t,\omega}$	Scheduled power charge [MW]
$p^{r+/-}_{t,\omega}$	Scheduled reserve delivery (raise +, lower -) [MW]
$u_{t,\omega}$	Unit commitment status

$s_{t,\omega}$	Unit start status
$S_{t,\omega}$	Battery state of charge
v, v^{fl}, v^{cap}	Executed contract volumes general, for cap, and for floor
φ_{ω}	Floating contract payments in scenario ω [$]
Φ_{ω}^{C}	Contract payoffs in scenario ω [$]
$\widetilde{\Phi}_{\omega}$	Net profit of resource in scenario ω [$]
Φ_{ω}	Gross profit of resource in scenario ω [$]; Φ_{ω}^{G}: Generation, Φ_{ω}^{S}: Storage
B_{ω}	Operational basis [$]
$U(\widetilde{\Phi}_{\omega})$	Resource's risk-aware utility [$ or ratio]

3.2 Modelling methodology

In the case study for this article, we are seeking to model hedge optimality given operating cashflow profiles of dispatchable firming resources under alternative risk-aware optimization approaches. Specifically, we aim to contrast a risk-constrained optimization (consistent with project financings) with risk return trade-off optimization, considering asymmetric measures of risk. The sequential decision analytics framework and data model for the problem is shown in Figure 2, which sets out the integration of state variables / exogenous parameters, models and decision variables / outputs.

Figure 2: Data flows for the contractual decision-making model



The methodology we deploy integrates a diverse set of decision-making models and data sources. First, the model takes in resource technical assumptions and exogenous prices and runs a sequential unit commitment model under imperfect foresight. The unit commitment decision-making model is based on the approach in Billimoria and Simshauser (2023) for storage and Simshauser (2020) for gas turbines. It models the commitment of dispatch decisions of storage and gas assets at 30-minute resolution under uncertainty for a set of base operating years. Key outputs from the unit commitment model are schedules and monthly resource gross profits across all base years. For brevity in the main text, we reproduce the full formulation in Appendix A.

Simultaneously, monthly contract payoffs are calculated for the base years for a given set of canonical contract designs. Gross profits and contract payoffs are then fed into a stochastic scenario generation transition function which transforms results for the set of base years (2017-2023) into 100 years of stochastic data following the approach in Simshauser (2020, 2026) and Gohdes (2025). The method for scenario generation is reproduced in Appendix A.

Stochastic gross profits and contract payoffs are then fed into an optimal hedging model, which combines relevant technical and capital assumptions to derive hedge contracting under different risk-aware optimization frameworks. This produces counterparty and volumetric exposures, financial outputs and risk measures as key outputs. To model re-contracting (which is the secondary participation of the resource in derivative markets, once an initial contract has been struck), an additional feedback loop is incorporated where counterparty and volumetric exposures form the operating cashflows, which are then re-inputted into the optimal hedge model to produce results on re-contracting decisions of the resource. Models are coded on Julia 1.11.6 and solved using Gurobi solver 12.0.3.

A range of resource are considered, (i) batteries of multiple durations; and (ii) an open cycle gas turbine (GT or OCGT), all trading in the NEM's real-time electricity spot market where energy and ancillary services are settled under zonal marginal pricing. Given small unit sizes, we assume these are price-taking agents and therefore self-commit their capacity into multiple non-exclusive energy and frequency control ancillary service markets[9] based on imperfect forecasts of exogenous prices. This approach enables an appreciation of observed price volatility and tail risk in a large-scale transitioning energy market.

The model reflects uncertainty in three different aspects. First in respect of price forecast uncertainty in scheduling; the unit commitment model integrates imperfect foresight as between the prices assumed in commitment decision making, and the actual price outturn. Second, the unit commitment model incorporates uncertainty via incorporating forced outages. Third, the optimal hedging model incorporates uncertainty and variation in operating margins and unit cashflows as part of contractual decision making on financial structuring and optimal risk-return trades. We set the methods for the hedging model below.

3.3 Hedging and operational risk

Given risk averse market participants, the theoretical model of hedging under uncertainty is a trade where both counterparties benefit from improved risk-aware utility through the executing of forward contracts.

Characterising uncertainty as a set of stochastic scenarios $\omega \in \Omega$, typical hedge contracts for firming and storage resources are structured as either two-way or single-way CfDs, exchanging a fixed (or less variable) payment stream ϕ for a floating (or variable) payment stream φ_ω (Billimoria and Simshauser, 2023). Contract payoffs for a unitary volume contract are set out in Eq.(1).

$$\Phi_\omega^C = (\phi - \varphi_\omega) \tag{1}$$

As a simple illustration, consider a generation or storage resource operating in the wholesale spot market over the time period $t \in T$, and the set of stochastic scenarios $\omega \in \Omega$. Given a generalised swap (i.e. fixed-for-floating contract form), the net margin of the resource $\widetilde{\Phi}_\omega$ in (2) is the sum of its wholesale gross profit Φ_ω and the product of the scenario payoffs from a single contract Φ_ω^C and

[9] The NEM does not have a centralised unit commitment schedule and instead relies upon participants self-committing into the market based on expectations of current and future prices.

contract volumes v[10]. To calculate the total contract payments, the contract payoff Φ_ω^C is multiplied by the volumetric exposure v.

$$\widetilde{\Phi}_\omega = \Phi_\omega + v\Phi_\omega^C \qquad (2)$$

In current implementations, the collar instrument can be looked at as a sharing scheme for an asset's net revenue or gross profit, which can be applicable to both generation and storage resources[11]. In its generalised form, collars are a combination of a series of call and put options on periodic net operational revenue or gross profit (say over a quarter or a year).

The contractual collar payouts to a project (which would buy the floor and sell the cap) are specified in (3)-(6) for all $\omega \in \Omega$. Four parameters are relevant: the put and call option strikes $\underline{S}$ and $\overline{S}$, and the volumetric exposure for the put and call v^{fl} and v^{cap}. The latter determines the effective net revenues that are shared between the project and the hedge counterparty.

Floor: $\Phi_\omega^{fl} = v^{fl}[-\phi^{fl} + \max(\underline{S} - \varphi_\omega, 0)]$ (3)

Cap: $\Phi_\omega^{cap} = v^{cap}[\phi^{cap} - \max(\varphi_\omega - \overline{S}, 0)]$ (4)

Collar: $\Phi_\omega^{C(n)} = v^{fl}[\max(\underline{S} - \varphi_\omega, 0) - \phi^{fl}] - v^{cap}[\max(\varphi_\omega - \overline{S}, 0) - \phi^{cap}]$ (5)

Centralized Collar: $\Phi_\omega^{C} = v^{fl}[\max(\underline{S} - \varphi_\omega, 0)] - v^{cap}[\max(\varphi_\omega - \overline{S}, 0)]$ (6)

Technically the collar contract would have a net premium associated with it $\phi^{cap} - \phi^{fl}$ based on the value of the floating payouts of the instruments. However, for centralised tenders, governments have tended not to levy (nor pay) net premiums on counterparties when executing collar CfDs. Importantly, this implies centralized programs may still create a net accrual of fair value based on the difference in collar valuations[12]. We return to this further below.

Practical implementations: bid variables and administrative settings
The approach to determining valuation parameters has evolved but continues to vary across processes. The Commonwealth's 'CIS' CfD and South Australia's 'FERM' CfD request that project participants bid floor and cap strikes, while volumetric exposures and imputed downside/ upside sharing, are set at 90% and 50%, respectively. Additionally, rather than two thresholds, South Australia's FERM adopts a single strike price as a bid variable (effectively $\underline{S} = \overline{S}$), operating more as a revenue sharing scheme. For the UK LDES process (OFGEM, 2025), thresholds and volumetric sharing are administratively set. Thresholds are set via a regulatory WACC calculation where the floor has no sharing[13] (i.e. a hard threshold, $v^{fl} = 1$) while the cap is shared 30% to the project ($v^{cap} = 1 - 0.3 = 0.7$). Figure 3 is illustrates, for three sample schemes, how different settings affects the project's net revenues. In the UK and Australian cases, projects are judged against a merit criteria scorecard.

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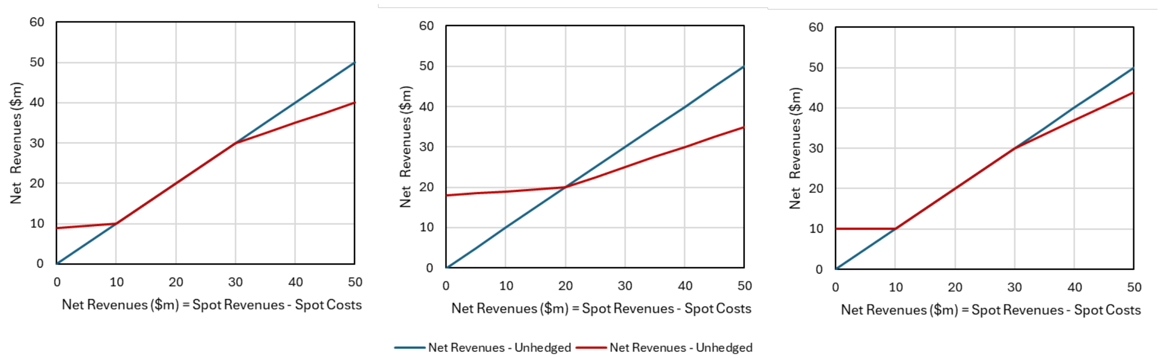
[10] For ease of reference, we drop the superscript G or S and use a generalized term for gross of a resource $\widetilde{\Phi}_\omega$
[11] For storage, this is more accurately described as a net revenue cap, floor or collar because of the energy costs associated with charging a storage unit in the wholesale market.
[12] The implied net accrual (or excise) of the fair value of the net contract payoff, $FV(\Phi_\omega^C)$. $FV(\Phi_\omega^C)$ < 0 implies a net accrual of fair value, and $FV(\Phi_\omega^C)$ > 0 implies a net excise.
[13] OFGEM has incorporated a soft-floor by requiring each LDES project to meet a minimum availability threshold to stay eligible for the floor, similar to the UK's interconnector cap and floor regime.

Figure 3: Illustrative project exposures for a storage project under three sample collar sharing schemes

[Floor threshold / share – Cap threshold / share]

[$10m/90% – $30m/50%] [$20m/90% – $20m/50%] [$10m/100% – $30m/30%]



Treatment of eligible derivative re-contracting

For the CIS, FERM and LTESA, as the most advanced schemes, the net revenue calculation is intended to include all sources of revenue that relate to the economic value of the project, including derivative contracts and ancillary services. While the UK LDES technical documentation does not directly specify how derivative and future hedge contracts are that treated, it does appear to support an expansive view where "all sources of revenue will be considered for assessment against the cap and floor" (OFGEM, 2025)

We specify in the formulation for a range of alternative contract structures that participants may seek to enter either *'ab-initio'* or after being awarded a collar contract. We have specified contracts that could form the basis for either derivative or risk-management contract trades.

Table 1: Additional Contract Structures

Financial Contract	**Floating payment formulation**
Description	
Traditional call option or price 'cap'	$\varphi_\omega = \sum_{t \epsilon T} \max(\lambda_{t,\omega} - \mathrm{S}, 0)$
Call option or "cap" with strike S (commonly set at $300/MWh) and fixed option premium ϕ.	
Spread 'top-bottom' X (TB-X) contract	$\varphi_\omega = \sum_{d \epsilon D_\omega} \sum_{m \epsilon X} \overline{\lambda^e_{d,m}} - \underline{\lambda^e_{d,m}}$
Floating payments referenced against sum of the difference between the top and bottom *X* hours in each trading day. For each trading day in scenario ω, $d \in D_\omega$ the ascending and descending ordered energy prices are $\overline{\lambda^e_{d,m}}$ and $\underline{\lambda^e_{d,m}}$.	
Virtual toll, also termed yardstick contract	$\varphi_\omega = \sum_{t \epsilon T} \boldsymbol{\lambda}_{t,\omega} \mathbf{p}^*_{t,\omega}$ ^
Floating cashflows referenced against ex-post hypothetical calculation of market revenues, assuming perfect foresight. Optimal values of energy and ancillary service dispatch are $\mathbf{p}^*$	

3.4 Optimal hedging model

We adopt a risk-return trade-off optimization to assess the optimality of re-contracting a storage or firming resource. The resource operator's risk-aware utility is denoted $U(\widetilde{\Phi}_\omega)$ and is a function of net margins. Optimal contract v^* volume can be determined by maximizing risk-aware utility i.e., $\max U(\widetilde{\Phi}_\omega)$. For the risk-aware utility, a symmetric Sharpe ratio is contrasted with the asymmetric Sortino ratio to provide a nuanced perspective on the desirability of portfolio hedging under different contract designs.

Underpinned by a Markowitz two parameter model of risk and return (i.e. mean-variance approach), the Sharpe ratio measures the difference between the expected returns of the investment π and the risk-free rate of return r^f, divided by the standard deviation of the investment returns.[14] Returns are defined as net margins over the investment cost.

$$\max_v U^{sh}(\widetilde{\Phi}_\omega) = \frac{\pi - r^f}{\sigma}, \text{ s.t. } \pi = \sum_{\omega \in \Omega} p_\omega \, i_\omega \, ; \, \sigma = \sqrt{\sum_{\omega \in \Omega} p_\omega \, (i_\omega - \pi)^2}; i_\omega = \widetilde{\Phi}_\omega / C^I \quad (7)$$

The Sortino ratio adopts an asymmetric risk measure, the downside deviation, which quantifies the potential for losses by measuring the deviation of investment returns below a minimum acceptable return (MAR). We adopt a MAR of 10% for the Sortino ratio calculation.

$$\max_v U^{so}(\widetilde{\Phi}_\omega) = \frac{\pi - r^f}{\underline{\sigma}}, \text{ s.t. } \pi = \sum_{\omega \in \Omega} p_\omega \, i_\omega \, ; \, \underline{\sigma} = \sqrt{\sum_{\omega \in \Omega} p_\omega \inf(0, i_\omega - MAR)^2}; i_\omega = \widetilde{\Phi}_\omega / C^I \quad (8)$$

Both decision problems result in non-convex programs, with bilinear terms (and in the case of Sortino ratio maximization, integer decision variables given the infimum operator). There are different mathematical approaches available to resolve these two problems including potential reformulations as mixed-integer programs (e.g., through binary expansion), or using approximations such as McCormick envelopes (see McCormick, 1976). Ultimately a simple distributed approach provides valuable insights into the directionality of outcomes at the level of granularity required for this exercise. This approach is set out below and involves calculating point estimates for Sharpe and Sortino ratios, for different values of contract volume v across the range (0.0,1.0) with step size, *x*.

3.4.2 Risk-constrained optimization: The investor's and hedge provider's perspective

In this article, we seek to understand hedge outcomes from the perspectives of different counterparties to the hedge. The investor or financier perspective is based on meeting the financial constraints imposed by various capital providers to a project. That is, the project is only built if it meets conventional bank credit committee (i.e., debt) and capital investment committee (i.e., equity) constraints. This includes constraints related to debt sizing (via gearing and DSCR constraints) and equity sizing (via minimum expected return requirements, and minimum distribution requirements). Second, it is important to model outcomes from the perspective of the central agency as the hedge provider. The central agency faces risk constraints arising from the use of its balance sheet to underwrite transactions. An important threshold relates to the risk-neutral or fair value of hedges. This equates with the expected value of hedge payoffs. Both perspectives necessitate the adoption of a risk-constrained optimization approach. For the investor perspective, we model a leveraged financing to calibrate collar thresholds that are consistent with project finance capital structures. We seek to understand the lowest possible floor threshold that would meet project bank credit committee constraints. Thus, this optimization problem seeks to minimize the floor threshold subject to hard constraints on risk. For debt capital, financial uncertainty is managed through a set of risk constraints on debt sizing. Similar constraints govern triggers for debt facility default, equity lockup and other stress conditions. These constraints along with definitions of cashflow waterfall metrics are consistent with the approach in Billimoria and Simshauser (2023), which we reproduce in Appendix B.

[14] Alternatively, Simshauser 2020 develops a "modified Sharpe ratio" calculated as the difference between the median and 90% probability of exceedance over the median. i.e. (PoE50 – PoE95)/PoE50.

$$\rho^{INV} = \min_W \underline{S}\, s.t.\{W \coloneqq (\underline{S}, \overline{S}, D, E)\} \quad (9)$$

Second, we model a central agency hedge provider perspective by understanding the collar thresholds that result in a *zero* fair-value hedge. A *zero* fair value is an important performance indicator of financial neutrality for the hedge originator. In other words, the hedge originator is (ex-ante) neither subsidizing nor gaining value from providing the forward derivative. Comparisons of hedge outcomes and thresholds that would support project financing against those implied by a requirement for zero fair value would provide an important indication of the extent of the accrual or otherwise provided by the central agency. The fair value is calculated as the expected value of the negative of the contract payoffs Φ_ω^C. In this problem, we set the floor threshold to be equivalent to the outcome of the leveraged financing model optimization above, and allow the cap threshold to be set based on the zero fair value constraint.

$$\rho^{CA} = \min_W \overline{S} \qquad \{W \coloneqq (\underline{S}, \overline{S})\} \quad (10)$$
$$s.t. \qquad \underline{S} = \underline{S}^* | argmin\, \rho^{INV*}$$
$$\int_{p_\omega} \Phi_\omega^C = 0$$

3.5 Data and assumptions

In the following section we undertake a case study based on SDES, LDES and GT firming resources in the NEM (nb. SDES = 2h and 4h. LDES = 8h and 12h). To reflect real-world stochasticity and tail risk, prices are exogenously determined from historical prices in the NEM. We assume firming resources are based in the world's most renewables-intensive power system, viz. the South Australian region (SA) of Australia's NEM. Resource costs and technical parameter assumptions for the modelled resources are set out in Table 2 for a GT, and in Table 3 for battery storage.

Table 2: Generator cost and technical assumptions

Tech	Pmax (MW)	Fuel cost ($/GJ)	c^I ($/kW)	c^f ($/kW/yr)	P^{min} (MW)	R^u /R^d (MW/min)	c^{st} ($/start)	Heat rate (GJ/MWh) HHV
GT	250	9.3	1600	12.2	0.5	22	1100	10.9

Source: AEMO (2026)

Table 3: Storage cost and technical assumptions

Tech	Pmax (MW)	Energy (MWh)	c^{I} ($/kW)	c^{f} ($/kW/yr)	q^{c} and q^{d} (%)	Cycling limit
BESS-2hr	250	500	1266	12	0.86	365 per yr
BESS-4hr	250	1000	1727	19	0.86	365 per yr
BESS-8hr	250	2000	2746	34	0.86	365 per yr
BESS-12hr	250	3000	3752	34	0.86	365 per yr

Source: AEMO (2026). For the 12-hr BESS are calculated based a linear interpolation of BESS energy costs (per MWh) and power costs (per MW) from shorter duration BESS.

In all cases, power capacity is assumed at 250MW reflecting a viable utility scale project. Annual single-cycle limits for storage are imposed (He *et al.*, 2021) given the assumed new vintage of the assets. Charge and discharge efficiencies are based on the Li-ion design adopted in He *et al.*, (2021). Energy utilization is assumed to 0.2 for regulation raise services, 0.1 for regulation lower services and zero for contingency services (see Gilmore et al., 2022).

In terms of fuel costs, GTs are assumed to be contracted over the long term at a fixed rate of $9.3/GJ with a $2/GJ combined haulage and line-pack charge. As part of the suite of sensitivities, we consider the impact of an uncontracted GT that procures fuel at the monthly average gas spot price at the Adelaide hub. Additional assumptions include auxiliary energy usage of 1% and start costs of $100/MW/start (Aurecon, 2023; AEMO, 2026). Economic assumptions comprise a risk-free rate of 4.3%, taxation rate of 30% and resource marginal loss factor (MLF) of 0.95. Operational dispatch and gross profit outcomes are calibrated against NEM project real-time margin outcomes, as set out in Appendix A. Financing assumptions are set out below. The costs of capital and sizing ratios reflect an investment in a contracted asset that has a minimum set of floor returns.

Table 4: Financing assumptions

Assumption	Value
Risk free rate	4.3%
Debt margin	1.8%
Equity margin	6.1%
Tax rate	30%
Dev and financing costs	5% of capital value
Financial sizing metrics	
Min. DSCR – P99	1.0
Min. DSCR – Ave	1.2
Max gearing	90%

For the collar, we set the cap and floor thresholds to 50% and 90% respectively, consistent with the Commonwealth's CIS (Department of Climate Change, 2024).

3.6 Re-contracting

We examine the potential for re-contracting that arises from a shift in risk-optimization preference occurring pre- and post-project capitalization where, for example, a project's portfolio hedge decision-making framework shifts from a risk-constrained optimization (typical of capital financing) to a risk-return trade-off optimization.

To implement re-contracting for a change in risk-optimization preferences, ceterus paribus, we feed gross profit back into the portfolio hedging model to understand the optimality of additional hedging post-financing, and with an initial collar awarded by a central agency (similar to that offered via the CIS). It is important to note the impetus for re-contracting in markets may arise from changes to state variables including market conditions, technical assumptions, forecast error and pricing distributions, which we return to in sensitivity testing.

Gross profit collar contracts restrict periodic margins from exceeding high and low thresholds or create different revenue sharing regimes beyond those thresholds. This essentially looks to bound financial performance – where downside management aims to assist in securing finance. What emerges in each case is the substitution of variable revenues for more bounded revenues.

4. Results and discussion

The purpose of our modelling exercise is to demonstrate interactions between contract design, risk perception and recontracting for generation and storage results. We demonstrate results for a central case considering multiple resources: GTs[15] and battery storages comprising multiple durations in the South Australian region of the NEM. Results provide insights on the alignment of asset characteristics with contract design, product standardisation and incentive alignment for re-contracting.

Merchant exposures

Figure 4 sets out the probability density functions of the merchant gross profit (as a percent of investment cost) for the GT and batteries of multiple durations, with statistical moments set out in Table 5. This is the underlying spot-exposed profit profile to be hedged by project developers. Key observations are as follows. Based on the scenarios with recent year pricing, mean returns for GTs and 4-hr batteries are broadly similar, but those returns decline significantly for battery storage with longer durations. This reflects the fundamental challenge of longer duration storage development in the absence of scarcity signals that support underlying merchant economics. With longer durations, volatility reduces but higher order moments like skew and downside deviation increase, indicating a more asymmetrical return profile.

[15] In the central case, the GT is assumed to be fully fuel-contracted.

Figure 4: Probability density function of merchant gross profits for GT and batteries (4-hr, 8-hr and 12-hr)

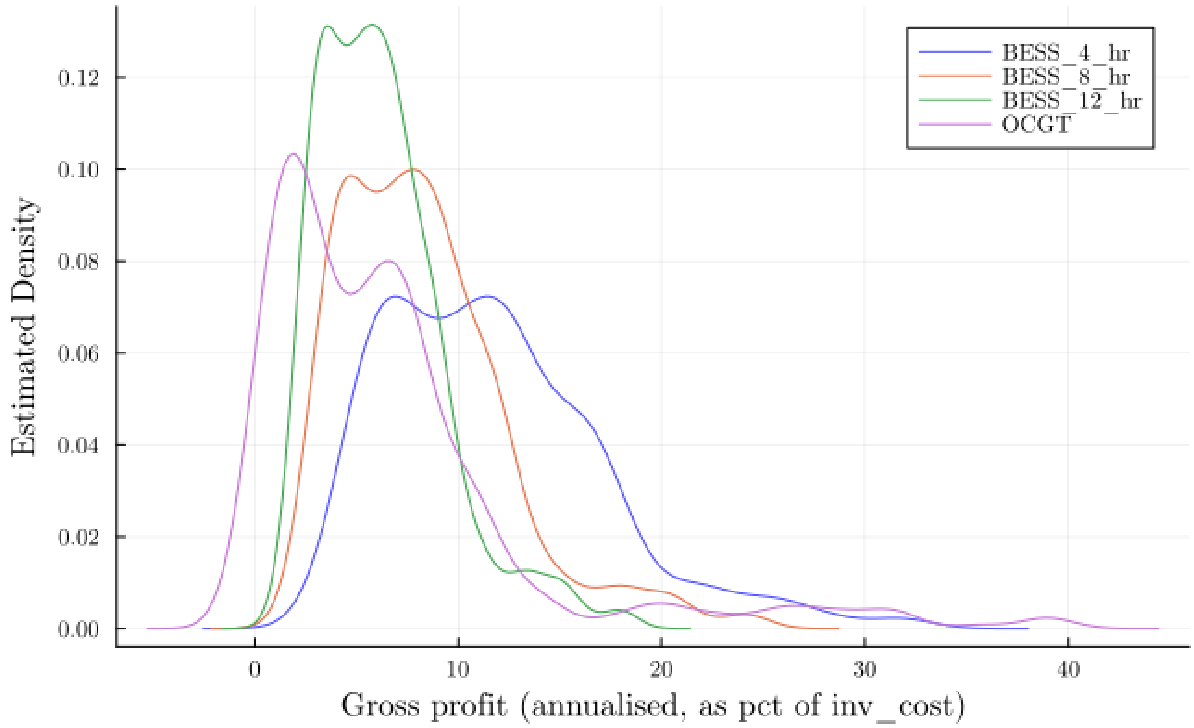


Table 5: Statistical moments for merchant gross profits for GT and batteries (4-hr, 8-hr and 12-hr)

Gross profits (as % of inv.cost)	Mean	Std.dev	Skew	Kurt.	Downside deviation
GT	13.5	17.1	1.4	1.4	3.3
4-hr BESS	11.7	5.5	1.0	1.2	3.3
8-hr BESS	8.3	4.1	1.2	1.9	2.4
12-hr BESS	6.2	3.2	1.2	1.7	1.8

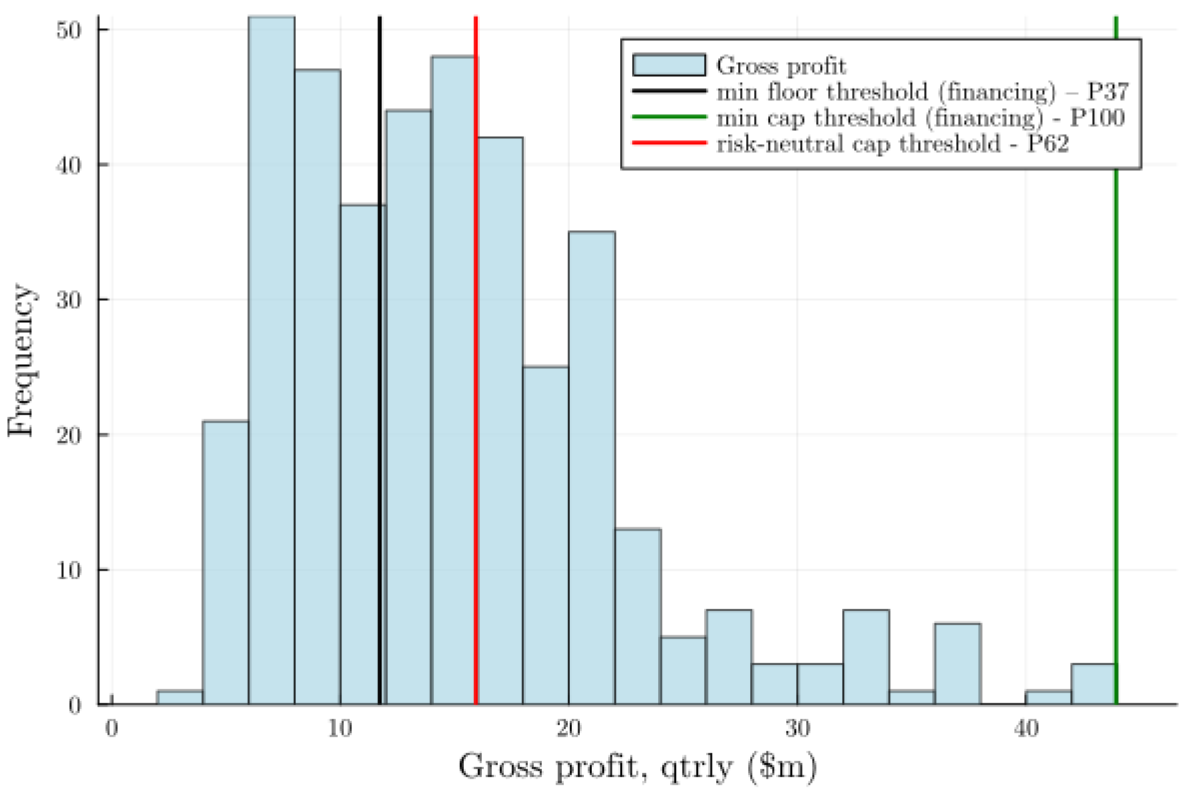
Setting cap-and-floor thresholds

In this section we test the impacts of differing approaches to determining the cap and floor thresholds of the collar. We first consider the perspective of an investor, who is seeking to finance the asset via project financing. This requires a risk-constrained optimization approach where hedge settings are optimized based on constraints imposed by both debt and equity providers. Using the risk-constrained optimization set out in Section 3.4.2, we determine the lowest viable floor threshold investors would bid while meeting all financing constraints (the cap threshold is also determined as part of this to meet the minimum debt and equity return requirements). Second, we consider the perspective of the counterparty or central agency providing the hedge. We set the floor threshold at the level implied by the financiers' problem, then calculate the cap threshold that ensures an ex-ante risk-neutral or zero fair value or hedge instrument. Comparing the outcomes from the investors problem against the hedge providers problem allows us to understand whether the collar provided to power project proponents to *'complete the market'* amounts to an effective fair value accrual to, or from, the private market.
We show results for a 250MW, 8-hr battery against the histogram of quarterly gross profits in Figure 5. Cap and floor thresholds are set to 50% and 90% in line with the Commonwealth's CIS. The lowest

floor threshold an investor can bid is $11.7 million per quarter (indicated by the black vertical line) for a 250MW storage asset. The floor threshold equates to the 37th percentile of the merchant gross profit distribution. Given this floor threshold, for the investor to make binding debt and minimum equity returns, the cap threshold would be set at ~$43.9m per quarter, which is at the maximum forecast of gross profits (the green vertical line) i.e. the cap would not have any material effect (be "in the money") under the current margin distribution. This would enable a gearing of ~80% in line gearing expected for heavily contracted assets with highly rated counterparties.

Considering outcomes from the counterparty (central agency) perspective, we examine the cap threshold to maintain a zero risk-neutral valuation of the cap-and-floor instrument, assuming that the floor is set at the 37th percentile. For a zero risk-neutral valuation, the cap equates to $15.9 million for a 250MW asset (the red vertical line), which would represent a threshold at the 62nd percentile of gross profits. We note the material disparity between the cap requirement for the investor and the central agency (i.e. to ensure a risk-neutral fair valuation). This amounts to a net fair value accrual to the investor of $1.2 million per quarter. Assuming a 5% annualised discount rate and a 10-year project hedge term, this accrues to $38.2 million.

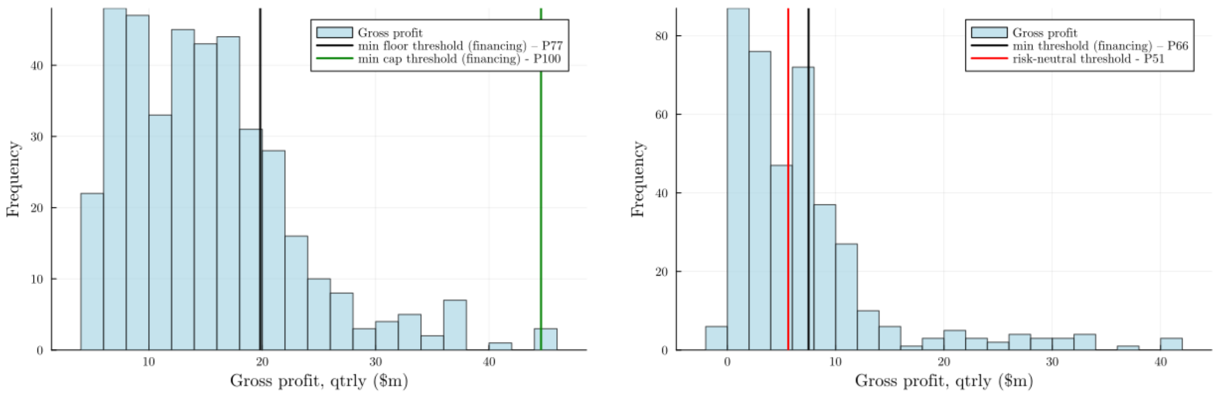
Figure 5: Setting floor and cap thresholds for a 250MW, 8hr battery under investor financing requirements, and under central-agency risk-neutral valuation requirements



We undertake similar analysis for a longer duration 12-hr BESS and GT, with similar trends emerging. For GTs, we consider a framework similar to the FERM which has a single threshold (i.e. minimum threshold to meet financing constraints, and separately, the threshold which achieves a zero risk-neutral hedge valuation). The 12-hour battery is unlikely to extract sufficient gross profits from the spot market. Consequently, it relies to a greater extent on the floor to maintain bankability (i.e. 77th percentile). As with the 8-hr battery, the minimum cap is set at the maximum merchant gross margin achievable in the spot market. At this level, the cap does not come into effect and achieving a zero fair valuation is commercially problematic. At this floor threshold for a zero risk-neutral zero valuation to be achieved. the cap threshold would be set at a level lower that the floor (i.e. commercially intractable). The effective fair valuation of the hedge accruals to the project owner for a 250MW 12-hr battery would amount to 168.3 million assuming a 10-year hedge term and a 5% discount rate.

Figure 6: Setting floor and cap thresholds for a 250MW, 12-hr battery (LHS) and a 250MW GT (RHS) under investor financing requirements, and central-agency risk-neutral valuation requirement

12-hr BESS GT



Sensitivities: Impacts of financing constraints

As with all simulations of this nature, they are sensitive to the key financing assumptions – and we present the extent of this in Table 6. What this sensitivity suggests is that fundamentally, the results are robust to changes in financing assumptions, but the magnitude of impacts is amplified as financing constraints become more stringent. Higher DSCR covenants require higher cap thresholds and increases the valuation of the hedge for project sponsors (the average DSCR constraints has no impact, the P99 DSCR is the binding constraint). The impact of equity return hurdles are similar with higher hurdles requiring a higher floor and cap threshold to be bankable, and vice-versa.

Table 6: Impact of financing sensitivities on cap-and-floor hedge metrics and capital structures for 8-hr battery

Sensitivity	Base*	P99 DSCR		Ave DSCR		Equity return hurdle	
		1.05x	1.10x	1.10x	1.30x	9.4%	11.4%
Thresholds ($m)							
Floor	11.7	12.2	12.5	11.7	11.7	11.1	12.2
Cap– financing	43.9	43.9	43.9	43.9	43.9	43.9	43.9
Cap– risk neutral	15.9	15.1	14.4	15.9	15.9	17.2	15.1
Percentile (%)							
Floor	P37	P40	P42	P37	P37	P34	P40
Cap– financing	P100	P100	P100	P100	P100	P100	P100
Cap– risk neutral	P62	P56	P54	P62	P62	P70	P56
Gearing (%)	81%	80%	78%	81%	81%	77%	83%
Hedge valuation ($m)**	-38.2	-43.7	-47.1	-38.2	-38.2	-31.5	-43.7

* The Base Case has a minimum DSCR requirement of 1.0 times, an average DSCR requirement of 1.2 times, and an equity hurdle of 10.4%

** We show the valuation of the cash flow accruals based on a 5% annual discount rate, and a hedge tenor of 10 years. A negative sign indicates a net accrual of fair value to the project counterparty.

Re-contracting

One of the postulated benefits of the collar contract design is that it purportedly preserves the incentive for resources to continue re-contracting in the derivative markets as the project retains spot market exposure when gross profits remain with the bounds of the collar. As such, a resource is not prevented from re-contracting via derivative trades to lock in revenues.

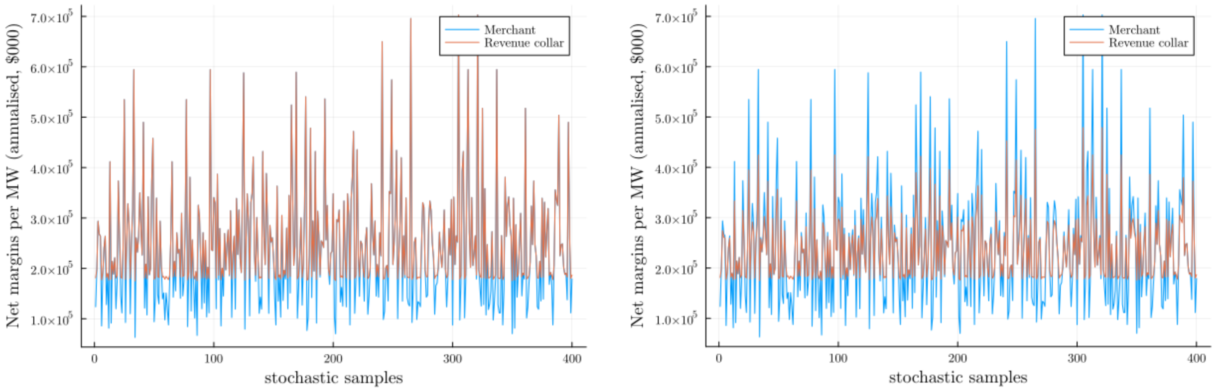
Here, we test this thesis from first principles by examining the impact of a collar[16] on incentives to re-contract. Figure 7 shows net margins per MW of capacity for an 8-hr battery across the 400 stochastic samples for two cases (i) a merchant battery, and (ii) when the collar is committed. We show this for two cap thresholds, the left-hand side panel indicates samples where the cap threshold is based on investor financing requirements, and the right-hand side panel indicates samples where the cap threshold is based on central-agency fair valuation requirement of zero hedge cost (RHS). This demonstrates that the collar limits downside variations – a desirable feature from a financing perspective.

In terms of upside, especially for the central-agency case, while the risk-sharing framework would see the project sacrifice some level of (extreme) windfall gains, for the stochastic samples considered, they nevertheless retain a significant amount of upside variation across the stochastic sample series. This is because merchant gross profits are significantly right skewed (see Figure 4) and a significant portion of returns are outsized. While the collar limits exposure to 'extra-high' events, material upside profits are realised.

[16] The collar specifications are: low and high margin thresholds set at the 25th and 85th percentile of the gross margin distribution, and project sharing of 50% of the upside and 10% of the downside)

Figure 7: Impact of a revenue collar contract on gross profits for 8-hr battery, with cap thresholds set based on financing constraints (left panel), and cap thresholds set a zero fair valuation of the hedge (right panel)

Financing constraints | **Zero fair-valuation of hedge**



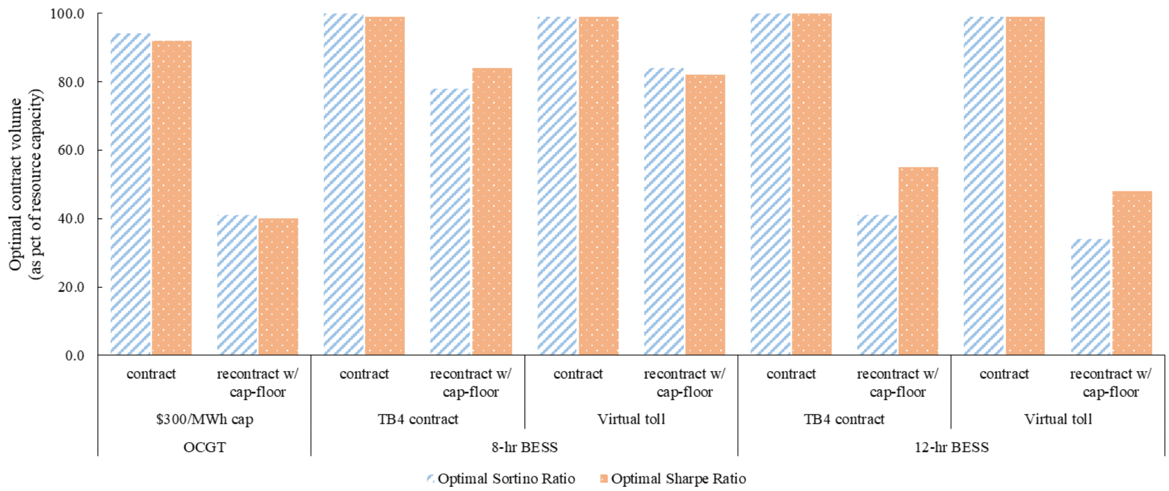
Floor threshold: 37th percentile
Cap threshold: 100th percentile

Floor threshold: 37th percentile
Cap threshold: 62nd percentile

This asymmetry impacts incentives to re-contract. Figure 8 sets out the optimal contract volumes for a set of contract designs (GT $100/MWh cap, storage TB4 contracts and a toll contract purchased at fair value), with and without a government-initiated collar. We show this for a GT, 8-hr and 12-hr batteries. We observe across all cases that when the chosen derivative contract is executed ab-initio (i.e. over merchant revenues), the project is incentivised to contract at near to full volumes. Once the collar is executed, the incentive to re-contract in the derivative markets is materially reduced.

Take the example of a TB4 as the primary contract. The optimal risk-return trade-off (Sortino ratio) is achieved at a contract portfolio volume of 100% of resource capacity. In theory, an 8-hr battery could fully defend a TB4 contract. If a collar contract is executed and downside returns are bounded, there are still benefits for the project in retaining upside exposure. This reduces the incentive for the project to re-contract in the derivative markets once the collar is in place. With a collar in place, re-contracting a TB4 contract at full capacity is sub-optimal. The Sortino ratio, and indeed under the Sortino ratio risk measure, the optimal volume is 78% of resource capacity once the collar is in place – some 22 percentage points lower than without the collar. Similar impacts are observed for the execution of a virtual toll once a collar is in place. Similarly for the GT, which is able to optimally defend a $300/MWh cap at 94% of its total capacity. With a revenue sharing collar mechanism in place, the optimal cap contract volume collapses to just 34%.

Figure 8: Incentives for recontracting - optimal contract volumes with and without zero-cost collar (financing case)



Effects are just as material for the 12h battery. The optimal contract volume for a TB4 contract with a pre-existing committed collar is 41% of resource capacity compared to 100% ab-initio without a collar. The longer duration storage asset needs a higher floor to be investable, thus reducing further the incentives to recontract.

The implications here are that contract designers need to be cognisant of incentives for re-contracting once revenue sharing collar contracts come into force. And, this can be expected to adversely impact the liquidity of forward derivatives market, and if sufficiently material, consumer prices. While it does not invalidate all trading following the execution of the collar, the presence of a collar visibility reduces incentives to re-trade and therefore derivative market liquidity. Resource owners will seek to extract value from upside critical events via retaining spot exposures just at the time consumers need hedges in place.

5. Policy Implications and Conclusions

In the context of the energy transition, hedging mechanisms are evidently a popular tool for policymakers to accelerate entry by completing forward markets vis-à-vis risk management. However, a key distinction between hedges provided by merchant counterparties and proprietary traders (cf. central agencies) are the incentives at play. Merchant counterparties face direct pecuniary incentives associated with the management of financial risk exposures, and naturally obtain economic gains or losses associated with the over- or under- valuation of hedges. In the absence of commercial participation, central agencies do not naturally face these risks and returns. Forward derivatives are considered a means by which to create cashflow stability and manage downside risks for investors (equity) and project banks (debt) on the one hand, and retail suppliers and consumer prices on the other. It is thus important to understand the value associated with hedges, and of adverse impacts to forward market liquidity. Our analysis demonstrates the potential for a discrepancy between the implied valuation of revenue collars to meet financier requirements relative to the fair value of the financial instruments. In particular, our analysis shows at current prices patterns, collar settings required to support a project financing would imply an accrual of positive fair value to investors relative to a fair-valuation of the hedge. That is; to enable a project financing, investors receive an effective fair value accrual particularly, for longer duration and firming assets. One line of future research could investigate deeper the potential causes of the disparity between risk-averse financing constraints and complete fair market valuations.

An important caveat of our work is that the price signals in our economic optimization are exogenously determined based on history. In part, this effect is implied by the lack of purely private investment in long-duration storage despite the scarcity observed in power markets in recent years (including during the 2022 energy crisis). However, this outcome could be different if price patterns change in the market. Nevertheless, it also implies the central agency would be reliant upon a fundamental change to price formation to justify a fair value for hedges. While price patterns may change, they are also subject to uncertainty and to contrasting views. For example, work by Mallapragada *et al* (2023) suggest that low-carbon systems are likely to experience more frequent periods of very low and very high prices (a bi-modal price distribution). By contrast, work by Brown *et al* (2025) suggest this effect could be significantly muted if there is even a small degree of load flexibility. To test the impact of price formation patterns we undertook a sensitivity on the robustness of the results to changes in price formation trends in Appendix D. Sensitivities suggest results persist even with material increases in expected gross profits of LDES – though there is a natural limit to the applicability of results where expected gross profits increase well above the tested base exogenous pricing period (where the gross profits for LDES ~50% above the base case). Nevertheless, this remains an important area for future work.

Overall, hedging mechanisms have been associated with a broader industrial policy. Consequently, that a fair value disparity exists is not totally surprising. Indeed, this may well be a recognised compromise of the framework given the challenges of full-strength price formation. Conversely, there may be a resilience benefit associated with providing insurance to the system from extrema that are not currently observable nor valued by individual participants (see reliability externality identified by Joskow and Tirole, 2007). The fair value disparity is effectively the price paid by the system for market incompleteness, such as the risks associated with unpriced externalities, energy transition sequencing, system resilience and insurance etc. Nevertheless, disparity against fair values suggests the need for fair and independent valuation of hedges to maintain transparency and accountability of central processes. It also serves as a metric for which governments and central agencies can adjudge the public benefits and costs associated with hybridised contracting. This requirement is independent of the type and design of the contract being adopted, though fair market valuations may be more apparent with standardised contracts (as below).

Additionally, while structures such as revenue collars are a popular form of resource-specific contract and adopted in central hedging schemes for storage, the impacts on incentives for derivative market participation require very careful consideration indeed. By socialising losses, our modelling suggests that government-initiated collar contracts dampen incentives for re-contracting given the skewed nature of electricity prices and gross profits. Participants may well recontract for portfolio-level reasons, but our modelling suggests natural limits to this given the design. This appears to be recognized given one of the key recommendations in the Nelson Electricity Review to shift away from resource-specific contracting towards a suited of standardised market contracts.

Hedge contracts are first and foremost a risk management tool, and contract design must be considered in that context. It requires a nuanced approach that balances the incentives of participants with the perceptions of market risk, and the implicit obligation held by the central policymaker as an agent of energy consumers and the public at large. Carefully analysing the policy objective of accelerating entry through government-initiated CfD collars against cost of potential losses of forward market liquidity, through unintended consequences, requires ongoing research as markets continuously hybridise.

Appendix A: Unit commitment and scenario generation modules

Unit commitment under uncertainty

In the unit commitment module, we seek to model the commitment and dispatch decision of storage and generation resources self-scheduling into a real-time spot market as a price-taker, consistent with prior approaches set out in (Simshauser, 2020; Billimoria and Simshauser, 2023).

Price forecast error

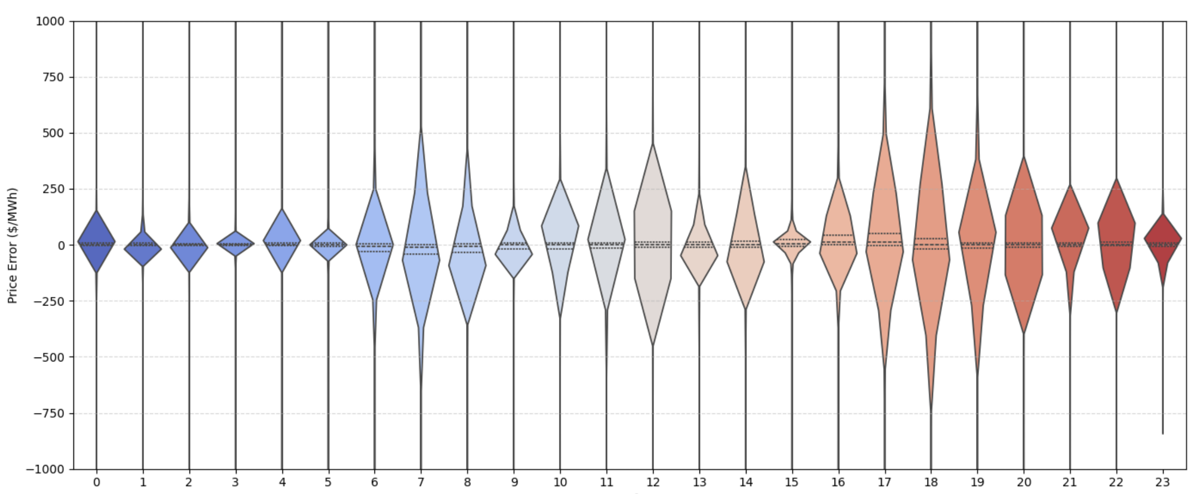
Unit commitment in real-time markets make operational decisions under uncertainty, and critically, including looming spot prices. Self-commitment is a core element of the NEM's market design, in contrast to centralised forward unit commitment in place in many other regions. Our modelling approach reflects this nuance.

Given price uncertainty in a set of ordered half-hourly trading intervals over a period $t \in T$, the energy price perceived by the resource will be the difference between the actual price and ε_t^e, a random variable representing the price forecast error $\hat{\lambda}_{t,\omega}^e = \lambda_{t,\omega}^e - \varepsilon_{t,\omega}^e$ (and similarly for reserves) (Xu, Korpas and Botterud, 2020), and similarly for ancillary services.

Price forecast error represents the difference between predicted prices and spot prices. Obtaining predications of prices is challenging because the forecasts used by market participants to inform bidding and scheduling strategies are not public or otherwise transparent. AEMO provides a base characterisation of implicit price uncertainty through its 'pre-dispatch' process. Pre-dispatch is a non-binding 48 hour-ahead run of the NEM Dispatch Engine publicly disclosed ahead of real-time, and continuously updated, with the aim of providing market participants with information about scheduled resource loading, ancillary service unit response and pricing to assist informed decisions vis-à-vis market participation. There is also an accompanying 5-minute pre-dispatch process run for a shorter period. Pre-dispatch provides an appropriate baseline to characterise the uncertainty set. However, it is to be noted that pre-dispatch also has a signalling impact on market outcomes and is designed to elicit adaptive responses by market participants.

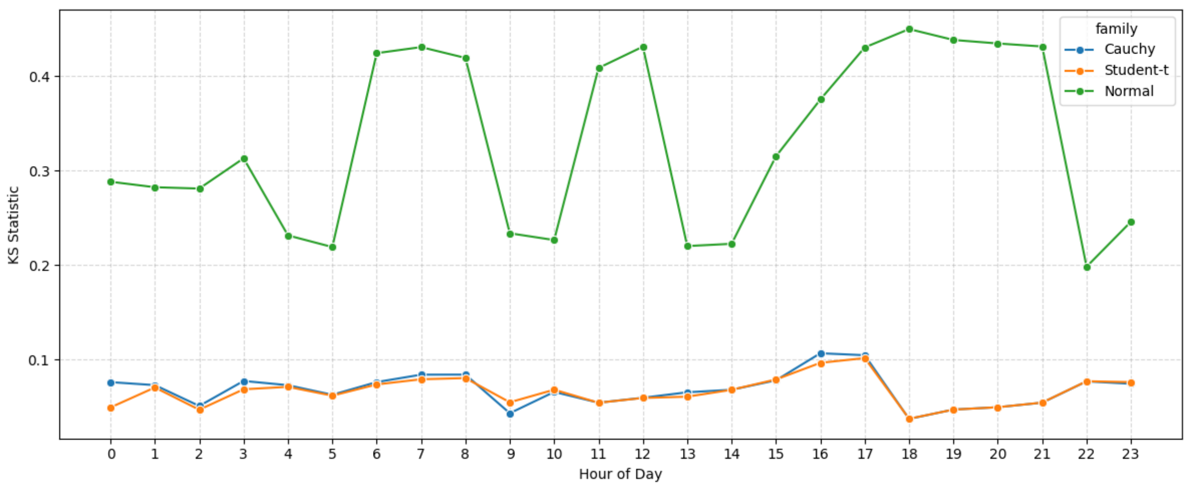
Empirically, pre-dispatch price errors in the NEM have occurred within a tight band with less common but material under- and over-forecasts with heavy tail characteristics (Prakash, Bruce and MacGill, 2025, Yurdakul and Billimoria, 2023). In Figure A1 we show pre-dispatch price errors for the South Australian region for the 2023 sample year.

Figure A.1: Violin plot of pre-dispatch price error: SA region 2023 sample year, by hour of day



To capture the heavy-tailed nature of price forecast errors, we model this random error via a Cauchy distribution (with distribution parameters x_0 and γ, best-fit against NEMDE pre-dispatch price errors on an hourly basis. We also tested alternative heavy tailed distributions including the Student-t distribution and alpha. Both the Cauchy and Student-t demonstrated good potential fit against the samples. See Figure A1 for the relative Kolmogorov statistics for the Cauchy and Student-t, with a normal Gaussian for comparison. The Anderson-Darling test illustrated similar results. While both were suitable candidates, the Cauchy was selected the relevance of tail observations (Weron, 2006) and the potential for extreme prices in the NEM (Akay, 2024).

Figure A.2: Kolmogorov Statistic (KS statistic) for fit of pre-dispatch price error in SA region 2023 sample year, by hour of day against Cauchy, Student-t and Normal distribution



A scaling factor z^{e} is adopted to reflect the potential for market participants to outperform or underperform the publicly available pre-dispatch. For simulations, a scaling factor of 1.0 is adopted demonstrating good calibration against a set of storage benchmarks returned to below. A similar approach is adopted for estimating price error for ancillary service reserve markets.

$$\varepsilon^{e}_{t,\omega} = z^{e}\,\varepsilon^{e-PD}_{t,\omega} \qquad \varepsilon^{e-PD}_{t,\omega} \sim Cauchy(x_0,\gamma) \quad \text{(A.1)}$$

The vectors of outturn prices is defined as $\boldsymbol{\lambda}_{\boldsymbol{\omega}} = [\lambda^{e}_{1,\omega} \dots \lambda^{e}_{T,\omega};\ \lambda^{r+}_{1,\omega} \dots \lambda^{r+}_{T,\omega}; \lambda^{r-}_{1,\omega} \dots \lambda^{r-}_{T,\omega}]$, and associated price forecast errors defined as $\boldsymbol{\varepsilon}_{\omega} = [\varepsilon^{e}_{1,\omega} \dots \varepsilon^{e}_{T,\omega};\ \varepsilon^{r+}_{1,\omega} \dots \varepsilon^{r+}_{T,\omega}; \varepsilon^{r-}_{1,\omega} \dots \varepsilon^{r-}_{T,\omega}]$. The matrix of prices perceived by the resource $\hat{\boldsymbol{\lambda}}_{\omega}$ is therefore calculated as below, based on the matrix of price forecast errors and bounded by the market price cap (MPC) and market price floor (MPF).

$$\hat{\boldsymbol{\lambda}}_{\boldsymbol{\omega}} = \mathbf{min}(\mathbf{max}(\boldsymbol{\lambda}_{\boldsymbol{\omega}} - \boldsymbol{\varepsilon}_{\boldsymbol{\omega}}, MPF), MPC) \qquad \text{(A.2)}$$

We now set out the operational decision framework for storage and generation. For a generation unit self-committing and scheduling into each trading interval, the gross margin across time intervals $t\epsilon T$ as perceived by a resource is described in equation (A.3) below. The vector of energy and ancillary service dispatch quantities for power generation are specified as $\mathbf{p}_{\boldsymbol{\omega}} = [p^{e}_{1,\omega} \dots p^{e}_{T,\omega}; p^{r+}_{1,\omega} \dots p^{r+}_{T,\omega}; p^{r-}_{1,\omega} \dots p^{r-}_{T,\omega}]$. In addition to energy and ancillary service dispatch, it is also relevant to mention the unit commitment status decision variable $u_{t,\omega}$ and start variable $s_{t,\omega}$. For illustration, only one raise and one lower reserve market is shown here (though the framework extends to multiple reserve markets, including frequency regulation and frequency contingency).

$$\hat{\Phi}^{G}_{\boldsymbol{\omega}} = \sum_{t\epsilon T} \hat{\boldsymbol{\lambda}}_{\boldsymbol{\omega}}.\mathbf{p}_{\boldsymbol{\omega}} + k^{+}\hat{\lambda}^{e}_{t,\omega}p^{r+}_{t,\omega} - k^{-}\hat{\lambda}^{e}_{t,\omega}p^{r-}_{t,\omega} - c^{v}_{t,\omega}(p^{e}_{t,\omega} + k^{+}p^{r+}_{t,\omega} + k^{-}p^{r-}_{t,\omega}) - c^{st}_{t,\omega}s_{t,\omega} \quad \text{(A.3)}$$

The first term represents the revenue opportunity of the unit based on price forecasts for energy and reserves. The second and third terms represent the energy revenues and cost associated with raise and lower reserve utilisation. The third and fourth terms represent the short-run variable costs (fuel and variable operating expenses) and start-up costs associated with the unit. As referred to above, the decision reflects the perception of prices given forecast uncertainty.

This is subject to technical and operational constraints associated with the resource as set out in equations (A.4)-(A.8). Constraint (A.4) apply a power capacity limit, scaled by the unit's availability and the unit's commitment status, to the delivery of energy and reserve. Constraint (A.5) restricts the delivery of lower reserve to the power generation quantity. Constraint (A.6) ensures that once committed a resource is generating at minimum load. Equation (A.7) specifies ramping constraints, and constraint defines a start. Equation (A.8) represents non-negativity and integrality constraints associated with variables u_t and s_t .

$$p^e_{t,\omega} + p^{r+}_{t,\omega} \leq A_{t,\omega} P \quad u_{t,\omega} \qquad \forall\, t \in T \quad \text{(A.4)}$$

$$p^e_{t,\omega} - p^{r-}_{t,\omega} \leq 0 \qquad \forall\, t \in T \quad \text{(A.5)}$$

$$p^e_{t,\omega} \geq A_{t,\omega} P^{min} u_{t,\omega} \qquad \forall\, t \in T \quad \text{(A.6)}$$

$$R^d P \quad \leq p^e_{t,\omega} - p^e_{t-1,\omega} \leq R^u P \qquad \forall\, t \in T \quad \text{(A.7)}$$

$$u_{t,\omega} - u_{t-1,\omega} \leq s_{t,\omega} \qquad \forall\, t \in T \quad \text{(A.8)}$$

$$p^e_{t,\omega} \geq 0, p^{r+}_{t,\omega} \geq 0, p^{r-}_{t,\omega} \geq 0, u_{t,\omega} \epsilon \{0,1\}, s_{t,\omega} \epsilon \{0,1\}$$

The state parameter for unit availability for battery and GT resources A_t is determined based on the approach in (Conejo, Carrion and Morales, 2010), with sequential failure and repair times each characterised by an exponential distribution with a mean time to failure and mean time to repair. Operational outage assumptions are sourced from AEMO (2026).

The gross margin perceived by battery storage (where superscript S denotes storage) over the time interval $t \epsilon T$ is in a similar form to a generation unit. It is set out in equation (7), where the first term reflects the revenue opportunity associated with energy charge and discharge; the second and third terms reflect the energy revenues and costs associated with reserve utilization. For storage resources, we denote the net power dispatch $p^e_{t,\omega}$ as the difference between the total energy discharge and charge quantities ($p^g_{t,\omega} = p^d_{t,\omega} - p^c_{t,\omega}$). Over the time period T the total gross margin is set out in (A.9).

$$\widehat{\Phi}^S_\omega = \sum_{t \epsilon T} \hat{\boldsymbol{\lambda}}_{\boldsymbol{\omega}} \cdot \mathbf{p}_{\boldsymbol{\omega}} + k^+ \hat{\lambda}^e_{t,\omega} p^{r+}_{t,\omega} - k^- \hat{\lambda}^e_{t,\omega} p^{r-}_{t,\omega} \qquad \text{(A.9)}$$

Technical constraints for battery storage are in equations (A.10) – (A.15); assuming symmetry between power charge and power discharge capacity. Equations (A.10) – (A.11) apply power capacity limits to energy charge, discharge and reserve delivery (assuming symmetrical charge and discharge power capacity). State of charge (SoC) is defined in equation (A.12) and SoC limits are applied in equation (A.13). To reflect degradation, temporal cycling constraints are reflected in (A.14). An important issue relates to the saturation of shallow reserve markets under a price-taker model of unit scheduling. The saturation of reserve markets can be reflected in the constraint (A.15) which limits the maximum reserve dispatch to a specified proportion (ς^{r+} or ς^{r-}) of power capacity P .

$$p^d_{t,\omega} - p^c_{t,\omega} + p^{r+}_{t,\omega} \leq P \qquad \forall\, t \in T \ \text{(A.10)}$$

$$P \quad + p^d_{t,\omega} - p^c_{t,\omega} \leq p^{r-}_{t,\omega} \qquad \forall\, t \in T \ \text{(A.11)}$$

$$S_{t,\omega} = S_{t-1,\omega} + q^c p^c_{t,\omega} - p^d_{t,\omega}/q^d \qquad \forall\, t \in T \ \text{(A.12)}$$

$$S_{t,\omega} \leq eP \qquad \forall\, t \in T \ \text{(A.13)}$$

$$\sum_{t \epsilon d} (p^d_{t,\omega} + p^c_{t,\omega} + k^+ p^{r+}_{t,\omega} + k^- p^{r-}_{t,\omega}) \leq eP \qquad \forall\, d \in D \ \text{(A.14)}$$

$$p^{r+}_{t,\omega} \leq \varsigma^{r+} P \qquad p^{r-}_{t,\omega} \leq \varsigma^{r-} P \qquad \forall\, t \in T \ \text{(A.15)}$$

The basic formulation above only shows one raise reserve and one raise lower reserve service however the formulation extends naturally to incorporate multiple reserve and ancillary service markets. The NEM currently has 10 frequency ancillary service (FCAS) markets – regulation FCAS and four contingency FCAS services in time periods 1 second, 6 seconds, 60 seconds and 5 minutes, all in raise and lower directions. We model regulation raise and lower; and 6-second, 60-second and 5-minute raise and lower contingency markets. The 1 second raise and lower contingency market is not modelled due to a very short price history (i.e. being a relatively new market). The frequency regulation and contingency services in the NEM have different compatibilities as per the FCAS market specification. Participation in multiple contingency reserve markets are possible due to differing time segmentations between the services. The delivery of regulation FCAS is mutually exclusive with the delivery of contingency reserves. Granular constraints underpinning these requirements are set out in Appendix A.

GT or battery storage will seek to maximise short run surplus over time, taking the form of a tractable LP able to be solved to optimality.

Gas: $\max_{V_g} \widehat{\Phi}_{\omega}^{G}\ s.t.(2)-(6), \{V_g^{*}:=(p_{t,\omega}^{e}, p_{t,\omega}^{r+}, p_{t,\omega}^{r-}, u_{t,\omega}, s_{t,\omega})\}$ (A.16)

Storage: $\max_{V_s} \widehat{\Phi}_{\omega}^{S}\ s.t.(8)-(13), \{V_s^{*}:=(p_{t,\omega}^{d}, p_{t,\omega}^{c}, p_{t,\omega}^{r+}, p_{t,\omega}^{r-}, S_{t,\omega})\}$ (A.17)

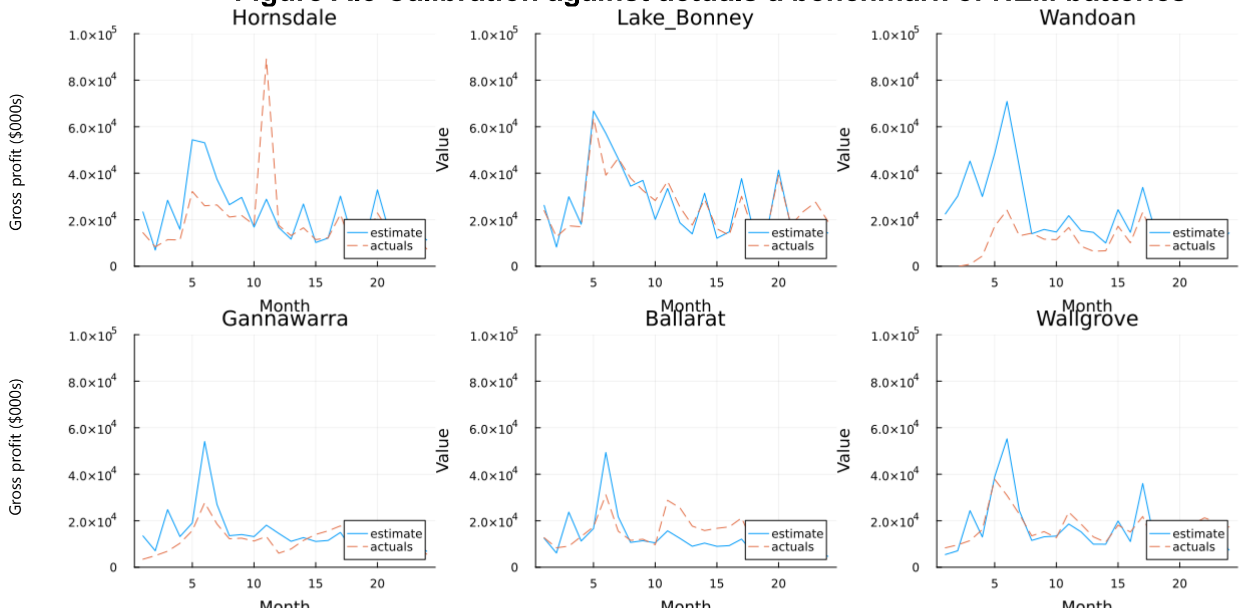
GTs and battery storage make operational decisions based an estimate of spot prices with the decision variables at optimality specified as V_s^{*} and V_g^{*}. The actual gross profits for each resource are based on actual outturn prices as per equations (A.18)-(A.19).

$\Phi_{\omega}^{\boldsymbol{G}} = \sum_{t\epsilon T} \boldsymbol{\lambda_{\omega}}.\mathbf{p_{\omega}} + k^{+}\lambda_{t,\omega}^{e}p_{t,\omega}^{R+} - k^{-}\lambda_{t,\omega}^{e}p_{t,\omega}^{R-} - c_{t,\omega}^{v}(p_{t,\omega}^{G} + k^{+}p_{t,\omega}^{R+} + k^{-}p_{t,\omega}^{R-}) - c^{st}s_{t,\omega} \mid V_g = V_g^{*}$ (A.18)

$\Phi_{\omega}^{\boldsymbol{S}} = \sum_{t\epsilon T} \boldsymbol{\lambda_{\omega}}.\mathbf{p_{\omega}} + k^{+}\lambda_{t,\omega}^{e}p_{t,\omega}^{R+} - k^{-}\lambda_{t,\omega}^{e}p_{t,\omega}^{R-} \mid V_s = V_s^{*}$ (A.19)

The approach was calibrated against the wholesale spot market results for a suite of batteries trading in the NEM for the 2022-2023 sample years (see also Billimoria and Simshauser, 2023). We caveat this given the limited set of battery projects operating consistently over the sample years. In addition, many of the early vintage battery projects were supported by centralized revenues from providing non-market system security services such as virtual inertia, voltage support, and system strength. The delivery of such services is likely to impact on the ability of units to participate in spot markets and thus will impact upon realized margin outcomes. The results show reasonable calibration against historical actuals. While deviations are apparent for certain months, this was considered a suitable approach for the directional guidance we seek to provide in this paper.

Figure A.3 Calibration against actuals a benchmark of NEM batteries



Scenario generation

We describe the module that generates stochastic scenarios from monthly outcomes under a range of base years. Using the unit commitment and contract payoff module described above, we model hypothetical GT and battery storage gross profits and contract payoffs for every month across base years 2018-2023, denoted as $\Phi_{\omega_{m,y}}$. That is, each time period $\omega_{m,y}$ represents a calendar month across the base years from 2018 to 2023; where $m \epsilon \{1..12\}, y \epsilon \{2018, \ldots, 2023\}$.

To create a larger suite of quarterly stochastic scenarios Φ_{ω_Q}, we draw samples uniformly from the relevant months across the base years. Our selection of a quarterly scenario periodicity reflects an alignment with credit covenants. We sample for 400 quarters (or 100 years of quarterly data) where $\omega_Q \epsilon \{1..400\}$. For each sample, the index $i = mod(\omega_Q, 4) + 1$ denotes the selection of relevant months for the sample as per equations (A.20)-(A.23). The quarterly scenarios once generated, then form the state variables of the optimal hedging decision problem.

$$if\ i = 1, \Phi_{\omega_Q} = \sum_{m=1}^{3} \Phi_{\omega_{m,x}}\ where\ x \leftarrow \text{Uniform}(2018, \ldots, 2023) \quad \text{(A.20)}$$

$$if\ i = 2, \Phi_{\omega_Q} = \sum_{m=4}^{6} \Phi_{\omega_{m,x}}\ where\ x \leftarrow \text{Uniform}(2018, \ldots, 2023) \quad \text{(A.21)}$$

$$if\ i = 3, \Phi_{\omega_Q} = \sum_{m=7}^{9} \Phi_{\omega_{m,x}}\ where\ x \leftarrow \text{Uniform}(2018, \ldots, 2023) \quad \text{(A.22)}$$

$$if\ i = 4, \Phi_{\omega_Q} = \sum_{m=9}^{12} \Phi_{\omega_{m,x}}\ where\ x \leftarrow \text{Uniform}(2018, \ldots, 2023) \quad \text{(A.23)}$$

Granular FCAS constraints for NEM simulation

The constraint formulation governing the delivery of multiple regulation and contingency services is set out below.

Consistent with NEM market design, we define a set of eight frequency control services r $\epsilon\, FR$ broken into regulation and contingency services. We denote these services based on the service category, between regulation services REG and contingency services C, and direction $+$ for up reserve and for $-$ for down reserve. Contingency markets are further classified by time period – 6 second (6), 60 second (60) and 5 minutes (5). For example, 60 second contingency down services are denoted as R^{C60-}, while the set of all contingency services are denoted as R^{C}. It is assumed that regulation and contingency services are mutually exclusive given that they both operate within a dispatch period, while contingency services are not mutually exclusive with each other.

$$p_t^d - p_t^c + p_t^{REG+} + p_t^r \leq P \quad \forall\, r \in \{R^{C+}\} \qquad \text{(A.24)}$$
$$P^r + p_t^d - p_t^c \leq p_t^{REG-} + p_t^r \quad \forall\, r \in \{R^{C-}\} \qquad \text{(A.25)}$$

Appendix B: Risk Constrained Optimization – Financing Model

Reformulation of max operator in cap-and-floor contract

The contract payoff for a net revenue cap-and-floor is defined as:

$$\Phi_\omega^C = v^{fl}\left[\max\left(\underline{S} - \varphi_\omega, 0\right)\right] - v^{cap}\left[\max\left(\varphi_\omega - \overline{S}, 0\right)\right] \forall\, \omega \in \Omega \qquad \text{(B.1)}$$

We provide a generalized formation to restate a max operator $a = \max(b, c)$ as a combination of mixed integer constraints. We define a dummy variable u, which indicates whether a or b and sufficiently small and large lower and upper bounds ($\underline{M}$ and $\overline{M}$) for variables a, b, c.

$$\underline{M} \leq a \leq \overline{M}; \underline{M} \leq b \leq \overline{M}; \underline{M} \leq c \leq \overline{M}; u \in \{0,1\} \qquad \text{(B.2)}$$

The max operator can be exactly reformulated as a combination of constraints as below:

$$a \geq b; a \geq c; a \leq b + \left(\overline{M} - \underline{M}\right)u;\ a \leq c + \left(\overline{M} - \underline{M}\right)(1-u) \qquad \text{(B.3)}$$

Financing constraints for risk constrained optimization

The financing constraints for the risk constraints have been specified as a combination of debt and equity constraints. Debt constraints are based on DSCR and gearing sizing metrics that are common in modern debt financings. Equity constraints are based on minimum and average return constraints.

$$\mathrm{VaR}_\alpha\left(\Pi_\omega^{CFADS}\right) \geq DSCR_\alpha\, D\rho \quad \forall\, \alpha \in \mathrm{A} \text{ (B.4)}$$
$$\textstyle\sum_{\omega\in\Omega} \Pi_\omega^{CFADS} \geq DSCR_{ave}|\Omega| D\rho \qquad \text{(B.5)}$$
$$D \leq (D + E)\overline{G} \qquad \text{(B.6)}$$
$$\mathrm{VaR}_\alpha\left(\Pi_\omega^{CFE}\right) \geq CFE_\alpha\, E \qquad \text{(B.7)}$$
$$\textstyle\sum_{\omega\in\Omega} \Pi_\omega^{CFE} = CFE_{ave}\, E \qquad \text{(B.8)}$$

We now set out the cashflow waterfall for the risk-constrained optimization, moving from the net margin to cashflows available for debt service and to equity.

$$\Pi_\omega^{EBITDA} = \widetilde{\Phi}_\omega - c^f P \qquad \text{(B.9)} \qquad \Pi_\omega^{CFADS} = \Pi_\omega^{EBITDA} - \Gamma_\omega \qquad \text{(B.10)}$$
$$\Pi_\omega^{CFE} = \Pi_\omega^{CFADS} - D.\rho \quad \text{(B.11)}$$

Constraints (B.9) to (B.11) define key financial flows in the cashflow waterfall. Earnings before Interest, Taxation, Depreciation and Amortization (EBITDA) Π_ω^{EBITDA} is defined as the sum of contract and spot market surplus minus fixed operating costs. In (B.10) CFADS $\Pi_\omega^{CFADS}$is defined as EBITDA minus taxation liabilities Γ_ω, while CFE Π_ω^{CFE} is the cashflows accessible to equity investors after accounting for fixed debt service payments, represented as the product of total debt and the annuity payment factor given the debt horizon and interest rate as set out in (B.11).

Taxation liabilities are calculated as a multiple of tax rate and EBITDA minus quarterly depreciation d_q with the depreciation schedule based on a flat rate on invested capital over the tax life of the asset.

$$\Gamma_\omega = \tau\left(\Pi_\omega^{EBITDA} - d_\omega - i_\omega\right) \qquad \text{(B.12)}$$

Debt service payments are based on a standard annuity mortgage repayment profile (B.13)-(B14).

$$\rho = r/1 - (1+r)^{-|\Omega|} \qquad \text{(B.13)} \quad i_\omega = \rho - p_\omega \qquad \text{(B.14)}$$

Constraint (B.15) ensures total invested capital is equivalent to the sum of debt D and equity E tranches.

$$c^I P \quad = D + E \quad \text{(B.15)}$$

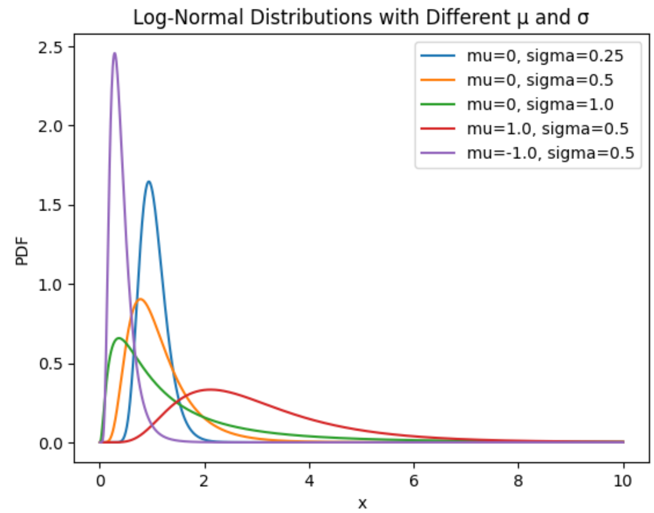
Appendix D: Price formation regime sensitivities

As highlighted in Section 5, the central results rely upon an exogenous determination of prices which are fed into our hedging model. To test the robustness of the fundamental results of the paper to changes in price formation we undertake in this section a set of sensitivities on alternative price formation regimes.

To undertake the sensitivity, distributions of gross profits of the 8-hour battery are fit to a log-normal distribution, consistent and representative of LDES market participation (Cambridge Energy Research

Associates, 2025). For a random variable x, two parameters describe a log-normal distribution. These are the mean μ and standard deviation σ, of the variable's natural logarithm ln(x). Changes to these parameters affect the symmetry and expected values of the resultant distribution.

Figure D.1: Probability distribution function of log-normal distribution with different parameters.



By adjusting the log-normal parameters and sampling from the distribution, we can proxy alternative price formation regimes. We undertake a set of sensitivities as below:

(i) the Asymmetric case models a regime with more asymmetric price formation for LDES but maintains the expected value of the samples of gross margin for LDES at levels consistent with the Base Case. This represents a regime where the patterns of returns for LDES change relative to the Base Case (more frequent periods of low margins, punctuated by less frequent periods of high margins) but the expected returns for LDES are unchanged.

(ii) the Asymmetric with high mean cases models asymmetric price formation but with a higher mean – this is representative of a regime where there is asymmetry in return distribution together with a higher expected value of returns over time. We model two scenarios where the rescaled mean is 1.3 and 1.5 times that of the Base Case. This would imply a higher revenue opportunity for LDES.

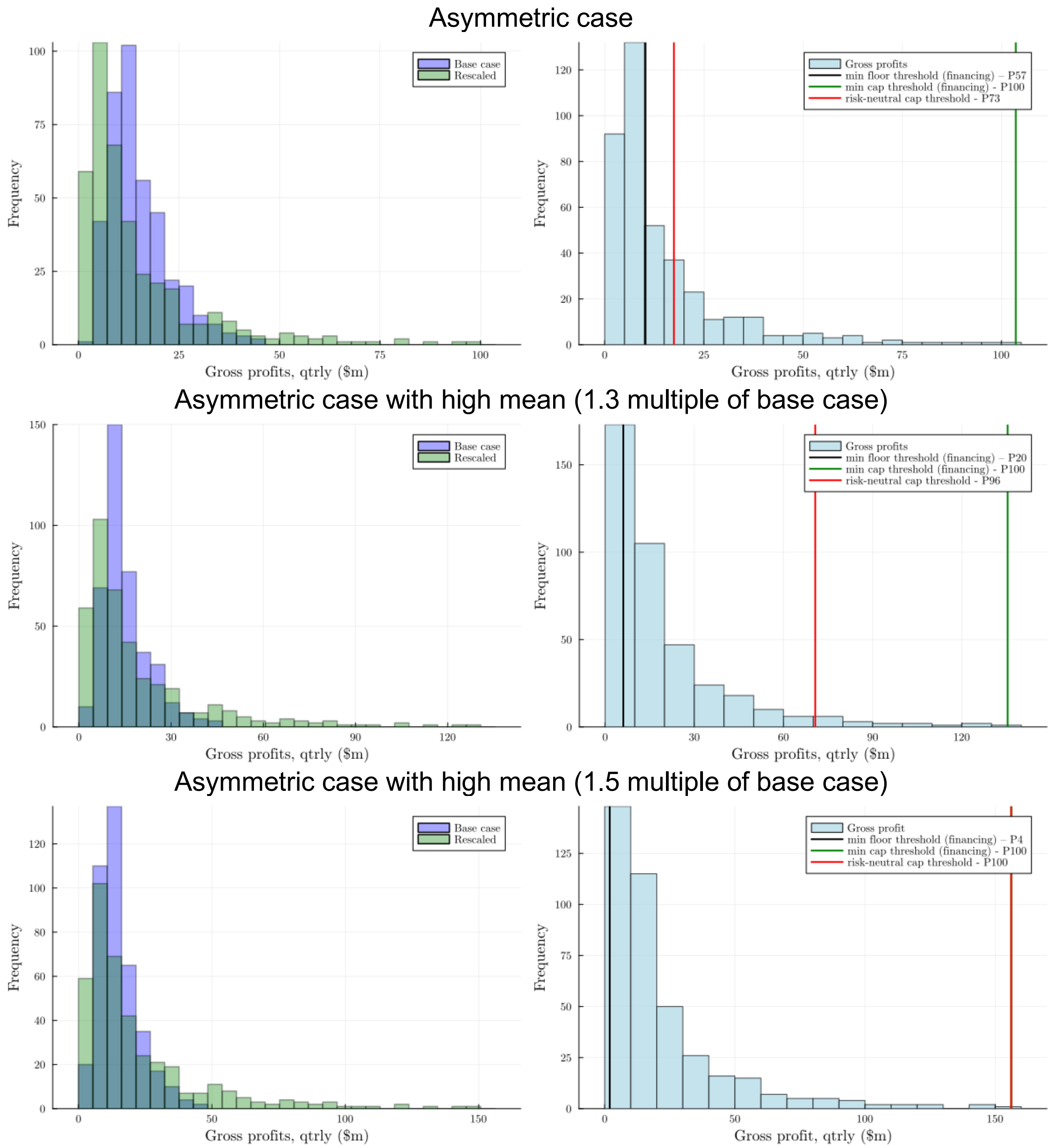
Table D.1: Price formation regime sensitivities for 8-hr storage – sample moments

Sample moments (000s)	Base case (sampled)	Asymmetric	Asymmetric with high mean	
			1.3 times base	1.5 times base
Mean	59.8	59.8	77.8	89.7
Std. Dev	30.6	65.7	85.9	99.0
Skewness	1.2	2.5	2.5	2.5
Kurtosis	1.5	7.2	7.2	7.7

The results are shown below in Figure D.2 for each of the three asymmetric cases. The left panels are a histogram of the rescaled cases relative to the base case. The right panels compare the floor and cap thresholds under the investor perspective (with financing constraints) against the cap threshold required for a fair risk-neutral valuation of the hedge. It demonstrates that paper's core results are quite robust to changes in price formation. The asymmetric case perpetuates and exacerbates the value transfer to investors - there remains a material differential between the cap thresholds required to meet financing requirements against that required for a risk neutral valuation. Indeed, the implied hedge valuation for investors amounts to ~$76 million. When asymmetric returns are also underpinned by higher expected storage margins the valuation gap reduces, though even with 30% higher expected gross profits, the effect persists and the implied valuation stands at ~$16m.

It is only when LDES expected gross profits are 50% higher than the base case that the cap thresholds for financing and fair value are near equivalent, reducing the implied valuation to ~ $0.5m.

Figure D.2 Price formation regime sensitivities for 8-hr 250MW BESS : Left panels - Histogram comparison between rescaled and base case Right panels– Floor/cap thresholds for investor financing and fair value comparison



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