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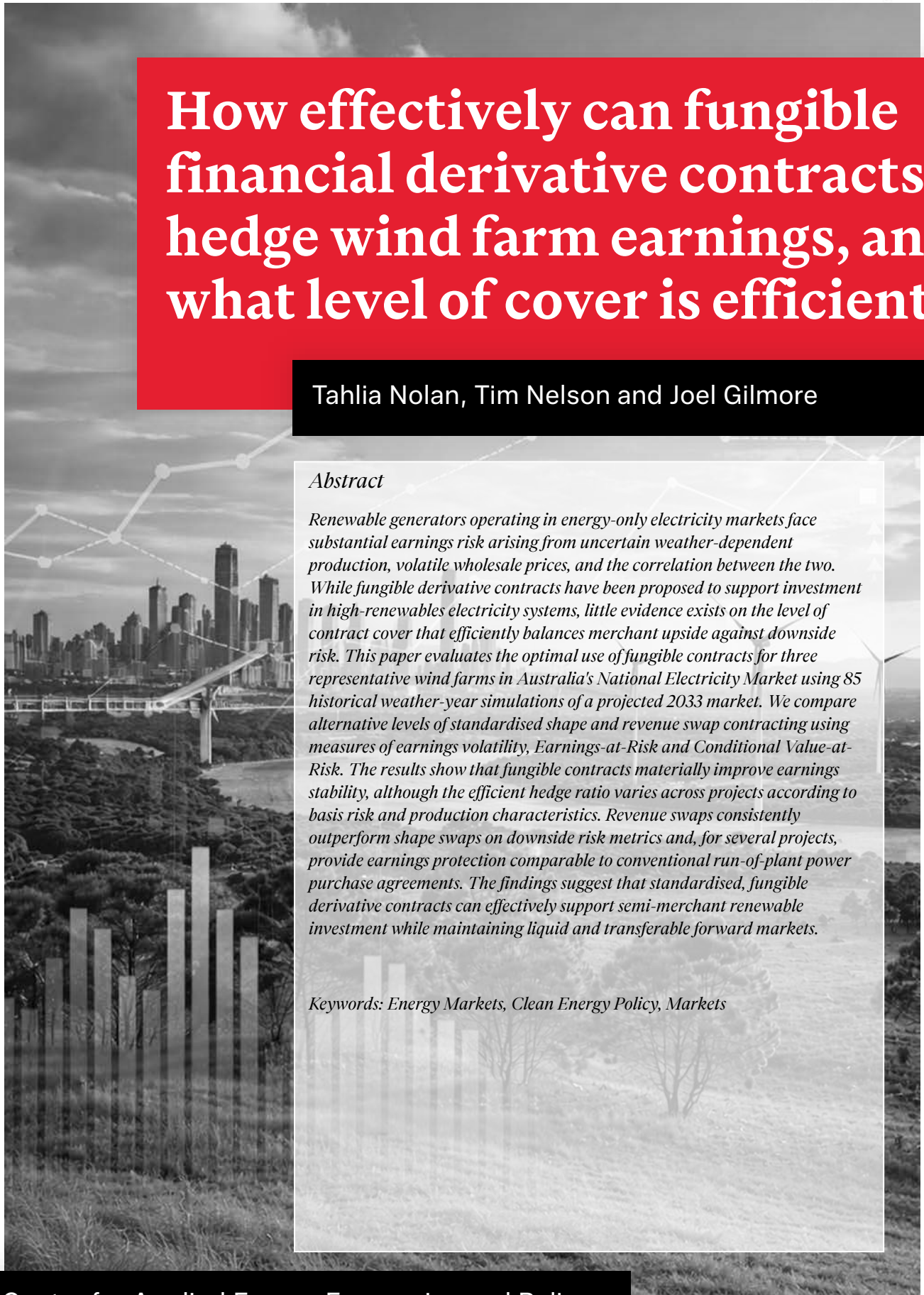

How effectively can fungible financial derivative contracts hedge wind farm earnings, and what level of cover is efficient?

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Abstract

Renewable generators operating in energy-only electricity markets face substantial earnings risk arising from uncertain weather-dependent production, volatile wholesale prices, and the correlation between the two. While fungible derivative contracts have been proposed to support investment in high-renewables electricity systems, little evidence exists on the level of contract cover that efficiently balances merchant upside against downside risk. This paper evaluates the optimal use of fungible contracts for three representative wind farms in Australia's National Electricity Market using 85 historical weather-year simulations of a projected 2033 market. We compare alternative levels of standardised shape and revenue swap contracting using measures of earnings volatility, Earnings-at-Risk and Conditional Value-at-Risk. The results show that fungible contracts materially improve earnings stability, although the efficient hedge ratio varies across projects according to basis risk and production characteristics. Revenue swaps consistently outperform shape swaps on downside risk metrics and, for several projects, provide earnings protection comparable to conventional run-of-plant power purchase agreements. The findings suggest that standardised, fungible derivative contracts can effectively support semi-merchant renewable investment while maintaining liquid and transferable forward markets.

Keywords: Energy Markets, Clean Energy Policy, Markets

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1 Introduction

Electricity markets utilising an energy-only, gross pool framework rely heavily on forward contracting. The forward market, operating through exchange-traded instruments, over-the-counter (OTC) derivative contracts and long-term bilateral Power Purchase Agreements (PPAs), is essential to the system's stability. Forward contracts synthesise future expectations of spot prices and allow risk to be managed. Derivative contracts provide the financial underpinning for new investment by securing predictable revenue streams, while also disciplining spot market behaviour by tying generator operational incentives to their contract exposures. For retailers, the availability of forward products is indispensable: it allows them to manage the volatility of wholesale prices and protect end-use customers from sudden cost shocks.

The transition from dispatchable thermal generation towards variable renewable energy (VRE) is, however, changing the nature of the risks that these forward markets must manage. In a thermal-dominated electricity system, uncertainty largely reflected variation in demand, fuel costs and unplanned plant outages. In a system increasingly supplied by wind and solar, both the quantity and market value of generation are weather dependent. Wind and solar generators face uncertain production volumes while simultaneously being exposed to wholesale prices that are increasingly correlated with renewable resource availability. High renewable output tends to suppress prices, while periods of low renewable availability can coincide with scarcity and high prices. The resulting interaction between volume and price risk makes the revenue of an uncontracted renewable generator particularly uncertain and increases the importance of effective mechanisms for transferring these risks.

Policymakers have increasingly responded to these investment risks through what can be characterised as hybrid electricity markets: investors first *compete for the market* through centrally administered auctions for long-term contracts, before subsequently *competing in the market* through participation in wholesale electricity markets (Joskow, 2022; Keppler et al., 2022). In Australia, the Capacity Investment Scheme (CIS) uses competitive tenders to award long-term revenue underwriting agreements to renewable generation. Similar arrangements have become central to European electricity policy. The United Kingdom has long allocated renewable Contracts for Difference (CfDs) through competitive auctions, while recent European Union electricity-market reforms require direct price support for new wind, solar and certain other low-carbon generation to take the form of two-way CfDs or equivalent arrangements.

While these hybrid arrangements can reduce the risks associated with financing new generation, they can also weaken the traditional relationship between the long-term investment market and the medium-term market for electricity derivatives. Historically, investment and risk management were linked through bilateral PPAs and forward contracting: parties seeking long-term revenue certainty ultimately transferred and managed those exposures through retailers, intermediaries and derivative markets. Government underwriting can instead allocate long-duration risk outside the commercial forward market. As the proportion of generation subject to bespoke government contracts increases, fewer long-term exposures may need to be intermediated through conventional derivative markets. This potentially reduces liquidity and price discovery precisely when the growing weather dependency of electricity supply makes effective risk transfer increasingly important.

The 2025 National Electricity Market (NEM) Review sought to address this problem by reconnecting the long-term investment, medium-term contracting and short-term spot markets (see Nelson et al., 2026, 2025). Rather than extending project-specific government underwriting indefinitely, the Review proposed an Electricity Services Entry Mechanism (ESEM) under which new investment in bulk energy, shaping and firming services could be supported through auctioning standardised and fungible financial contracts. These contracts would provide long-term revenue certainty where private contracting tenor is insufficient, but could subsequently be recycled into the forward market as their delivery period approaches. The objective is therefore not simply to underwrite investment, but to create long-dated contractual instruments capable of being held, traded and used for risk management by generators, retailers, intermediaries and large customers.

Whether such an approach is viable depends critically on the risk-management properties of the underlying contracts. A fungible contract based on regional renewable output cannot perfectly replicate a project-specific run-of-plant (RoP) PPA: individual wind farms differ in capacity factor, generation profile, captured price and correlation with the regional renewable index. Standardisation therefore creates basis risk. The relevant question is not whether an ESEM contract eliminates merchant risk, but whether it can reduce that risk sufficiently to provide earnings stability comparable with conventional project-specific contracting and, importantly, what level of contract cover provides the most efficient hedge.

This paper examines that question for three representative NSW wind farms using 85 historical weather-year simulations of a projected 2033 NEM. We compare merchant earnings with alternative levels of cover under two fungible ESEM contract structures, a shape swap and revenue swap, and a conventional RoP PPA. Rather than treating contracting solely as a binary question of project bankability, we treat the choice of contract cover as a portfolio optimisation problem, examining the trade-off between retained merchant exposure and earnings risk using volatility, Earnings-at-Risk (EaR), Conditional Value-

at-Risk (CVaR) and hedge-effectiveness measures. This allows us to identify both whether fungible contracts can replicate the risk-management properties of conventional PPAs and the contract quantities required to do so.

The remainder of the paper is structured as follows. Section 2 summarises the literature on contracting, risk allocation, and earnings stability in an energy-only market for wind farms. Section 3 details the methodology used to answer the central question of whether fungible contracts can replicate the risk-management properties of conventional PPAs and the contract quantities required to do so. Section 4 explores the results of the analysis with a discussion in Section 5 and a conclusion in Section 6. Further details on the model architecture can be found in the Appendix in Section 8.

2 Literature Review

Electricity market reform has increasingly produced hybrid market structures in which generators compete both *for the market*, through government auctions for CfDs and other mechanisms allocating long-term investment contracts, and subsequently *in the market*, through participation in wholesale electricity spot markets. Much of the associated literature has focused on whether long-term contracting arrangements provide sufficient revenue certainty to support investment, adequate project financing outcomes and appropriate capital structures. Less attention has been given to the intermediate layer of electricity market design: the forward and derivative markets through which existing generators, retailers and customers manage the financial risks created by exposure to short-term spot markets. This distinction is increasingly important as electricity systems have greater penetrations of weather-dependent generation. VRE introduces production risk that is correlated with wholesale prices, while long-term project-specific contracting can transfer these risks away from investors without necessarily creating liquid and transferable instruments through which risks can subsequently be reallocated among market participants. This section reviews these issues in three parts. Section 2.1 considers the traditional role of forward contracting in energy-only electricity markets. Section 2.2 examines the distinctive risks faced by VRE generators and the evolution of contracting structures to manage these risks, including project-specific PPAs and semi-merchant investment structures. Section 2.3 considers emerging proposals for standardised and fungible contracts, including those proposed through the ESEM, which seek to reconnect long-term investment support with medium-term risk management and short-term wholesale market participation. Emerging research about the bankability of these contract structures is presented with critical gaps identified that this article addresses.

2.1 Energy-only markets, forward contracting and risk allocation

Energy-only electricity markets have formed the architecture of wholesale electricity markets in many jurisdictions, including Australia, Texas and parts of Europe. Under this design, generators are remunerated for energy dispatched at prevailing spot prices rather than through both energy generated and a separate payment for installed capacity. In principle, periods of scarcity produce sufficiently high prices and scarcity infra-marginal rents to remunerate existing capacity and provide signals for new investment where required (Cramton, 2003; Hogan, 2005).

In practice, however, an energy-only market cannot be understood solely through the operation of spot markets. Spot electricity prices are highly volatile because supply and demand must be continuously balanced while both are subject to uncertainty arising from demand fluctuations, weather events, fuel prices and generator outages (Borenstein, 2002; Wolak, 2000) . Generators therefore face substantial uncertainty over future revenues. Investment intractability due to uncertainty can be compounded where price caps, regulatory intervention or political constraints restrict the scarcity prices required to recover fixed costs, contributing to the so-called 'missing money' problem (Hogan, 2013; Joskow, 2008). Conversely, retailers and electricity consumers are exposed to the possibility of sustained high or extreme spot prices, which can rapidly erode retail margins and threaten financial viability. The consequences of inadequate hedging were particularly evident during the 2021 Texas electricity crisis, when extreme wholesale prices contributed to retailer failures (Joskow, 2021).

Forward contracting provides the principal mechanism through which these risks are reallocated. Electricity contracts may include exchange-traded futures and options, bilateral OTC derivatives, and longer-term PPAs. Although their structures differ, these instruments allow uncertain future spot-market revenues and costs to be transformed into financial obligations more consistent with participant risk preferences. For generators, contracting provides more predictable revenues and can support the financing of capital-intensive generation investments (Bunn and Yusupov, 2015; Newbery, 1998). This function is particularly important for renewable generators characterised by high upfront capital costs and comparatively low operating costs, for which long-term revenue certainty can materially affect financing costs and investment viability (Pollitt and Anaya, 2016). PPAs and related contracting structures have consequently played an important role in supporting VRE entry and managing financial risks arising as a result of decarbonisation policies (Hollmén et al., 2022; Hundt et al., 2021).

The same contracts perform the opposite risk-management function for retailers and large customers. Retailers typically sell electricity to customers at prices that cannot instantaneously adjust to wholesale spot prices. Forward purchases therefore transform uncertain wholesale acquisition costs into more predictable costs and allow retailers to offer customers relatively

stable retail prices. Contracting consequently supports both retailer financial viability and consumer protection from wholesale market volatility (Bushnell, 2007). Viewed in this way, the forward market links the risk preferences of generators seeking revenue certainty with retailers and customers seeking expenditure certainty.

Forward contracts also influence behaviour within the spot market itself. The incentive of a generator to exercise market power depends partly on its contractual position. A generator with substantial uncontracted exposure may benefit from higher spot prices, whereas a heavily contracted generator receives less benefit from increasing the spot price and may instead have strong incentives to maximise physical output against its contractual position. Theoretical and empirical literature has therefore identified forward contracting as an important mechanism for moderating strategic bidding and non-transient market power (Allaz and Vila, 1993; Wolak, 2007, 2003). In this sense, forward contracting does more than transfer financial risk: it creates a linkage between participants' financial positions and their incentives in the physical spot market.

Despite this systemic importance, contract markets have received considerably less academic attention than electricity spot markets. There is an extensive literature examining spot-market design, price formation and strategic bidding (Borenstein, 2002; Green and Newbery, 1992; Wolak, 2000), but a comparatively smaller literature examining forward-market liquidity, price discovery and the interaction between contract and spot markets (Bunn and Yusupov, 2015). OTC markets are particularly difficult to examine empirically because bilateral transactions are often opaque. Similarly, while the role of contracting in supporting investment during the energy transition has received increasing attention (Biegler-König et al., 2022; Schlecht et al., 2024), the implications of emerging contract forms, including corporate PPAs, environmental attributes and hybrid financial instruments, for the broader functioning of forward markets remain comparatively underexplored.

The central implication of this literature is that forward contracting is not ancillary to an energy-only market. The short-term spot market establishes the marginal value of electricity, but forward markets allow the resulting risks to be distributed across time and between participants. They transform volatile spot-market revenues into financeable generator cashflows and volatile wholesale costs into manageable retailer and customer exposures. Effective energy-only market design therefore depends upon the relationship between the short-term physical market and the medium- and long-term markets through which participants manage risk.

2.2 VRE risk, project-specific PPAs and semi-merchant generation

The transition from dispatchable thermal generation to wind and solar generation changes the nature of the risks that must be managed by financial derivative contracts. Wind generators operating in an energy-only electricity market face three interrelated sources of revenue uncertainty: production or volumetric risk arising from the stochastic availability of the wind resource itself; wholesale price risk; and the systematic relationship between production and wholesale prices (i.e. if its windy, prices tend to be lower due to excess supply). These characteristics distinguish wind generation from conventional dispatchable generation and complicate the design of an effective financial hedge that is separable from the physical asset itself.

Wind production varies across hours, seasons and years according to prevailing meteorological conditions (Gilmore et al., 2025). A wind generation business cannot know in advance precisely how much electricity will be available for sale. At the same time, the revenue earned from this uncertain production depends upon the wholesale price prevailing at the time electricity is generated. Wholesale electricity prices are themselves volatile and, in systems with increasing VRE penetration, progressively influenced by weather-dependent supply conditions (Nelson, 2026). The financial exposure of a wind project therefore reflects the interaction of uncertain quantity and uncertain price rather than either risk independently.

Importantly, these two risks are systematically related. At times of higher winds or solar irradiation, there is an increase in low-marginal-cost electricity supply which tends to suppress wholesale prices, while periods of low renewable availability can contribute to tighter supply conditions and substantially higher prices. The resulting decline in the captured price of renewable generation as penetration increases, the cannibalisation effect, has been widely identified for both wind and solar generation (Das et al., 2020; Dillig et al., 2016; López Prol et al., 2020; Reichenberg et al., 2023; Woo et al., 2011). Consequently, correlated VRE produces its greatest physical volumes precisely when electricity is least valuable, while being less able to take advantage of high-price scarcity periods when its output is low. Reichenberg et al. (2023) frame the policy response to this problem in terms of either increasing the cost of carbon-intensive generation or reducing the market risks borne by VRE investors.

The conventional response to these risks in the Australian National Electricity Market (NEM) has been the project-specific run-of-plant (RoP) PPA. Historically, utility-scale renewable projects were commonly developed with close to full revenue contracting against forecast generation through a long-term PPA with an investment-grade counterparty. Because the contracted volume is linked directly to the physical output of the individual asset, the RoP PPA transfers a substantial proportion of both electricity price risk and the associated revenue uncertainty from the project to the offtaker. This revenue certainty supported project-finance structures with substantial debt gearing and became an important component of renewable project bankability.

Gohdes et al. (2022) demonstrate the importance of the contractual counterparty to this financing model. Higher PPA counterparty credit quality can support greater project gearing, lower required equity returns and a lower overall cost of capital because revenue risk is effectively repackaged and transferred from project equity to the PPA offtaker. This helps explain why near-full contracting became closely associated with bankable renewable project finance during the earlier stages of renewable investment in the NEM.

Declining wind and solar generation costs have, however, changed this investment thematic and with the emergence of semi-merchant renewable projects blending contracted revenues with direct exposure to volatile wholesale spot markets. Simshauser (2020) identifies this development in South Australia, examining merchant wind generation alongside peaking gas capacity and demonstrating that mixed portfolios containing intermittent generation can produce tractable cashflows and support some fixed-volume forward contracting. More broadly, increasing renewable penetration creates market interactions that are particularly relevant for projects retaining merchant exposure. Nelson et al. (2024) for example, show how embedded household solar PV exports that are not required to participate dynamically in the wholesale market can increase supply and enable vertically integrated renewable firms to drive wholesale prices lower, potentially stranding the output of RoP PPA contract-for-difference generators with a $0/MWh price floor. Such effects directly influence captured prices and therefore the expected revenues of PPA contracted and semi-merchant generators.

Gohdes et al. (2023), using stochastic project-finance modelling for the NEM, find that wind projects with 60–65% debt can remain viable with PPA coverage of approximately 73–78%, implying merchant exposure of 22–27%. Comparable analysis for utility-scale solar identifies tractable structures with approximately 70–80% PPA coverage and 20–30% merchant exposure while maintaining gearing of approximately 60–70% (Gohdes, 2023). These studies suggest an equilibrium in which contracting is sufficient to satisfy project-finance constraints without unnecessarily surrendering merchant upside.

Extending the stochastic analysis across alternative levels of PPA coverage, Gohdes (2025) finds that contracting above approximately 80% can transfer returns to the PPA counterparty without adding corresponding value to project equity. The relationship between contracting and default risk is also non-linear: some semi-merchant structures can support debt levels comparable with fully contracted projects without materially increasing financial distress. The implication is that full contracting should not automatically be treated as the optimal financial structure simply because it minimises revenue volatility.

This insight connects the renewable project-finance literature with a broader portfolio and hedging literature. Optimal contracting can instead be understood as a choice between expected merchant returns and alternative dimensions of earnings risk. For example, Nordtveit et al. (2013) used a copula-based Monte Carlo framework to model the relationship between wind production and prices and evaluated optimal hedge ratios using variance, hedge effectiveness, cash-flow-at-risk and conditional cash-flow-at-risk. Across these measures, the estimated optimal hedge ratio lies between approximately 35% and 60% of expected production. Related work on optimal trading strategies for wind producers similarly demonstrates that preferred contracting and trading positions depend upon the producer's degree of risk aversion (Papakonstantinou et al., 2019).

This literature also highlights the importance of the risk measure used to assess contracting. Conventional mean-variance approaches measure overall earnings volatility but penalise positive and negative deviations from expected earnings symmetrically (Gabrielli et al., 2022; Nordtveit et al., 2013). This is potentially problematic in electricity markets, where earnings distributions may be highly asymmetric and investors can be particularly concerned with low-probability downside outcomes. Conditional Value-at-Risk (CVaR) has therefore been widely applied to electricity-market and portfolio optimisation problems because it measures outcomes within the lower tail of the distribution rather than merely identifying a percentile threshold (Kraft et al., 2021; Krokhmal and Palmquist, 2002; Ralston et al., 2010; Thatte et al., 2013).

Even so, Value-at-Risk and related tail measures provide only a partial representation of risk and may be sensitive to the particular tail and timeframe examined. Billimoria et al. (2025) therefore emphasise the value of considering multiple measures of risk rather than relying on a single tail statistic. Assessing contract cover using measures of overall earnings volatility alongside Earnings-at-Risk (EaR) and CVaR can consequently provide a richer representation of the trade-off faced by a semi-merchant generator.

There has been an important shift from treating renewable contracting as a binary distinction between a bankable contracted project and an unbankable merchant project. Contract coverage can instead be treated as a continuous portfolio choice. Nevertheless, most of the NEM literature continues to evaluate that choice using project-specific PPAs (not tradeable derivative contracts) and primarily through the financing constraints imposed by project debt. Less attention has been given to the optimal level of contracting where the hedge is a standardised derivative referenced to a broader market index rather than the physical production of the individual asset. This distinction becomes important if electricity markets seek to retain the risk-management benefits of contracting while moving away from bespoke project-specific contracts.

2.3 Fungible contracts and reconnecting investment with electricity risk markets

The distinction between project-specific and standardised contracting has become increasingly important as governments have assumed a greater role in supporting electricity-sector investment. When investment support is provided through bespoke contracts tied to individual assets, the resulting financial exposures are not necessarily transferable between market participants. The mechanism to provide investment certainty can therefore solve the immediate problem of project bankability but weakens the medium-term derivative markets through which generators, retailers and customers subsequently manage electricity-market risk.

This issue is particularly relevant to the NEM as the market transitions towards weather-dependent generation. The 2025 National Electricity Market Review conceptualised the market across three interrelated horizons: the short-term spot market, the medium-term derivatives market and the long-term investment market (Nelson et al., 2026). Rather than identifying the regional energy-only gross pool itself as the principal impediment to investment, the Review argued that the commercial and institutional linkages between these horizons had weakened as the electricity system became more weather dependent, less dispatchable and increasingly influenced by distributed and price-responsive resources.

The Review recommended development of standardised derivative products corresponding to three electricity services required in a renewables-dominated power system: bulk energy, shaping and firming. These products would be developed through an industry-led co-design process and supported, where necessary, by a permanent Market Making Obligation intended to strengthen forward-market liquidity. The underlying proposition is that conventional baseload swaps and caps evolved around a thermal electricity system in which dispatchable generation responded to variable demand, whereas a weather-dependent system requires financial instruments capable of allocating a different combination of price, volume and shape risks.

At the longer investment horizon, the Review proposes a long-term contracting mechanism (the Electricity Services Entry Mechanism: ESEM) which would utilise the derivative contracts selected by the industry co-design group noted above. Under the proposed framework, new providers of bulk energy, shaping and firming services would compete for standardised, tradeable financial contracts (competition *for the market)*. As the timeframe for energy delivery approaches, contracts would progressively be recycled into the market. The intended effect is therefore materially different from a conventional project-specific government PPA: public intervention would initially facilitate long-duration contracting, but the resulting exposures would be represented by instruments capable of subsequently being traded and held by private market participants.

The concept of fungibility is central to this design. A project-specific RoP PPA can provide a highly effective hedge because payments are directly linked to the output of the individual generator. However, that specificity also limits the extent to which the contract represents a standard electricity-market exposure capable of being readily transferred to another participant. A standardised derivative based upon a regional generation index necessarily introduces basis risk because the output profile, capacity factor and captured price of an individual generator will not perfectly correspond with those of the index. In exchange, standardisation potentially creates a fungible instrument capable of being traded across generators, retailers, customers and financial intermediaries, strengthening liquidity and price discovery in the broader forward market.

This trade-off between project-specific hedge effectiveness and market-wide fungibility is not yet well resolved in the literature. Recent work on alternative contract design in the NEM has examined whether fungible derivative structures can generate cashflows consistent with project bankability and has found that standardised contracts need not be inferior to traditional RoP PPAs in terms of revenue quality (Gohdes et al., 2026).

However, bankability is only one test of contract performance. For a generator deciding how much merchant exposure to retain, the relevant question is also how effectively the contract hedges the distribution of project earnings for a project at different contract levels. A regional-index contract may be financeable while nevertheless leaving significant residual basis risk for particular projects. Conversely, a standardised contract need not perfectly replicate project output to provide an economically effective hedge. Its performance depends upon the covariance between project merchant earnings and contract payments, the relative volatility of those exposures, and differences between the project's production profile and captured price and those represented by the underlying index.

This leaves an important gap between the renewable project-finance literature and the emerging literature on fungible electricity contracting. Existing semi-merchant studies primarily ask how much project-specific PPA coverage is required to satisfy financing constraints and preserve investor returns. Emerging ESEM research asks whether standardised contracts can support bankable cashflows. Neither establishes how effectively a fungible derivative can hedge the annual earnings of heterogeneous individual wind farms, how hedge effectiveness changes with the quantity of contract cover, or whether the efficient level of cover differs according to the investor's preferred measure of risk.

This paper addresses that gap by treating fungible contracting as a portfolio optimisation problem. Rather than imposing a predetermined level of contract coverage or defining efficiency solely through a project-finance constraint, it examines the full distribution of annual earnings as contract cover changes. Alternative contract positions are evaluated using overall earnings volatility, Earnings-at-Risk, Conditional Value-at-Risk and hedge-effectiveness measures. The analysis therefore tests two related propositions arising from the literature: whether a standardised and fungible ESEM derivatives contract can provide earnings protection comparable with a project-specific RoP PPA, and what level of contract cover most efficiently balances retained merchant exposure against earnings risk for individual wind projects.

3 Methodology

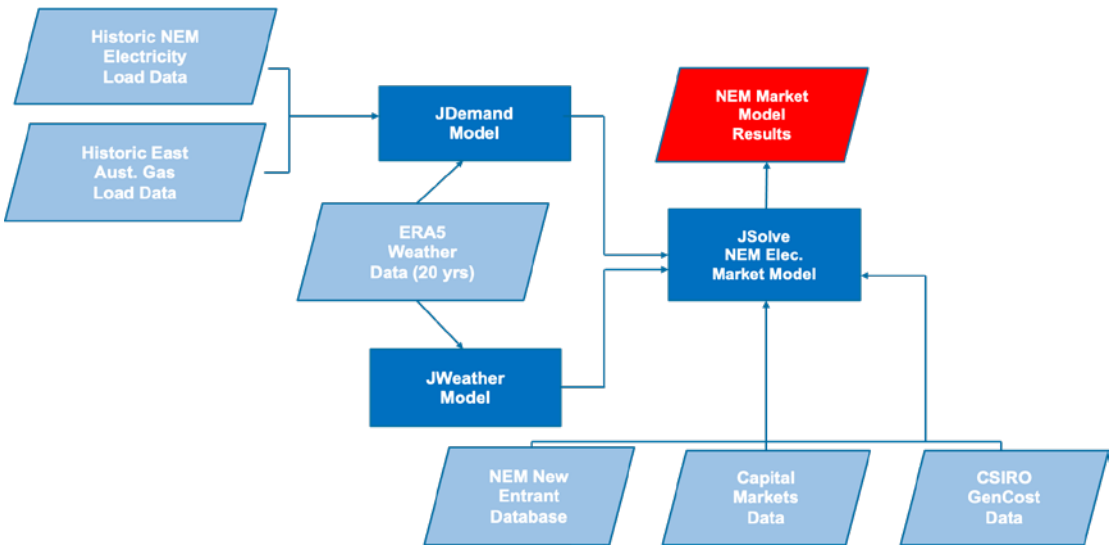
3.1 Overview

The analysis is in four stages. The first constructs the market environment. An 85-iteration set of the New South Wales (NSW) electricity market in 2033 is simulated, with each iteration drawing a different historical weather year. The second stage specifies the contracts. Three financial contracts are defined: two fungible instruments settled against a NSW regional wind index (a shape swap and a revenue swap) which are contemplated under the ESEM, and a project specific RoP PPA representing conventional practice. All three contracts are struck at fair value over the set, so that each has zero expected payoff over the 85 iterations. The third stage sweeps contract cover. For each project and contract structure, hedged earnings are evaluated at 31 levels of contract cover between zero and 150% of project nameplate capacity, producing a distribution of annual earnings across 85 iterations. The final stage evaluates those distributions using measures of total earnings volatility, downside risk and hedge effectiveness, and the level of cover that maximises each risk adjusted measure is identified. Section 3.2 describes the dataset and the simulated market. Section 3.3 sets out contract specifications and Section 3.4 the contract sweep. Section 3.5 defines the risk measures and Section 3.6 sets out the limitations.

3.2 Dataset and simulated market

The analysis draws on two hourly datasets produced by the JSolve energy market modelling system (1) a long-historical record of capacity factor traces for individual NEM wind generators spanning 1941–2025, and (2) an hourly dispatch simulation of the 2033 NEM that produces regional spot prices and aggregate wind output for each iteration. JSolve combines capacity-expansion planning with detailed market dispatch. Its modelling logic and joint treatment of weather-dependent supply and demand are documented in Simshauser and Gilmore (2026) and below in Section 8. Figure 1 outlines the model logic. At a high level, historical weather reanalysis datasets are used to train hourly demand (JDemand) and renewable trace (JWeather) forecasting models, which are used to develop 85 years of historical renewable traces. Unit cost data is sourced from the CSIRO GenCost report that provides projections of technology costs. Finally, the JSolve partial equilibrium dispatch model solves for the least-cost capacity expansion plan to satisfy reliability constraints in response to coal closures and load growth. Note that partial equilibrium linear programming models typically underestimate volatility in the NEM's high price cap marginal price setter market. A final pass incorporates volatility by withholding some unit capacity to prices above each unit's marginal running cost, consistent with historically observed market bidding behaviour. Section 8 (Appendix) provides more details on the model logic.

Figure 1: Overview of the JSolve modelling framework and key data inputs



The 2033 reference year was selected as a likely year in which an ESEM contract will be operational for bulk energy. By 2033 the NEM is projected to have undergone significant structural change relative to current conditions, including over six gigawatts of coal-fired generator retirements, nine gigawatts of large-scale VRE expansion and electrification-driven demand growth. Table 1 summarises the generator-capacity assumptions in NSW underpinning the 2033 dispatch case. These structural shifts amplify both the volume and the price risk faced by weather-dependent generators, motivating the forward-looking choice of pricing year over a backward-looking historical pricing base.

Table 1: Simulated NSW installed capacity

	Wind MW	Solar MW	Coal MW	Battery MW	Battery MWh	Hydro MW	PHES MW	PHES MWh	Gas MW
NSW	9,402	7,914	2,353	4,432	11,143	2,592	2,200	220,000	3,303

The 2033 market is simulated across *M* = 85 iterations, each iteration drawing a different historical weather year (1941–2025) from the weather reanalysis dataset. The selected weather year jointly drives (i) the hourly capacity-factor trace at each wind generator location, and (ii) the hourly demand profile fed to the dispatch model, with all other assumptions generator capacity mix, fuel costs, network topology, and policy settings held constant at the 2033 reference case. Each iteration therefore yields an internally consistent hourly time series of regional spot prices, regional aggregate wind output, and unit-level wind capacity factors under one possible weather realisation of the 2033 market. Pairing supply and demand drivers through a common weather year preserves the empirical correlation between wind resource availability and electricity demand that underpins merchant-captured prices and is the central source of the volume–price-risk interaction this paper analyses.

Three representative wind projects from the NSW region are selected for the contracting analysis: Project 1 — Cobar North, Project 2 — Bodangora, and Project 3 — Crookwell 2). The selection spans existing operational assets and a candidate REZ project, and covers a range of annual capacity factors, intra-day generation shapes, and correlations with the NSW regional wind aggregate. This allows the methodology to be exercised against projects with different levels of basis risk relative to the ESEM contract.

3.3 Contract specifications

Each contract is modelled as a financial swap between the project and counterparty. The project's merchant revenue is unchanged by the swap. The hedge PnL adds to (or subtracts from) merchant revenue to give hedged earnings.

The following notation in Table 2 is used throughout. Subscript *y* indexes weather-year iteration (*y* = 1, …, 85), subscript *h* indexes hour within an iteration.

Table 2: Notation and variable definitions used in the contract modelling

Symbol	Meaning	Units
N	Project nameplate capacity – held at 100 MW for cross project comparability	MW
q	Contract fraction - 1 = contracted capacity equals project nameplate	dimensionless
Δt	Length of settlement interval	hours
$CF_{unit,y,h}$	Project capacity factor in hour (*y,h*)	dimensionless
$CF_{index,y,h}$	Regional wind index capacity factor in hour (*y,h*)	dimensionless
$spot_{y,h}$	Regional spot price in hour (*y,h*)	$/MWh
K	Contract strike (varies by contract, specified below)	See below

The regional wind index capacity factor is $CF_{index,y,h} = \frac{MW_{index,y,h}}{N_{index}}$, where $MW_{index,y,h}$ is the total regional wind sent-out generation and N_{index} is total installed wind capacity.
The project's merchant revenue (eq. (1)) in a given hour is:

$$R_{y,h}^{merchant} = CF_{unit,y,h} \times N \times spot_{y,h} \times \Delta t \quad (1)$$

And its hedged earnings under any contract are (eq.(2)):

$$R_{y,h}(q,K) = R_{y,h}^{merchant} + HedgePnL_{y,h}(q,K) \quad (2)$$

The three contract specifications differ only in the form of $HedgePnL_{y,h}(q,K)$ and the fair-value strike *K*.

3.3.1 Shape swap

The shape swap shown in eq. (3) settles per MWh of the regional wind index's generation, at the strike price K^{shape} ($/MWh) and the settlement volume tracks the reference:

$$HedgePnL_{y,h}^{shape}(q,K^{shape}) = q \times N \times CF_{index,y,h} \times \Delta t \times (K^{shape} - spot_{y,h}) \quad (3)$$

The strike K^{shape} is set to the volume-weighted captured price of the regional wind index *pooled across all 85 wind-year iterations and all hours within each iteration* (eq. (4))

$$K^{shape} = \frac{\sum_{y=1}^{85}\sum_h CF_{index,y,h} \times spot_{y,h}}{\sum_{y=1}^{85}\sum_h CF_{index,y,h}} \quad (4)$$

where the inner sum runs over all hours *h* in wind-year iteration *y*. This is the unique value satisfying E[HedgePnL | q] = 0 across the full ensemble by construction, equivalent to striking the contract at the long-run wind-volume-weighted price expected over the ensemble of historical wind years. It isolates risk-reduction effects from any first-moment mispricing and ensures the contract is fair *ex ante* under the ensemble's empirical distribution.

3.3.2 Revenue swap

The revenue swap shown in eq. (5) settles per MW of contracted capacity, at strike price K^{rev} ($/MW/hour). The fixed leg is a constant payment per period; the floating leg equals the regional wind index's revenue per MW.

$$HedgePnL_{y,h}^{rev}(q,K^{rev}) = q \times N \times \Delta t \times (K^{rev} - CF_{index,y,h} \times spot_{y,h}) \quad (5)$$

The floating leg $CF_{index,y,h} \times spot_{y,h}$ is the regional wind index's realised revenue per MW of installed capacity in hour (*y*, *h*). Multiplying by $q \times N$ scales to the contracted capacity. Under fair-value pricing, shown in eq. (6):

$$K^{rev} = \frac{1}{N_y N_h}\sum_{y=1}^{85}\sum_h CF_{index,y,h} \times spot_{y,h} \quad (6)$$

This is the unique value satisfying E[HedgePnL | q] = 0 across the full ensemble by construction.

3.3.3 Run-of-Plant PPA

The RoP PPA shown in eq. (7) is modelled as a financial CfD in which the project sells its output at a fixed strike price per MWh. The settlement volume is the project's own generation.

$$HedgePnL_{y,h}^{RoP}(q,K^{RoP}) = q \times CF_{unit,y,h} \times N \times \Delta t \times (K^{RoP} - spot_{y,h}) \quad (7)$$

Unlike the shape and revenue swaps, the settlement volume tracks the project's own capacity factor rather than the regional index. Under fair-value pricing (eq. (8)):

$$K^{RoP} = \frac{\sum_{y=1}^{85}\sum_h CF_{unit,y,h} \times spot_{y,h}}{\sum_{y=1}^{85}\sum_h CF_{unit,y,h}} \quad (8)$$

The RoP PPA strike is project-specific. This distinguishes the RoP PPA from the fungible contract structures, whose strikes are region-specific and shared across all projects contracting under them.

3.4 Contract mix sweep

Because hedge PnL is linear in *q*, portfolio revenue at any *q* can be reconstructed in a single multiply-and-add from strike-independent precomputed components (the corresponding floating leg per hour). The sweep evaluates 31 contract levels (*q* = 0, 5%, …, 150% of nameplate); for each level we aggregate hourly portfolio cashflow to annual earnings per iteration, producing an empirical distribution of 85 annual outcomes per (project, *q*) pair.

3.5 Risk metrics

For each combination of project, contract structure, and contract fraction *q*, the model produces a distribution of 85 annual earnings outcomes, one per weather year iteration.

This is represented as set $\{R_1, R_2, \dots, R_M\}$ with *M* = 85. From this distribution we compute the statistics described below to characterise both the level of earnings and the risk around that level.

The mean (μ) and the standard deviation (σ) summarise the expected level of earnings and the total volatility around it. The percentiles P_α at $\alpha \in \{5\%, 10\%, 50\%, 90\%, 95\%\}$. For example, P_5 is the fifth-percentile annual earnings, the outcome at which the worst 5% of weather years fall. P_{50} is the median.

The standard deviation treats good and bad years symmetrically. Because wind projects are more sensitive to downside outcomes (a bad year threatens debt service), two measures are computed that focus specifically on the lower tail of the distribution.

Conditional Value at Risk ($CVaR_{5\%}$) is the mean earnings across the iterations sitting below or at the 5th percentile (eq. (9)):

$$CVaR_{5\%} = \frac{1}{|\tau_5|} \sum_{y \in \tau_5} R_y \ where\ \tau_5 = \{y: R_y \le P_5\} \tag{9}$$

Earnings at Risk (EaR) measures the drop from a typical year (the median) to a bad year (the fifth percentile) (eq. (10)):

$$EaR = P_{50} - P_5 \tag{10}$$

Risk-adjusted ratios are used to find the effective contracting level for each project. Higher values indicate more efficient risk-adjusted returns. The risk-adjusted ratios used in the analysis are the Sharpe-like ratio (eq. (11)), CVaR-adjusted (eq. (12)) and EaR adjusted (eq. (13)):

$$Sharpe\ like\ ratio = \frac{\mu}{\sigma} \tag{11}$$

$$CVaR - adjusted = \frac{\mu}{\mu - CVaR_{5\%}} \tag{12}$$

$$EaR - adjusted = \frac{\mu}{EaR} \tag{13}$$

Two further metrics quantify how much of the merchant variability is eliminated by the contract, by comparing the hedged earnings (R^{hedged}) against the unhedged merchant baseline ($R^{merchant}$). The ratios used to assess this are the Hedge Effectiveness Ratio (*HER*), shown in eq. (14) and the Downside Variance Reduction (*DVR*), shown in eq. (15). A *HER* of 100% means the contract has completely eliminated year-to-year variability in earnings, a *HER* of 0% means the contract has done nothing to reduce variance and a negative value means the contract has introduced more variance to earnings.

$$HER = 1 - \frac{Var(R^{hedged})}{Var(R^{merchant})} \tag{14}$$

DVR focuses on the below mean variance:

$$DVR = 1 - \frac{LPM_2(R^{hedged})}{LPM_2(R^{merchant})} \tag{15}$$

where the "lower partial moment" $LPM_2(R)$ measures downside variance only (eq. (16)):

$$LPM_2(R) = \frac{1}{N_y} \sum_{y=1}^{N_y} \max(0, \mu - R_y)^2 \tag{16}$$

The contract level q^* at minimising variance is derived analytically and verified against the empirical minimum identified in the sweep (eq. (17)). This is the standard minimum-variance hedge ratio (Ederington, 1979). There is no closed-form solution for the values of q that maximise CVaR adjusted or EaR-adjusted ratios, because these functions are not differentiable at the tail-defining quantile. These optima are identified by grid search across q = 0, 5%, …, 150%, and their location confirmed by inspection of the objective maximum.

$$q^* = \frac{-Cov(R^{merchant}, HedgePnL^{q=1})}{Var(HedgePnL^{q=1})} \quad (17)$$

3.6 Limitations

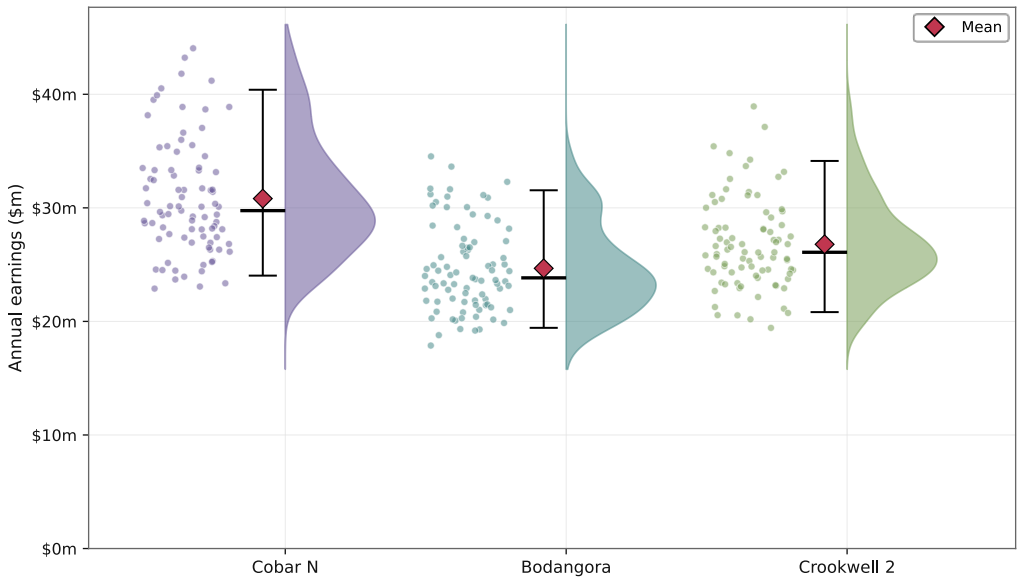
The model addresses revenue and contract cash flow only; capex, opex, debt service, and tax are excluded. Efficient frontiers reported should therefore be interpreted as *revenue-side* trade-offs rather than equity-IRR frontiers.

4 Results

4.1 Merchant earnings risk and project-index fit

Figure 2 presents the distribution of annual merchant earnings for three representative wind projects in NSW across 85 weather-year iterations. The iterations differ materially in both level and spread. Cobar North records the highest merchant earnings and the widest distribution, with an annual revenue standard deviation of $5.03 million per 100 MW. Bodangora and Crookwell 2 exhibit lower and more concentrated merchant earnings distributions, with annual revenue standard deviations of $3.86 million and $3.95 million, respectively. The results establish that projects exposed to the same regional spot market may face different merchant revenue risks due to differences in production profiles, volumes and captured price.

Figure 2: Merchant earnings distribution



The project characteristics reported in Table 3 further illustrate this heterogeneity. Cobar North has the highest capacity factor, and a fair value of $99.23/MWh, closely aligned with the NSW wind index strike of $98.71/MWh. However, its output has the lowest correlation with the regional wind index, at 0.54. By comparison, Bodangora has the highest correlation with the index, at 0.85, but a lower fair value of $87.96/MWh. Crookwell 2 sits between, with a correlation of 0.67, a capacity factor of 33.4% and a fair value of $91.62/MWh.

Table 3: Project merchant earnings and alignment with the NSW wind index

Project	Fair Value ($/MWh)	Capacity Factor	Annual merchant revenue std	Correlation with regional wind index
Cobar North	$99.23	35.5%	$5.03m	0.54
Bodangora	$87.96	32.0%	$3.86m	0.85
Crookwell 2	$91.62	33.4%	$3.95m	0.67
ESEM strike (NSW index)	$98.71	31.0%	$3.76m	1

The three projects provide distinct tests of whether the shape swap and revenue swaps can stabilise merchant earnings in the presence of different production profiles, captured values and levels of basis risk.

4.2 Earnings stability under increasing fungible contract cover

Figure 3, Figure 4 and Figure 5 show the distribution of earnings as contract cover increases for the shape and revenue swaps. At zero contract cover, both structures reproduce the merchant earnings distribution. As cover increases, the P5-P95 and P10-P90 earning bands narrow materially across all three projects. The lower tail rises as the upper tail declines, indicating that the contracts exchange merchant upside for greater protection against weak annual earnings outcomes. Mean and median earnings remain comparatively stable, consistent with the contracts being struck at fair value across the simulated iterations.

The degree of earnings compression differs across projects and contract structures. For Cobar North, both shape and revenue swaps reduce the wide merchant distribution, with relatively similar performance. For Bodangora, the revenue swap produces visibly tighter earnings distribution than the shape swap. A similar pattern is evident for Crookwell 2, where the revenue swap generally provides stronger compression of the lower and upper tails.

For each project, the improvement in earnings stability is non-linear. Initial increases in contract cover deliver substantial reduction in the distribution of annual earnings. Beyond a project-specific level, the distribution ceases to narrow and begins to widen again. At these higher contract levels, the hedge becomes oversized relative to the project's merchant exposure, increasing rather than reducing earnings risk.

Figure 3: Cobar North annual earnings distribution under ESEM contract %

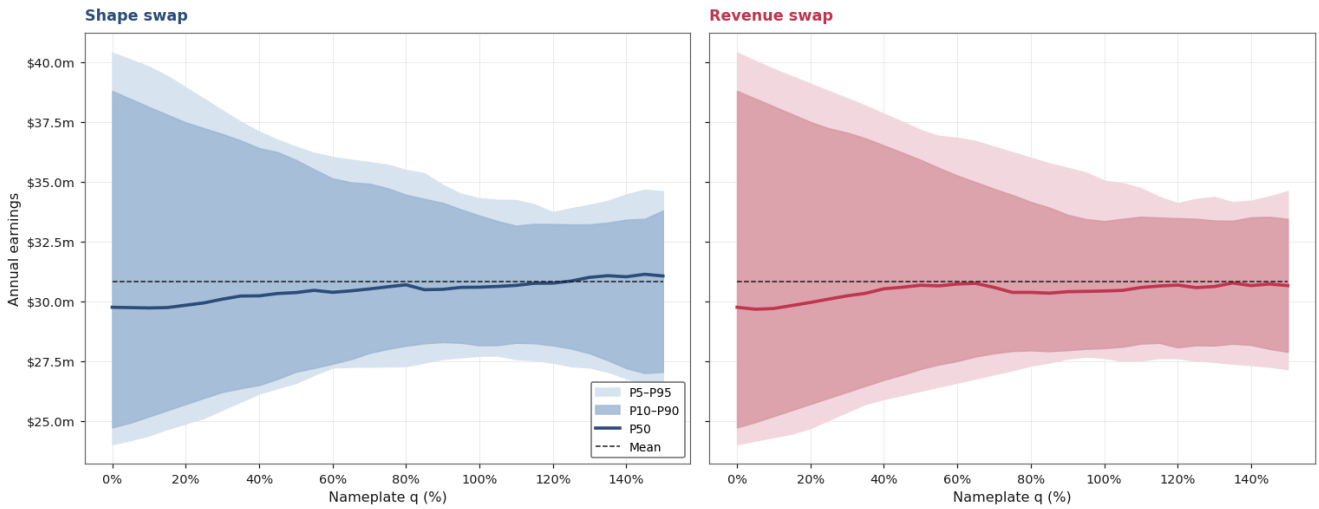


Figure 4: Bodangora annual earnings distribution under ESEM contract %

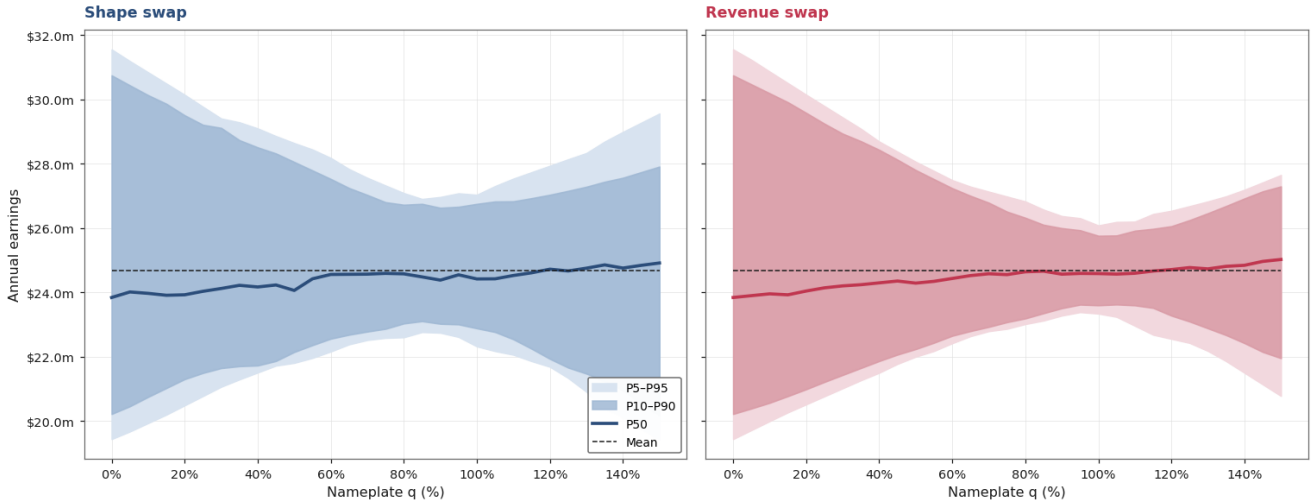
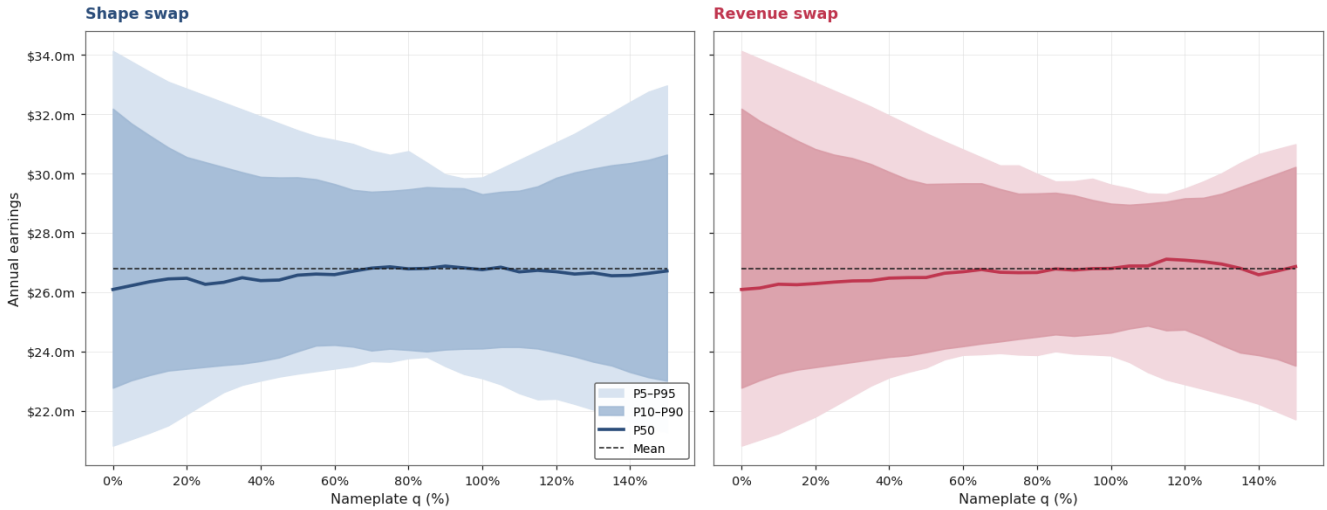


Figure 5: Crookwell 2 annual earnings distribution under ESEM contract %



The results establish that both fungible contract structures can materially stabilise wind farm earnings. Each project and contract exhibits an interior region in which earnings volatility and downside exposure are minimised. The precise location of that region is examined in the following section using the alternative risk-adjusted performance measures.

4.3 Efficient contract cover

Figure 6, Figure 7 and Figure 8 plot the three risk-adjusted return profiles as a function of fungible contract cover *q* (expressed as a percentage of project nameplate capacity):

- a mean-to-volatility ratio, which rewards mixes that reduce total earnings volatility.
- CVaR-adjusted return, which rewards mixes that lift the mean of the worst-five-per cent of outcomes.
- EaR-adjusted return, which rewards mixes that lift the fifth percentile of annual earnings

These three measures reflect distinct operator preferences of reducing earning volatility, mitigating extreme downside risk and lifting the threshold of a poor year, respectively. The maximum of each ratio is where the contract mix is efficient for that risk-adjusted measure.

Figure 6: Risk-adjusted performance of shape and revenue swaps across contract cover – Cobar North

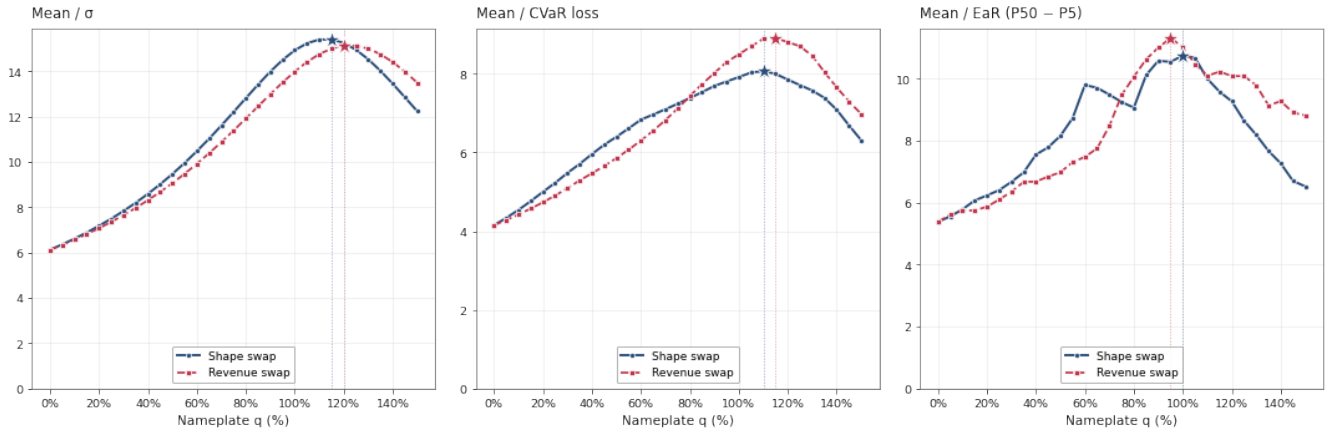


Figure 7: Risk-adjusted performance of shape and revenue swaps across contract cover – Bodangora

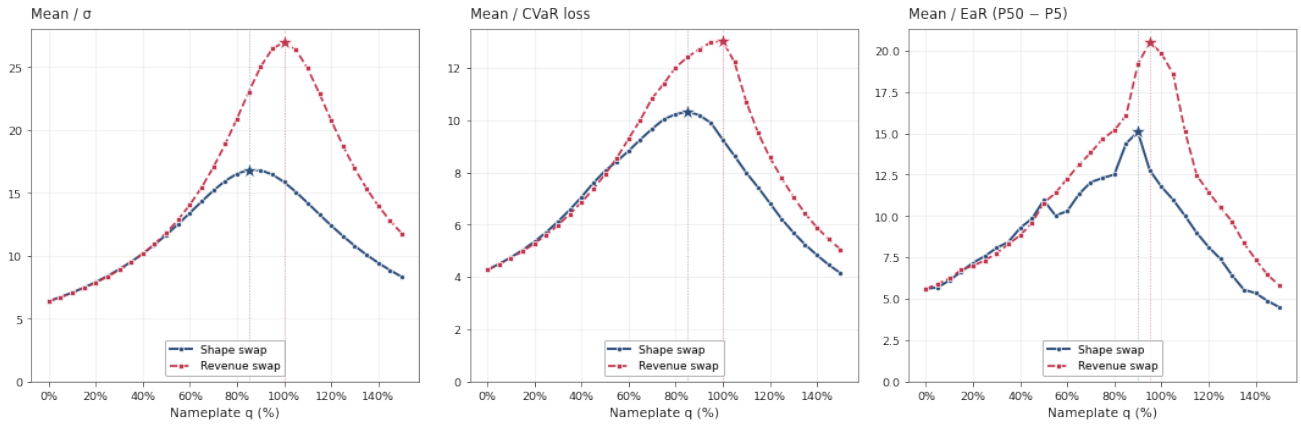
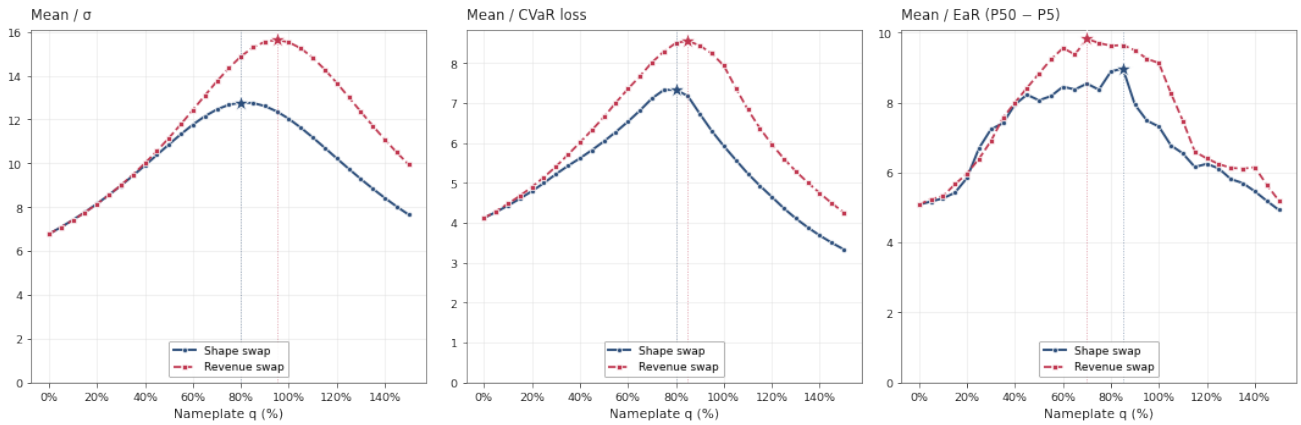


Figure 8: Risk-adjusted performance of shape and revenue swaps across contract cover – Crookwell 2



The efficient contract levels under each measure are reported in Table 4. For all three representative projects, the optimum lies in a range of high contracting levels. For Cobar North, the efficient level of shape cover ranges from 100% to 115% of nameplate capacity, while the revenue swap ranges from 95% to 120%. The mean-to-volatility and CVaR-adjusted measures favour the higher levels of cover, whereas the EaR-adjusted measure is at somewhat lower levels.

Bodangora has a narrower, more consistent range of efficient contract levels. The shape swap is maximised at 85-90% of nameplate across the three measures, while the revenue swap is maximised at 95-100%. The close alignment across the measures indicates that the contract levels that minimise overall volatility also provide similar protection against both extreme and fifth-percentile downside outcomes.

For Crookwell 2, the shape results are also tightly grouped, with efficient cover 80–85% of nameplate capacity. The revenue swap produces a wider range, from 70% under the EaR-adjusted measure to 95% under the mean-to-volatility measure. This spread indicates that the contract level that minimises total earnings variability is not the same as the level that protects the fifth-percentile outcome. An operator focused on broad earnings stability would therefore select a materially higher contract level with a revenue swap than one primarily concerned with limiting the deterioration between median and poor-year earnings. However, as shown in Figure 8, the EaR-adjusted measure is relatively close between 60–85%.

Table 4: Efficient contract cover for shape swap and revenue swaps for each risk measure

Project	ESEM product	max μ/σ	max μ/(μ−CVaR$_5$)	max μ/EaR
Cobar North	Shape Swap	115%	110%	100%
	Revenue Swap	120%	115%	95%
Bodangora	Shape Swap	85%	85%	90%
	Revenue Swap	100%	100%	95%
Crookwell 2	Shape Swap	80%	80%	85%
	Revenue Swap	95%	85%	70%

Project differences in efficient cover reflect hedge fit. Hedge fit includes the strength of the negative correlation between merchant project earnings and the contract payoff, the relative volatility of the two exposures and basis differences in capacity factor and captured price.

Contract cover above 100% of nameplate should not be interpreted as physical over-contracting. The contract notional is expressed relative to project capacity, but the efficient hedge ratio is determined by the relationship between project merchant earnings and the indexed contract payoff. Differences in capacity factor, captured price and curtailment mean that one MW of contract notional does not necessarily hedge the earnings associated with one MW of project capacity. A hedge ratio above 100% may therefore represent a matched earnings hedge rather than an economically short physical position.

4.4 How fungible contracts compare with conventional hedges

Figure 9, Figure 10 and Figure 11 compare the annual earnings distributions under the merchant case and each contract structure at its CVaR-efficient level of cover. All three contracts materially compress the earnings distribution relative to merchant exposure. For Cobar North, the RoP PPA produces the narrowest distribution and strongest downside protection. For Bodangora and Crookwell 2, the revenue swap provides earnings stability comparable to, and in some measures greater than, the RoP PPA. The shape swap also substantially reduces earnings dispersion, although its residual distribution is generally wider than under the revenue swap.

Figure 9: Annual earnings distributions under alternative contract structures — Cobar North

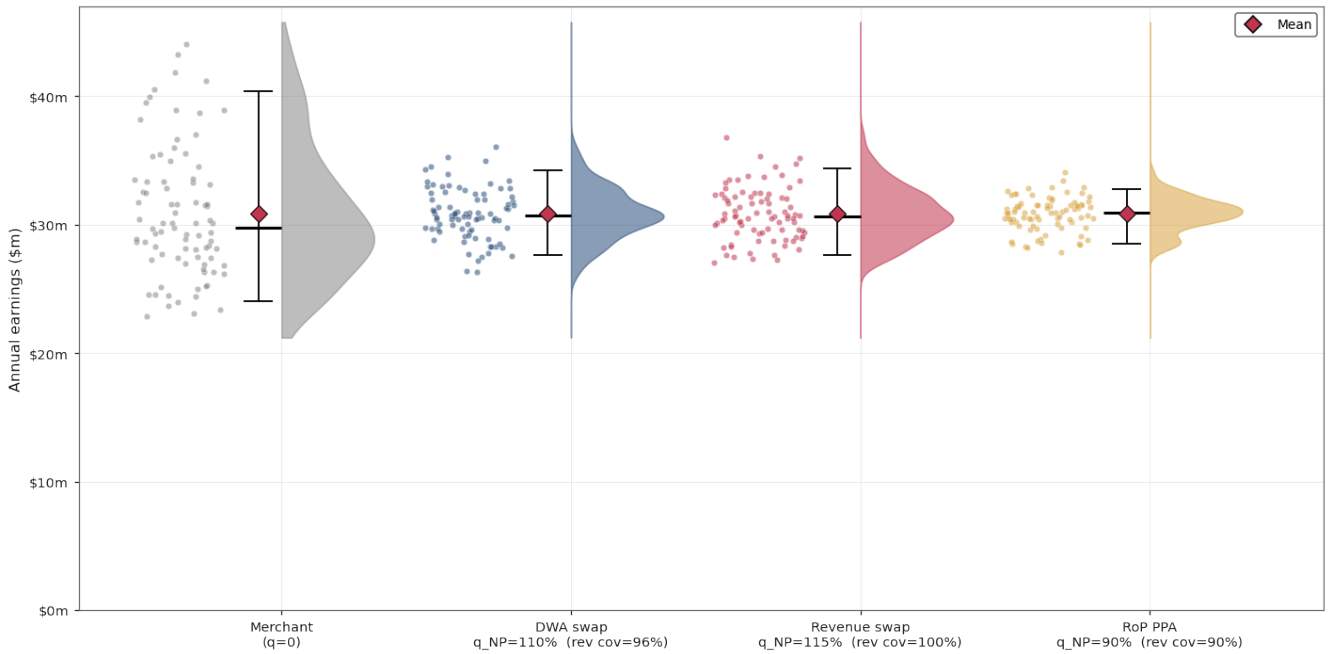


Figure 10: Annual earnings distributions under alternative contract structures – Bodangora

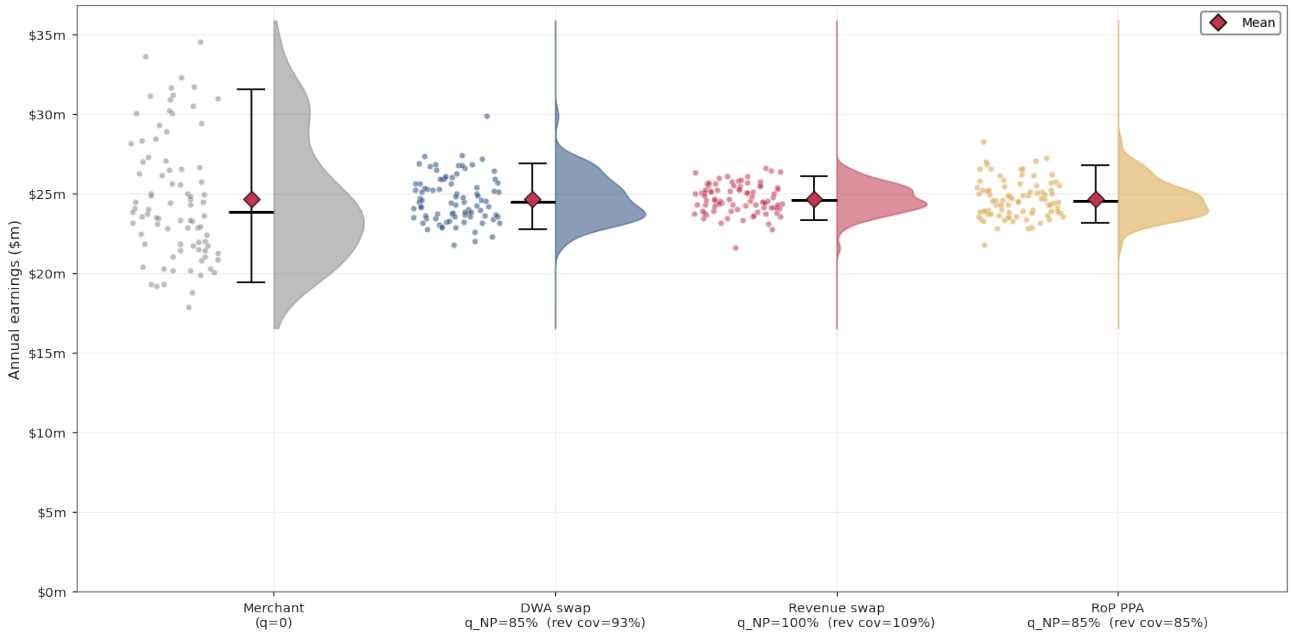
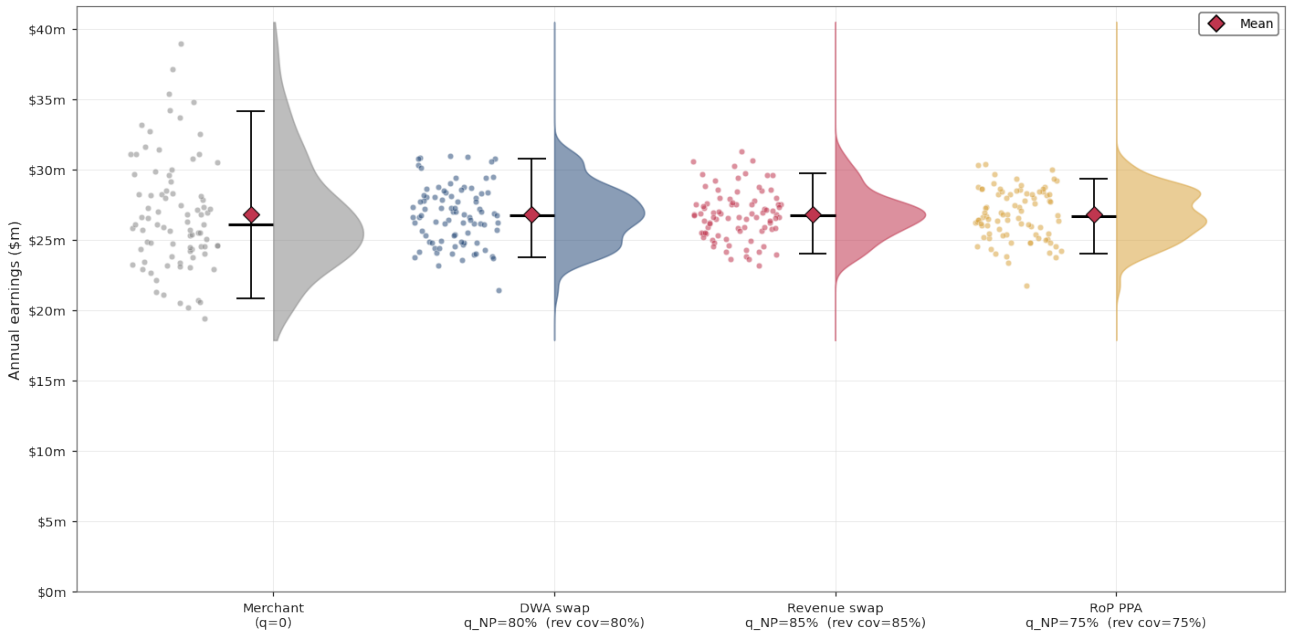


Figure 11: Annual earnings distributions under alternative contract structures – Crookwell 2



Each contract is shown at the level of cover that maximises the CVaR-adjusted earnings measure. Points show annual earnings across the 85 weather-year simulations; shaded densities show the distribution of outcomes; diamonds indicate mean earnings; and whiskers show the central earnings range. Contract cover is reported as a percentage of project nameplate capacity and expected revenue cover.

Table 5 compares shape swap, revenue swap and RoP PPA at the contract level selected at CVaR adjusted objective. All three structures materially improve downside earnings and reduce total and downside variance relative to merchant exposure.

The revenue swap outperforms the shape swap for each project at the CVaR uplift and generally provides greater reductions in total and downside variance. For Cobar North the RoP PPA is the strongest hedge, delivering a $4.86m uplift in earnings for 100MW, an HER of 93.4% and DVR of 90.7%. For Bodangora the revenue swap records the strongest

results, with an HER of 94.4% and DVR of 92.7% compared with 90.5% and 89.9% under a RoP PPA. The revenue swap also marginally outperforms a RoP PPA for Crookwell 2 across all three measures.

Table 5: Comparative hedge effectiveness at the CVaR-efficient contract level

Project	Contract type	q*	CVaR uplift	HER	DVR
Cobar North	Shape swap	110%	$3.61m	84.2%	80.4%
	Revenue swap	115%	$3.96m	83.3%	80.8%
	RoP PPA	90%	$4.86m	93.4%	90.7%
Bodangora	Shape swap	85%	$3.39m	85.6%	84.8%
	Revenue swap	100%	$3.88m	94.4%	92.7%
	RoP PPA	85%	$3.79m	90.5%	89.9%
Crookwell 2	Shape swap	80%	$2.85m	71.8%	65.2%
	Revenue swap	85%	$3.37m	80.3%	77.2%
	RoP PPA	75%	$3.07m	79.7%	73.3%

Overall, the results show that fungible ESEM contracts can provide earnings protection comparable to conventional project-specific contracting. The revenue swap is generally the stronger fungible hedge, although relative performance remains project-specific.

5 Discussion

The results provide three main insights into the use of fungible contracts to manage wind farm earnings risk. First, substantial earnings stabilisation can be achieved using contracts settled against a regional wind index rather than project-specific generation. Second, efficient contract cover is consistently high across the three representative wind projects. Third, the revenue swap generally provides stronger downside protection than the shape swap because it more directly hedges variation in indexed revenue.

5.1 Fungible contracts can be used as effective earnings hedges for wind farms

A central finding is that earnings stabilisation can be achieved using the fungible contracts being considered for the ESEM. Although settlement against a regional wind index introduces basis risk between project earnings and the contract payoff, both the shape and revenue swaps remove a large proportion of merchant earnings risk across the three wind projects analysed. As shown in Figure 3, Figure 4, and Figure 5, the shape and revenue swaps compress the annual earnings distributions of all three projects, notwithstanding differences in their capacity factors, captured prices and correlations with the NSW wind index. This result is reinforced by the comparison with the project specific RoP PPA. Figure 9, Figure 10, Figure 11 and Table 5 show that the fungible contracts provide earnings protection of a similar order to the RoP PPA.

The use of a regional wind index is important to this result. The index is constructed from aggregate wind generation across the region. Aggregation diversifies some of the idiosyncratic production variability of individual wind farms and produce a smoother reference exposure with retaining the common weather and price conditions that drive project merchant earnings. The resulting contract payoff remains negatively correlated to project merchant earnings, allowing the hedge to provide protection in low-earnings years despite imperfect project index matching. The fact that Cobar North, Bodangora and Crookwell 2 exhibit different characteristics and relationship with the NSW wind index, yet all achieve earnings compression, suggests that effective hedging does not require close replication of an individual project's physical output.

Fungibility also provides a broader benefit to an asset-linked RoP PPA. Because the contract is not tied to the output of a particular project, it can in principle be traded and recycled through the forward market. This allows generators and counterparties to increase or reduce their contracted position over time by buying or selling contract exposure, rather than

remaining locked into a bespoke project specific contract. A more liquid market in standardised bulk energy contracts would also improve price discovery by revealing market value for regional wind generation and the associated bulk energy service. This is consistent with the ESEM design objective of recycling contracts into the market as delivery approaches, strengthening the medium-term derivative markets.

The results have potential relevance for project finance as well as market design. Both fungible structures materially reduce earnings volatility and lift downside outcomes including the lower tail of the annual earnings distribution. While this paper does not model debt service or financing covenants directly reducing the probability and severity of low earnings years should improve the predictability of cashflows available to meet minimum earnings and debt-service requirements. Therefore, the analysis provides evidence that fungible contracts can perform an earnings stabilisation function relevant to bankability without requiring the contract to be physically tied to project output.

5.2 Efficient contract cover clusters at high levels of contracting

The consistently high efficient contract levels across the three risk measures analysed in this paper are consistent with the fungible contracts operating as genuine hedges. As shown in Section 4.3, efficient cover is concentrated between 80-115% of nameplate capacity for the shape swap and between 70-120% for the revenue swap, although the precise level varies by project and risk objective.

The appropriate hedge ratio is determined by the relationship between project earnings and contract payoff, rather than nameplate capacity alone. In particular, hedge effectiveness depends on the strength of the negative correlation between project earnings and the hedge payoff, which the relative volatility of those exposures determines the scale of contract required. This is most evident in the analysis for Cobar North, where efficient cover exceeds 100% of nameplate under several risk objectives. Cobar North project earnings are more volatile than the corresponding hedge payoff while remaining negatively correlated with it, requiring a larger contract notional to nameplate to minimise earnings risk. Accordingly, contract positions above 100% of nameplate should be interpreted as an earnings hedge ratio rather than physical over-contracting.

The alternative risk measures produce slightly different efficient hedge ratios because total earnings volatility and lower tail risk are not equivalent. A contract level that minimises overall variance doesn't necessarily maximise protection of the fifth-percentile or worst-tail outcomes. Nevertheless, the preferred levels generally cluster within a relatively narrow range, suggesting that there is a broad region of high contract cover over which the principal earnings risk objectives are improved.

The efficient RoP PPA levels in the analysis provide a useful comparison with the existing semi-merchant literature. At the CVaR maximising point, RoP PPA cover ranges from 75-90% across the three projects. This is broadly consistent with (Gohdes, 2025; Gohdes et al., 2023), who identify PPA coverage of approximately 70-80% as viable in semi-merchant wind projects. Their optimisation problem is different, focusing on debt capacity, financing covenants and equity returns rather than annual earnings risk, but both sets of results point towards relatively high, though not necessarily complete, contracting as an efficient position for wind projects.

5.3 Revenue swaps provide stronger downside protection than shape swaps

The revenue swap provides stronger downside protection that the shape swap across all three projects, with higher CVaR uplift and generally greater downside variance reduction, show in Table 5 in Section 4.4.

The difference reflects the exposure retailed within each structure. Under the same shape swap, both fixed and floating settlements remain to the regional wind generation, leaving index volume risk within the hedge. The revenue swap instead exchanges variable indexed revenue doe a fixed payment per MW, providing greater protection when low generation and weak captured prices combine to reduce merchant earnings.

The comparison with the RoP PPA shows that effective earnings hedging does not require the contract to replicate project output. A RoP PPA matches project specific spot exposure but retains production risk, where the revenue swap introduces basis risk but hedges variation in indexed revenue arising from both price and volume. For Bodangora and Crookwell 2, this produces downside protection comparable to, and slightly greater than, the RoP PPA. For Cobar North, the RoP PPA remains the stronger hedge.

6 Conclusion

The results of this analysis suggest that fungible contracts can effectively hedge wind farm earnings despite introducing basis risk, with earnings protection comparable in some cases to conventional RoP PPAs. Earnings stability is important for generators managing investment risk and undertaking business planning. As the literature demonstrates, forward contracting provides the principal mechanism through which electricity-market risks are reallocated, and fungible contracts can provide an additional instrument through which these risks are managed.

Efficient contract cover is generally high, although the efficient hedge ratio varies across projects according to basis risk and production characteristics. Importantly, the hedge ratio should be understood as an earnings hedge rather than a measure of physical output contracted. The results also show that the revenue swap provides stronger downside protection than the shape swap by hedging variation in indexed revenue arising from both price and volume.

These findings support standardised regional indexed contracts as a plausible mechanism for combining earnings risk management with a tradeable forward market. They suggest that the benefits of standardisation and fungibility do not necessarily require sacrificing effective earnings protection at the project level. However, this paper evaluates earnings stability rather than project financing directly and therefore does not establish the implications of these contracts for debt capacity or broader bankability.

Further research should examine the design of the regional index underlying these contracts. In particular, the geographical composition of the index, its representativeness of projects seeking to hedge, and changes in the composition of regional generation over time may affect hedge effectiveness. Understanding whether a regional index continues to provide effective protection as the generation mix evolves will therefore be an important consideration in the design of fungible ESEM contracts.

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8 Appendix

8.1 JDemand

The JDemand model produces forecasts of aggregate final electricity and gas demand on a weather-adjusted basis (hence the link to 'ERA5' weather data). These demand forecasts form foundational inputs to our electricity and gas market models.

JDemand is implemented as a random forest walk machine learning model, rained on historical NEM electricity[1] (AEMO, 2026) and gas market data[2] (Energy Edge, 2026), suitably matched to Australian calibrated ERA5 weather re-analysis data (Copernicus Climate Change Service, 2023; Hersbach et al., 2023) given the most recent three years of observations. JDemand then produces representative demand timeseries for electricity and for gas at a NEM region level based on historical weather conditions (as per ERA5 data). 85 years of weather traces are then produced, representing the anticipated vary in the system of today given the weather of the past century. As we are modelling a system in the early 2030s, underlying demand is scaled up based on projections provided by AEMO in the 2025 ESOO (AEMO, 2025).

An electrification module within JDemand splits gas demand into two sectors (residential and industrial) and converts these to electrical loads, which is then added to our electricity demand forecasts. Assumptions on typical load shapes and the relative efficiency of electric water heating, electric heat pumps and reverse cycle air conditioners drive conversions at the residential level. In particular, space heating is modelled with a coefficient of performance (COP) linearised between 3.5 and 5.0 for zero to 20 degree Celsius operating temperatures, typical of modern energy efficient reverse cycle air conditioners.

8.2 JWeather: Forecasting hourly wind and solar output

This model generates usable utility-scale wind, utility-scale solar, and rooftop solar PV production functions at hourly resolution, time-stamped, location-stamped, and matched to coincident aggregate final electricity demand.

This model also relies on ERA5 weather re-analysis (Hersbach et al., 2023) as a crucial input. JWeather internalises open source software *pvlib* (Anderson et al., 2023) and *windpowerlib* (Haas et al., 2019) to produce solar PV and wind generation traces. Representative sites have been aggregated by region to deliver single weighted 'region-wide' wind traces and solar traces with hourly resolution over an 85-year period. Australia has by far the highest rooftop solar PV take-up rate in the world. Consequently, it has become an important resource in Australia's NEM. NEM-wide rooftop capacity is currently ~26GW (cf. maximum system demand of 38GW).

8.3 JSolve: Electricity Market Model

JSolve is a dynamic, time-sequential, partial equilibrium electricity market model that simulates the mainland NEM states at hourly resolution. Tasmania is treated as an energy-limited hydro generator[3]. As with all such models, JSolve seeks to minimise generation costs subject to reliability and emissions constraints. However, the novel contribution of JSolve beyond the standard modelling framework is the use of 85 years of historic weather conditions (hourly resolution) in each simulation run. Crucially, this approach captures the extreme variability, and interactions between, wind output, solar output and weather adjusted aggregate final electricity demand using 85 years of weather variation.

The model's objective function seeks to minimise the cost of supply, subject to transmission interconnector, weather, water storage, and above all – reliability and CO_2 emissions – constraints. Regional interconnectors constrain generation flows between NEM regions but within regions the model follows the copper-plate assumption.

[1] Electricity load from AEMO. Data is publicly available at AEMO | Nemweb data

[2] Daily gas load from Energy Edge's GMAT. Gas Market Analysis Tool | Energy Edge (gmat.com.au) is EnergyEdge's proprietary software tool which stores, collates and analyses the East Australian gas network, including pipeline flows, loads by node, gas field production and gas storage assets.

[3] Tasmania is dominated by a single (interconnected hydro) generator and consequently this simplifies our modelling task considerably.

The model logic is as follows. Let T be the ordered (time sequential) set of dispatch periods, with $|T|$ being the total number of periods, and periods labelled by index t such that in eq. (18)

$$t \in (1..|T|) \quad (18)$$

Each period has a duration Δt.

Let R be the ordered set of regions in our interconnected electricity market with $|R|$ being the total number of regions in the set, and each region denoted by index i such that in eq. (19)

$$i \in (1..|R|) \quad (19)$$

Let $D_{i,t}$ be the aggregate demand for all consumer segments at node i in time period t, expressed in MW, which may be negative due to non-market or embedded generation. Let V_i be the set of generators at node i. Let P_{ij} be the maximum productive capacity of supplier j in region i, expressed in MW, and let $p_{ij,t}$ be the production (in MW) of generator j in region i in time period t, where j (eq. (20)):

$$j \in (1..|V_i|) \quad (20)$$

Generation is limited by nameplate capacity and availability percentage $A\%_{ij,t}$ in any period:

$$0 \leq p_{ij,t} \leq A\%_{ij,t} \times P_{ij} \leq P_{ij} \; \forall \; i,j,t \quad (21)$$

Availability may be reduced either by underlying renewable trace determined by JWeather, or by planned or forced outages, or both. For thermal units, a baseline availability of 75% for coal and 85% for gas peaking units is assumed, representing typical N-1 reserve margins employed by prudent portfolio managers in Australia. All dispatch is treated linearly, i.e., no unit commitment decisions are incorporated into the model (which is roughly appropriate for a future grid with few large thermal coal units).

For storage assets: let S_i be the subset of generator indices of in region i with energy storage. Let the storage capacity for the relevant generator be Q_{ij} and the available storage level at the start of period t be $q_{ij,t}$. Let $c_{ij,t}$ be the charging rate in MW of the asset, where maximum charge and generation rates are assumed to be symmetric, such that the charging rate $c_{ij,t}$is limited by the nameplate capacity:

$$0 \leq c_{ij,t} \leq P_{ij} \; \forall \; t \; \wedge \; i \in (1..|R|) \wedge j \in S_i \quad (22)$$

Charging is assumed to have efficiency η_{ij}, which is assumed to capture the roundtrip efficiency. Storage levels are tracked and constrain generation through the balancing equation such that generation $p_{ij,t}$ cannot exceed stored energy (eq.(23)), charging $c_{ij,t}$ cannot exceed available storage headroom (eq.(24)), and storage $q_{ij,t}$ must be balanced between periods (eq.(25)):

$$p_{ij,t} \times \Delta t \leq q_{ij,t} \quad \forall \; i,j,t \quad (23)$$

$$c_{ij,t} \times \Delta t \times \eta_{ij} \leq Q_{ij} - q_{ij,t} \quad \forall \; i,j,t \quad (24)$$

$$q_{ij,t+1} = q_{ij,t} - p_{ij,t} \times \Delta t + c_{ij,t} \times \Delta t \times \eta_{ij}, \quad \forall \; i,j,t \quad (25)$$

To prevent edge effects a circular charge level constraint is applied such the available charge in the initial period $q_{ij,0}$ is linked to the charge in the final period $q_{ij,t_{max}}$ minus net generation in the final period.

$$q_{ij,0} = q_{ij,t_{max}} - p_{ij,t_{max}} \times \Delta t + c_{ij,t_{max}} \times \Delta t \times \eta_{ij} \quad \forall \; i,j \quad (26)$$

For this study, JSolve simulates only a single simulation year, but simultaneously solves multiple weather reference years to reduce the sensitivity of capacity build to stochastic weather conditions. Let Y be the set of all reference years modelled (with total years $|Y|$) and let T_y for $y \in Y$ be the set of ordered time indices for that year, and $T_{y,m}$be the set of indices. All indices are included such that the ordered concatenation yields the total ordered set of indices (i.e., time sequential ordering is preserved, and each reference year immediately follows the previous, to ensure storage usage is not overfitted within a single year):

$$T_{1,1} \frown T_{1,2} \frown \ldots \frown T_{1,12} \frown T_{2,1} \ldots T_{|T|,11} \frown T_{|T|,12} = T \quad (27)$$

Total storage throughput has an annual cycle limit ζ_j, typically as required by battery warranty or maintenance schedules, such that the annual sum of generation $p_{ij,t}$ is limited to the nameplate storage multiplied by allowed annual cycles:

$$\sum_{t \in T_y} p_{ij,t} \Delta t \leq Q_{ij} \times \zeta_j \quad \forall \; y \in Y \; \wedge \; i \in (1..|R|) \wedge j \in S_i \quad (28)$$

For existing hydro generators, minimum and maximum monthly and annual limits apply based on historical inflows and outflows for the corresponding reference year. These take the form of annual $\xi_{j,y}$ and monthly $\xi_{j,y,m}$ energy limits such that:

$$\sum_{t\in T_y} p_{ij,t}\Delta t \ \leq \xi_{\mathrm{j,y}} \quad \forall\, i,j,y \text{ if } j \text{ is a hydro unit} \tag{29}$$

$$\sum_{t\in T_{y,m}} p_{ij,t}\Delta t \ \leq \mathrm{Q_{ij}} \times \xi_{\mathrm{j,y,m}} \quad \forall\, 1 \leq m \leq 12, i,j,y \ , \text{if } j \text{ is a hydro unit} \tag{30}$$

For interconnectors: let IC be the ordered set of transmission interconnectors in the system and $|IC|$as the number of transmission lines in the set. Let interconnector t_k $(0 < k < |IC|)$ connect nodes $r_{t_{k,-}}$ and $r_{t_{k,+}}$. Let flows from the negative to positive region be $f_{k,t}$, limited to the forward and reverse interconnector flow limits $F_{k,+}$ and $F_{k,-}$,

$$F_{k,-} \ \leq f_{k,t} \leq F_{k,+} \quad \forall\, k,t \tag{31}$$

Supply must match demand in all regions in all periods, such that the sum of all generation in the region ($\sum_{j\in V_i} p_{ij,t}$) plus interconnector inflows ($\sum_{k \mid r_{t_{k,+}}=r_i} f_{k,t}$) minus interconnector outflows ($\sum_{k \mid r_{t_{k,-}}=r_i} f_{k,t}$) plus load shedding ($USE_{i,t}$>0, in megawatts) must equal the regional demand ($\mathrm{D_{i,t}}$) plus curtailment of negative demand $\gamma_{i,t} > 0$ (e.g., curtailment of behind the meter rooftop PV, in megawatts).

$$\sum_{j\in V_i} p_{ij,t} + \sum_{k \mid r_{t_{k,+}}=r_i} f_{k,t} - \sum_{k \mid r_{t_{k,-}}=r_i} f_{k,t} + USE_{i,t} = \mathrm{D_{i,t}} + \gamma_{i,t} \tag{32}$$

$$\forall\, t \ \wedge \ i \in (1..|R|)$$

Capital costs are converted to annualised $/MW/year figures through $C_{P,ij}$ for unit j in region i, and let $C_{Q,ij}$ be the analogous total annualised capex ($/MWh/year) for storage capacity and let $R_{ij,t}$ be the marginal running cost, including fuel, O&M, etc. VCR_i is the value of customer reliability ($/MWh) in region i, i.e., the cost attributable to $USE_{i,t}$. It is assumed to be constant in all periods, but could be made time dependent (e.g., higher or lower values in summer or winter). The Objective Function can therefore be expressed as:

$$\mathrm{Obj} = \sum_{i=1}^{|R|}\sum_{j=1}^{|V|}\left(\left[C_{P,ij} \times P_{ij} \times |Y| + C_{Q,ij} \times Q_{ij} \times |Y|\right] + \sum_{t=1}^{|T|} R_{ij,t} \times g_{ij,t} \times \Delta t\right) + \sum_{i=1}^{|R|}\sum_{t=1}^{|T|} VCR_i \times USE_{i,t} \times \Delta t \tag{33}$$

where the initial sum is over all regions and generators, $C_{P,ij} \times P_{ij} \times |Y|$ is the pro rata capital costs of capacity for generator i,j (noting $|Y|$ is the total number of weather reference years simulated), $C_{Q,ij} \times Q_{ij} \times |Y|$ is the pro rata capital costs for storage, $\sum_{t=1}^{|T|} R_{ij,t} \times g_{ij,t} \times \Delta t$ is the total production costs across all weather reference years, and $\sum_{i=1}^{|R|}\sum_{t=1}^{|T|} VCR_i \times USE_{i,t} \times \Delta t$ is the total unserved energy across all weather reference years. No discounting terms are included as each weather year is effectively a probabilistic outcome for the single simulation year (although final costs could be discounted to a net present value if required).

Finally, an iterative price volatility simulation stage is applied to drive greater price spreads that might stress test the contracts under consideration. Available capacities P_{ij} are fixed at the first stage values, and the availabilities $\mathrm{A\%_{ij,t}}$ for gas peaking units is set to 90% and for coal units to the historical hourly availability for calendar year 2025. The marginal running cost term of the objective function is replaced by a sum over strategic bid bands $k \in (1..|K|)$, where $R_{ijk,t}$ represents the bid price for bid band *k* for generator *j* in region *i*, and $g_{ijk,t}$ represents the corresponding generation in that bid band, such that the objective function is:

$$\mathrm{Obj} = \sum_{i=1}^{|R|}\sum_{j=1}^{|V|}\left(\left[C_{P,ij} \times P_{ij} \times |Y| + C_{Q,ij} \times Q_{ij} \times |Y|\right] + \sum_{t=1}^{|T|}\sum_{k} R_{ijk,t} \times p_{ijk,t} \times \Delta t\right) + \sum_{i=1}^{|R|}\sum_{t=1}^{|T|} VCR_i \times USE_{i,t} \times \Delta t \tag{34}$$

subject to the additional constraint that the percentage of capacity β_{ijk} offered in each bid band β_{ijk} will cover all generation,

$$\sum_{k} \beta_{ijk} = 100\% \tag{35}$$

For coal units, the first bid band is set with a marginal cost of -$1000, the NEM market floor, representing the minimum stable load of those units (and set at a volume consistent with recent dispatch behaviour during low price periods). The majority of capacity is then offered at the unit's marginal running cost $R_{ij,t}$ with the balance of capacity (5% for coal units, 25% for gas peaking units) distributed in asymptotically declining volumes to bid bands between the unit's marginal running cost and the NEM market price cap. To be clear, the distribution of bid bands and subsequent volatility does not allow a single unique solution. In practice, the level of transient market power required to sustain bid prices above marginal running costs varies significantly depending on not just short-term market conditions but portfolio composition and market contracting levels. (For example, portfolios that are highly contracted have limited incentives to withhold capacity above their running cost; conversely, portfolios that are long generation may seek opportunities to recover long-term fixed costs through periods of elevated pricing.) This final step is therefore iterated to ensure that the level of volatility delivers returns for new investments consistent with the least-cost expansion plan; investment cases are unchanged from the initial simulation, but price volatility may be higher or distributed differently between weather years.

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