

Project finance with Asian wind swaps: are 'average price' derivatives bankable in Australia's NEM?

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Abstract

This article examines whether zonal average-price wind swaps, more accurately defined as Asian wind swaps, are a 'bankable' instrument. Specifically, can a derivative that references the wind fleet's average price underwrite a bespoke project financed new entrant wind farm in Australia's National Electricity Market? Prima facie, long-dated Asian swaps referencing the wind fleet's dispatch-weighted average price present as a material departure from convention, viz. site-specific fixed price (run-of-plant) Power Purchase Agreements. Using South Australia as a deliberately demanding test case, ten years of chronologically matched 30-minute spot-price and wind-production data are block-bootstrapped into 10,000 synthetic years of market data. This data is then utilised within a hedge optimisation and stochastic project finance models across heterogeneous wind farms with explicit strike-price calibration and debt-sizing to stress-test the 'bankability' of Asian wind swaps. Results confirm when hedge quantities are optimised, and strike prices calibrated to entry costs, Asian wind swaps reduce revenue volatility and support project finance, with debt sizing at broadly equivalent levels to a conventional PPA. Findings suggest an Asian wind swap can plausibly replace bespoke government-originated CfDs, which in turn raises the prospect of seamless divisible re-trading and the creation of liquid secondary markets – a necessary precondition for a healthy retail supplier market.

Keywords *project finance, Asian wind derivatives, Asian swaps, renewables, energy-only markets.*

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

1. Introduction

The instrument largely responsible for underwriting renewable plant entry in Australia's National Electricity Market (NEM) has been the run-of-plant Power Purchase Agreement (PPA). With project finance a dominant source of debt capital, PPAs have been a necessary pre-condition for 'bankability' – that is – where equity proponents successfully take a renewable power project to financial close with commercial levels of project debt within the capital structure (i.e. 60–80% debt). PPAs fix the (real) price of renewable output over the term of the agreement, with tenors typically spanning 10–15 years in line with requirements of risk-averse project banks.

Historically, the primary driver of bilateral PPA transactions in Australia's NEM was the 20% Renewable Energy Target (RET), a certificate-based scheme in which retail suppliers were required to purchase a certain amount of their electricity portfolio from renewable resources. To summarise, the RET was legislated in 2000 and increased gradually to the final target of ~20% market share by 2020. The scheme end date for liable parties is 2030, which as an aside, means large numbers of PPAs may terminate in December 2030.

The 20% RET was largely met by 2018. However, bilateral PPA transactions between energy retailers, corporates and renewable developers continued at pace from 2019 onwards due to the falling cost of wind and solar projects (Simshauser and Gilmore, 2022). Indeed, by 2019 renewable entry costs had fallen below the marginal running costs of mid-merit coal and gas plant (Simshauser and Gilmore, 2026).

Yet what appeared to be a renewable investment supercycle in the NEM began to slow from 2023. Sharply rising global demand for renewables and transmission plant, tighter supply chains following Covid-19 and the Russia-Ukraine war, and rising Australian interest rates sent equipment and financing costs sharply higher. Renewable entry costs consequently rose in steps, producing a form of '*sticker-price shock*' in the bilateral market for PPAs, thus slowing investment commitments.

Slowing investment commitments coincided with ambitious Commonwealth renewable targets for 2030. In late-2023, the Commonwealth announced a taxpayer-funded auction for renewable Contracts-for-Differences (CfDs), known as the Capacity Investment Scheme or 'CIS'. Whether intended or not, the CIS appeared to further slow investments just as bilateral PPAs appeared to be recalibrating (Rystad Energy, 2026). The CIS may have induced a '*winner's curse*' (Capen et al., 1971; Thaler, 1988), amplified by lengthy lags between auction award and viable investment commitment dates – a problem also witnessed in European markets (see Malleret et al., 2024).

The CIS was not intended to be permanent policy. It was a bridging scheme while a longer-term market-based solution was identified. The task of doing so was handed to Professor Tim Nelson in his review of Australia's NEM (see Nelson et al., 2025). Amongst the array of recommendations was a long-dated derivative contract designed to help manage what Newbery (2016) has described as the *incomplete markets* problem (see also Stiglitz, 1994). NEM forward markets are liquid for up to three years ahead (Flottmann et al., 2025). Conversely, risk averse project banks require new entrants to secure longer-dated 10–15 year revenue continuity (Gohdes, 2025).

One of two novel instruments highlighted in the Nelson Review of Australia's five-zone NEM was a technology-specific derivative, settled against the zonal fleet average price (Nelson et al., 2025; Gohdes et al., 2026). From a financial economics perspective, such an instrument can be defined as a technology-specific Asian swap (i.e. an average-price swap). To be clear, an *Asian wind swap* is a price-based derivative. This is distinctly different from the better-known volumetric *wind speed* derivatives which seek to deal with the quantity risks associated with existing wind farm PPAs (Gersema and Wozabal, 2017). Volumetric wind derivatives hedge against low wind conditions (Alexandridis and Zapranis, 2013). By contrast, and in plain English terms, the seller of an Asian wind swap is seeking to hedge an otherwise merchant wind project and simulate a PPA by swapping the floating dispatch-weighted price or 'DWP' of the wind fleet in exchange for a fixed price, as follows:

$$\text{Sold Asian Wind Swap} = \underbrace{(\text{Strike Price})}_{\text{Fixed leg}} - \underbrace{(\text{DWP of all Wind Farms})}_{\text{Floating leg}} \times \text{time} \times \text{quantity}$$

Can long-dated Asian wind swaps 'bank' new entrant wind projects? This topic was canvassed in recent articles by Gohdes et al., (2026) and Nolan et al., (2026). Both found an average price wind derivative to produce stable revenues with *broadly equivalent quality* to conventional run-of-plant PPAs. Despite these early results, there is an emerging view within Australia's renewable development and financing

community that wind derivatives *are not bankable*¹. Such an *a priori* view reflects dominant thought by reference to two intuitively logical variables:

1. An Asian wind swap settles against notional quantities, a seemingly significant departure from run-of-plant PPAs. Asian wind swaps thus appear to introduce a material 'quantity risk' exposure; and
2. An Asian wind swap settles against the dispatch-weighted price of the aggregate wind fleet, not the plant-specific dispatch-weighted price as per run-of-plant PPAs (or government-initiated CfDs). Asian wind swaps thus appear to introduce a material 'basis (i.e. price) risk' exposure.

The core of these claims is correct. Selling an Asian wind swap does introduce both quantity and price risk (cf PPAs). The relevant question is whether such risks are manageable. Thermal generators in the NEM, including new entrants, have long relied on derivatives to stabilise revenues, including project-financed peaking plants backed by long-dated \$300 Cap derivatives. These plants faced analogous quantity and price exposures yet were banked and have not exhibited financial distress. Their performance turns on hedging limits and dispatch protocols (Simshauser, 2020, 2026).

Whether a wind farm underwritten by an Asian wind swap is bankable cannot be assessed by intuition alone. It requires granular quantitative analysis linking residual price and quantity exposures to debt-sizing tests used by project banks. This article extends prior research by reorientating the modelling framework contained in Simshauser (2026), viz. from gas turbines in the NEM's Queensland region, to wind farms in NEM's South Australian region. Within this modelling suite is a block-bootstrapping model that converts 10 years of historic 30-minute market data into 10,000 synthetic years of prices and wind production. This dataset is then used in a unit commitment and financial settlements model to identify the optimal risk-adjusted Asian wind swap hedge levels under uncertainty for multiple wind farms. From this point, results are stress-tested for bankability through a dynamic project finance model that sub-samples the 10,000 years of data into 1000 debt-sizing and project valuation iterations, which again, is undertaken across multiple wind farms.

This article makes a number of contributions to the literature. First, it stress-tests Asian wind swaps using a very large synthetic dataset (viz. 10,000 synthetic market years with the dependence between wind output, price formation, negative-price events, congestion and scarcity-price episodes all preserved). Second, the analysis optimises hedge positions across heterogeneous wind farms with materially different annual capacity factors, fleet-wide correlations, and dispatch-weighted prices. Third, it explicitly calibrates Asian wind swap strike prices to project-financed entry costs and plant-specific basis differentials, making transparent the link between auction design, basis risk and revenue sufficiency. Finally, it carries the resulting stochastic revenue streams through a commercial project and corporate finance model, so bankability is dynamically tested through 1000 iterations of debt-sizing constraints, credit metrics and gearing outcomes rather than analysing revenue volatility alone.

The NEM's South Australian region is an ideal zone to test Asian wind swaps. South Australia is a tough test-case. As Mountain (2025) observes, it has the world's highest intermittent renewable market share (>74%) under conditions of imperfect interconnection, and, has completed its transition out of coal.²

The research question collapses down to whether individual wind farms in South Australia can rely on an Asian wind swap that references the wind fleet average price rather than a wind farm's own price. *Prima facie*, a wind farm that is perfectly correlated with the wind fleet should be able to do so with some degree of confidence. What is less obvious is whether the array of wind farms that comprise the aggregate could all reliably do so. To that end, the analysis that follows examines an Asian wind swap against multiple wind farms in the same pricing zone. The wind farms examined are characterised by differing levels of correlation to the wind fleet (from 0.51 to 0.82), and with differing annual capacity factors (from 25% to 40%, compared to the fleet average 32%).

¹ By way of example, see RenewEconomy: [The most significant structural reform to Australia's NEM in a generation – but will financiers actually bank it?](#) The author has also been in various forums where the dominant view expressed was that such an instrument is highly problematic due to volumetric risks associated with transmission congestion (cf. PPA).

² The South Australian region has aggregate final electricity demand of ~15TWh and maximum demand of ~3.5GW. Households exhibit the highest take-up rates of rooftop solar PV (2.4GW, ~55% adoption rate, 22% energy market share) and the region has 22 utility-scale wind farms comprising ~2.7GW of capacity that produce 7.4TWh pa (46.5% market share). Data sourced from [Open Electricity: South Australia](#)

Results indicate long-dated Asian wind swaps are bankable under the assumptions and calibrations used here³. Debt sizing consistently reaches commercial gearing levels of ~70% with comparatively predictable equity returns achieved. Revenue variability presents as virtually identical to a run-of-plant PPA, albeit for different reasons. PPA volatility is driven by quantity variations, whereas Asian wind swap variability reflects both quantity and basis imperfections which are partially offset. Given the potential for secondary trade, an Asian wind swap warrants further policymaker, project banker and equity investor research.

This article is structured as follows. Section 2 reviews relevant literature. Section 3 introduces our models and data. Sections 4 and 5 explore model results. Policy implications and concluding remarks follow.

2. Review of literature

Literature relevant to the current analysis includes (1) a primer on project finance, (2) why merchant power projects are difficult to project finance, and (3) the origins of PPAs for renewables in Australia.

2.1 Primer on project finance

Project finance involves single-asset financing through a Special Purpose Vehicle or 'SPV' (Jadidi *et al.*, 2025). It is prominent for power projects in Germany, Australia and the US (Steffen, 2018). Although project finance transaction costs exceed those of corporate finance (Steffen, 2020), substantially contracted revenues and commensurately higher gearing can lower the weighted average cost of capital and entry costs (Simshauser and Gilmore, 2020).

Project finance is distinguished by its non-recourse nature (Esty, 2004). In default, there is limited recourse to the sponsoring parent company (Farrell, 2003), so lenders rely on collateral and future SPV cash flows (Gómez-Valencia *et al.*, 2024). This drives an intense focus on the stability of expected cash flows and downside risks (Billimoria and Simshauser, 2026), consistent with asymmetric information and asymmetric lender payoffs (Stiglitz and Weiss, 1981; Sharpe, 1990; Bezemer *et al.*, 2023).

A key insight from the literature is that banks do not simply raise interest rates (to adjust for risky projects) to clear the market. They ration credit systematically (Bezemer *et al.*, 2023). Underpinning this is that, for a given SPV, upside returns are captured by equity sponsors while project bank returns are capped at the contracted interest rate and amortisation schedule (Esty, 2002). If financial distress occurs, lenders may lose the outstanding loan balance less salvage value (Farrell, 2003).

Management of risks by project banks therefore occurs through rigorous due diligence processes upfront, debt sizing constraints, and a collateral or security package which has the symmetrical effect of increasing borrower's access to credit lines (Ioannidou *et al.*, 2022), and typically includes:

- Establishment of Debt Service Reserve Accounts and Maintenance Reserve Accounts, which maintain cash collateral buffers to accommodate transient market downturns and unexpected lumpy maintenance costs (Jadidi *et al.*, 2025);
- Equity cures, where equity proponents agree to inject cash in the event the power project experiences cost overruns or where financial ratios fall below certain limits (Abraham, 2025);
- Right to assign Project Contracts, which enables the banking syndicate to take collateral over all critical agreements; and finally
- Cashflow waterfalls, pledges and sweeps, which effectively comprise a series of security charges whereby revenues flow to operational costs first, debt repayment obligations second, with equity sponsors having the residual claim (Borgonovo and Gatti, 2013). Cashflow sweeps mean if certain financial ratios are breached, all residual cash is directed to debt reduction until ratios are restored (Gohdes, 2025).

2.2 Project finance and the bankability of merchant power plants

Electricity industry liberalisation established wholesale spot and forward markets to underpin customer contestability and competitive retail markets (Newbery, 2021; Schmalensee, 2021; Simshauser, 2021).

³ It is to be noted implicit assumptions include investment-grade counterparty credit, satisfactory collateral arrangements, settlement and regulatory design and enforceability over tenor.

Generators consequently shifted from stable monopoly cost recovery to the 'canonical merchant generator' (Finon, 2008), viz. stand-alone plants selling into spot markets, hedging forward up to three years ahead and underpinned by long-dated project finance (Rai and Nelson, 2021). More than 230GW of plant was banked on this basis in the United States between 1997–2005 (Joskow, 2006), while Australia project-financed around 9GW of privatised coal plant and most of the NEM's 200+ renewable projects (Nelson and Simshauser, 2013; Simshauser and Gilmore, 2020).

As customer switching rates steadily increased, demand for forward wholesale electricity contracts by risk-neutral retail suppliers concentrated on short-dated instruments spanning one to three years in tenor in line with end-use customer preferences (Gohdes et al., 2026). Liquidity in over-the-counter (OTC) and futures markets for electricity derivatives would increase sharply, but only in this 1–3 year window (Flottmann et al., 2025).

From ~2004, project financed merchant power plants began to encounter episodes of electricity market oversupply, low prices and in turn, serious financial distress events (see Finon, 2008). This became evident almost simultaneously across multiple jurisdictions including the US, British and Australian markets (Simshauser, 2010). As Joskow (2006) noted at the time, almost 125GW of the 230GW project financed plants in the US filed for bankruptcy or were sold in financial distress.

At this point, project banks tightened lending requirements considerably (Nelson and Simshauser, 2013). Put simply, to project finance a new power plant, a long-dated PPA of 10–15 years in tenor would be required. However, there was no liquid market for long-dated PPAs (Newbery, 2016). Demand for forward contracts by risk neutral retail suppliers continued to exhibit a distinct short-tenor bias (Flottmann et al., 2024). The reason for this was that if a retailer committed to long-dated PPAs, it would then face the risk that rival retailers with shorter, more flexible portfolios could undercut an incumbent's tariffs and steal market share during cyclical downturns (Green, 2006; Anderson et al., 2007; Howell et al., 2010; Flottmann et al., 2024).

Newbery, in his many articles on the topic, would eventually frame the underlying problem facing power project investors as one of 'incomplete markets' (Newbery, 2016). That is, forward markets would fail to originate the full set of long-dated instruments needed to coordinate power plant entry at the efficient cost and level, viz. the revenue-stabilising contracts demanded by risk-averse project banks (Gohdes et al., 2023).

2.1 Renewables and PPAs

Australia's NEM exhibited incomplete markets. Trade in forward contracts was very liquid at the front-end of the forward curve (Flottmann et al., 2025), but well short of the tenor required for project-financing new entry (Gohdes, 2023). Where PPAs naturally emerged was (1) under conditions of new entrant plant enjoying a decisive cost advantage over an incumbent fleet (Simshauser and Gilmore, 2020) or (2) through policy initiatives such as the Renewable Energy Target. Under the RET, retail suppliers had a compliance obligation to purchase set level of renewables within their portfolio or face steep penalties (Nelson et al., 2013).

Although the RET was substantially met by 2018, bilateral PPAs and renewable investment commitments continued at pace (Simshauser and Gilmore, 2022). At this point unsubsidised utility-scale wind and solar costs had fallen below the marginal running cost of mid-merit plant, consequently corporate PPAs surged (Simshauser and Gilmore, 2026). A semi-merchant model also emerged, with wind and solar projects optimally entering with about 70–80% PPA coverage and residual output exposed to favourable spot, short-term forward and RET market dynamics (Gohdes, 2023; Gohdes et al., 2023). From 1998–2023, the RET and corporate PPAs drove more than 200 wind and solar projects with capital value of AUD \$66.8 billion⁴, lifting renewables to around 40% of supply in a system formerly dominated by coal plant (Simshauser and Gilmore, 2026).

Yet from 2022 the cost of wind and transmission equipment began to rise sharply (see Section 4) and after two years of 'cost shocks' to the levelized cost of entry, a lull in investment activity followed. The Commonwealth Government responded by introducing the taxpayer-funded CIS (Flottmann, 2024). About 35.5GW of government-originated CfDs have been announced across 109 projects. At the time of drafting, only 14 of the 109 announced projects had reached financial close – six of which had already

⁴ All financial results are in AUD unless otherwise specified.

commenced construction when awarded a CfD⁵ (Rystad Energy, 2026). Regardless, the CIS was only ever intended as an interim step while some other market-based solution was identified with the Nelson Review identifying fungible derivative instruments, auctioned centrally (Nelson et al., 2025).

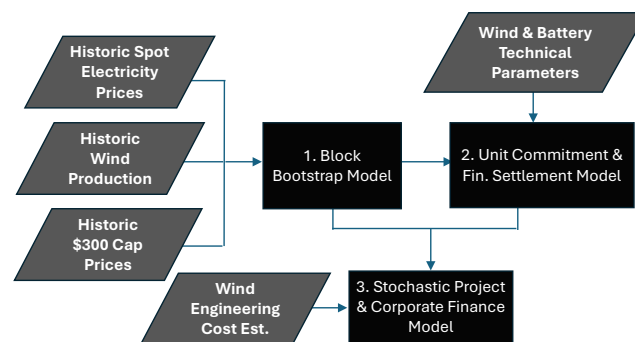
3. Models and Data

Analysing the bankability of Asian wind swaps requires a suite of models. First and foremost, the valuation of new entrants, the sizing of debt facilities and the *bankability* of any power project requires robust forecasts of future electricity prices and expected production. Baker et al., (1998) and Pindyck (1999) observed long ago an array of approaches exist for this purpose, including spread option models (Fleten and Näsäkkälä, 2010), tree methods to capture generator non-convexities (Abadie and Chamorro, 2008; Elias et al., 2017), stochastic techniques (Cassano and Sick, 2013; Abadie, 2015) and structural LP models (Marshman et al., 2020; Marshman et al., 2022).

Structural LP models dominate due diligence processes of utility investors and project-bank credit committees. They capture plant stock, demand, non-convexities, weather dynamics, fuel costs and other drivers at hourly resolution. One limitation is that the extremities of market prices, driven by idiosyncratic features of energy-only markets (e.g. network outages, network congestion, transient variations to ramp rates and fuel costs, erratic bidding behaviour) are also exceedingly difficult to model (Simshauser, 2020, 2026).

To analyse the bankability of an Asian wind swap, the modelling sequence deployed in this research combines stochastic and structural techniques through three sequential models: (1) a block-bootstrapping model that draws on 10 years of historic 30-minute data to produce 10,000 synthetic years of spot electricity prices and wind production; (2) a unit commitment and financial settlement model that generates production, spot revenues and derivative settlements; and (3) a stochastic project and corporate finance model that sub-samples from the prior models to produce distributions of plant valuations, debt sizing and financing structures. The interaction between data and models is presented in Fig.1.

Figure 1: Models and Data



3.1 Block bootstrapping model for spot and forward prices

To stress-test the viability of an Asian wind swap, the distributional properties of historic spot-price volatility should ideally be captured and amplified. The derivative can then be assessed against live historic data and thousands of representative synthetic years of data while preserving temporal dependencies and causal relationships. Durability under these conditions would support bankability, and subsequently, divisible trade in secondary markets.

Block bootstrapping is a non-parametric technique that resamples continuous time-series data by drawing blocks of observations rather than isolated observations (Dudek et al., 2016). Monthly blocks preserve temporal, seasonal and chronological dependencies including daily peaks, seasonal patterns and causal relationships between wind-intensive (and non-wind intensive) periods and low (high) spot prices.

⁵ See [Capacity Investment Scheme faces problems in achieving Labor's clean energy goals as experts call for policy reset amid renewables project delays](#)

The base dataset comprises ten years of observed 30-minute spot prices from South Australia (2017–2026) with matched wind production data for the entire wind fleet.

The *block bootstrapping* model logic is as follows:

Let $X = (Z_1, Z_2, \dots, Z_T)$, where Z denotes the original time series, and each observation corresponds to a half-hourly spot electricity market trading interval or a traded quarterly Cap contract (daily resolution).

Given block length b , there are evidently $M = T/b$ non-overlapping blocks where:

$$B_i = (Z_{(i-1)b+1}, Z_{(i-1)b+2}, \dots, Z_{ib}) \text{ for } i = 1, 2, \dots, M. \quad (1)$$

To preserve underlying seasonal effects, blocks are divided into S subsets $\{B_i^{(1)}, B_i^{(2)}, \dots, B_i^{(S)}\}$ each representing a month, quarter, half-year or other specified seasonal period. For each subset, extract $k = \frac{T_s}{b}$ where $b|T_s$ blocks with replacement, where T_s is the total observations within period s . At this point, the k blocks need to be concatenated in chronological order to form the new 'synthetic' time series.

$$Z^* = (Z_1^*, Z_2^*, \dots, Z_N^*), \quad (2)$$

This process is then repeated (R) to generate a set of synthetic years:

$$\{Z^{*(1)}, Z^{*(2)}, \dots, Z^{*(R)}\} \rightarrow R = 10,000, \quad (3)$$

There are 17,520 half-hourly spot electricity prices and wind production data points in a year ($N = 17,520$). Temporal and chronological dependencies across prices and production have been preserved in each block B_i .

3.2 Unit Commitment and Financial Settlement model

Once the set of synthetic spot prices and chronologically matched wind production data is created, it is then fed into the Unit Commitment and Financial Settlements model. The purpose of this model is to determine aggregate wind production, spot revenues, and Asian wind swap settlements. For spot market revenues, let p_t^s be the electricity spot price in trading interval t . Within each half-hour trading interval, production is bounded by non-negative prices:

$$q_t = \text{if}\{p_t^s > MC_t, \max(q_t, q^{max}), 0\} \mid MC_t \sim 0 \quad (4)$$

where:

MC_t is a plant's marginal running cost (and with wind, taken to be zero)
 q_t is production output,
 q^{max} is the wind farm's maximum power output.

Gross Profit π_t in each trading interval t captures spot revenues and settlement of the Asian wind swap at price p_t^s , settled against the ex-post dispatch-weighted price of the South Australian wind fleet p_t^{as} . For the purpose of modelling, the derivative quantity v_t is assumed to be divisible in 1MW parcel sizes as follows:

$$\pi_t = \left[\underbrace{q_t \cdot \max\{p_t^s - MC_t, 0\}}_{\text{spot market}} + \underbrace{v_t \cdot [p_t^s - \max\{0, p_t^{as}\}]}_{\text{Asian wind swap}} \right] \mid p_t^{as} = \frac{\sum_{w=1}^W (q_{w,t} \cdot p_t^s)}{\sum_{w=1}^W q_{w,t}} \quad (5)$$

3.3 Stochastic Project & Corporate Finance Model

Testing the bankability of an Asian wind swap culminates in the sizing of project debt facilities and valuation of the power project – all of which are stress-tested within the 'PCF Model'. The PCF Model is a commercial-grade financial model that undertakes power project finance (and on-balance sheet corporate financings if required) across an array of industrial organisational settings. Model logic simultaneously solves for an equity IRR constraint (post-tax, post-financing) along with debt sizing – the latter constrained by observed banking covenants and established credit metrics. Taxation variables are also co-optimised endogenously.

A feature of the PCF model is the incorporation of a stochastic Monte Carlo engine that sub-samples the 10,000 synthetic-year dataset drawn from (1) the block bootstrapping and (2) unit commitment and financial settlement models, on a matched basis. Specifically, the sub-sampling process populates each future operational year of the wind farm with chronologically matched stochastic spot prices, wind production data and settlement of the Asian wind swap. The Monte Carlo engine iterates 1000 times, thus producing 1000 unique debt-sizing and plant valuations for each test case, as in Simshauser (2020, 2026).

Full PCF Model logic appears in Appendix I (noting Eq.A14 contains the critical debt-sizing constraint). A summary-level exposition of the i^{th} valuation of wind farm project $WF1$ is calculated as follows:

$$PV_{WF1}^i = PV_{WF1}^i \left[\left[\sum_{Y=1}^{35} \sum_{j=1}^{WF1} \left(\sum_{t=1}^N \left[q_t \cdot \max\{p_t^s - MC_t, 0\} \right] + v_t \left[p_t^c - \max\{0, p_t^w\} \right] \right) \right] FC_{WF,t} - D_{WF,t} - \tau_{WF,t} \right] \right] \quad (6)$$

where

PV_{WF}^i = Present Value of Wind Farm (i^{th} iteration)
 $FC_{WF,t}$ = Fixed Costs (i.e. Fixed Operations & Maintenance, Insurances etc)
 $D_{WF,t}$ = Financing costs – see Appendix I Eq.(A11-A15)
 $\tau_{WF,t}$ = Cash taxes payable

With 1000 iterations, the final wind farm project $WF1$ valuation is therefore:

$$PV_{WF1} = Median(\{PV_{WF1}^1, PV_{WF1}^2, \dots, PV_{WF1}^{1000}\}), \quad (7)$$

30-minute spot price data from the NEM's South Australian region forms the base of the block bootstrapping process. The dataset comprises ~168,000 observations and spans an entire electricity market business cycle (Arango and Larsen, 2011), including periods of over-weight and under-weight capacity, merit order and rebounds effects (i.e. low prices with 'renewables on', high spot prices with 'renewables off'). A statistical summary is presented in Tab1. Of note are the elevated Skewness and Kurtosis statistics, and the ratio of the time weighted average spot price (Line 2) to the wind fleet's dispatch weighted price (Line 12), with the result presented at Line 13. To summarise, the dispatch-weighted price (DWP) of the aggregate South Australian wind fleet as a ratio of the time-weighted spot price spans a range of 59.6% to 81.7%.

Table 1: Spot electricity prices (2017-2026, real 2026\$)

	SA Region	2026\$	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	AVG
1	Observations	#	17,520	17,520	17,520	17,568	17,520	17,520	17,520	17,568	17,520	10,130	167,906
2	Average Spot	\$/MWh	140.2	130.5	127.4	55.4	62.9	181.7	87.6	105.7	89.3	87.5	107.6
3	Max Spot	\$/MWh	17,966.5	18,586.2	18,754.3	15,478.4	17,989.8	17,109.5	12,665.6	17,506.6	16,678.5	20,300.0	17,303.6
4	Min Spot	\$/MWh	-723.0	-598.5	-1,000.0	-1,000.0	-788.2	-996.3	-567.5	-1,000.0	-381.7	-314.2	-736.9
5	-ve Prices	Hrs pa	69	111	398	857	1,700	1,664	2,292	2,288	2,666	1,187	1,338.1
6	Std Deviation		337.2	350.9	549.9	226.2	300.5	494.3	339.2	487.9	409.7	546.6	412.7
7	Skewness		40.0	35.0	30.4	48.4	32.5	18.9	21.6	22.5	24.4	30.4	29.5
8	Kurtosis		1,846.6	1,509.4	972.2	2,835.7	1,430.5	477.0	585.9	615.9	704.7	1,016.2	1,075.3
9	PoE10 Spot	\$/MWh	194.8	176.7	177.7	89.9	135.6	406.5	204.2	225.0	182.8	149.9	199.2
10	PoE90 Spot	\$/MWh	67.2	65.5	42.9	0.0	-37.9	-49.6	-55.2	-48.0	-26.8	-7.8	-4.7
11	Volatility*	(Line 6 / 2)	2.4	2.7	4.3	4.1	4.8	2.7	3.9	4.6	4.6	6.2	3.8
12	Wind Price**	\$/MWh	114.6	104.5	96.2	40.8	40.6	131.8	55.9	69.6	60.4	52.1	78.0
13	Wind Discount^	(%)	81.7	80.1	75.6	73.6	64.6	72.5	63.8	65.9	67.7	59.6	72.4

• * The volatility statistic is the coefficient of variation. ** The wind price is the Dispatch-Weighted Price or 'DWP'.

• ^ The wind discount is measured against the time-weighted average spot price in Line 2.

Source: Australian Energy Market Operator, Australian Bureau of Statistics.

Plant costs Engineering plant cost estimates and associated technical parameters form essential inputs to any power project valuation model. The wind farms to be modelled are all taken to be 100MW in size, and a 40MW battery is also assessed (to test 'firming assistance'). As Tab.2 notes, the overnight capital cost for a 100MW wind farm equates to \$3569/kW (including contingency) and an investment cost of \$356.9m. Battery capital costs are assumed at \$631/kW and \$260 per kWh.

Table 2: Wind project parameters

		Wind	Battery
Project Capacity	(MW)	100	40
- Storage Capacity	(Hrs)	-	4
Overnight Capital Cost	(\$/kW)	3,244	631
- Storage	(\$/kWh)	-	260
- Contingency		10%	-
Plant Capital Cost	(\$/kW)	3,569	1,670
Plant Capital Cost	(\$ M)	356.9	66.8
Operating Life	(Yrs)	30	20
Annual Capacity Factor	(%)	25-40%	14.7%
Transmission Loss Factor	(MLF)	0.970	1.000
Transmission REZ Costs	(\$/MW/a)	22,500	1,000
Fixed O&M	(\$/MW/a)	47,500	10,000
Variable O&M	(\$/MWh)	0.0	0.0
FCAS	(% Rev)	-1.0%	4.0%

FCAS = Frequency Control Ancillary Services.

Source: Nolan et al., (2026), Simshauser (2026)

Capital markets data Capital markets data is presented in Tab.3 and includes debt sizing parameters and covenants applied by risk averse project banks, based on 100% revenue contracted, and at the other extreme, 100% merchant. Interest rate swaps and credit spreads are combined to form the headline interest rate for each of Term Loan B (Bullet) and Term Loan A (Amortising) facilities – with the latter structured as a ‘Mini-Perm’ (i.e. a mini-permanent facility set within a notional amortisation period of 25 years). These represent observed capital markets data along with well-documented debt sizing parameters (see for example Simshauser and Nelson, 2012; Gohdes et al., 2022; Gohdes, 2023; Simshauser, 2026). The post-tax equity IRR under conditions of 100% contracted revenues is 10% and rises to 12% for merchant.

Table 3: Capital markets

Project Finance		100% Contracted	Merchant
Debt Sizing Constraints			
- DSCR	(times)	1.25x	1.80x
- Gearing Limit	(%)	80%	40%
- Default	(times)	1.05x	1.05x
PF Facilities - Tenor			
- Term Loan B (Bullet)	(Yrs)	5	5
- Term Loan A (Amortising)	(Yrs)	7	7
- Notional amortisation	(Yrs)	25	25
PF Facilities - Pricing			
- Term Loan B Swap	(%)	4.72%	4.72%
- Term Loan B PF Spread	(bps)	195	255
- Term Loan B PF Rate	(%)	6.67%	7.27%
- Term Loan A Swap	(%)	4.81%	4.81%
- Term Loan A PF Spread	(bps)	229	309
- Term Loan A PF Rate		7.10%	7.90%
- Refinancing Rate	(%)	6.88%	7.33%
Expected Equity Returns	(%)	10.0%	12.0%

DSCR = Debt Service Coverage Ratio. PF = Project Finance.

Sources: Bloomberg, Simshauser (2026).

4. Model Results

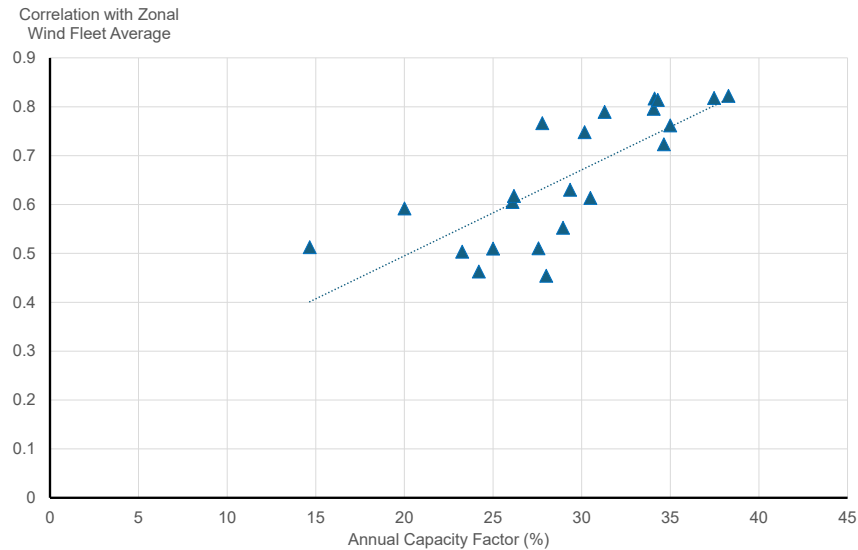
The South Australian wind fleet comprises 2.7GW of installed capacity across 22 (onshore) wind projects. This fleet produces 46.5% of aggregate final demand (and 63.7% grid-supplied energy market share⁶). Output from all 22 wind farms is positively correlated to aggregate wind farm output and span the range of 0.45 to 0.82 as illustrated in Fig.2 (y-axis). Fig.2 presents long-run (10-year) coefficients and each year varies around the average. For example, a high-capacity factor wind farm with a 0.82 long-run (i.e. 10-

⁶ Aggregate final demand is ~15TWh pa and rooftop solar PV is ~4.6TWh pa, meaning the demand for utility-scale power is 11.4TWh. Wind output of 7.6TWh pa is therefore 63.7%.

year) correlation exhibits annual results ranging from 0.78-0.87. Similarly, a low-capacity factor wind farm with a 10-year correlation coefficient of 0.52 varies from 0.44-0.65.

For this reason, the subsequent analysis will stress-test individual wind farms with low (25%) ACF / and low (0.52) fleet correlations, and high (40%) ACF / high (0.82) fleet correlations, along with middle-range wind farms exhibiting ACFs of 30-35%.

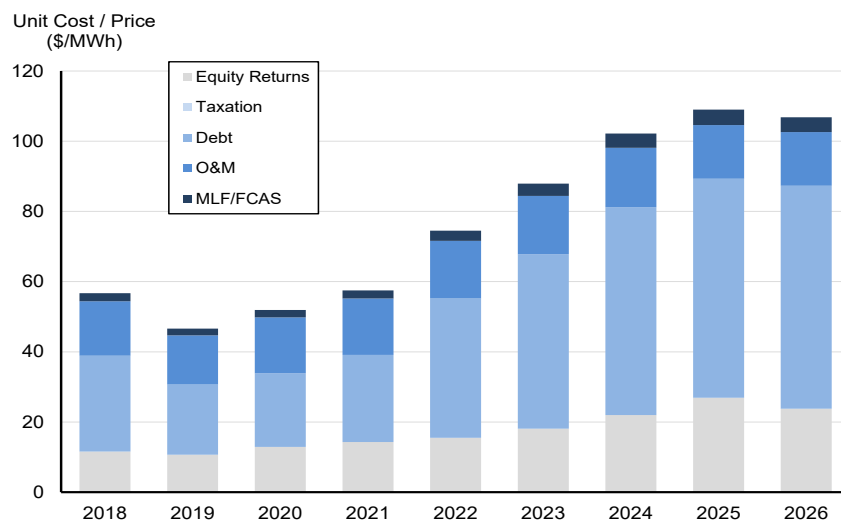
Figure 2: Long run Annual Capacity Factors and Correlations for 22 wind farms in South Australia over the period 2017-2026 (30-minute data)



Before proceeding with such analysis, it is first helpful to examine recent trends in wind cost dynamics. As with many jurisdictions⁷, wind entry costs have increased sharply.

After falling to record low unit costs during the period 2019-2020, Australian onshore wind projects experienced steadily rising entry costs through to 2025. The PCF Model has been used to generate high-resolution (project financed) entry cost estimates for a template wind farm each year from 2018-2026 with results illustrated in Fig.3 (at a constant 35% ACF). Critical revenue assumptions align with the dominant contractual model over this period, 75% PPA and 25% merchant exposure (Gohdes et al., 2023). Note unit costs reached their nadir during 2019 at \$46.6/MWh (~US\$33/MWh) before rising to \$106.8.

Figure 3: Wind entry costs (35% ACF, nominal dollars)



⁷ See for example the US data contained in [Lazard Releases 2026 Levelized Cost of Energy+ Report | Lazard](#)

The cause of cost increases spans the series of variables captured in the Fig.4 waterfall chart. Results reflect median capital cost data from more than 60GW of wind project due diligence reports used in banking processes over the period⁸. Turbine supply and civil costs have added considerably to entry costs, but the dominant impact is the cost of money – yields on 10-year Commonwealth government bonds have increased from 0.57% to 5.20% over the period 2020–2026. Rising rates flowed through to debt facility costs and (expected) equity returns.

Figure 4: Change in costs 2019-2026 (nominal dollars)

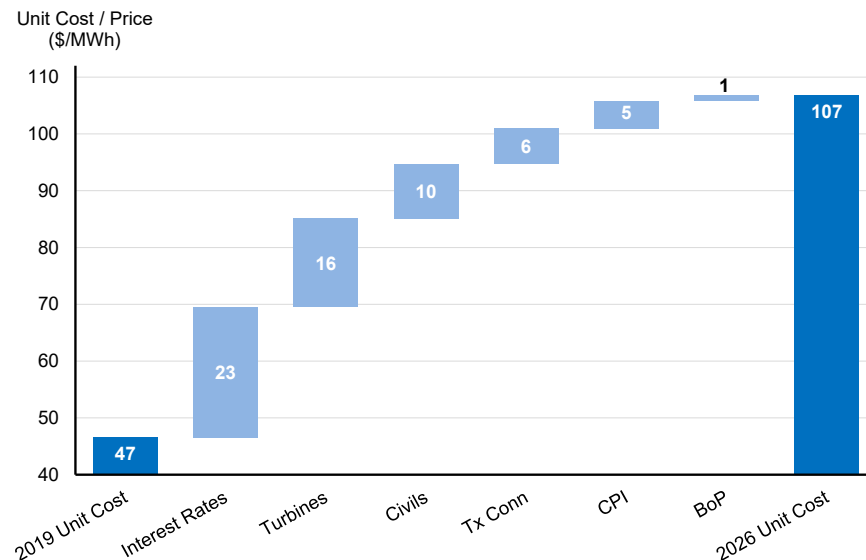
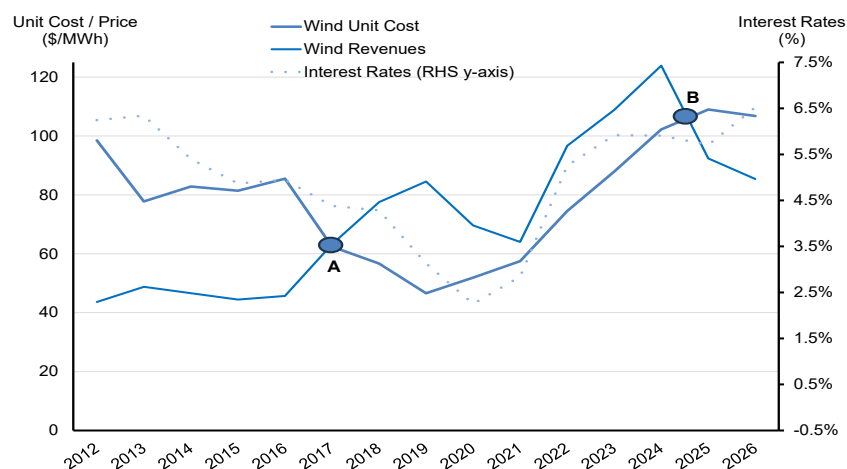


Fig.5 illustrates this by contrasting wind costs (thick dark blue line series, LHS axis) with interest rates (dotted light blue line, RHS axis). Fig.5 also plots the dispatch-weighted price of wind in the NEM (LHS axis). Notice from 2017 the dispatch-weighted price of wind surpassed entry costs (point 'A') but fell below from 2024 (point 'B'). This suggests that in the absence of falling costs or rising spot prices, some form of certificate, carbon price or government-initiated contract will be an important mechanism to underwrite entry.⁹

Figure 5: Wind unit costs vs Interest Rates & NEM Wind Revenues



⁸ The author is indeed grateful to Mr Paul Gleeson and his team of engineers from advisory firm Aurecon for kindly providing the very unique median capital cost timeseries data that enabled this analysis to be undertaken.

⁹ At the time of drafting Large-scale Renewable Generation Certificates (known as LGCs) are trading within the range \$2-10/MWh – done considerably from the historic trading range of \$25-45/MWh. This reflects the fact that the scheme is scheduled to close in 2030.

4.2 Block bootstrap model results

The next set of results are those from the block bootstrap model. Fig.6 presents historic spot prices (triangle markers) and synthetic block-bootstrapped spot prices (scatter plot). The y-axis measures average annual spot prices, while the x-axis examines intra-period volatility (i.e. the extent to which > \$300/MWh spot prices contributed to the annual average).

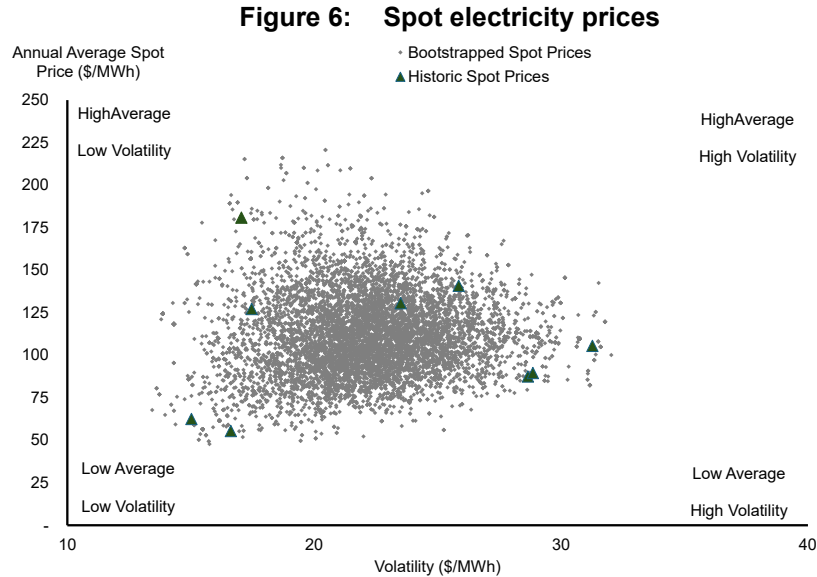


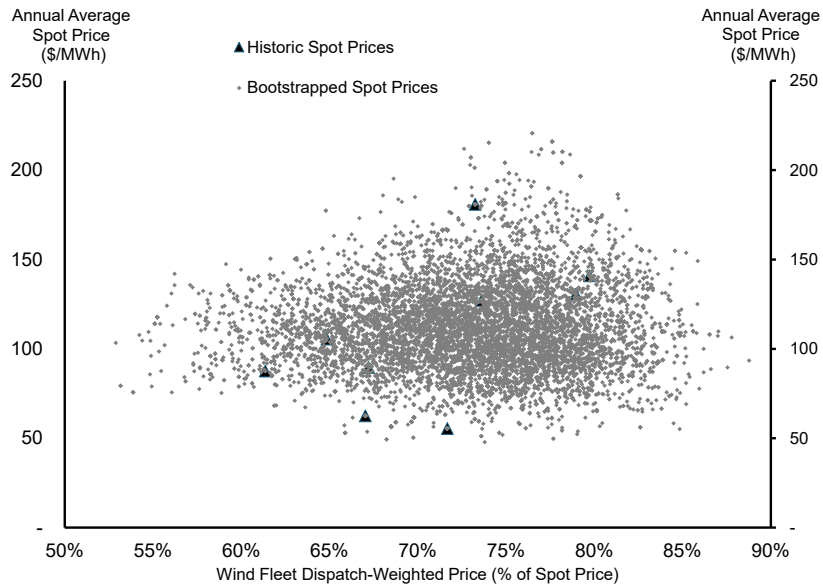
Table 4 provides a statistical comparison between the historic and bootstrapped prices.

Table 4: Historic vs Synthetic Spot Prices

SA Region			Historic	Bootstrap
			2017-2026	10,000 Yrs
			A	B
1	Observations	#	167,906	175,357,680
2	Average Spot	\$/MWh	106.8	111.6
3	Max Spot	\$/MWh	181.7	220.7
4	Min Spot	\$/MWh	55.4	47.7
5	-ve Prices	Hrs pa	1,323.0	1,285.1
6	Std Deviation		38.5	25.7
7	Skewness		0.6	0.5
8	Kurtosis		0.1	0.6
9	PoE10 Spot	\$/MWh	144.3	143.2
10	PoE90 Spot	\$/MWh	62.1	80.6
11	Volatility*	(Line 6 / 2)	0.4	0.2
12	Wind D-W Price**	\$/MWh	78.0	82.0
13	Wind Discount^	(%)	0.7	0.7
* Coefficient of Variation			** Dispatch Weighted Price	

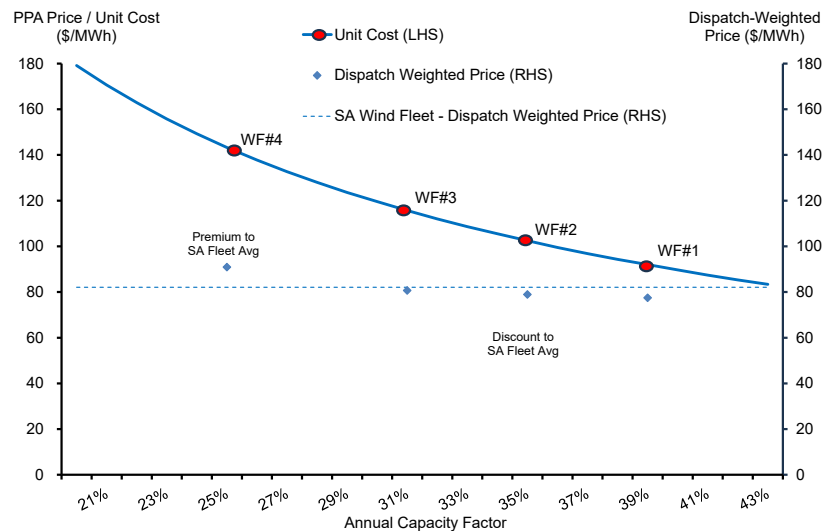
Another important set of results from the block bootstrapping model is the average spot price of electricity (y-axis) vs the dispatch-weighted price of wind (x-axis). These results represent the (chronologically matched) settlement price for the Asian wind swap.

Figure 7: Spot prices vs wind fleet dispatch-weighted price



Wind farms to be modelled Four of the existing 22 wind farms (WF) are examined in detail, and assumed to be new entrants. Recall from Tab.3 the capital cost of a new wind farm is ~\$3600/kW. The capital cost is held constant and so unit costs vary according to ACFs, and thus form part of a downward-sloping entry cost curve (Fig.8). WF#1 has a 40% ACF (x axis) and an entry cost of ~\$90/MWh (y-axis). Conversely, WF#4 has a 25% ACF and ~\$140/MWh entry cost. The historic dispatch-weighted price of each WF (diamond markers) presents in reverse order, while the median dispatch-weighted price of the South Australian wind fleet is represented by the horizontal dashed blue line at ~\$78/MWh. WF#4 is 111% of the fleet average, whereas WF#1 is 94% of the fleet average. These ratios prove to be important variables in deriving optimal hedge positions (in Section 4.4).

Figure 8: Entry cost curve



4.3 Optimal hedging under uncertainty with an Asian wind swap

Recall from Eq.(5) gross profit for a wind farm in a 30-minute trading interval comprises spot market revenues and two-way settlement of the Asian wind swap. Interval data is aggregated into reporting periods, which in this research is annual. Given 10,000 years of simulated wind farm results, the (*ex ante*) optimal hedge position under uncertainty can be derived for a given level of risk. Markowitz's (1952) two-parameter model of portfolio risk and return provides the basis. Markowitz's model applied to financial assets vis-à-vis expected portfolio returns above the risk-free rate (numerator), and standard deviation of portfolio returns (denominator), which in turn is known as Sharpe Ratio. In this research, this ratio is

modified and translated from financial markets to commodity markets by substituting expected stock returns for expected or PoE50 gross profits (numerator) and substituting the standard deviation of returns for the expected downside deviation or PoE95 gross profit (denominator). Hereafter, this will be referred to as the *Modified Sharpe Ratio* (see Simshauser, 2020, 2026).

The key modification to Markowitz's two-parameter model is the denominator – using the downside deviation (PoE95) rather than standard deviation of gross profits. With 10,000 years of gross profits calculated within the Unit Commitment & Financial Settlements model, the PoE95 (and PoE50) result is readily available for each wind farm.

The PoE95 gross profit result is important for two reasons. First, spot electricity prices in energy-only markets are asymmetric given very high market price caps (currently set to \$23,200/MWh). The risk associated with short positions must therefore be carefully analysed on behalf of shareholders. Second, project banks face an asymmetric payoff and consequently, aligning hedge positions to optimise downside earnings ensures the best possible result for debt sizing.

Results of hedge optimisations for the four WFs are presented in Fig.9. The Unit Commitment & Financial Settlements model extracts the PoE50 and PoE95 gross profit result from the 10,000 iterations for each of WF#1-4 for any level of hedging (LHS y-axis). Dividing the PoE50 line by the PoE95 line produces the *Modified Sharpe Ratio* (light blue line series, RHS y-axis). The objective function is to identify the nadir of Sharpe ratio, which in turn identifies the optimal hedge position under uncertainty, measured in MW on the x-axis.

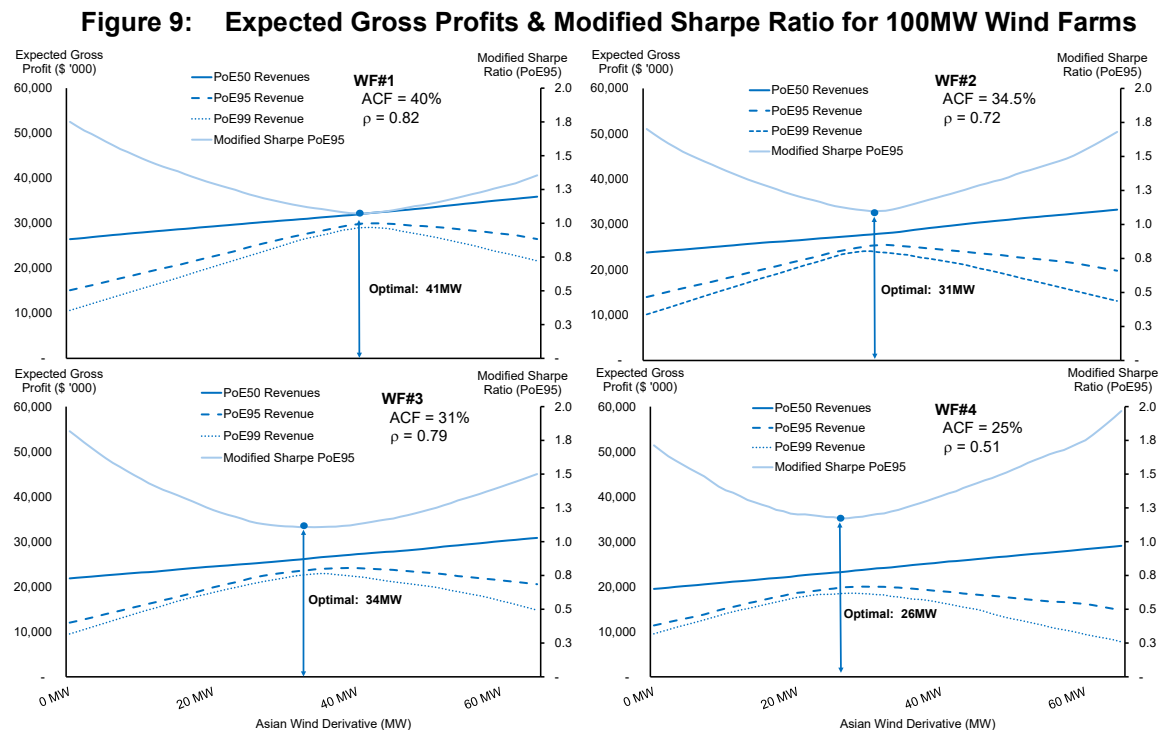


Fig.9 represents a key insight from this research. The top-left chart plots the simulation results for WF#1. Note the solid dark blue line traces PoE50 gross profit, which is gently upward sloping. This is because the Asian wind swap strike price has been set to entry costs, which is higher than the PoE50 dispatch-weighted price of WF#1. Consequently, at PoE50, more hedging equates to more profit, ex ante.

However, focusing on PoE50 results is a partial analysis. The downside deviation PoE95 gross profit needs to be examined carefully (dashed blue line). This provides a sense of potential downside scenarios arising from under- or over-hedging. Running from left to right, the PoE95 line initially rises, then plateaus, then falls. For WF#1, the PoE95 result plateaus at ~40–45MW of hedging (y-axis). This provides a sense of where optimality in hedging lies. Then, dividing PoE50 by PoE95 results produces the *Modified Sharpe Ratio* – represented by the light blue line series (RHS y-axis). This sharpens the result to the optimal risk-adjusted ex ante hedge position – which occurs at the nadir of this line series at 41MW.¹⁰

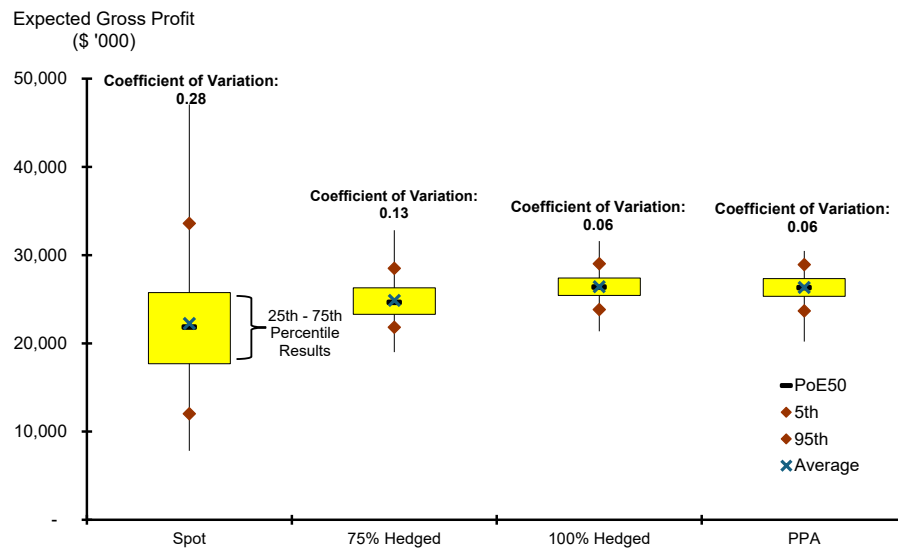
¹⁰ From a sensitivity perspective, this result is robust for the range PoE95 to PoE99 at +/- 1MW.

This same analysis is then repeated for WF#2-4. To generalise, the optimal level of hedging under uncertainty for a 100MW wind farm is approximately equal to its installed capacity, multiplied by its ACF, with any marginal difference attributed to the stability of plant correlation with the wind fleet, and the plant's own dispatch-weighted spot price relative to the fleet average (see also Simshauser, 2020; Nolan et al., 2026).

4.4 Quality of hedging with an Asian wind swap

Section 4.4 results identify optimal hedging under uncertainty. This optimality has been stress tested against 10,000 years of synthetic spot price data at a 5% confidence limit (i.e. PoE95). While optimising hedge levels was tractable, of utmost importance is the quality of gross profit, ex post. In this instance, one of the more variable wind farms from an output perspective (WF#3) is analysed in detail through the Fig.10 box plot. Specifically, Fig.10 comprises 4 distinct box plots for WF#3 spanning from (1) a purely merchant industrial form (i.e. no hedges), (2) with 75% of the optimal Asian wind swap cover (i.e. roughly equal to 75% of its annual capacity factor), then (3) 100% of the optimised Asian wind swap cover (i.e. roughly equal to its annual capacity factor), and finally, (4) 100% run-of-plant PPA cover for comparative purposes.

Figure 10: Comparison of Merchant, Asian Wind Swap and PPA gross profit

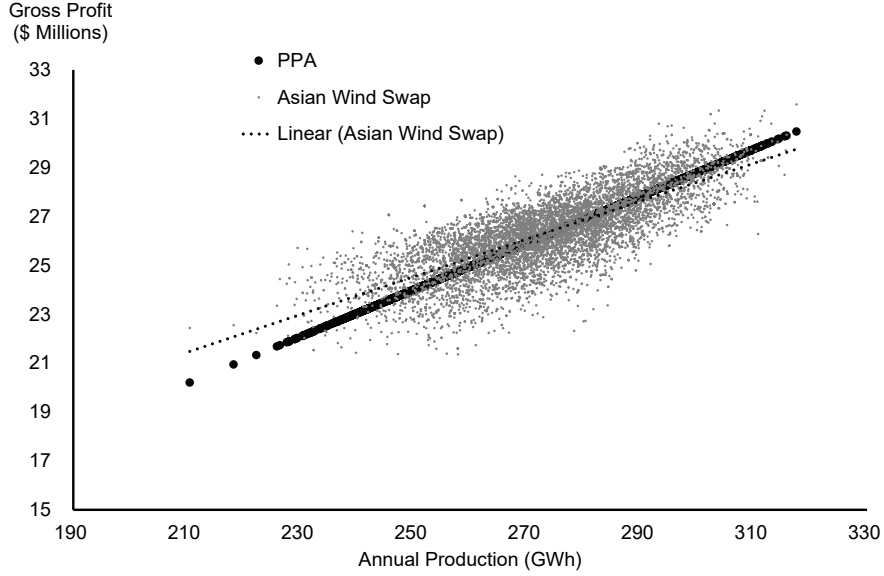


The first box plot illustrates the inherent riskiness of spot market revenues through a representation of 10,000 years of spot revenues. Notice the coefficient of variation is 0.28 and gross profits span \$7.8m to \$46.9m with a median result of ~\$20m. In the second box plot, the Asian wind swap is applied at 75% of the optimal hedge level under uncertainty (i.e. 75% of 34MW). Revenue volatility reduces sharply, with the coefficient of variation falling from 0.28 to 0.13. The third box plot shows optimal hedging under uncertainty with the Asian wind swap. Note the coefficient of variation reduces by half again, from 0.13 to 0.06, suggesting a very tight range for gross profits.

The distribution of gross profits arising from the optimal level of hedging with an Asian wind swap (compared to a run-of-plant PPA) is a striking result. The Asian wind swap and the run-of-plant PPA distributions appear identical. Indeed, the PoE50 gross profit and the distribution of gross profit are *almost* identical, at 0.06 coefficient of variation. Yet, the correlation coefficient between the 2 x 10,000 sets of gross profits is not, at 0.77 (i.e. strong, but *not* perfectly correlated). PPA volatility is driven by variation in annual wind speeds, network constraints and negative prices. Asian wind swap volatility is driven by positive and negative basis risk, and positive and negative quantity exposures arising from wind speeds, congestion and negative prices.

Fig.11 presents the 10,000 gross profit results for each of the PPA and the Asian wind swap. The PPA follows a linear pattern in that gross profit (x axis) is driven completely by wind output (y-axis). Conversely, the Asian wind swap is positively, but not perfectly, correlated to output because it is first and foremost a cash-settled derivative. Once set for WF#3 at 34MW, the Asian wind swap is settled regardless of WF#3 output. In the event, sometimes this is highly beneficial – particularly during low wind years (cf. PPAs), and other times the reverse is true. On average, the derivative provides subtly better downside deviation protection as wind speeds reduce, and less upside at high wind speeds, as the dashed line of best fit suggests.

Figure 11: 0,000 Gross profit results – PPA vs Asian Wind Swap



5. PCF Model Results: are Asian wind swaps bankable?

Thus far, the use of market-wide prices and wind production data has been used to construct and settle Asian wind swaps. 10,000 years of bootstrapped data stress tested the instrument, and optimal hedging under uncertainty for a given level of portfolio risk was determined. When spot revenues for wind farms were combined with the Asian wind swap, box plots in Fig.10 confirmed gross profits were constrained to a tight range, and from a downside deviation perspective, replicated a PPA.

This suggests a 100MW wind farm hedged with a long-dated Asian wind swap at the optimal level may be a bankable proposition. To be certain, testing must occur through the PCF Model. The PCF Model operates in two modes: (1) entry-cost mode and (2) valuation mode. Cost mode was used to generate initial entry costs presented in Fig.8. It is now necessary to utilise the PCF Model in valuation mode. Here, the PCF Model populates each future operating year of the wind farm with volatile prices, varying production and Asian wind swap settlements data. The Model utilises a sub-sampling engine to randomly draw from the 10,000 years of stochastic, chronologically matched wind production, spot price and Asian swap settlements data.

At this point, the strike price of the Asian wind swap needs to be determined. If the four WFs were bidding into a central auction for a conventional CfD, under competitive market conditions they would offer their levelized cost (see Fig.8). In a discriminatory price auction (as is customary in Australia) for 300MW of wind, clearing prices would then be set at \$90, \$100 and \$115 for 3 x 100MW WF#1-3 respectively, adjusted by their marginal loss factor (viz. transmission loss coefficient).

Under equivalent conditions, the strike price of an Asian wind swap (p_y^c) offered at auction would be derived by taking the levelized cost and adjusting for 'basis risk', as follows:

$$p_y^c \cong \left(\frac{AC_w}{MLF_w} \right) \cdot \left(p_t^{as} / \sum_{y=1}^n \sum_{t=1}^{Ty} \left(\frac{q_{y,t} \cdot p_{y,t}^s}{y \cdot q_t} \right) \right) \quad (9)$$

Where

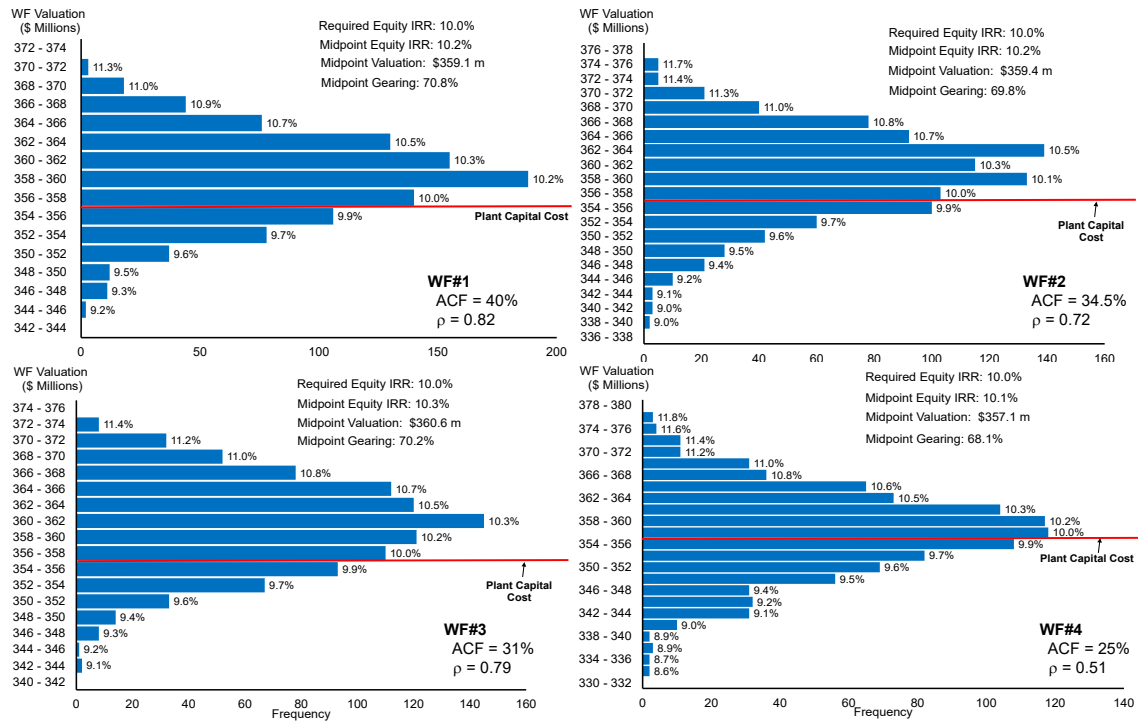
AC_w is the entry or average cost of project financed wind farm w
 MLF_w is the marginal loss factor of the wind farm w

The first term in Eq.(9) is the same calculation used for a conventional CfD auction, viz. the levelized cost of the plant (Fig.8) divided by its marginal loss factor (MLF_w) listed in Tab.2. The second term adjusts the price by calculating the ratio of the dispatch-weighted price of the wind fleet to the dispatch-weighted price of wind farm w . This second term is important and adjusts for basis differentials which can be less

than or greater than 1.0 (viz. the diamond shaped markers relative to the fleet average represented by the horizontal line in Fig.8).

Once each future operating period of the wind farm's useful life has been populated with spot revenues and Asian wind swap settlements, the PCF model's debt sizing algorithms proceed to co-optimize the Bullet and Amortising 'mini-perm' project finance facilities within the bounds of covenants imposed by risk-averse project banks (outlined in Tab.3). This sub-sampling routine and individual valuation process in the PCF Model is then iterated 1000 times over. This in turn produces a distribution of plant valuations and associated debt-sizing results (see Fig.12).

Figure 12: WF#1-4 project valuations (1000 iterations)



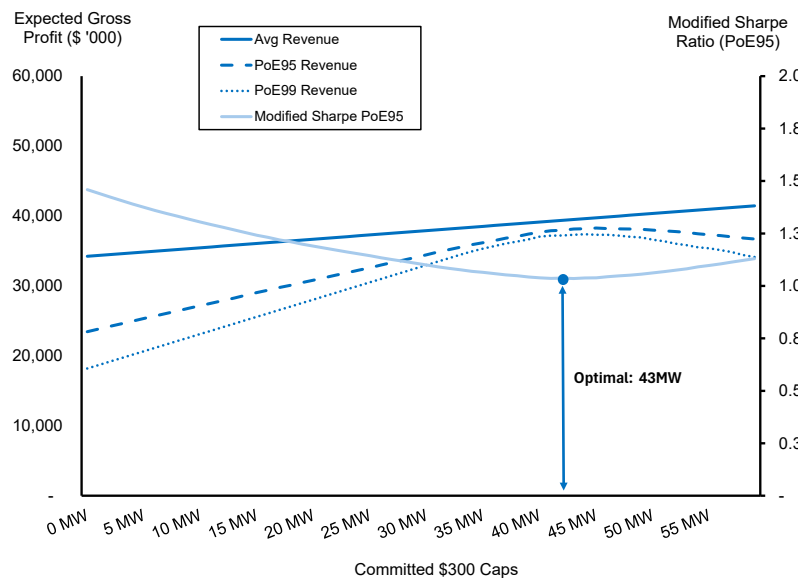
In Fig.12, the y-axis in each chart captures the range of plant valuations in \$2 million buckets, while the x-axis measures the frequency of valuations in each bucket. The capital cost of the wind farm is highlighted by the red horizontal line at \$356m. Each wind farm (WF#1-4) presents as bankable under the optimal hedge design, with debt sizing consistently producing gearing levels of ~70% +/-2%. Note the PPA equivalent result obtains 71% gearing.

There is variability in equity returns, which is to be expected. The extent of variability is (broadly) inversely correlated to wind farm ACFs. Put simply, the lower the expected ACF, the higher the dispersion of equity returns. Regardless, in each case the midpoint valuation achieves a 10% equity IRR hurdle for a 100% contracted wind farm, with expected returns spanning a comparatively tight range of 9-12% across the 1000 valuations. A complete summary of the all market and financial results (Figs.9 and 12) appears in Tab.5.

Table 5: Market Results and Financial Results for WF#1-4

		WF#1	WF#2	WF#3	WF#4	Fleet
Markets						
Annual Capacity Factor	(%)	40	35	31	25	32
Correlation with Fleet	(%)	82	72	79	51	100
DWP at PoE50	(\$/MWh)	77.5	78.9	80.7	90.9	82.0
DWP ratio to Fleet	(%)	94	96	98	111	100
Entry Cost*	(\$/MWh)	88.3	101.6	112.4	140.1	
Asian Wind Swap	(\$/MWh)	93.4	105.6	114.2	126.4	
Optimal Hedge	(MW)	41	33	34	26	
PoE50 Gross Profit	(\$m)	32.2	28.1	26.3	23.2	
PoE95 Gross Profit	(\$m)	29.7	25.5	23.3	19.4	
Modified Sharpe Ratio		1.09	1.10	1.13	1.20	
Coefficient of Variation		0.04	0.05	0.06	0.08	
Financials						
Capital Cost	(\$m)	357.0	357.0	357.0	357.0	
Median Valuation	(\$m)	359.1	359.4	360.6	357.1	
Valuation Range	(\$m)	344-372	338-376	342-374	332-378	
Midpoint Gearing	(%)	70.8	69.8	70.2	68.1	
Midpoint Equity IRR	(%)	10.2	10.2	10.3	10.1	
Equity IRR Range	(%)	9.2-11.3	9.0-11.7	9.1-11.4	8.6-11.8	

Does adding a battery help? Given Australia has the 3rd highest deployment of utility-scale batteries globally (and by far the highest deployment rate on a per capita basis), a logical line of inquiry is whether adding a small battery assists with financial results. Current battery deployments are dominated by 4h, so in the following analysis a 40MW 4h battery is added to WF#1 (this result can be generalised to all four WFs). Interestingly there is no substantive gain. The optimal level of hedging moves a mere 2MW. And while not illustrated here, variations in gross profit are amplified. This result is consistent with the findings in Newbery (2026).

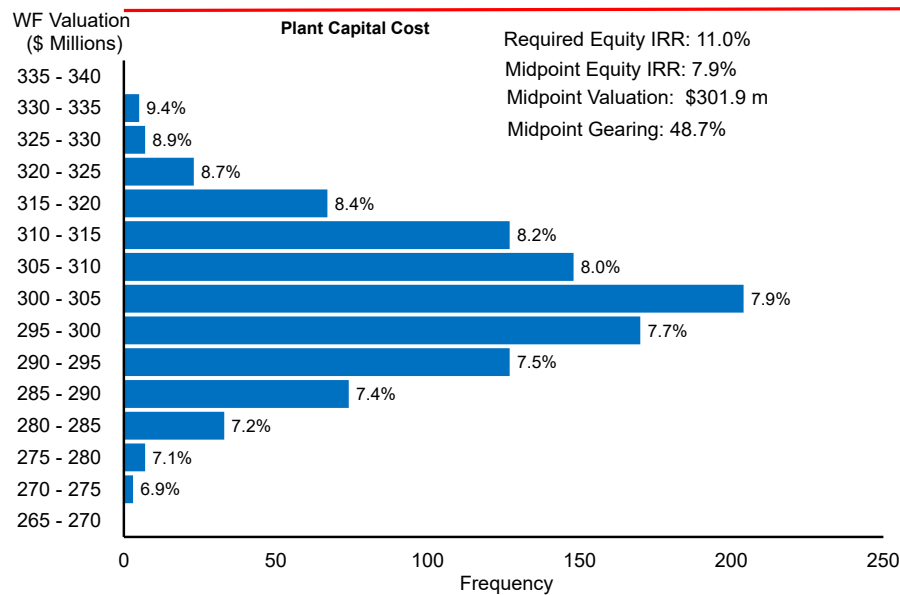
Figure 13: WF#1 (100MW, 40% ACF) and 40MW 4h battery

5.2 Semi-merchant and merchant

The final set of results examine the dominant entry model in Australia's NEM, the semi-merchant renewable plant. Here, we follow results in Gohdes et al., (2023) which identify ~75-80% as the optimal level of PPA cover. Results focus on WF#1 (and once again, can be generalised to all four WFs).

For a semi-merchant plant, there are three key changes. First, required equity returns increase from 10% to 11%. Second, debt sizing becomes more constrained because a lower share of revenues is contracted and a larger share is exposed to spot-price outcomes. Third, the valuation becomes more sensitive to gaps between the Asian wind swap strike price and expected merchant earnings.

Figure 14: WF#1 semi merchant results



Results are clear and not unexpected given the cost assumptions. In the current environment, the historically dominant semi-merchant model fails to replicate the same metrics as the optimally hedged plant, largely due to elevated entry costs of wind. Recall the strike price of the Asian wind swap (p_t^c) is set to entry cost, and for now, this exceeds the expected earnings from the bootstrapped spot market prices (noting RET certificate revenue has been excluded). Therefore, hedging is profitable through to the optimal setpoint (Fig.9). Should RET certificates recover in prices from their historic lows, this may alter the result.

The findings in Section 5 have certain limitations. The analysis is region-specific and relies on South Australian price and wind-output relationships over 2017–2026. Outcomes may differ in other zones and other jurisdictions with lower wind market share, stronger interconnections, or different congestion dynamics. However, it is to be noted that in Nolan et al., (2026) found equivalent results when modelling the NEM's New South Wales region using 85 weather years.

Another potential limitation arises from bootstrapping historical data. Doing so preserves historical dependence structures across an elongated business cycle, but this may not be able to replicate a structural break beyond the observed sample. Finally, the bankability results depend on strike-price calibration to entry costs.

These limitations do not undermine the central findings, but they define the conditions under which results should be interpreted. Conversely, the modelling framework presented herein can be adjusted to relevant market conditions.

6. Policy implications and concluding remarks

In this article, the bankability of Asian wind swaps was analysed. Model results were consistently tractable. This suggests that, given the prospects for seamless secondary trade, Asian wind swaps are worthy of further research vis-à-vis specific product design.

In reviewing the literature on renewable investments, a persistent theme is the requirement for long-dated revenue stability to meet critical credit-rationing requirements imposed by project banks. Where markets struggle to originate requisite long-dated PPAs, solutions frequently default to government-initiated CfDs (which in Australia, is underwritten by taxpayers). Rarely is there a connection back to retail markets and longer-term impacts on electricity consumers. This appears to have been a guiding principle of the Nelson

Review and in this context, Asian wind swaps present as a potentially important market development for at least five policy reasons:

1. Taxpayer-funded CfDs extract primary hedge capacity from forward markets (Simshauser, 2019). While this may not matter at the margins, as government-initiated CfDs accumulate in volume and market share, the loss of hedge capacity may reach a damaging level where primary issuance triggers the exit of secondary traders, at which point liquidity can (and has¹¹) collapsed. This adversely affects customer pricing and presents an intolerable situation for non-integrated retail suppliers vis-à-vis hedging, ultimately leading to foreclosure (see Flottman et al., 2023; Flottman et al., 2024). A well designed derivative may be capable of *seamless re-trading* in secondary markets, in divisible tenors and quantities. This may reinstate primary contract capacity more readily for retail supplier portfolio hedging (Gohdes et al., 2026).
2. Unlike bespoke PPAs, an Asian wind swap may concentrate secondary trade and maximise market liquidity, a necessary precondition of efficient forward markets (Ausubel and Cramton, 2010) and essential for guiding investment timing in energy-only markets (Simshauser, 2021). Conversely, existence of a specific derivative does not preclude run-of-plant PPAs for counterparties with different risk appetites. After all, OTC trade exists in all markets alongside standardised exchange-based derivatives.
3. In Australia, 200+ renewable projects were originated under the RET (Simshauser and Gilmore, 2026). The RET terminates in 2030. A non-trivial portion of existing bilateral PPAs may terminate in December 2030. Creating a liquid market for Asian wind swaps, with tenors spanning the usual forward trading range, may assist with a more orderly market transition for buyers, investors and project banks by mitigating large PPA cliff edges (i.e. single contract expiry events) in retail hedge books, investor portfolios, and project debt facility contracted revenues.
4. From a retail supplier perspective, establishing liquid markets for Asian wind swaps (i.e. OTC and on-exchange) at quarterly resolution will assist with emerging portfolio construction, especially for 2nd and 3rd tier retailers incapable of banking long-dated PPAs due to credit constraints (Gohdes et al., 2022)¹². A derivative also removes buy-side exposure to single asset risk, which can be highly problematic for smaller 2nd and 3rd tier retailers.
-
5. From an investor perspective, establishing liquid markets for Asian wind swaps at quarterly resolution will enable long-dated positions to be trimmed if conditions change. 15-year transactions span a long time-horizon. With an established position, being able to marginally adjust or trim hedged positions upwards or downwards at quarterly resolution will invariably be valuable if structural breaks occur in marginal loss factors or correlations with fleet averages. The ability to trim quantities aides-longer dated risk management.¹³

Overall, the analysis indicates the bankability problem created by incomplete markets need not be solved exclusively through bespoke government-initiated CfDs. Asian wind swaps can reproduce the revenue-stabilising properties required by project banks while introducing a level of standardisation, divisibility and re-trading potential that currently does not exist, and is required by forward market participants (i.e. retail suppliers) on behalf of customers.

Results do not claim derivatives removes basis risk or quantity risk, nor that South Australian outcomes will necessarily generalise mechanically to every NEM region or other jurisdictions around the world. Rather, it is that these risks can be identified, measured, priced and managed within a project financed framework. This makes Asian wind swaps a credible candidate for bridging the gap between renewable investment bankability on the one hand, and competitive retail-market design on the other. On this basis, considerable policymaker, project banker and equity investor effort seems warranted to identify a suitable reference product, and, continue the necessary market-development work.

¹¹ See for example Simshauser (2019) and Flottmann et al., (2025).

¹² The issue here is that to be bankable, the PPA buyer must have an investment grade credit rating. Many 2nd and most 3rd tier retailers are unrated and supplementary credit support for long dated PPAs (e.g. Bank Guarantees) would be too onerous.

¹³ By way of simple example, if a plant's marginal loss factor deteriorated, Asian swaps could be purchased in certain quarters to hold the modified Sharpe ratio broadly constant.

7. References

- Abadie, L.M. (2015) 'Operating flexibility at power plants: A market valuation', *International Journal of Electrical Power and Energy Systems*, 64, pp. 41–49. Available at: <https://doi.org/10.1016/j.ijepes.2014.07.011>.
- Abadie, L.M. and Chamorro, J.M. (2008) 'Valuing flexibility: The case of an Integrated Gasification Combined Cycle power plant', *Energy Economics*, 30(4), pp. 1850–1881. Available at: <https://doi.org/10.1016/j.eneco.2006.10.004>.
- Abraham, J.K. (2025) *The use of Equity Cures in Debt Contracts* *. Available at: [dx.doi.org/10.2139/ssrn.4944497](https://doi.org/10.2139/ssrn.4944497) (Accessed: 5 September 2026).
- Alexandridis, A. and Zapanis, A. (2013) 'Wind Derivatives: Modeling and Pricing', *Computational Economics*, 41(3), pp. 299–326. Available at: <https://doi.org/10.1007/s10614-012-9350-y>.
- Anderson, E.J., Hu, X. and Winchester, D. (2007) 'Forward contracts in electricity markets: The Australian experience', *Energy Policy*, 35(5), pp. 3089–3103. Available at: <https://doi.org/10.1016/j.enpol.2006.11.010>.
- Arango, S. and Larsen, E. (2011) 'Cycles in deregulated electricity markets: Empirical evidence from two decades', *Energy Policy*, 39(5), pp. 2457–2466.
- Ausubel, L.M. and Cramton, P. (2010) 'Using forward markets to improve electricity market design', *Utilities Policy*, 18(4), pp. 195–200. Available at: <https://doi.org/10.1016/j.jup.2010.05.004>.
- Baker, M., Mayfield, E.S. and Parsons, J. (1998) 'Alternative Models of Uncertain Commodity Prices for Use with Modern Asset', *The Energy Journal*, 19(1), pp. 115–148.
- Bezemer, D. et al. (2023) 'Credit policy and the "debt shift" in advanced economies', *Socio-Economic Review*, 21(1), pp. 437–478. Available at: <https://doi.org/10.1093/ser/mwab041>.
- Billimoria, F. and Simshauser, P. (2026) Caps-and-Floors for Long Duration Storage and Firming: Contract Design Under Risk and Price Asymmetry.
- Borgonovo, E. and Gatti, S. (2013) 'Risk analysis with contractual default. Does covenant breach matter?', *European Journal of Operational Research*, 230(2), pp. 431–443. Available at: <https://doi.org/10.1016/j.ejor.2013.04.047>.
- Capen, E., Clapp, R. and Campbell, W. (1971) 'Competitive bidding in high risk situations', *Journal of Petroleum Technology*, 23(6), pp. 641–653. Available at: www.archive.org.
- Cassano, M. and Sick, G. (2013) 'Valuation of a spark spread: an LM6000 power plant', *European Journal of Finance*, 19(7–8), pp. 689–714. Available at: <https://doi.org/10.1080/1351847X.2011.617763>.
- Dudek, A.E., Paparoditis, E. and Politis, D.N. (2016) 'Generalized seasonal tapered block bootstrap', *Statistics and Probability Letters*, 115, pp. 27–35. Available at: <https://doi.org/10.1016/j.spl.2016.03.022>.
- Elias, M.R. us S., Wahab, M.I.M. and Fang, L. (2017) 'Integrating weather and spark spread options for valuing a natural gas-fired power plant with multiple turbines', *Engineering Economist*, 62(4), pp. 293–321. Available at: <https://doi.org/10.1080/0013791X.2016.1258746>.
- Esty, B. (2002) 'Returns on project financed investments: evolution and managerial implications', *Journal of Applied Corporate Finance*, 15(1), pp. 71–86. Available at: <https://doi.org/10.1111/j.1745-6622.2002.tb00342.x>.
- Esty, B.C. (2004) 'Why study large projects? An introduction to research on project finance', *European Financial Management*, 10(2), pp. 213–224. Available at: <https://doi.org/10.1111/j.1354-7798.2004.00247.x>.
- Farrell, L.M. (2003) 'Principal-agency risk in project finance', *International Journal of Project Management*, 21(8), pp. 547–561. Available at: [https://doi.org/10.1016/S0263-7863\(02\)00086-8](https://doi.org/10.1016/S0263-7863(02)00086-8).
- Finon, D. (2008) 'Investment risk allocation in decentralised electricity markets. The need of long-term contracts and vertical integration', *OPEC Energy Review*, 32(2), pp. 150–183.
- Fleten, S.E. and Näsäkkälä, E. (2010) 'Gas-fired power plants: Investment timing, operating flexibility and CO2 capture', *Energy Economics*, 32(4), pp. 805–816. Available at: <https://doi.org/10.1016/j.eneco.2009.08.003>.
- Flottmann, J. (2024) 'Australian energy policy decisions in the wake of the 2022 energy crisis', *Economic Analysis and Policy*, 81, pp. 238–248. Available at: <https://doi.org/10.1016/j.eap.2023.11.025>.
- Flottmann, J. et al. (2025) 'The forward market dilemma in energy-only electricity markets', *Energy Economics*, 148. Available at: <https://doi.org/10.1016/j.eneco.2025.108676>.
- Flottmann, J., Wild, P. and Todorova, N. (2024) 'Derivatives and hedging practices in the Australian National Electricity Market', *Energy Policy*, 189. Available at: <https://doi.org/10.1016/j.enpol.2024.114114>.
- Gersema, G. and Wozabal, D. (2017) 'An equilibrium pricing model for wind power futures', *Energy Economics*, 65, pp. 64–74. Available at: <https://doi.org/10.1016/j.eneco.2017.04.032>.

- Gohdes, N. (2023) 'Unhedged risk in hybrid energy markets: Optimising the revenue mix of Australian solar', *Economic Analysis and Policy*, 80, pp. 1363–1380. Available at: <https://doi.org/10.1016/j.eap.2023.10.004>.
- Gohdes, N. (2025) 'On spot revenues, capital structure and trade off theory: Analysing investment risk for contracted renewables', *Energy Economics*, 148. Available at: <https://doi.org/10.1016/j.eneco.2025.108703>.
- Gohdes, N., Nelson, T. and Hirschhorn, P. (2026) 'Alternative Contract Design: Analysing the Bankability of Fungible Derivative Contracts in Energy-Only Markets', *Australian Journal of Agricultural and Resource Economics* [Preprint]. Available at: <https://doi.org/10.1111/1467-8489.70149>.
- Gohdes, N., Simshauser, P. and Wilson, C. (2022) 'Renewable entry costs, project finance and the role of revenue quality in Australia's National Electricity Market', *Energy Economics*, 114. Available at: <https://doi.org/10.1016/j.eneco.2022.106312>.
- Gohdes, N., Simshauser, P. and Wilson, C. (2023) 'Renewable investments, hybridised markets and the energy crisis: Optimising the CfD-merchant revenue mix', *Energy Economics*, 125, p. 106824. Available at: <https://doi.org/10.1016/j.eneco.2023.106824>.
- Gómez-Valencia, S., Gonzalez-Ruiz, J.D. and Marín-Rodríguez, N.J. (2024) 'Perspectives on project finance and renewable energy infrastructure research', *Journal of Infrastructure, Policy and Development*, 8(7). Available at: <https://doi.org/10.24294/jipd.v8i7.6041>.
- Green, R. (2006) 'Market power mitigation in the UK power market', *Utilities Policy*, 14(2), pp. 76–89. Available at: <https://doi.org/10.1016/j.jup.2005.09.001>.
- Hlouskova, J. et al. (2005) 'Real options and the value of generation capacity in the German electricity market', *Review of Financial Economics*, 14(3–4), pp. 297–310. Available at: <https://doi.org/10.1016/j.rfe.2004.12.001>.
- Howell, B., Meade, R. and O'Connor, S. (2010) 'Structural separation versus vertical integration: Lessons for telecommunications from electricity reforms', *Telecommunications Policy*, 34(7), pp. 392–403.
- Ioannidou, V., Pavanini, N. and Peng, Y. (2022) 'Collateral and asymmetric information in lending markets', *Journal of Financial Economics*, 144(1), pp. 93–121. Available at: <https://doi.org/10.1016/j.jfineco.2021.12.010>.
- Jadidi, H. et al. (2025) 'Risk mitigation in project finance for utility-scale solar PV projects', *Energy Economics*, 143. Available at: <https://doi.org/10.1016/j.eneco.2025.108221>.
- Joskow, P.L. (2006) Competitive electricity markets and investment in new generating capacity. 06–009.
- Malleret, S. et al. (2024) 'Profitability dynamics of offshore wind from auction to investment decision', *Renewable and Sustainable Energy Reviews*, 199. Available at: <https://doi.org/10.1016/j.rser.2024.114450>.
- Markowitz, H. (1952) 'Portfolio Selection', *The Journal of Finance*, 7(1), pp. 77–91.
- Marshman, D. et al. (2020) 'Performance of wholesale electricity markets with high wind penetration', *Energy Economics*, 89. Available at: <https://doi.org/10.1016/j.eneco.2020.104803>.
- Marshman, D., Brear, M. and Ring, B. (2022) 'Impact of unit commitment and RoCoF constraints on revenue sufficiency in decarbonising wholesale electricity markets', *Energy Economics*, 106. Available at: <https://doi.org/10.1016/j.eneco.2021.105763>.
- Mountain, B. (2025) 'An analysis of electrical storage demand and cost in South Australia', *Energy Economics*, 143. Available at: <https://doi.org/10.1016/j.eneco.2025.108224>.
- Nelson, J. and Simshauser, P. (2013) 'Is the Merchant Power Producer a broken model?', *Energy Policy*, 53, pp. 298–310.
- Nelson, T. et al. (2013) 'An analysis of Australia's large scale renewable energy target: Restoring market confidence', *Energy Policy*, 62, pp. 386–400.
- Nelson, T. et al. (2025) *National Electricity Market wholesale market settings review (Final Report)*. Available at: www.energy.gov.au/energy-and-climate-change-ministerial-council/energy-ministers-.
- Newbery, D. (2006) *Market design*, EPRG Working Paper. EPRG Working Paper No.0515.
- Newbery, D. (2016) 'Missing money and missing markets: Reliability, capacity auctions and interconnectors', *Energy Policy*, 94(January), pp. 401–410.
- Newbery, D. (2021) 'Strengths and weaknesses of the British market model', in J.-M. Glanchant, P. Joskow, and M. Pollitt (eds.) *Handbook on Electricity Markets*, pp. 156–181.
- Newbery, D. 2026. Trading off capacity factors, location, storage, access charges and curtailment for renewable electricity, *Energy Economics* 162 at <https://doi.org/10.1016/j.eneco.2026.109558> WP at <https://www.jbs.cam.ac.uk/wp-content/uploads/2026/06/eprg-wp2608.pdf>
- Nolan, T., Nelson, T. and Gilmore, J. (2026) *How effectively can fungible financial derivative contracts hedge wind farm earnings*. CAEPR Working Paper 2026-06, Griffith University.
- Pindyck, R.S. (1999) 'Long-run evolution of energy prices', *Energy Journal*, 20(2), pp. 1–27. Available at: <https://doi.org/10.5547/issn0195-6574-ej-vol20-no2-1>.

- Rai, A. and Nelson, T. (2021) 'Financing costs and barriers to entry in Australia's electricity market', *Journal of Financial Economic Policy*, 13(6), pp. 730–754. Available at: <https://doi.org/10.1108/JFEP-03-2020-0047>.
- Rystad Energy (2026) Australia Renewables & Power Trends Report.
- Schmalensee, R. (2021) 'Strengths and weaknesses of traditional arrangements for electricity supply', in J. Glanchant, P. Joskow, and M. Pollitt (eds.) *Handbook on Electricity Markets*. Cheltenham UK: Edward Edgar Publishing, pp. 13–35.
- Sharpe, S. (1990) 'Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships', *The Journal of Finance*, 45(4), pp. 1069–1087. Available at: <https://doi.org/10.1111/j.1540-6261.1990.tb02427.x>.
- Simshauser, P. (2010) 'Vertical integration, credit ratings and retail price settings in energy-only markets: Navigating the Resource Adequacy problem', *Energy Policy*, 38(11), pp. 7427–7441.
- Simshauser, P. (2019) 'On the Stability of Energy-Only Markets with Government-Initiated Contracts-for-Differences', *Energies*, 12(13), p. 2566.
- Simshauser, P. (2020) 'Merchant renewables and the valuation of peaking plant in energy-only markets', *Energy Economics*, 91, p. 104888.
- Simshauser, P. (2021) 'Lessons from Australia' s National Electricity Market 1998 – 2018 : strengths and weaknesses of the reform experience', in J. Glanchant, P. Joskow, and M. Pollitt (eds.) *Handbook on Electricity Markets*. Cheltenham, UK: Edward Edgar Publishing, pp. 242–286.
- Simshauser, P. (2026) 'Are gas turbines "bankable" in transitioning energy-only markets?', *Energy Economics*, 158, p. 109329. Available at: <https://doi.org/10.1016/j.eneco.2026.109329>.
- Simshauser, P. and Gilmore, J. (2020) 'On entry cost dynamics in Australia's national electricity market', *Energy Journal*, 41(1), pp. 259–287.
- Simshauser, P. and Gilmore, J. (2022) 'Climate change policy discontinuity & Australia's 2016–2021 renewable investment supercycle', *Energy Policy*, 160(August 2021), p. 112648. Available at: <https://doi.org/10.1016/j.enpol.2021.112648>.
- Simshauser, P. and Gilmore, J. (2026) 'The counterfactual policy scenario: are renewables cheaper?', *Energy Policy*, 215, p. 115253. Available at: <https://doi.org/10.1016/j.enpol.2026.115253>.
- Simshauser, P. and Nelson, T. (2012) 'The second-round effects of carbon taxes on power project finance', *Journal of Financial Economic Policy*, 4(2), pp. 104–127.
- Steffen, B. (2018) 'The importance of project finance for renewable energy projects', *Energy Economics*, 69, pp. 280–294. Available at: <https://doi.org/10.1016/j.eneco.2017.11.006>.
- Steffen, B. (2020) 'Estimating the cost of capital for renewable energy projects', *Energy Economics*, 88. Available at: <https://doi.org/10.1016/j.eneco.2020.104783>.
- Stiglitz, J.E. and Weiss, A. (1981) Credit Rationing in Markets with Imperfect Information, *The American Economic Review*.
- Thaler, R.H. (1988) 'Anomalies: The Winner's Curse', *Journal of Economic Perspectives*, 2(1), pp. 191–202.

Appendix 1: PCF Model

The PCF Model operates in one of two modes, (1) cost mode, or (2) valuation mode. When run in the 'cost-based' format, the model is seeking to identify the minimum obtainable unit cost or price (e.g. PPA price) for a given technology whilst co-optimising debt finance and taxation variables given a normal profit constraint, and debt covenant constraints.

Conversely, when run in the profit-based valuation mode, debt finance and taxation variables are co-optimised given debt covenant constraints and exogenously determined annual revenues. In this format, profits and equity returns are an outcome of modelling.

In the PCF Model, prices and costs increase annually by a forecast general inflation rate (CPI).

$$\pi_j^{R,C} = \left[1 + \left(\frac{CPI}{100} \right) \right]^j, \quad (A1)$$

Energy output q_j^i from each plant (i) in each period (j) is a key variable in driving revenue streams, unit fuel costs, fixed and variable Operations & Maintenance costs. Energy output is calculated by reference to installed capacity k^i , capacity utilisation rate CF_j^i for each period j . CF_j^i may be determined endogenously (cost-based) or exogenously (profit-based). Plant auxiliary losses Aux^i arising from on-site electrical loads are deducted. Plant output is measured at the Node and thus a Marginal Loss Factor MLF^i coefficient is applied.

$$q_j^i = CF_j^i \cdot k^i \cdot (1 - Aux^i) \cdot MLF^i, \quad (A2)$$

For cost-based simulations, a convergent electricity price for the j^{th} plant (p^{ie}) is calculated in year one and escalated per eq. (A1). Thus revenue for the j^{th} plant in each period j is defined as follows:

$$R_j^i = (q_j^i \cdot p^{ie} \cdot \pi_j^R), \quad (A3)$$

For profit-based simulations, exogenously determined spot and forward hedging revenues are required and is derived from the block bootstrapping model and the unit commitment and financial settlements models (per Fig.1).

If thermal plant are to be modelled, marginal running costs need to be defined per Eq. (4). The thermal efficiency for each generation technology ζ^i is defined. The constant term '3600'¹⁴ is divided by ζ^i to convert the efficiency result from % to kJ/kWh. This is then multiplied by raw fuel commodity cost f^i . Variable Operations & Maintenance costs v^i , where relevant, are added which produces a pre-carbon short run marginal cost. Under conditions of externality pricing CP_j , the CO₂ intensity of output needs to be defined. Plant carbon intensity g^i is derived by multiplying the plant heat rate by combustion emissions $\hat{g}^i$ and fugitive CO₂ emissions $\hat{g}^i$. Marginal running costs in the j^{th} period is then calculated by the product of short run marginal production costs by generation output q_j^i and escalated at the rate of π_j^C .

$$\vartheta_j^i = \left\{ \left[\left(\frac{3600}{\zeta^i} \cdot f^i + v^i \right) + (g^i \cdot CP_j) \right] \cdot q_j^i \cdot \pi_j^C \right\} g^i = (g^i + \hat{g}^i) \cdot \frac{3600}{\zeta^i}, \quad (A4)$$

Fixed Operations & Maintenance costs FOM_j^i of the plant are measured in \$/MW/year of installed capacity FC^i and are multiplied by plant capacity k^i and escalated.

$$FOM_j^i = FC^i \cdot k^i \cdot \pi_j^C, \quad (A5)$$

Earnings Before Interest Tax Depreciation and Amortisation (EBITDA) in the j^{th} period can therefore be defined as follows:

$$EBITDA_j^i = (R_j^i - \vartheta_j^i - FOM_j^i), \quad (A6)$$

¹⁴ The derivation of the constant term 3,600 is: 1 Watt = 1 Joule per second and hence 1 Watt Hour = 3,600 Joules.

Capital Costs (X_0^i) for each plant i are Overnight Capital Costs and incurred in year 0. Ongoing capital spending (x_j^i) for each period j is determined as the inflated annual assumed capital works program.

$$x_j^i = c_j^i \cdot \pi_j^c, \quad (A7)$$

Plant capital costs X_0^i give rise to tax depreciation (d_j^i) such that if the current period was greater than the plant life under taxation law (L), then the value is 0. In addition, x_j^i also gives rise to tax depreciation such that:

$$d_j^i = \left(\frac{x_0^i}{L} \right) + \left(\frac{x_j^i}{L-(j-1)} \right), \quad (A8)$$

From here, taxation payable (τ_j^i) at the corporate taxation rate (τ_c) is applied to $EBITDA_j^i$ less Interest on Loans (I_j^i) later defined in (16), less d_j^i . To the extent (τ_j^i) results in non-positive outcome, tax losses (L_j^i) are carried forward and offset against future periods.

$$\tau_j^i = \text{Max}(0, (EBITDA_j^i - I_j^i - d_j^i - L_{j-1}^i) \cdot \tau_c), \quad (A9)$$

$$L_j^i = \text{Min}(0, (EBITDA_j^i - I_j^i - d_j^i - L_{j-1}^i) \cdot \tau_c), \quad (A10)$$

The debt financing model computes interest and principal repayments on different debt facilities depending on the type, structure and tenor of tranches. There are two types of debt facilities – (a) corporate facilities (i.e. balance-sheet financings) and (2) project financings. Debt structures available in the model include bullet facilities and semi-permanent amortising facilities (Term Loan B and Term Loan A, respectively).

Corporate Finance typically involves 5- and 7-year bond issues with an implied 'BBB' credit rating. Project Finance include a 5-year Bullet facility requiring interest-only payments after which it is refinanced with consecutive amortising facilities and fully amortised over an 18-25 year period (depending on the technology) and a second facility commencing with tenors of 5-12 years as an Amortising facility set within a semi-permanent structure with a nominal repayment term of 18-25 years. The decision tree for the two Term Loans was the same, so for the Debt where $DT = 1$ or 2 , the calculation is as follows:

$$if_j \begin{cases} > 1, DT_j^i = DT_{j-1}^i - P_{j-1}^i \\ = 1, DT_1^i = D_0^i \cdot S \end{cases} \quad (A11)$$

D_0^i refers to the total amount of debt used in the project. The split (S) of the debt between each facility refers to the manner in which debt is apportioned to each Term Loan facility or Corporate Bond. In most model cases, 35% of debt is assigned to Term Loan B and the remainder to Term Loan A. Principal P_{j-1}^i refers to the amount of principal repayment for tranche T in period j and is calculated as an annuity:

$$P_j^i = \left(\frac{DT_j^i}{\left[\frac{1 - (1 + (\mathbb{R}_{Tj}^z + C_{Tj}^z))^{-n}}{\mathbb{R}_{Tj}^z + C_{Tj}^z} \right]} \right) \cdot z \begin{cases} = VI \\ = PF \end{cases} \quad (A12)$$

In (12), $\mathbb{R}_{Tj}$ is the relevant interest rate swap (5yr, 7yr or 12yr) and C_{Tj} is the credit spread or margin relevant to the issued Term Loan or Corporate Bond. The relevant interest payment in the j^{th} period (I_j^i) is calculated as the product of the (fixed) interest rate on the loan or Bond by the amount of loan outstanding:

$$I_j^i = DT_j^i \times (\mathbb{R}_{Tj}^z + C_{Tj}^z) \quad (A13)$$

Total Debt outstanding D_j^i , total Interest I_j^i and total Principal P_j^i for the j^{th} plant is calculated as the sum of the above components for the two debt facilities in time j . For clarity, Loan Drawings are equal to D_0^i in year 1 as part of the initial financing and are otherwise 0.

One of the key calculations is the initial derivation of D_0^i (as per eq.A11). This is determined by the product of the gearing level and the Overnight Capital Cost (X_0^i). Gearing levels are formed by applying a cash flow constraint based on credit metrics applied by project banks and capital markets. The variable γ in the PCF Model relates specifically to the legal structure of the business and the credible capital structure achievable. The two relevant legal structures are Vertically Integrated (VI) merchant utilities (issuing 'BBB' rated bonds) and Independent Power Producers using Project Finance (PF).

$$if \gamma \begin{cases} = VI, \frac{FFO_j^i}{I_j^i} \geq \delta_j^{VI} \forall j \mid \frac{D_j^i}{EBITDA_j^i} \geq \omega_j^{VI} \forall j \mid FFO_j^i = (EBITDA_j^i - x_j^i) \\ = PF, \min(DSCR_j^i, LLCR_j^i) \geq \delta_j^{PF}, \forall j \mid DSCR_j^i = \frac{(EBITDA_j^i - x_j^i - \tau_j^i)}{P_j^i + I_j^i} \mid LLCR_j^i = \frac{\sum_{j=1}^N [(EBITDA_j^i - x_j^i - \tau_j^i) \cdot (1 + K_e)^{-j}]}{D_j^i} \end{cases} \quad (A14)$$

Credit metrics¹⁵ (δ_j^{VI}) and (ω_j^{VI}) are exogenously determined by credit rating agencies and are outlined in Table A1.

Table 6: Table A1 Capital Markets Data

Project Finance	100% Contracted	Merchant	Balance Sheet Corporate Financings	
Debt Sizing Constraints			Credit Metrics (BBB Corporate)	Merchant
- DSCR	(times)	1.25x	- FFO / I	(times) 4.2
- Gearing Limit	(%)	80%	- Gearing Limit	(%) 40.0
- Default	(times)	1.05x	- FFO / Debt	(%) 20%
PF Facilities - Tenor			Bond Issues	
- Term Loan B (Bullet)	(Yrs)	5	- 5 Year	(%) 5.73%
- Term Loan A (Amortising)	(Yrs)	7	- 7 Year	(%) 5.90%
- Notional amortisation	(Yrs)	25	- 10 Year	(%) 6.16%
PF Facilities - Pricing			Commonwealth Bonds	
- Term Loan B Swap	(%)	4.72%	- 10 Year	(%) 4.87%
- Term Loan B PF Spread	(bps)	195	Expected Equity Returns	(%) 11.0%
- Term Loan B PF Rate	(%)	6.67%		
- Term Loan A Swap	(%)	4.81%		
- Term Loan A PF Spread	(bps)	229		
- Term Loan A PF Rate		7.10%		
- Refinancing Rate	(%)	6.88%		
Expected Equity Returns	(%)	10.0%		

Values for δ_j^{PF} are exogenously determined by project banks and depend on technology (i.e. thermal vs. renewable) and the extent of energy market exposure, that is whether a Power Purchase Agreement exists or not. For clarity, FFO_j^i is 'Funds From Operations' while $DSCR_j^i$ and $LLCR_j^i$ are the Debt Service Cover Ratio and Loan Life Cover Ratios. Debt drawn is:

$$D_0^i = X_0^i - \sum_{j=1}^N [EBITDA_j^i - I_j^i - P_j^i - \tau_j^i] \cdot (1 + K_e)^{-j} - \sum_{j=1}^N x_j^i \cdot (1 + K_e)^{-j} \quad (A15)$$

At this point, when operating in the cost-based format, all of the necessary conditions exist to produce estimates of the long run marginal cost of power generation technologies along with relevant equations to solve for the price (p^{ie}) given expected equity returns (K_e) whilst simultaneously meeting the constraints of δ_j^{VI} and ω_j^{VI} or δ_j^{PF} given the relevant business combinations. The primary objective is to expand every term which contains p^{ie} . Expansion of the EBITDA and Tax terms is as follows:

$$0 = -X_0^i + \sum_{j=1}^N [(p^{ie} \cdot q_j^i \cdot \pi_j^R) - \vartheta_j^i - FOM_j^i - I_j^i - P_j^i - ((p^{ie} \cdot q_j^i \cdot \pi_j^R) - \vartheta_j^i - FOM_j^i - I_j^i - d_j^i - L_{j-1}^i) \cdot \tau_c] \cdot (1 + K_e)^{-j} - \sum_{j=1}^N x_j^i \cdot (1 + K_e)^{-j} - D_0^i \quad (A16)$$

The terms are then rearranged such that only the p^{ie} term is on the left-hand side of the equation:

Let $IRR \equiv K_e$

$$\sum_{j=1}^N (1 - \tau_c) \cdot p^{ie} \cdot q_j^i \cdot \pi_j^R \cdot (1 + K_e)^{-j} = X_0^i - \sum_{j=1}^N [-(1 - \tau_c) \cdot \vartheta_j^i - (1 - \tau_c) \cdot FOM_j^i - (1 - \tau_c) \cdot (I_j^i - P_j^i + \tau_c \cdot d_j^i + \tau_c L_{j-1}^i) \cdot (1 + K_e)^{-j}] + \sum_{j=1}^N x_j^i \cdot (1 + K_e)^{-j} + D_0^i \quad (A17)$$

The model then solves for p^{ie} such that:

$$p^{ie} = \frac{X_0^i}{\sum_{j=1}^N (1 - \tau_c) \cdot p^{ie} \cdot q_j^i \cdot \pi_j^R \cdot (1 + K_e)^{-j}} + \frac{\sum_{j=1}^N [(1 - \tau_c) \cdot \vartheta_j^i + (1 - \tau_c) \cdot FOM_j^i + (1 - \tau_c) \cdot (I_j^i + P_j^i - \tau_c \cdot d_j^i - \tau_c L_{j-1}^i) \cdot (1 + K_e)^{-j}]}{\sum_{j=1}^N (1 - \tau_c) \cdot q_j^i \cdot \pi_j^R \cdot (1 + K_e)^{-j}} + \frac{\sum_{j=1}^N x_j^i \cdot (1 + K_e)^{-j} + D_0^i}{\sum_{j=1}^N (1 - \tau_c) \cdot q_j^i \cdot \pi_j^R \cdot (1 + K_e)^{-j}} \quad (A18)$$

¹⁵ For Balance Sheet Financings, Funds From Operations over Interest, and Net Debt to EBITDA respectively. For Project Financings, Debt Service Cover Ratio and Loan Life Cover Ratio.