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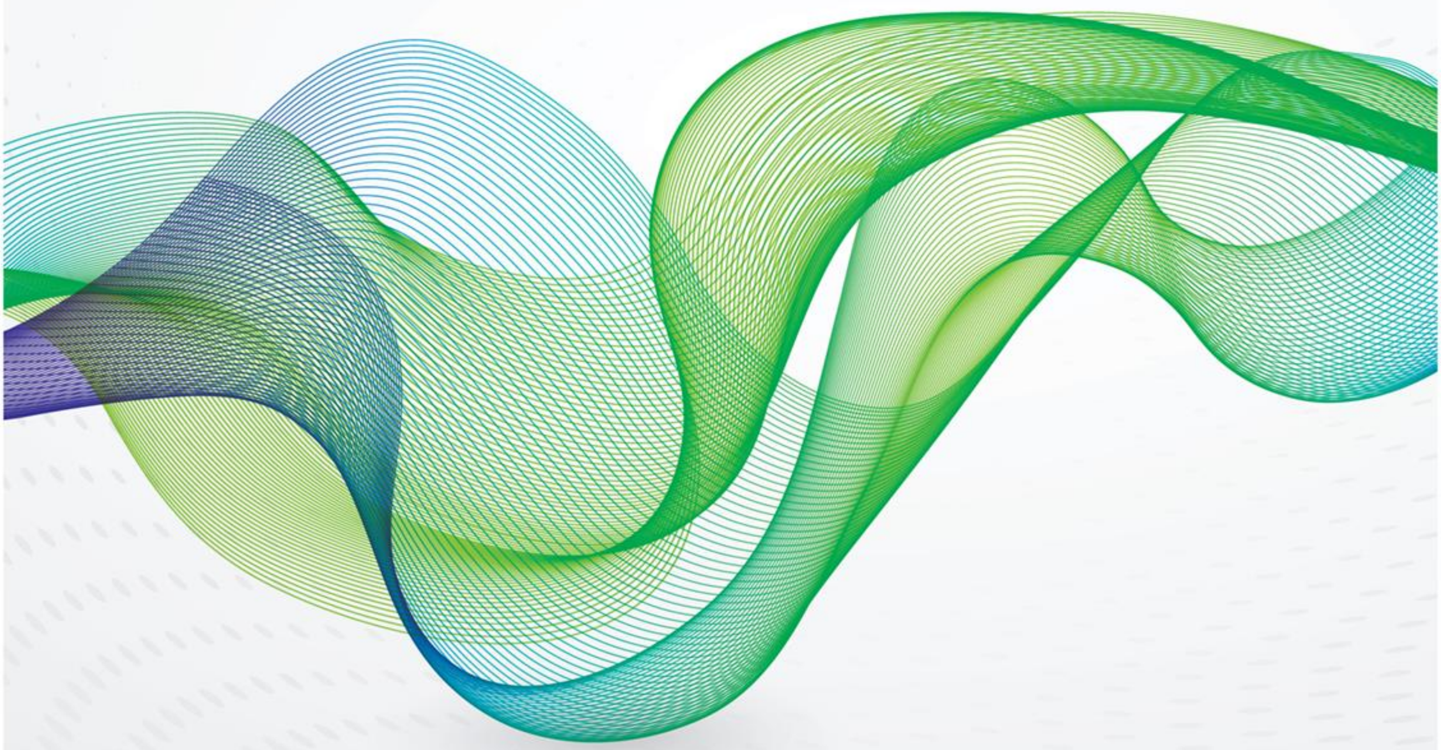
Hedging and Tail Risk in Electricity Markets



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Abstract

A concern persistent in scarcity-based market designs for electricity over many years has been the illiquidity of markets for long-term contracts to hedge away volatile price exposures between generators and consumers. These missing markets have been attributed to a range of factors including retailer creditworthiness, market structure and the lack of demand side interest from consumers. Using a stochastic equilibrium model and insights from insurance theory, we demonstrate the inherent challenges of hedging a legacy thermal portfolio that is dominated by volatile fat-tailed commodities with significant tail dependence. Under such conditions the price required for generators to provide such hedges can be multiples of the expected value of prices. Our key insight is that when the real-world constraints of credit and financing are considered, the volatility of thermal fuels and their co-dependence under extremes may be a key reason as to why electricity markets have been incomplete in terms of long-term hedging contracts. Counterintuitively, in the context of the energy transition, our results show that, ceteris paribus, increasing the penetration of low carbon resources like wind, solar and energy storage, can add tail-diversity and improve contractability.

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Introduction

This paper seeks to address the issue of the viability of long-term hedges in transitioning electricity markets.

The fundamentals of modern electricity market design are based on seminal works (Joskow & Schmalensee, 1983; Schweppe et al., 1988) that advocate a canonical design based on a centrally cleared, security-constrained economic dispatch (SCED), with generation and load executed in real-time and settled on the basis of locationally and temporally granular spot prices for electricity (locational marginal prices, or LMP).[1] The volatility brought on by full-strength price formation is intended as a feature rather than a bug of the canonical design. Dynamic prices provide theoretically efficient short-term signals for generation, storage, and load resources. It also provides incentives for hedging and risk-trading based on the given risk preferences of consumers and electricity providers.

Nevertheless, in full-strength markets, there are concerns commonly raised as to the sufficiency of hedge markets and the capability to secure long-term contracts to underpin investment in capital-intensive generation plants (ACCC, 2022). The lack of liquidity and depth of contracting markets is a common refrain, especially for smaller or non-integrated market participants. Relatedly, the costs of hedging are also seen as high, and in some cases prohibitive, leading to under-hedging. In exchange-traded and over-the-counter (OTC) derivative markets, in addition to the hedge risk premia, participants must also incur expenses related to margining and collaterisation requirements. The market for long-term contracts, which are important to securing financing for generation investment, is an area of particular concern. Liquidity in wholesale derivative markets typically only extends to ~1-3 years ahead, while retail contracts too have embedded optionality for retailers to reprice and consumers to switch. The repercussions on the system, often felt after extreme conditions in the market, include retailer bankruptcies and insufficiently resilient generation resources to support extreme load and weather conditions (Mays et al., 2022).

The 2022 energy crisis brought concerns around long-term hedging and price formation to the forefront of attention (Gabel, 2022). Of relevance in this crisis was the integrated nature of international commodity supply across fuels and geography. The almost simultaneous record spikes in coal, gas, and oil prices (all three fuels being integral to legacy power systems) were a stark demonstration of the linkages between these partial substitutes. Global supply chain integration also meant that events affecting one part of the world could and did constrain availability in many other otherwise geographically disparate locations. Further complicating this has been the trend towards spot pricing in fuel markets. Legacy fixed-price contracts for coal and gas roll off and are replaced by shorter-term or spot-indexed contracts (though oil-price escalation in gas contracts has been common for some time) and shorter-term forward derivative products (Losz et al., 2023. This has been a particular challenge in regions with tight supply balances such as the UK, Europe, and Australia (Lewis Grey Advisory, 2023).

This paper seeks to introduce a novel perspective on the market for long-term hedges by framing the problem as one of insurability. That is, while the inherent risk attitude of market participants is relevant for the desire to contract, we incorporate the requirement for hedge providers to be able to financially deliver on the hedge during normal and extreme scenarios. This provides a unique insight into why hedging may continue to pose a challenge for systems without truly diversified tail exposures. With respect to diversification, a critical question is whether concerns around long-term hedging in electricity markets will persist, exacerbate, or soften with the transition to low-carbon sources of supply, such as wind, solar, and energy storage. Indeed, while recent studies point to the higher volatility of renewable-dominated portfolios, the question of whether this extends to the hedgeability of such portfolios is still open. Our scope is restricted to system marginal costs in the context of fuel costs and resource

[1] Many regions, particularly in the US and Europe, also augment the real-time market with central short-term forward markets, typically cleared in day-ahead or intraday timeframes. In the US a security-constrained unit commitment process will accompany a day-ahead SCED incorporating non-convexities associated with certain plant (minimum generation levels, minimum/maximum run times, startup costs etc). Other regions such as Australia and New Zealand have long operated real-time only markets (with decentralised participant self-commitment).

availability – we defer consideration of other contributing issues (for example, network reliability, system security, or market power) to future work.

An insurance business model depends upon being able to financially support any insurance products that are sold (Rees & Wambach, 2008). This means they must have access to enough capital or reinsurance to compensate losses even under the extremes of the probability distribution. Thus, insurers are often managed to meet solvency or reserve constraints, as determined by regulation, rating agencies, or internal firm decisions. While there are limited formal capital adequacy and regulatory reserving provisions in electricity markets, the concepts are transferrable. Hedge providers manage exposures through offsetting contracts, or through the operation of assets in the organized spot market (as in, defending the contract). For example, a gas peaker selling a call option (or cap) at a $300 strike will seek to run when prices exceed the strike to offset hedge exposures. Margin and credit requirements in exchange and OTC markets also apply to ensure that the hedge provider has sufficient creditworthiness to perform on the hedge contract (Simshauser, 2021). Climate change has become a major challenge for the insurance sector, with the increasing frequency and severity of losses and disruptions from extreme weather. Climate change is considered among the top risks, if not the top risk exposure, for insurers and re-insurers (Swiss Re, 2017; Wagner, 2022). In recent times, major insurers have stopped offering common insurance lines (for instance, home insurance) in certain regions. Kousky and Cooke provide an underlying rationale for this through the idea of the ‘unholy trinity’ in insurance markets: three phenomena – fat tails, tail dependence, and micro-correlations – which can make the traditional insurance of such risks in an era of climate change not just expensive, but unfeasible (Kousky & Cooke, 2012).

Applying the concept to the electricity markets, we provide an underlying basis for the challenge of contracting for long durations in thermal dominated systems. We describe key drivers of market incompleteness as being the fat-tailed nature of underlying coal and gas fuel markets and the tail dependence between them. Under such loss distributions, small changes in risk perception can result in large changes in consumer contracting appetite. We posit this as a potential rationale for why long-term hedging contracts between consumers and energy suppliers have been challenging to obtain and execute in practice. Going forward, we show how the underlying economics of zero-marginal cost resources may alter the long-term hedgeability of resource portfolios as systems progress through the energy transition. Our key insight is that while spot markets may become more volatile, low-carbon portfolios can benefit from a more diversified exposure to tail-correlated risks. This then shifts the focus of risk management towards understanding potential tail and common-mode risks in renewables and storage-heavy grids. This should include inter-alia a consideration of policy uncertainty and political intervention under extrema, and of tail-resilient market designs.

We illustrate the role of the ‘unholy trinity’ in insurance and financial markets and extend this concept to electricity markets using extreme value theory (EVT). This provides an understanding of the nature and extremity of risk that has been inherent to electricity markets. We then construct an instance of a stochastic equilibrium model and demonstrate how such tail risks may shift over the energy transition. In our case study, the value of tail diversity from renewable additions to the portfolio more than offsets variability risk. The rest of the paper is structured as follows. Section 1 reviews recent research findings as it relates to electricity risk hedging. It also outlines the ‘unholy trinity’ of risks to insurability and extends this concept to electricity markets. Section 2 sets out the results of the modelled case study (Methods and the formulation of the model are explained in Appendix A). The final section discusses critical policy implications and concludes.

1. Risk hedging in electricity markets

The literature on price formation and hedging in electricity markets is extensive but tends to fall into one of two categories. One set considers price formation in the context of archetypes of electricity market design – these works can be either qualitative or have simulated outcomes (generally as an output of capacity expansion planning models, equilibrium models or agent-based models); while the second set undertakes empirical and statistical analyses of historical prices. There have been relatively few attempts to reconcile them.

The volatility of electricity prices is a necessary component in the theory of competitive electricity markets (Boiteux, 1960; Caramanis et al., 1982; Chao, 1983; Harvey & Hogan, 2019). 'Getting the prices right' for an inelastic good, such as electricity, will invariably involve volatility or price spikes during scarcity (Hogan, 2014).

To manage the risks associated with spot prices, participants can hedge, or trade risk based on their individual preferences (Biggar & Hesamzadeh, 2022). Derivative products (including forwards, swaps, and options) have evolved to allow generators and retailers to exchange volatile spot exposures for more stable cashflows (Deng & Oren, 2006), including a suite of products catered towards variable renewables (Billimoria, 2021; Lucy & Kern, 2021). However, obtaining contract of long tenor has been a concern, with a set of literature arguing there are 'missing markets' for long-term contracts, which are seen as necessary to support capital-intensive generation investment when participants are risk-averse (Abada et al., 2019; Neuhoff & De Vries, 2004; Newbery, 2016; Roques & Finon, 2017; Simshauser, 2019). This is often linked to broader notions of the incompleteness of markets (de Maere d'Aertrycke et al., 2017; Mays et al., 2022; Willems & Morbee, 2010).

The nature of the hedging challenge can vary significantly among resource types. For renewable projects, multi-year commercial power purchase agreements can be common (Gohdes et al., 2022; Simshauser, 2020). Interestingly such demand appears driven not only by retailers, but also by corporate and smaller institutional energy consumers driven by price and decarbonisation imperatives. Non-traditional risk-traders with diverse market exposures, such as insurance companies and hedge funds, have also entered long-term contracts for difference as net energy buyers (Billimoria, 2021).

The assumption of market completeness is important in characterising how literature integrates the issue of long-term hedging into electricity market design. Under complete markets, hedging can be considered secondary to market design, given that participants are best placed to design, price, and execute risk-hedging decisions, in the presence of appropriate scarcity incentives (Hogan, 2022). In this context, Biggar and Hesamzadeh integrate dispatch and risk-averse hedging under a set of qualifications – complete markets, symmetric risk-preferences, and a hedge price that approximates the expected value of hedge cashflows (Biggar & Hesamzadeh, 2022).

The diagnosis of incompleteness and implications for hedging is an active area of research. Mays et al., 2022 set out underpinning factors for market incompleteness that include fuel market curtailment regulations, and the uncompensated value of the consumer 'forced outage' hedge. Schittekatte, Batlle et al attribute much to the lack of demand-side interest in hedging driven by implicit (and explicit, in the case of the recent European energy crisis) pricing support and assistance from central governments (Batlle et al., 2023; Schittekatte T, 2023). Another stream of literature points to structural protections in retail tariffs and lack of retail creditworthiness (Neuhoff & De Vries, 2004). Integrating retail with generation operations to provide a physical hedge (also known as integrated generator-retailers, or 'gentailers') has been a response to this issue in full-strength markets (Simshauser, 2021; Simshauser et al., 2015). Despite vertical integration extending to the fuel source itself, long-term demand has not been forthcoming given the risk of being undercut by new entrant retailers with short-dated portfolios (Simshauser, 2018).

Yet the question of whether these factors are a cause or symptom of an underlying problem would assist in clarifying whether these issues will persist as the electricity system transitions to low-carbon resources. In considering this, a common focus is upon the impact of the changing supply mix on spot prices. Higher penetrations of zero-marginal cost resources are expected to increase the frequency of very low prices (when renewables are abundant), but also the frequency of very high prices (when renewables are unavailable, and prices are set by load or firming resources) (Hogan, 2019, 2022; Mallapragada et al., 2023). Taken to an extreme this would result in a bid-curve that is “L-shaped”, and a bi-modal distribution of prices. Recently, Mays (2023) invites some scepticism of this notion in the context of sequential market clearing under uncertainty. In terms of risk-hedging implications, a surprising result from Mays and Jenkins (2023) is that overall investment risk may be lower in systems dominated by variable renewables due to reduced exposure to fuel price uncertainty.

A current gap in the research relates to the consideration of hedging under a granular resolution of tail cases for energy systems. Under such events, risk is inherently asymmetric, normal relationships between resources can break down – and traditional measures of correlation or co-movement tend to have less relevance. Importantly, risk-hedging should be understood from a range of tail risk parameters, not just a single set point – because risk preferences across the market (including for both resources and consumers) are not transparent; and the assessment of tail exposure requires a degree of comprehension of the risk (Leslie et al., 2022).

1.1 Insurance markets and the ‘Unholy Trinity’

To provide a new perspective on this issue we draw from other risk hedging markets, and most specifically insurance. A central principle of risk management is aggregation. Firms hold not one contract, but a portfolio of contracts, diversified across location, customer type and time. Holding such bundles offers diversification benefits and stabilizes losses. This is common in risk management in many sectors – for example, insurance companies will cover claims across a range of loss lines, diversified by region, customer, and timeframe.

However, climate change has been argued to pose significant challenges for insurability. In many regions, especially where physical risks are increasing, insurers have struggled to provide insurance at viable rates, and consumers have had consistently low penetration rates of certain coverage lines – many of which are related to catastrophes or extreme events (Kousky, 2023).

Looking to the underlying reason for such under-insurance, Kousky and Cooke (2009, 2012) seek to explain the reasons for why consumers persistently fail to hedge against extreme risks, by not purchasing catastrophe insurance. They argue that there are three factors: fat tails, tail dependence and micro-correlations (which together they call the ‘unholy trinity’) that challenge traditional risk management.

> *“With fat-tailed losses, the probability declines slowly, relative to the severity of the loss. Tail dependence is the propensity of dependence to concentrate in the tails, such that severe losses are more likely to happen together. Micro-correlations are negligible correlations between risks which may be individually harmless, but very dangerous when aggregated. These three phenomena – types of catastrophic and dependent risks – undermine traditional approaches to risk management.”* – Kousky and Cooke (2009).

Fat tails are a statistical concept used to describe the distributions where the tails decline very slowly.[2] The precise mathematical definition of fat tails is a probability distribution where the tail of the distribution degrades in line with a power law (i.e., the probability that a random variable X exceeds x is $\alpha x^{-\beta}$ where $\alpha, \beta > 0$)[3]. This is a particularly extreme form of tail degradation, for our purposes the focus is less upon a direct empirical fit than an understanding of the loss outcomes at distribution extremities. Fat tails can be diagnosed using a range of indicators and metrics in extreme value theory (EVT). They are particularly problematic in risk markets due to the high likelihood of extreme events at the very ends of the distribution; and a higher proportion of events concentrated around the median. Without an

[2] For the normal distribution, an event larger than 3 standard deviations from the mean occurs only 0.13 per cent of the time. For a typical fat tailed distribution (say a Pareto distribution with a tail parameter equal to three) a 3 times standard deviation event occurs with probability 1.5 per cent, more than ten times as often a normal distribution.

[3] Parameters α and β: These constants shape the distribution’s tail. Specifically: α can be viewed as a scaling parameter that affects the overall level of the probability. A higher α would generally mean a higher probability for X to exceed x, all else being equal. β is a shape parameter that controls the rate at which the probability decreases as x increases. A higher β means the probability P(X>x) declines more rapidly as x grows.

appreciation of the importance of extreme events for such distributions, risk can often be underestimated. However, when this type of risk is incorporated into insurance analyses the tail outcomes can often skew the characterisation and pricing of risk (Kousky & Cooke, 2009). The challenge of extreme outcomes extends to financial markets more broadly, where the failure to properly account for fat tails has resulted in large scale private losses and systemic risk.[4]

Tail dependence relates to the tendency of random variables to co-occur in the extremes; that is, the random variables will be concentrated in the tails (Cooke et al., 2010). The failure to consider tail dependence can result in a significant underestimate of insurance loss exposure, as it can undermine traditional measures of portfolio diversification such as (Pearson's) correlation. Quoting from Kousky and Cooke (2009), 'the upper tail dependence of a set of variables X and Y is defined as the limit (if it exists) of the probability that X exceeds its r-percentile, given that Y exceeds its r-percentile, [the conditional probability] as r goes to 100' (Kousky & Cooke, 2009). Percentile scatter plots provide one means of visualising such dependence.

Micro-correlations are small positive correlations between variables that can be amplified when claims (or exposures) are aggregated. This is of evident concern to risk managers, as it will compromise risk management based on diversification (Cooke et al., 2010). The example is provided in Kousky & Cooke (2009) of the link between crop insurance indemnities and flood insurance claims – which can demonstrate low correlations with each other, but when groups of claimants are aggregated the exposure can be magnified. Such correlations can often go undetected and can be counter-intuitive to traditional claim diversification strategies.

The key conclusion of Kousky and Cooke (2012) is that under conditions of fat tails, tail-dependence and micro-correlation (or the *unholy trinity* as it is named), the benefits of aggregation and portfolio diversity tend to fall away. When insuring risks with loss distributions characterised by the *unholy trinity* insurers need to charge a price that is many times the expected loss in order to ensure solvency. At this price, homeowners with budget constraints may thus rationally forgo such insurance if their budgets do not allow for it, notwithstanding the potential utility of such insurance.

Yet this framework may have applications beyond the insurance sector and could potentially be applied to any hedging instrument that seeks to provide protection against extrema. To this end, our paper seeks to make a novel application of the theory of the *unholy trinity* to provide an underlying rationale for why markets in long-term risk trading have been missing in the electricity sector.

1.2 The Unholy Trinity in Electricity Markets

This section provides empirical observations on the application of extreme value theory to electricity markets, with a focus upon price and resource availability variables in the National Electricity Market of Australia (the NEM). Our focus is upon the three elements of the 'unholy trinity' of risk – namely the potential for fat tails, tail dependence, and aggregative risk. Our Online Companion also provides a full set of results for all regions, time periods and seasonal aggregations (Billimoria et al., 2024).

Fat Tails

Several studies have looked at the statistical properties of electricity prices in a range of markets. Many have found evidence of heavy and fat tails via the application of EVT (Boothe & Glassman, 2003; Byström, 2005; Huisman & Huurman, 2003; Weron, 2005), supported by findings of significant higher order moments, such as positive skewness[5] and high kurtosis (Knittel & Roberts, 2005). These studies are predominantly conducted on thermal dominated systems. Empirical and EVT analyses of electricity prices in the NEM are consistent with this theme[6]. It is important to note that aggregation matters here,

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[4] See for example Jorion (2000); Taleb (2007); Taleb & Martin (2012).

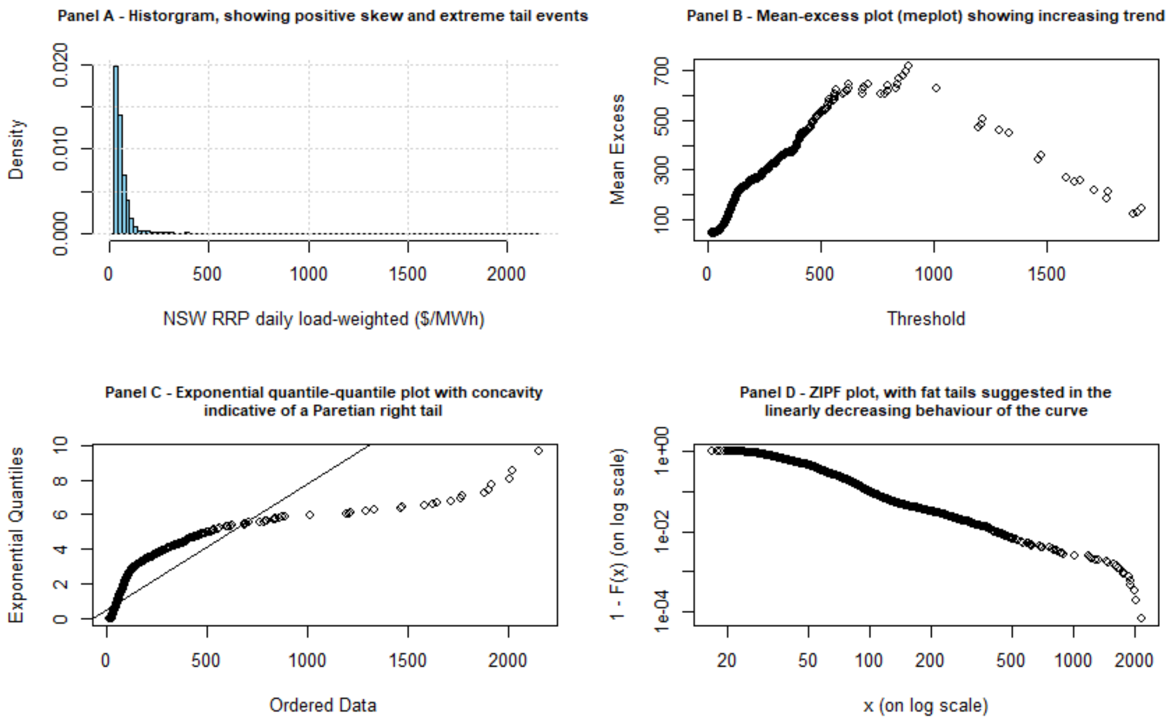
[5] Positive skewness in electricity prices indicates that the distribution of prices is asymmetric, with a longer right tail, representing infrequent but substantial spikes in prices above the average, rather than frequent small increases.

[6] The Australia National Electricity Market (NEM) has traditionally been an energy-only design, with wide administrative settings - a market price cap of $16,600/MWh, a cumulative price cap of ~$1.49 million, and a price floor of -$1000/MWh. A rule change (currently under consideration) recommends an increase in the market price cap to $21,500/MWh and the cumulative price cap

because the prices that consumers ultimately see and are sensitive to are typically weighted aggregations across time, such as the periodicity at which electricity bills come due.

Figure 1 sets out a panel of common graphical tools for diagnosing fat tails as applied to monthly load-weighted wholesale prices in the Victoria region of the NEM, as an example. Panel A shows the histogram of load-weighted prices where the distribution appears highly skewed and tail events (load-weighted prices above $400/MWh are observable). In Panel B the analysis is complemented with a mean excess function plot, which is an intuitive way to understand tail behaviour. If a random variable X is possibly fat tailed, its mean excess function $e_X(\mathrm{u}) = E[X - u\,|X \geq u]$ should grow linearly in u, at least above a certain threshold, which is as observed via the increasing trend.[7] The presence of a fat tail is also supported by the quantile-quantile plot in Panel C, where the exponential distribution is used as a benchmark. The concave behaviour observed in the plot is also indicative of sub-exponential decline and potential fat tails (Cirillo & Taleb, 2016, 2020). Finally in the log-log or Zipf plot in Panel D, possible fat tails can be identified in the presence of a linearly decreasing behaviour of the curve.[8] Importantly such trends appear consistent for all the mainland regions, across aggregation periods (daily, weekly, quarterly) and across seasons, with results available in the Online Companion (Billimoria et al., 2024). Table 3 provides statistical moments and percentiles on wholesale price distributions for two mainland regions in the NEM. Heavy skewing and kurtosis of prices are evident. Anderson-Darling tests are applied confirming the non-normality of the sample distributions.

Figure 1: Graphical analyses of tail risks in wholesale electricity prices for New South Wales, on a CPI-adjusted daily load-weighted basis from FY2002-2022



to ~$2.19 million. Though there have also been recent initiatives that have looked to supplement scarcity price formation, including triggered retailer reliability obligations, state-based revenue support hedges and the national Capacity Investment Scheme. Power market bidding is relatively unfettered, though subject to good faith obligations.

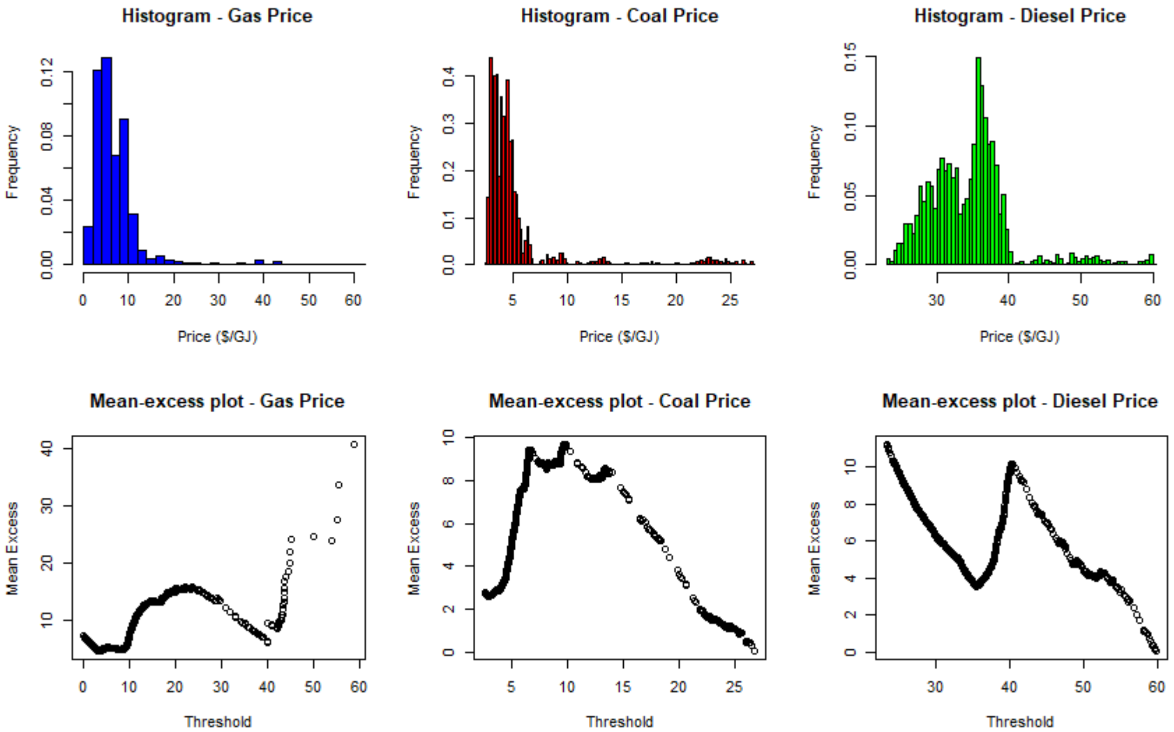
[7] Kousky and Cooke (2009) provides an example of the intuition of the mean-excess plot comparing a thin-tailed normal distribution, with a fat-tailed distribution.

[8] This is further supported by concentration plot profiles and Hill estimator results with goodness of fit statistics (see the Online Companion (Billimoria et al., 2024)).

A range of fundamental factors of electricity markets support the statistical assessment that fat tails are inherent to electricity markets. First, demand for electricity is relatively inelastic – often due to consumers being implicitly protected via tariff structures and aspects of market design (Billimoria & Poudineh, 2019; Mays et al., 2022). Second, with electricity markets clearing on marginal prices, small changes in supply or demand can result in large shifts in prices[9]. In this respect, the exercise of market power, especially during scarcity, may also be relevant. Finally, an important underlying driver in fossil fuel-dominated electricity markets has been the volatility in the underlying fuel markets themselves.

With fossil fuels dominating the supply mix over the last 20 years, understanding the fatness of tails for fuel prices could inform the historical patterns of price formation for electricity, and guide discussion on the future. The top row of Figure 2 shows histograms for the local gate or hub prices for natural gas, thermal coal, and liquid fuel (diesel). The bottom row shows mean excess plots for these commodities. The graphs demonstrate a sharply increasing trend above thresholds of ~$10/GJ for gas, $5/GJ for coal and $35/GJ for diesel. This is indicative of heavy-, and possibly fat-tailed behaviour. There are also levels beyond which the mean excess begins to decline again (at ~$25-30/GJ for gas, $10/GJ for coal and $40 for diesel), though given the sparsity, such data points are of less significance for EVT tails (Cirillo & Taleb, 2016, 2020). Thus, it would be reasonable to infer that the extended tail volatility of primary fuels, when unhedged, would reasonably have played a role in the intensity of tail exposure in intermediate wholesale electricity markets.

Figure 2: Graphical analyses of tail risks in histograms and mean-excess plots for fuel commodities – coal, natural gas, and diesel



Source: Natural gas prices – Short-Term Trading Market (STTM) Sydney Hub – daily; Coal prices – daily front-month Newcastle Coal futures contract (6000kcal/kg net calorific value, translated to AUD at the prevailing exchange rate); AIP daily diesel terminal gate price for Sydney.

[9] Merit order curves in the NEM are highly non-linear and often have a ‘knee point’ where above a certain quantity the offered prices increase dramatically. This can mean that the electricity bid curve jumps up in orders of magnitude over a few hundred MWs

Examining the statistical profiles of generation unavailability is also important for this study (noting that we neglect consideration of system security and network constraints in this study). Histograms and mean-excess plots for the unavailability of the coal and natural gas generation fleet in the NEM are shown in Figure 3 (with gas broken into OCGT and CCGT generation). Actual historical unavailability is shown for coal and gas generation. For renewables, given the limited dataset of actual outcomes, a long-term backcast of renewable availability based on actual weather outcomes over the last 20 years in the NEM is adopted (further information is provided in the subsequent sections).

Figure 4 shows histograms and mean-excess plots for wind, solar (between the hours of 0500 and 2000), and a combined 70/30 wind-solar portfolio. As a comparator, a recently computed 80 year backcasted dataset for ERCOT from Gruber et al (2022) is also shown.

By contrast with the results on fuel prices, the mean-excess plots of renewable and thermal generation availability do not appear to have a consistently increasing trend even after a particular threshold. It does not immediately suggest that the statistical distributions are fat-tailed in nature. In terms of weather patterns of the historical data period, while geographical regions covered by the NEM have experienced periods of extreme heat and drought, extreme freezing events are less notable. Hence it is caveated that the applicability of this data set is limited for areas that have experienced major winter freeze events, for example ERCOT during Winter Storm Uri.

Figure 3: Histograms and mean-excess plots for historical unavailability of the generation fleet in the NEM – coal and natural gas (OCGT and CCGT)

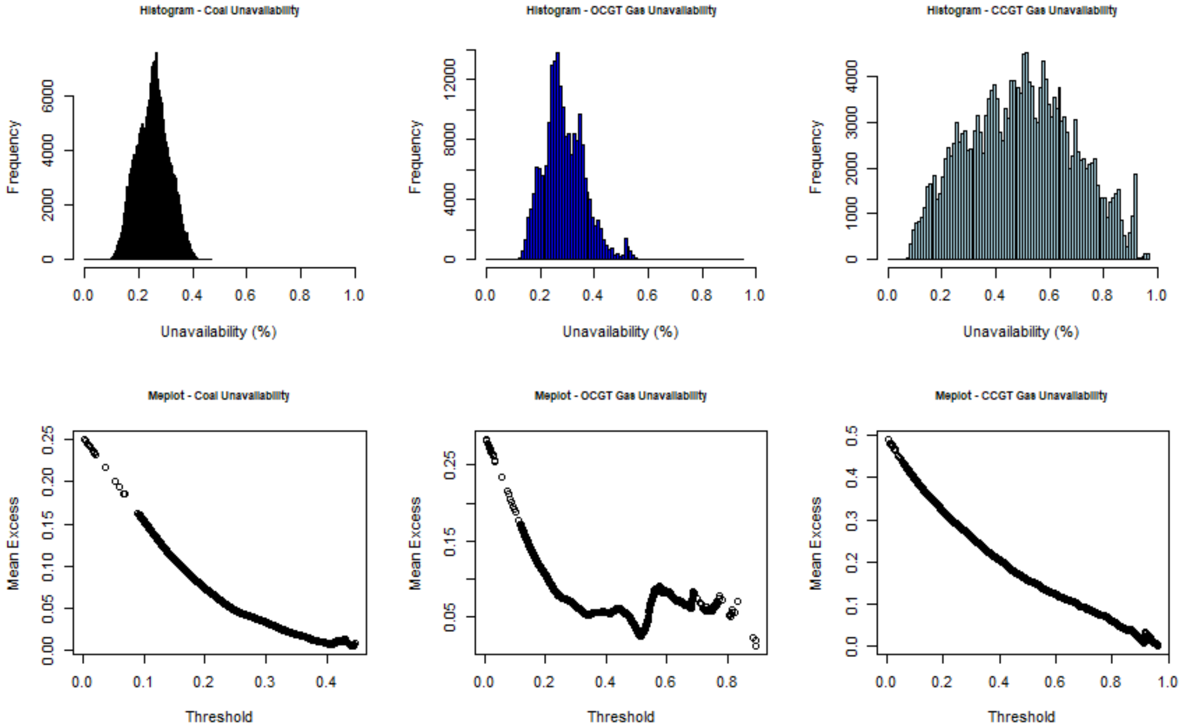
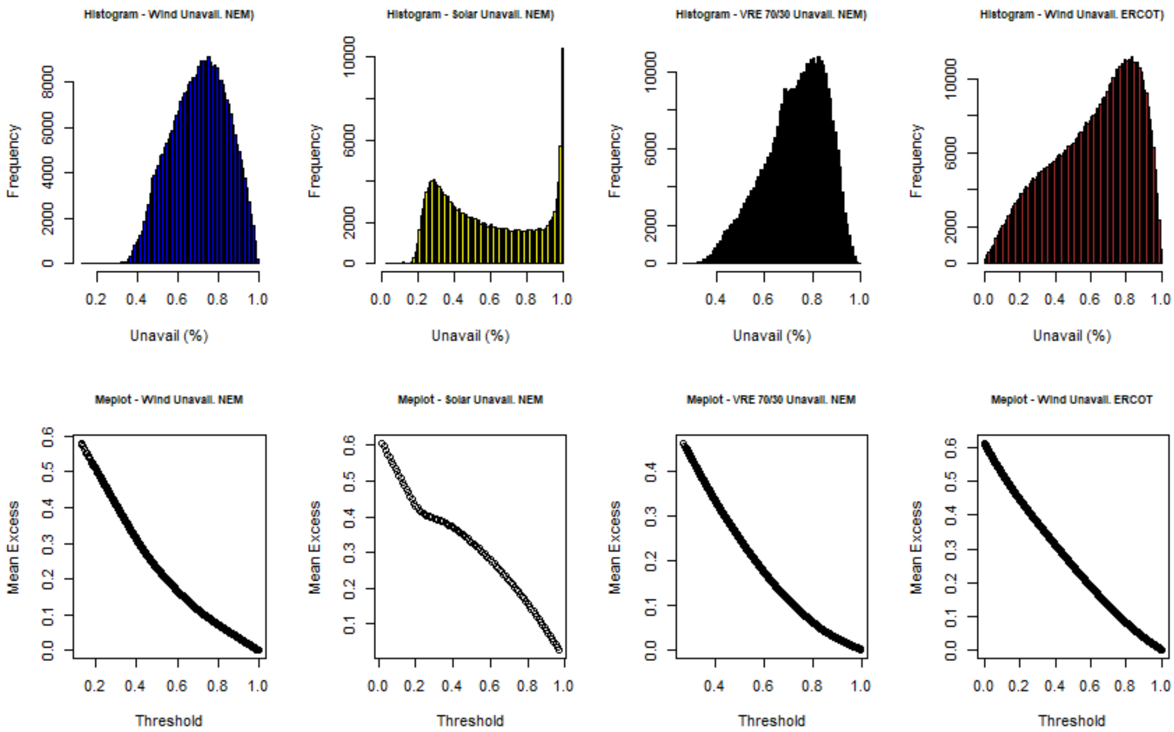


Figure 4: Histograms and mean-excess plots for wind and solar* unavailability – long-term historical backcast



* Solar data restricted to the hours 0500-2000.

Tail Dependence and Aggregation

The second factor in the unholy trinity of insurability relates to tail dependence. In electricity markets with prices formed by primarily fossil fuel generation, a key issue relates to the tail dependence between the fuel commodity costs.

There are physical factors to suggest that tail dependence could exist between fossil fuel commodities, which is to say the highest periods of pricing for such fuels tend to occur at the same time. The integrated nature of commodity supply chains suggests that common-mode factors may impact the price of such fuels similarly. Fuels are partially substitutable (at least on an energy portfolio basis), and with adjacent physical supply and logistics infrastructure that may be commonly vulnerable to physical events. Furthermore, as evident in the energy crisis of 2022, there are common sources of supply that can be affected by geo-political and other events.

How does this flow into the statistics? Based on Australian commodity data, the conditional probability of daily coal prices exceeding the 50th percentile (P50), when gas prices exceed their 50th percentile, is 0.71; at the 75th percentile a similar level of 0.67 is observed, while at the 95th percentile (P95) this increases to 0.81. Under a monthly aggregation of prices over the P50, P75 and P90 conditional probabilities are 0.76, 0.66 and 0.88, respectively. Diesel to gas conditional probabilities are 0.48 (P50), 0.37 (P75) and 0.80 (P95) for daily prices, and 0.47 (P50), 0.37 (P75) and 0.88 (P95) for monthly aggregations (plots of the conditional probabilities in 5 per cent increments are shown in Appendix B, Figures B4-B7). Percentile scatter plots (Figure B1-B3) as shown in Appendix B lend support to this, and importantly also illustrate that such tail dependence is not restricted to the recent 2022 supply crisis. This issue may have been less concerning in less integrated markets where coal and gas could be contracted at fixed prices over multi-year timeframes, but it takes on an increasing relevance where contracts are increasingly shorter-term or indexed to spot.

A similar analysis is conducted in relation to tail dependence between the availability of different forms of generation and with demand. Both the conditional probabilities and scatter plots on NEM actual and backcasted (for renewables) data suggest limited tail dependence to date (see Appendix B) with the conditional probabilities declining as the n^{th} percentile increases. While events like the Winter Storms Uri and Elliot in the US are observations of the weather sensitivity of fossil generation (particularly natural gas), it is interesting to observe that in the NEM that higher availability tends to be associated with periods of higher demand. This is intuitive in a market where generators are not centrally committed, but self-commit into the spot market based on expectations of electricity scarcity and prices, noting that this includes scheduling of planned maintenance. As indicated above, there have been relatively few freezing events in the empirical dataset to date.

Finally micro-correlations under aggregation are also relevant because of the time periods over which consumers perceive price risks. Given consumers pay electricity bills over aggregated periods, say a month, this would suggest that the willingness and ability to hedge is guided by perceptions of risk over similar periods, returned to in what follows.

2. Case Study and Results

We provide a mathematical framework for analysing risk hedging strategies in electricity markets amid the transition to low-carbon energy sources. The model employs a non-cooperative game-theoretic approach to capture the decision-making processes of market participants, specifically focusing on two risk-averse agents: a consumer and an energy generation supplier. This approach allows for the examination of individual strategies within the market's structure, considering the agents' risk-aversions and market incompleteness. The model considers the conditional value-at-risk (CVaR) to model aversion to downside outcomes, recognising the asymmetry in risk perception between upside gains and downside losses. Furthermore, it introduces a stochastic equilibrium model that integrates the operation of generation and storage assets in response to market dynamics and contractual arrangements. The detail of this model is presented in Appendix A.

This section provides data, assumptions and results of a case study conducted to investigate the impacts of different electricity mix on long-term risk hedging. The case study is conducted on the National Electricity Market or NEM, which is the largest electricity system in Australia covering the states along the eastern seaboard. The study is restricted to the mainland regions of the NEM, excluding Tasmania. The NEM provides an interesting example of a grid in transition with already high levels of renewable penetration (recently recording its highest instantaneous penetration of 68 per cent), and significant additional renewables and storage deployment expected in the near term. The optimal decarbonisation pathway identified by the Australian Energy Market Operator (AEMO) in its Integrated System Plan (ISP) provides useful datapoints as to resource capacity trajectories and cost structures. Further the market has a high degree of transparency and there is rich and granular dataset for the numerical experiment.

NEM has an energy-only style market design with high scarcity-based market settings; a market price cap of $16,600/MWh and market price floor of -$1,000/MWh, based on a minimum reliability standard of 0.002 per cent expected unserved energy (EUSE). To the extent that the reliability settings are expected to be breached, a range of additional measures apply to source resources in a quantity sufficient to meet the standard, including the Retailer Reliability Obligation (RRO), and the Reliability and Emergency Reserve Trader function. The retail market is contestable, with a high portion of the market served by gentailers. Over much of its history the NEM has relied upon market participants to make hedging and investment decisions. However, most recently in November 2023, the Commonwealth government announced plans for a large-scale Capacity Investment Scheme, a state-initiated risk-hedge program for up to 32GW of resource capacity (Commonwealth Government, 2023).

2.1 Assumptions and Data Sources

This section outlines the assumptions and sources of data underpinning this case study. The case study considers nine types of generation and storage resources including thermal generation, namely black coal, natural gas and liquid-fuelled (diesel) generators; variable renewable generation (wind and solar PV) and battery storage (of multiple durations). The technical assumptions for each form of resource (including ramp rates, auxiliary losses, heat rates, and storage efficiency), are based on the Integrated System Plan (ISP) produced by the market operator (AEMO, 2022a) and set out in Table 1.

Table 1: Resource Cost and Technical Assumptions

Resource	c^v (base)* ($/MWh)	c^I ($/kW)*	c^f ($/kW/yr)	$r^{\uparrow}/r^{\downarrow}$ (%/min)	q^e/q^c (%)	Heat Rate - HHV	Aux Losses (%)
Black Coal	40	0#	55	0.3	-	9.0	6.7
Gas CCGT	55	1792	11	0.02	-	7.5	1.8
Gas OCGT	132	898	16	10	-	10.9	0.7
Liquid Fuel RE	375	1400	16	10	-	10.5	0.6
Solar PV	0	936	18	100	-	-	0.2
Wind	0	1959	26	100	-	-	0.3
1-hr BESS	0	706	7	100	0.9	-	-
2-hr BESS	0	859	11	100	0.9	-	-
4-hr BESS	0	1220	17	100	0.9	-	-
8-hr BESS	0	1971	28	100	0.9	-	-

* The base variable cost (AEMO, 2022a) is indexed by fuel indices as below. Figures in A$ unless indicated. Black coal capital costs assumed to be wholly written down.

The time-series data covers a period of approximately 20 years (from January 2004 to October 2023), which results in 237 scenarios each of approximately a month in duration[10]. To reflect the inherent correlations and co-movement between different time-variant parameters, the time-series data is sourced from actual historical data where available, and supplemented by a calibrated backcast where historical data is not available.

Generation availability for thermal plant is based on the historical availability of thermal plant in the NEM over using the NEMOSIS package and based on data from AEMO's NEMWEB repository (AEMO, 2022c; Gorman et al., 2018). In the absence of long-term historical data on wind and solar availability for modern turbines of the scale and form implemented in the NEM, a back-casting approach is adopted. We select sites from nine of the largest wind and solar generators in the NEM[11], and then simulate wind and solar availability using *Renewables.ninja* (Pfenninger & Staffell, 2016), which is derived from reanalysis models and satellite observations. The technical parameters of each wind farm (turbine model, hub height etc) were sourced from AEMO Generation Information (AEMO, 2022b) and developers' websites. For solar, the azimuth was set based on the latitude of each farm, system loss was set at 1 per cent, an azimuth of 180º with farms having single-axis tracking. Electricity demand is based on historical gross operational demand, which is adjusted for an assumed penetration of consumer energy resources (CER), in the form of rooftop solar. To do so, the historical demand is first grossed up for actual historical consumer energy generation to create a set of scenarios for 'native demand'. To integrate CER, a rooftop solar generation time-series is created using *Renewables.ninja*. Scheduled demand is then calculated by netting off the CER generation from native demand based on an assumed penetration of rooftop solar in each NEM mainland region. To ensure appropriate calibration against actual data, we follow the approach in Gilmore et al (2022) to rescale the *Renewables.ninja* time-series for wind, solar and CER availability, which is calibrated against actual availability data from

[10] Adjusted to keep all scenarios with the same number of dispatch intervals.

[11] These generators comprise for wind – Stockyard Hill Wind Farm, Coopers Gap Wind Farm, Hornsdale Wind Farms (1-3), Dundonnell Wind Farm, Moorabool Wind Farm, Gullen Range Wind Farm, Macarthur Wind Farm, Sapphire Wind Farm, Silverton Wind Farm, and Lincoln Gap Wind Farm; and for solar – Darlington Solar Farm, Daydream Solar, Coleambally Solar Farms, Limondale Solar, Finely Solar Farm, Ross River Solar, Sunraysia Solar, Bungala One Solar Farm, and Nevertire Solar Farm.

2021 and 2022 calendar years. Linear interpolation is used to convert from hourly to half-hourly trading intervals.

Generation fuel costs over time are indexed based on actual historical monthly averages of fuel prices, with natural gas prices sourced from the Short-Term Trading Market (STTM) Sydney Hub, coal prices from the front-month Newcastle Coal futures contract (6000kcal/kg net calorific value, translated to AUD at the prevailing exchange rate), liquid fuel at the Australian Institute of Petroleum (AIP) diesel terminal gate price.

Dispatch is cleared at half-hourly trading intervals, with the supplier and consumer maximising their risk-averse utility, based on approximately monthly[12] aggregations of surplus. The monthly aggregation is adopted for two reasons. First, electricity consumers are billed on a monthly basis in the NEM, and thus is a natural point at which consumer would observe bill volatility. While some retailers also report metering over shorter periods – a weekly or daily basis – this is not consistent across the market. Second, the monthly period is also relevant for generators and gentailers. While debt service and financing covenant reporting typically occurs over quarterly (or longer) periods, the monthly reporting cycle is important in terms of corporate liquidity and credit assessment. As such, a month was considered an appropriate period over which consumers and generators may assess and comprehend risk.

In understanding supplier and consumer appetite for hedging, four resource cases are considered, reflecting different stages of the energy transition, based on the capacity mix trajectory outlined in the NEM ISP. This is intended to approximate an emissions trajectory progressing towards legally binding 2015 Paris Agreement targets. To approximate the NEM's legacy portfolio and the path towards net-zero, the model in Case 1 is initiated with an exogenous resource capacity for thermal, renewable, and storage resources for the 2017-18 year (as set out in the 2016 National Transmission Network Development Plan), with the capacity of OCGT firming resources sized to an expected or risk-neutral utility measure of *zero*. This additional resource capacity is required to supplement for hydro-generation and other generation resources, which are not modelled in this study. This results in a EUSE of 0.0013 per cent, which is well below the threshold of 0.002 per cent as per the NEM's reliability standard, thereby implying that existing market intervention measures to procure additional capacity (such as the Reserve and Emergency Trader function) would be unlikely to be utilised. For the remainder of the cases, the model is initiated with resource capacity that aligns with the relevant forecast year per the 2022 ISP (Low VRE: 2023-24, Mid VRE: 2029-30, and High VRE: 2035-36). Firming resources are then adjusted to ensure that the EUSE in higher VRE scenarios is in line with the original legacy system, (equating to 0.0013 per cent), noting this does imply higher levels of OCGT gas than that set out in ISP projections.

For the VRE Cases (Cases 2-4), the investment costs of renewable generation and storage are discounted to reflect potential cost reductions and low-carbon subsidy schemes to drive low-carbon deployment to reach Australia's net zero target. The level of discount is sized to an expected or risk-neutral utility measure of *zero*. While it is recognised that renewable generation has to date been subsided via a production-based credit, there are potential impacts associated with this type of structure on bidding and price formation. Thus, this paper abstracts from the question of the optimal subsidy form via the capital cost discount.

[12] The aggregation is ~30.4 days rather to ensure that each scenario is of the same length, so all have the same number of dispatch intervals.

Table 2: Resource Capacity (GW) by Case

Case	Thermal Dominated 1	Low VRE 2	Mid VRE 3	High VRE 4
Black Coal	24700	21300	9000	3000
Gas CCGT	4400	4100	4100	2600
Gas OCGT*	10300	11180	18700	25900
Liquid Fuel RE	700	700	700	700
Solar PV	200	8400	12200	18700
Wind	3700	11500	31500	42900
1-hr BESS	-	190	190	190
2-hr BESS	-	560	560	720
4-hr BESS	-	250	3000	4300
8-hr BESS	-	-	160	800
CER - Rooftop PV Peak MW	10100	10100	10100	10100
Renewable Gen Share (%)	6	28	61	79
Emissions (mil. kg-CO^2eq/mo)	11.4	8.5	4.0	1.9
ISP/NTNDP Base Yr	2017-18	2023-24	2029-30	2035-36

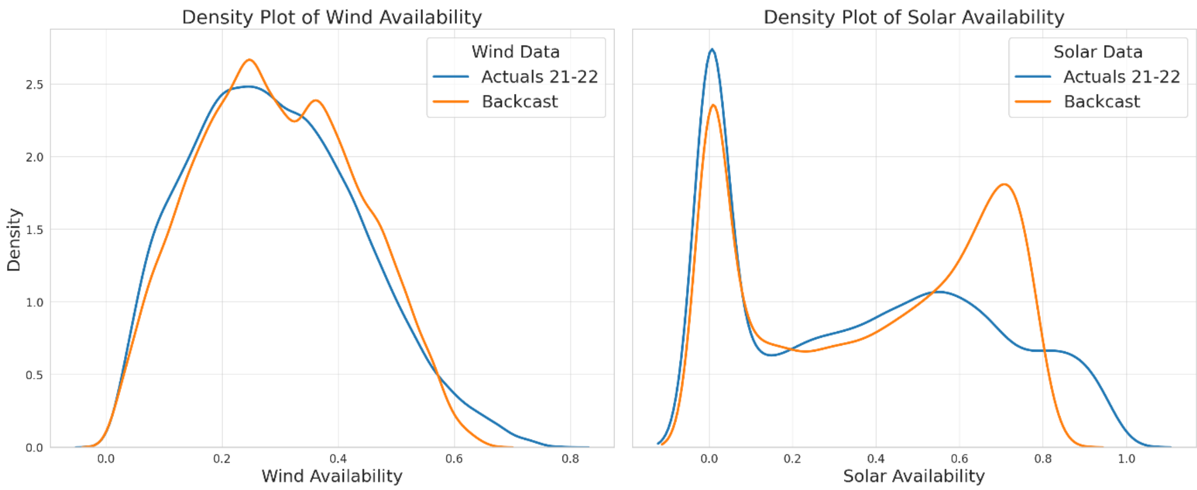
* Denotes firming resource.

2.2 Calibration and Price Statistics

The statistical parameters of the estimated backcasted availability of wind and solar (over the hours 0500-2000) over the period of the case study are compared with actual outcomes over dispatch intervals between 2020-21, showing good calibration of low order statistical moments. The density plots also are a reasonable comparison against the 2020-21 actuals, though we specifically call out a disparity in the distribution of actual and backcast outcomes over higher availabilities. The backcast data tends to be more concentrated at approximately 0.7 with minimal availability predicted beyond 0.8, where the actual data tends be more smoothly distributed across such horizons. As such it is possible that the backcasted data for solar may represent a more conservative perspective on resource risk as it does not reach availability points as high as the actual data.

Figure 5: Statistical Parameters and Density Plot of Wind and Solar Availability

	Wind		Solar (b/w 0500-2000hrs)	
	Actuals 20-21	Backcast	Actuals 20-21	Backcast
Mean	0.29	0.29	0.36	0.37
Std.Dev	0.15	0.14	0.30	0.28
P10	0.11	0.11	0.00	0.00
P50	0.28	0.29	0.36	0.40
P90	0.49	0.49	0.80	0.73



Note: Solar availability between 0500-2000hrs.

For the purposes of this paper, it is important to consider the calibration of the left tails of wind and solar over extended periods of low availability. In the absence of relevant long-term historical data we compare the periods of lowest average availability (Figure 6) for the backcast estimates for wind, solar, and 70/30 and 60/40 wind-solar portfolios, with a recent long-term reanalysis study of renewable droughts in the NEM by Gilmore et al (2022). The backcast data shows the worst availability increasing from 0-0.2 over a single day to 0.4-0.6 over a 10-day period, tapering out thereafter. These levels are consistent with Gilmore et al (2022), if not a slightly conservative estimate of the extended availability of wind and solar.

Figure 6: Periods of Lowest Average Availability

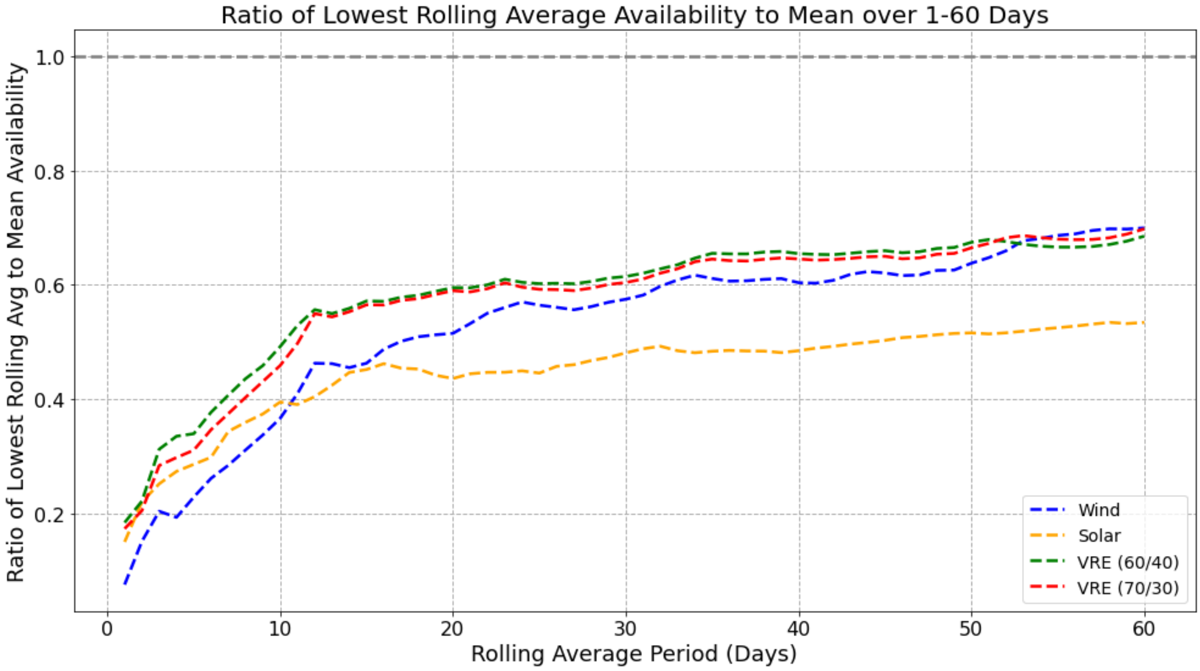


Table 3 provides the statistical metrics of wholesale spot price outcomes under each of the four cases, compared with historical prices between 2002 and 2022 for two mainland regions, New South Wales (NSW) and Victoria (VIC). As the modelling exercise aims to identify directional trends rather than recreate price outcomes, the price calibration is concerned primarily with orders-of-magnitude comparisons between the Thermal Dominated (Case 1) and historical outcomes. Differences can be attributed to a range of factors including, but not limited, to the impacts of network and security constraints, bidding dynamics, and the extent of market competition.

Table 3: Price Statistics

	Modelled				Historical 2002-22	
Case	Thermal Dominated 1	Low VRE 2	Mid VRE 3	High VRE 4	NSW	VIC
Price Statistics ($/MWh, Load Weighted Monthly Basis)						
Mean	66	64	66	61	56	52
Std. Dev	63	60	58	75	35	38
Skew	4	4	5	9	3	3
Kurtosis	18	15	31	100	10	19
α-VAR						
α = 0.5	47	46	49	45	49	40
α = 0.9	108	109	103	88	92	99
α = 0.95	174	193	151	114	105	111
α = 0.99	329	365	365	346	199	182

2.3 Results

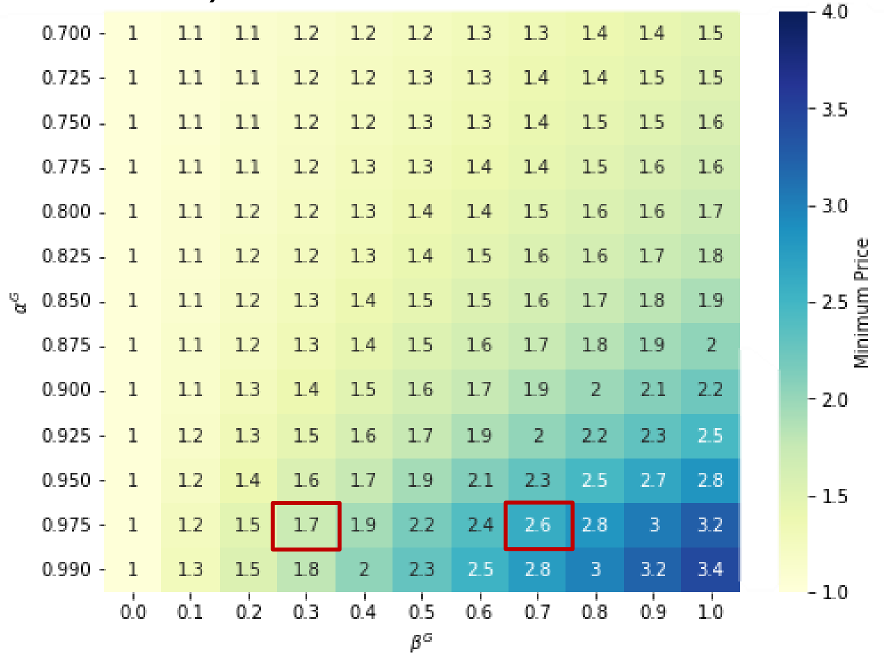
This section provides the modelled results on the insurability of long-term hedges in electricity systems.

First, we consider the willingness of the supplier to offer, and consumers to purchase long-term hedges under differing risk attitudes under a set of exogenously determined resource capacity mixes. Using the Thermal Dominated case as an illustration, Figures 10-12 show a set of density plots (heatmaps) under different risk parameters – risk-aversion β and tail risk thresholds α. Figure 7 sets out the minimum contract price required for a supplier to provide a full volumetric risk hedge for a range of risk attitudes $0.0 \leq \beta^G \leq 1.0$ and $0.7 \leq \alpha^G \leq 0.99$. (the contract price at which risk-averse utility of the supplier is *zero*). The minimum contract price is provided on a relative basis as a proportion of the risk-neutral or expected value of the hedge cashflows. Figure 8 records the proportion of scenarios in the supplier's problem that have a negative surplus, for the same range of β^G and α^G values.

It is observed that at low levels of risk-aversion and low tail risk thresholds (relatively low values of β^G and α^G, respectively), the supplier would be willing to execute contracts at, or close to the expected value of spot prices. However, for such risk parameters the supplier experiences negative surplus in a higher proportion of scenarios, where total revenues from the spot and contract markets in those scenarios are insufficient to pay fixed and variable costs (for example, ~26 per cent in the risk-neutral case). The key implication for the deliverability of contracts relates to potential counterparty credit or solvency risk given insufficient revenue in a higher proportion of scenarios.

At higher levels of risk-aversion and risk comprehension, solvency risk improves (with negative surplus in a much lower percent of scenarios, as per <2-3 per cent). However, the required contract prices for the supplier to deliver full volume contracts also increases, reaching ~2-3 *times* of the expected value of hedge cashflows. For example, where spot prices average at $66/MWh in Case 1 – the hedge contract would need to be priced at above $150-225 per MWh.

Figure 7: Minimum Contract Price* for Full Volumetric Hedge (Case 1 – Thermal Dominated)



* Contract Price specified on a relative basis as a proportion of expected (risk-neutral) hedge cashflows.

The implicit trade-off between contract price and participant solvency suggests that a risk-averse – or at the least risk-constrained attitude – is required to support the execution of long-term contracts in electricity markets. This result is consistent with similar work in insurance markets, when insuring fat-tailed and tail-dependent loss distributions.

This then leads to the question of consumer appetite to enter long-term contracts. Figure 9 provides a density plot of consumer volumetric demand for the hedge contract based on two particular pricing points – a low supplier risk-aversion case (with $\beta^G = 0.3$, $\alpha^G = 0.975$), and a high supplier risk-aversion case (with $\beta^G = 0.7$, $\alpha^G = 0.975$). This is to reflect different perspectives on the extent of solvency risk that is willing to be borne when contracting. For both, at lower values of β^D and α^D there is no consumer willingness to contract (as demonstrated by zero volumetric demand). At particular risk-aversion and tail-risk thresholds the appetite to contract increases dramatically, often seeking to contract at close to full load volumes. As an illustration of the gradient of change, for the zero volumes are demanded at $\alpha^D = 0.95$, $\beta^D = 0.1$, increasing to 0.77 at $\alpha^D = 0.95$, $\beta^D = 0.2$. Similar trends are observed for thresholds. Given the presence of fat tails, small changes in risk parameters can result in substantial changes in contracting appetite. As is discussed in Section 0, this has significant consumer protection implications if consumer risk comprehension depends upon prior loss experience.

Figure 8: Proportion of Scenarios with Negative Surplus
(Case 1 – Thermal Dominated)

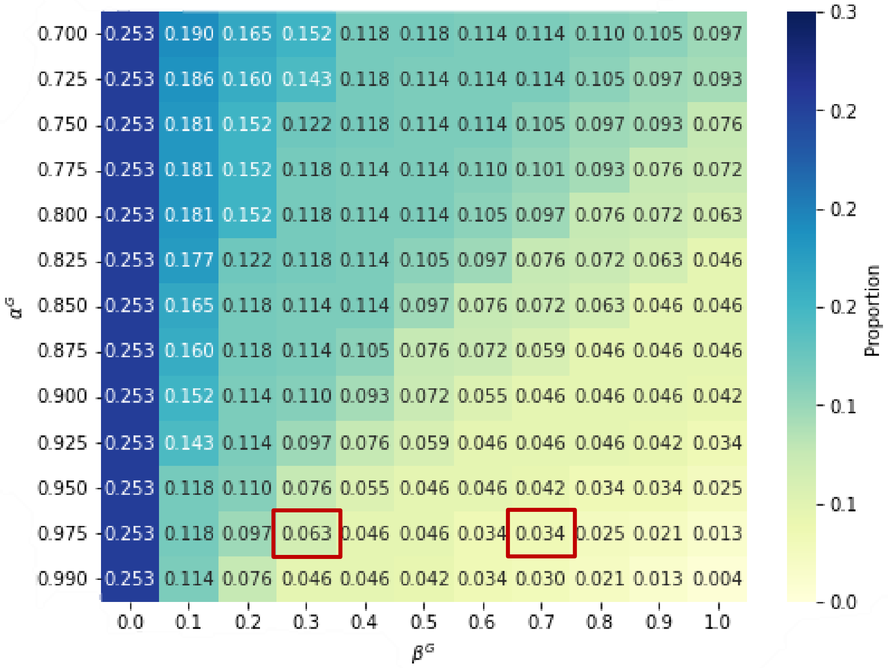
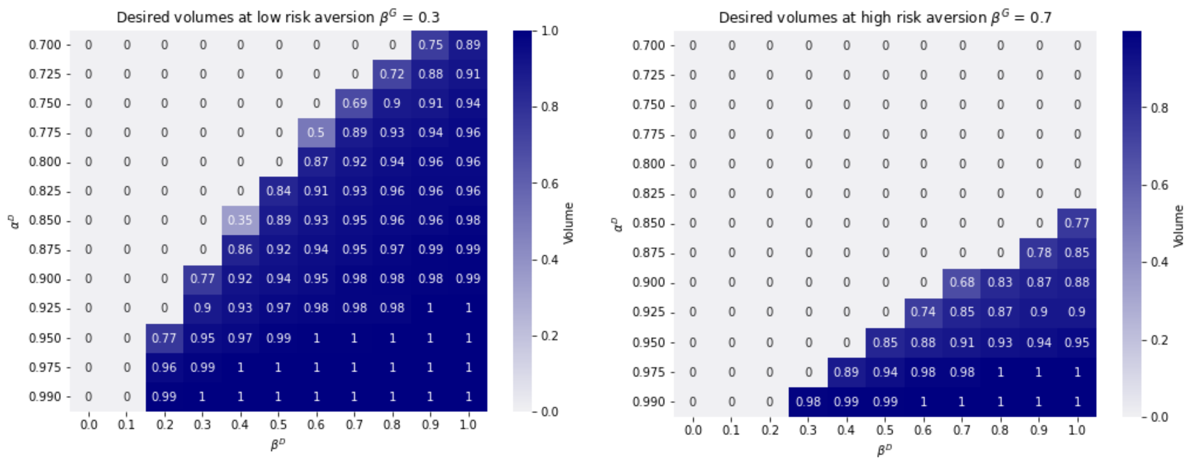


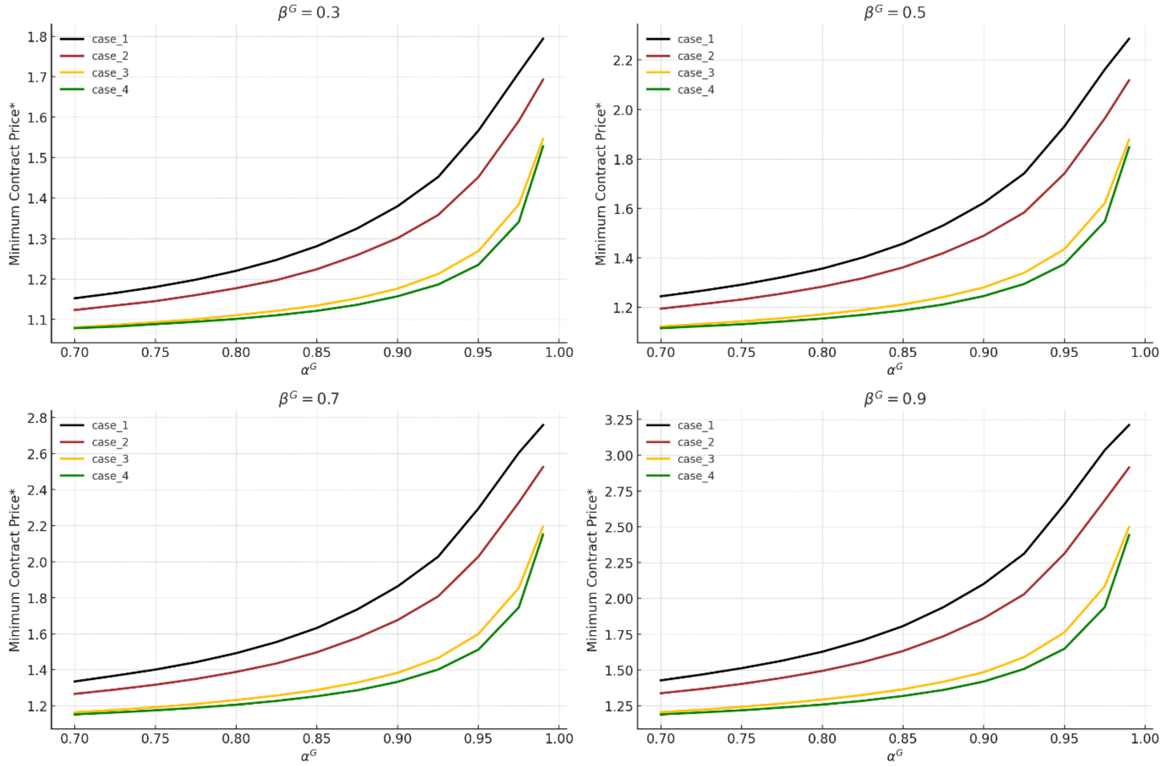
Figure 9: Consumer Volumetric Appetite for Long-Term Hedges under low ($\beta^G = 0.3$) and high ($\beta^G = 0.7$) generator risk aversion



For the Thermal Dominated case, the results suggest that there is an implicit trade-off between contract deliverability and price – however it is the scale of such change in the context of tail risk that is relevant. To provide contract deliverability, the supplier needs to offer at multiples of risk-neutral value. This has significant competitive implications in a contestable retail market. Adding to the challenge is the apparent steepness of the gradient in consumer volumetric appetite under fat tails, tail dependence and aggregation.

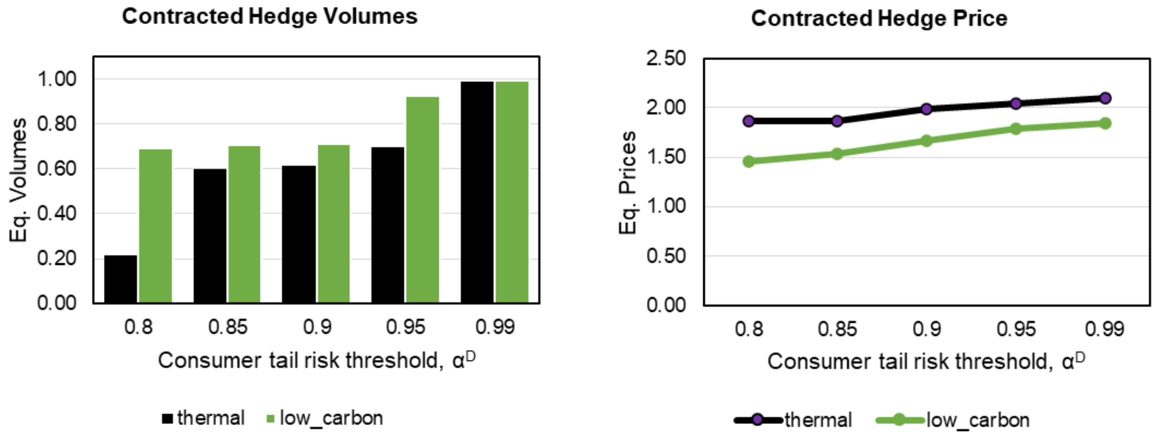
How then may deliverability, price and appetite of contracts evolve under a changing generation mix towards low-carbon resources? Figure 10 sets out the minimum contract offered price for different resource mix (cases 1-4) for four levels of supplier risk-aversion. It is observed that as we move from case 1 with a thermal-dominated grid, to cases 2-4, with increasingly high renewables and storage penetration there are reductions in the minimum required contract price. The directional trend reductions are consistent across different tail risk thresholds and risk-aversion levels. It is noticeable that the largest relative changes seem to occur from low-VRE to mid-VRE cases (from case 2 to case 3), a reduction of ~14 per cent for the most tail risk averse case shown (i.e., with $\beta^G = 0.9$, $\alpha^G = 0.99$), given better tail risk diversity from a diverse resource portfolio. The benefits appear to taper off in the shift from mid-VRE to high-VRE (case 3 to case 4), reducing by ~2 per cent in the risk-averse case.

Figure 10: Minimum Contract Price for Resource Mix Cases 1-4, for four levels of supplier risk-aversion ($\boldsymbol{\beta^G = \{0.3, 0.5, 0.7, 0.9\}}$)



The patterns observed for the cases with an exogenous resource mix are also directionally consistent with the results when running an equilibrium search where the resource mix is endogenously determined. Two cases are compared. First a thermally dominated portfolio initiated with the resource mix initiated as per case 1 and adjusted based on Algorithm 1, with the restriction that no incremental investment in renewables (wind, solar) or storage is allowed. Second, a renewables-heavy, low-carbon case with the resource mix initiated as per case 3, with no restrictions on incremental resource investment. The supplier risk preferences are fixed at $\beta^G = 0.3$, $\alpha^G = 0.975$. Consumer risk-aversion is fixed at a $\beta^D = 0.5$, a midpoint between risk-neutrality and full risk aversion, while the tail risk threshold, α^D, is varied from 0.8 to 0.99. Outcomes are shown with final equilibrium contract volumes shown in the left panel, and final equilibrium contract prices are shown in the right panel. For the cases shown, the low-carbon case has higher contract volumes and low contract prices in equilibrium. It also appears there are steep gradients in contract volumes associated with changes to tail risk thresholds, especially for the thermal case.

Figure 11: Equilibrium Contract Volumes and Prices under Thermal and Low-Carbon Cases



Portfolio results attribution

To assess the underlying drivers of the results we discuss the attribution of portfolio and resource surplus below. Figure 12 illustrates the portfolio surplus across the worst 20 scenarios (defined as scenarios with the lowest portfolio surplus), with total surplus broken down into that attributable to generator surplus, storage surplus, contract derivative inflows and outflows. It is observed that in all but the worst case, supplier profits across the portfolio are lower for the thermal dominated than the mid-VRE case, despite high marginal prices (as reflected in derivative outflows). In the former, the supplier must contend with having to pay out on fixed derivative cashflows but is liable to pay out on fuel costs. Fat tails and tail-dependence across thermal fuels exacerbates cost recovery in such situations where the generator cannot hedge its fuel risk. This can be observed by examining resource surplus in Figure 13 for Scenario 224 (which records the sixth-worst surplus for the thermal dominated and the mid-VRE case). For the thermal dominated case, while spot revenues are positive for thermal fuels this is offset by high variable costs. In the mid-VRE case, the VRE component of the resource portfolio records significant positive surplus, with such diversity able to improve the overall portfolio position.

Figure 12: Portfolio Surplus Attribution – Worst 20 Scenarios, Cases 1 and 3

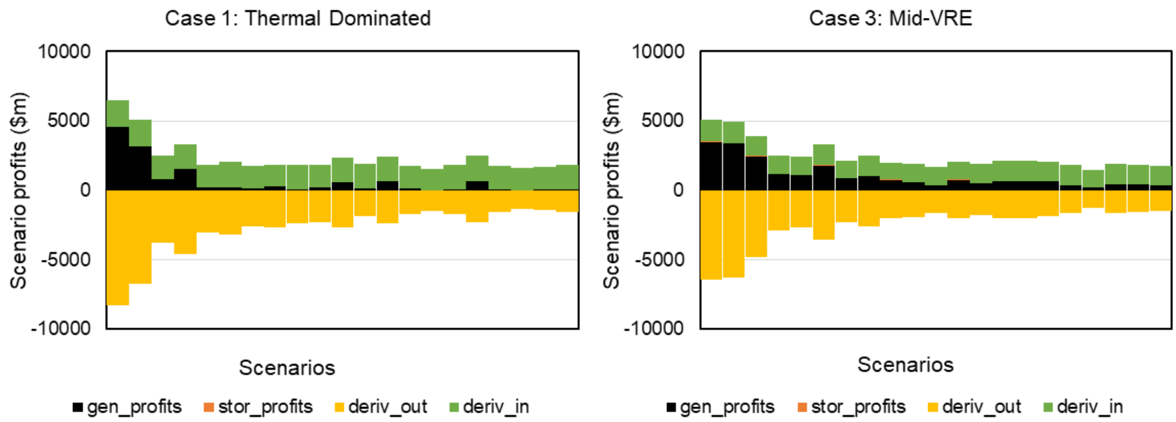
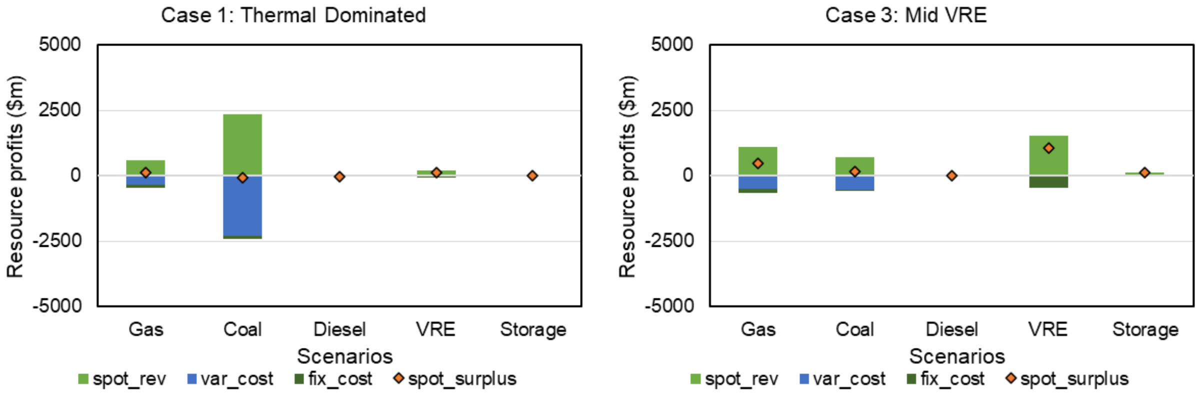


Figure 13: Resource Surplus Attribution, Scenario 224, Cases 1 and 3



Notwithstanding the relevant results, there are limitations of this numerical study, which can be overcome in future works. First, to facilitate the analysis, issues related to transmission and distribution networks and power system security, such as network constraints, voltage, and frequency deviations, were not explicitly modelled (an issue of relevance in inverter-dominated grids). Second, our framing of scenario risks is based upon historical availability for thermal generation, and backcasted availability for renewables based on historical weather outcomes. A key issue for the future will be how climate change affects tail risk relating to the availability of zero-carbon resources. Third, this work reflects index-linked, or short-term fuel contracting – and results could be affected if long-term fuel contracting became viable. Moreover, while degrees of risk-aversion have been modelled, there will be a wide range of preferences and behaviours for participants that may not be as transparent in practice.

Conclusions and Policy Implications

This paper considered how the hedgeability of long-term risk trades in electricity markets are affected by a shift towards variable renewables and storage. Using a stochastic equilibrium model applied to real-world data in the Australian electricity markets it is demonstrated first that when it comes to the extremes, thermal dominated power systems can be expensive to hedge. This is primarily due to the heavy-tailed nature of thermal commodity prices, and the common-mode exposures between them. This has parallels in insurance, where fat tails, tail dependence and micro-correlations explain the declining rates of take-up of catastrophe insurance. Shifting to a more diversified power system, and importantly one that is less co-dependent in the tail, has the potential to improve the prospects for long-term hedging and contracting.

The results point to four further considerations for policy and research inquiry in market design as electricity systems progress further down the path of decarbonisation.

First is the relevance of credit worthiness and solvency in long-term risk contracting. In such situations, the ignorance of solvency risk in contracts may paint an overly optimistic picture of the viability of commercial hedging, especially if such information is non-transparent. This is especially so where the underlying exposures have heavy tails and are potentially tail dependent. In this respect, low-carbon power systems may benefit from improved tail diversity across resource types; that is, the factors that catalyse and precipitate extreme tail events could have more dispersed impacts across the portfolio. However, it should be cautioned that the results are specific to a case study, and consideration should be given to the specificities of different regions, markets, and energy systems. As such, the integration of solvency and credit constraints in equilibrium analyses of different market designs is an important area of future work.

Second is the need for tail risk assessment of systems and markets to expand in breadth towards the integration of financial, physical, and digital systems. Consideration should also be given to potential common modes across low-carbon systems, including the impacts of system and network security in renewable pockets. Further, the extension to a larger class of system and participant risks could include cyber-physical systems and the integration of new energy system fuels and vectors (hydrogen, mobility, heat, et al). The more generalised policy implication to be drawn here is the focus on encouraging and incentivizing comprehensive tail analysis and risk management by planners and market participants. Market reform should thus be focused upon mitigating the impact of implicit and explicit 'protections' that may dull incentives to manage such risk (Mays, 2021; Mays et al., 2022). System and cumulative price caps (the latter of which precipitated the suspension of the NEM in 2022) are prime examples of such. Comprehensive reform should consider the integration of demand-side not only into spot price formation, but into risk-hedging markets as well. Much of the focus of market design has been directed to the former.

The third consideration relates to how consumers perceive risks. The results demonstrate the sensitivity of contract appetite to risk parameters. Such parameters are non-transparent, and for consumers the perception of risk can be coloured by many factors, including prior exposure to tail events (Leslie et al., 2022). This has relevance to market designs with contestable, and regulated, retail. For the former, attention should be given to how consumer preference can be better revealed via contractual instruments (Billimoria et al., 2022), as well as alternative retail tariff structures that enable demand-side flexibility but also provide price protection. For regulated markets, tariff structures are relevant, but the more holistic question is how and to what degree utilities should be obligated to hedge retail exposure. The implied risk tolerance in such regulations will greatly impact financing, investment, and ultimately reliability outcomes. A classic response to tail situations is a political intervention post the event – for example to cap prices. This can be sub-optimal, but also create expectations of protection from consumers. Consideration of market designs that integrate the political economy of tail risk is a worthy future research area.

Fourth is the critical role of energy storage in enabling effective hedging strategies, especially in grids with high renewable penetration, which underscores the need for specific policies that remove barriers and promote the deployment and innovation of storage technologies. This could involve financial incentives, research and development support, and regulatory frameworks that appropriately recognize the value of storage in enhancing grid reliability and facilitating renewable integration.

Finally, parts of this analysis also influence questions on the degree of decentralization of decision making in electricity market design. In many power markets central governments and agencies have taken a more direct role in investment decisions, through subsidies and the initiation of long-term risk hedging contracts. Notwithstanding perspectives on the inevitability of hybrid markets in the context of energy transition, tail risk under such approaches is not eliminated but merely reallocated.

Appendix A: Models of Risk Hedging in Electricity Markets

This section proposes mathematical formulations underpinning the modelling in this paper. The decision-making problems of the risk-averse agents in the market and the model of spot market dispatch is set out, and an algorithm to search for a contractual equilibrium between parties is provided.

A.1 Decision-making models for agents

A non-cooperative game-theoretic approach was considered most appropriate as it can describe the decision-making of individual agents given a particular market design, as well as those interactions arising between agents within the market design. This provides insight into the incentives of agents under risk-aversion and market incompleteness.

To keep the formulation as simple as possible, we consider two risk-averse agents – a consumer agent and an energy generation supplier (who owns a portfolio of generation and storage resources) and seeks to provide a long-term retail risk hedge to consumers. The specification of risk in this context is important. While symmetric measures of risk, such as variance, have been applied in electricity markets (Biggar & Hesamzadeh, 2022) these measures consider upside and downside variations from a mean to be risk equivalent. This is unsuited to this paper as we are concerned primarily with hedging incentives as it relates to downside tail risk. We consider instead the conditional value-at-risk (CVaR) as it models aversion to downside outcomes only and can be calibrated to different perceptions of tail risk. Moreover, it is a coherent and convex risk measure with a convenient linear programming formulation and has applicability both in electricity and insurance markets (Krokhmal et al., 2002).

The supplier model is formulated as a two-stage decision model, with investment and contracting decisions in the first stage made subject to anticipated spot market outcomes in the second stage, drawing upon prior work in Shu & Mays (2023). The set of resources $r \in \mathcal{R}$ comprises generation $\mathcal{G}$ and storage $\mathcal{S}$ with $\mathcal{R} = \mathcal{G} \cup \mathcal{S}$. It is assumed that uncertainty is observable (that is to say, the probability of each state of the world occurring is known in advance) and that agents are assumed to have the same knowledge of uncertainty. In this framework, uncertainty is represented by scenarios $\omega \in \Omega$ to represent states of the world.

The surplus of the energy supplier Ψ^G_ω in each scenario ω is the sum of net surplus from the spot market Ψ^M_ω (that is, the market revenues generated by storage and generation resources minus any fixed costs), plus the net surplus from contracts Ψ^C_ω (equation A.1a). For storage resources, net generation $p^G_{rt\omega}$ for resource r in each time period t and scenario ω is the difference between energy discharge $p^{G-}_{rt\omega}$ and charge $p^{G+}_{rt\omega}$ i.e. ($p^G_{rt\omega} = p^{G-}_{rt\omega} - p^{G+}_{rt\omega}$).

$$\Psi^G_\omega = \Psi^M_\omega + \Psi^C_\omega \qquad \forall\omega \in \Omega \qquad \text{(A.1a)}$$

$$\Psi^M_\omega = \sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}}(\lambda^E_{t\omega} - C^{vc}_{rt\omega})p^G_{rt\omega} - C^I_r\overline{P_r} \qquad \forall\omega \in \Omega \qquad \text{(A.1b)}$$

$$\Psi^C_\omega = v^G \sum_{t\in\mathcal{T}}\left(\lambda^F - \lambda^E_{t\omega}\right)p^D_{rt\omega} \qquad \forall\omega \in \Omega \qquad \text{(A.1c)}$$

In this paper, we model (equation A.1c) a simple retail contract in the form of a load-weighted contract-for difference, where the supplier receives a (fixed) energy price λ^F in return for the (floating) spot price $\lambda^E_{t\omega}$ at each time and scenario. The variable v^G represents reflects the volumetric exposure, defined as the percentage of demand that the contract is exposed to. This is akin to existing fixed price retail contracts, deferring consideration of alternative retail contract structures to future work (see also Shu & Mays (2023)).

Consistent with a risk-averse model of decision making (Mays et al., 2022), the supplier's utility is defined (in A.1e) as a convex combination of the expected surplus and the CVaR of the surplus, where parameter β^G, ranging between 0 and 1, weights expected returns against CVaR based on the agent's preferences, and parameter α^G specifies the tail risk characterisation – i.e. what part of the tail the agent is concerned about. For example, $\alpha^G = 0.01$ implies that the supplier is averse to risk (as defined by CVAR) for the worst 1 per cent of outcomes. The CVAR ($\widetilde{c^G}$) is defined in equation (A.1f), via its linear formulation with auxillary variables VaR^G and $\varrho^G_\omega$and constraints in equations (A.1g-h).

$$GEN: \max_{v^G, VaR^G, \varrho_\omega^G} U^G = (1-\beta^G)\sum_{\omega\in\Omega}\pi_\omega\Psi_\omega^G + \beta^G\,\widetilde{c^G} \quad \text{(A.1e)}$$

$$\widetilde{c^G} = VaR^G - \frac{1}{\alpha^G}\sum_{\omega\in\Omega}\pi_\omega\,\varrho_\omega^G \quad \text{(A.1f)}$$

$$VaR^G - \Psi_\omega^G \le \varrho_\omega^G \qquad \forall\omega\in\Omega\ [a_\omega] \quad \text{(A.1g)}$$

$$\varrho_\omega^G \ge 0 \qquad \forall\omega\in\Omega\ [b_\omega] \quad \text{(A.1h)}$$

Under perfect competition, the supplier seeks a zero risk-averse utility (Shu & Mays, 2023). Given a particular resource mix, the contractual price that resolves this condition is denoted as $\lambda^{F*} \in \arg\max U^G = 0$. In a game-theoretic context this represents the minimum price that a supplier would be willing to offer a full volumetric contract (i.e. with $v^G = 1$). This value can be calculated as per Appendix C.

The consumer's decision problem is similarly defined, with the key differences being how the consumer's market surplus $\Psi_\omega^{M(D)}$ is defined in terms of the difference between the value of lost load (VOLL) and spot price (in equation A.1n), and the contract surplus (in equation A.1o) $\Psi_\omega^{C(D)}$ as the consumer is taking the counter-side of the contract cashflows.

$$CON: \max_{v^D, VaR^D, \varrho_\omega^D} U^D = (1-\beta^D)\sum_{\omega\in\Omega}\pi_\omega\Psi_\omega^D + \beta^D\,\widetilde{c^D} \text{ s.t.} \quad \text{(A.1i)}$$

$$\widetilde{c^D} = VaR^D - \frac{1}{\alpha^D}\sum_{\omega\in\Omega}\pi_\omega\,\varrho_\omega^D \quad \text{(A.1j)}$$

$$VaR^D - \Psi_\omega^D \le \varrho_\omega^D, \qquad \forall\omega\in\Omega \quad \text{(A.1k)}$$

$$\varrho_\omega^D \ge 0, \qquad \forall\omega\in\Omega \quad \text{(A.1l)}$$

$$\Psi_\omega^D = \Psi_\omega^{M(D)} + \Psi_\omega^{C(D)} \qquad \forall\omega\in\Omega \quad \text{(A.1m)}$$

$$\Psi_\omega^{M(D)} = \sum_{t\in\mathcal{T}}(C_{t\omega}^{voll} - \lambda_{t\omega}^E)p_{t\omega}^D \qquad \forall\omega\in\Omega \quad \text{(A.1n)}$$

$$\Psi_\omega^{C(D)} = v^D\sum_{t\in\mathcal{T}}(\lambda_{t\omega}^E - \lambda^F)p_{rt\omega}^D \qquad \forall\omega\in\Omega \quad \text{(A.1o)}$$

A.2 Economic dispatch

Suppliers and consumers make investment and contracting decisions based on outcomes from the economic dispatch of the spot market. A model of spot market dispatch is formulated in equations (A.2a-j). We seek to keep the formulation as straightforward as possible. While the dispatch is ramp-constrained, we assume a copper-plate network and neglect impacts of network and security constraints and frequency reserve products at this stage. For ease of notation, any decision variables and parameters that vary over time are denoted in **bold**. For example, the vector of energy dispatched over time from a resource r, $\mathbf{p_{r\omega}^G} := [p_{r1\omega}^G, \dots, p_{rt\omega}^G, \dots, p_{rT\omega}^G]$ where time period $t \in \mathcal{T} := \{1, \dots, T\}$. Dual variables are shown in square brackets next to each constraint.

$$ED_\omega: \quad \min \sum_{r\in\mathcal{R}} \mathbf{C_{r\omega}^{vc}} \cdot \mathbf{p_{r\omega}^G} - \mathbf{C_\omega^{voll}} \cdot \mathbf{p_\omega^D} \text{ s.t.} \quad \text{(A.2a)}$$

$$0 \le \mathbf{p_{r\omega}^G} \le \mathbf{A_{r\omega}^G}\overline{P_r} \qquad \forall r\in\mathcal{G},\ \omega\in\Omega \qquad [\underline{\boldsymbol{\mu}_{r\omega}^G}, \overline{\boldsymbol{\mu}_{r\omega}^G}] \quad \text{(A.2b)}$$

$$0 \le \mathbf{p_\omega^D} \le \overline{\mathbf{P_\omega^D}} \qquad \forall\omega\in\Omega \qquad [\underline{\boldsymbol{\mu}_{r\omega}^D}, \overline{\boldsymbol{\mu}_{r\omega}^D}] \quad \text{(A.2c)}$$

$$\sum_{r\in\mathcal{R}} \mathbf{p_{r\omega}^G} = \mathbf{p_\omega^D} \qquad \forall\omega\in\Omega \qquad [\boldsymbol{\lambda}_\omega^E] \quad \text{(A.2d)}$$

$$-\overline{P_r}\,R^{\downarrow} \le p_{rt\omega}^G - p_{r(t-1)\omega}^G \le \overline{P_r}\,R^{\uparrow} \quad \forall r\in\mathcal{G}, t\in\{\mathcal{T}/1\},\ \omega\in\Omega \qquad [\underline{\boldsymbol{\delta}_{r\omega}^G}, \overline{\boldsymbol{\delta}_{r\omega}^G}] \quad \text{(A.2e)}$$

$$0 \le \mathbf{p_{r\omega}^{G+}} \le \mathbf{A_{r\omega}^G}\overline{P_r} \qquad \forall r\in\mathcal{S},\ \omega\in\Omega \qquad [\underline{\boldsymbol{\mu}_{r\omega}^{G+}}, \overline{\boldsymbol{\mu}_{r\omega}^{G+}}] \quad \text{(A.2f)}$$

$$0 \le \mathbf{p_{r\omega}^{G-}} \le \mathbf{A_{r\omega}^G}\overline{P_r} \qquad \forall r\in\mathcal{S},\ \omega\in\Omega \qquad [\underline{\boldsymbol{\mu}_{r\omega}^{G-}}, \overline{\boldsymbol{\mu}_{r\omega}^{G-}}] \quad \text{(A.2g)}$$

$$\mathbf{0} \leq \mathbf{S_{r\omega}} \leq e_r\overline{P_r} \qquad \forall r \in \mathcal{S}, \omega \in \Omega \qquad [\underline{\boldsymbol{\mu}^{S}_{r\omega}}, \overline{\boldsymbol{\mu}^{S}_{r\omega}}] \qquad \text{(A.2h)}$$

$$S_{rt\omega} = S_{r,t-1,\omega} + q_r^+ p^{G+}_{rt\omega} - \frac{1}{q_r^-} p^{G-}_{rt\omega}, \ \forall r \in \mathcal{S}, t \in \{\mathcal{T}/1\}, \omega \in \Omega \qquad [\mu^{Soc}_{rt\omega}] \qquad \text{(A.2i)}$$

$$S_{r1\omega} = S_{r,T,\omega} + q_r^+ p^{G+}_{1t\omega} - \frac{1}{q_r^-} p^{G-}_{r1\omega}, \qquad \forall r \in \mathcal{S}, t = 1, \omega \in \Omega \qquad [\mu^{Soc}_{r1\omega}] \qquad \text{(A.2j)}$$

The objective function of the economic dispatch ED_ω in each scenario $\omega \in \Omega$ is to minimise system costs (generation costs and demand shortage costs). Equation (A.2b) ensues that resource dispatch is constrained by availability limits. In equation (A.2c) dispatched demand is constrained to the maximum demand at each time and scenario. Equation (A.2d) enforces energy balance with the dual $\boldsymbol{\lambda}^{\mathbf{E}}_{\boldsymbol{\omega}}$ being the marginal cost at each time and scenario. Equation (A.2e) enforces ramp rate limits. Equations (A.2f) and (A.2g) limits charge and discharge to inverter capacity. The state of charge (SoC) is limited to the energy storage duration in (A.2h) and is calculated from the prior interval in (A.2i). To avoid trivial solutions, in (A.2i) the SoC is constrained to have the same value at start and end of the considered period.

The total inframarginal rents available to each form of resource in each scenario ω is specified as below, with the derivation provided in Appendix D.

$$\text{Generator:} \qquad \overline{\overline{\boldsymbol{\mu}^{G}_{r\omega}}} = \overline{\boldsymbol{\mu}^{G}_{r\omega}}.\mathbf{A^{G}_{r\omega}}\overline{P_r} + \overline{P_r}\, R^{\uparrow} \cdot \overline{\boldsymbol{\delta}^{G}_{r\omega}} + \overline{P_r}\, R^{\downarrow} \cdot \underline{\boldsymbol{\delta}^{G}_{r\omega}} \ \forall r \in \mathcal{G} \qquad \text{(A.2k)}$$

$$\text{Storage:} \qquad \overline{\overline{\boldsymbol{\mu}^{S}_{r\omega}}} = \overline{\boldsymbol{\mu}^{G+}_{r\omega}} \cdot \mathbf{A^{S}_{r\omega}}\overline{P_r} + \sum_{t\in\mathcal{T}} \overline{\boldsymbol{\mu}^{G-}_{r\omega}} \cdot \mathbf{A^{S}_{r\omega}}\overline{P_r} + e_r\overline{P_r} \cdot \overline{\boldsymbol{\mu}^{S}_{r\omega}} \ \forall r \in \mathcal{S} \qquad \text{(A.2l)}$$

A.3 Equilibrium search

Given a particular set of agents and available resources, this section formulates a distributed algorithm to search for an equilibrium in resource investment between buyer (consumer) and seller (supplier). The algorithm is developed to compute an equilibrium whereby given a particular resource mix, different contract prices are trialled based on the contract volumes sold and purchased by the supplier and consumer, respectively. The algorithm draws most heavily upon the work of Shu & Mays (2023), where a price is updated based on the differential between buy and sell quantities of the relevant contract. This approach is a variant of the Gauss-Seidel diagonalisation method and is used for contract balancing and price setting. Uniqueness and existence under such conditions remain an open issue, beyond simple case study analysis (Shu & Mays, 2023).

The initialisation of the algorithm begins with an initial instance of resource capacities and contract prices. For iteration *k*, the problems GEN and CON are run, and the contract price is updated based on the differential arising between the quantities purchased and the quantities sold (that is, if purchased volumes are greater than sold volumes, the price is incremented upward, and vice versa) (a contractual tatonnement). The tatonnement is terminated when the difference between the quantities purchased and sold for each insurance contract is negligible. Once the tatonnement concludes, the resource mix is updated, and the tatonnement is repeated. This loop continues until the utility of the supplier is near zero (i.e. below a trivial threshold; in this work the trivial threshold was set at 0.03). This approximates a zero-utility condition, i.e. an equilibrium in perfect competition. Relative to other work involving a resource portfolio, such as Shu & Mays (2023), this algorithm updates resource capacity by a single unit at a time, based on the unit that has the highest contribution to the supplier's utility. The factor Γ_r reflects this contribution and is derived in Appendix C. The factor Δ represents the increment to resource capacity; and r^* is the resource with highest contribution. As with the diagonalisation method, this algorithm does not provide guarantees relating to convergence or solution uniqueness (Shu & Mays, 2023)

Algorithm 1: Equilibrium search

Input: Initialisation of resource capacity, $P_r \forall r \in \mathcal{R}$
Output: Near-equilibrium solution

set parameters for resource update loop $\Delta, \epsilon_1, \delta_1$, iteration counts *k*, max iterations K
set parameters for tatonnement loop ϵ_2, δ_2 iteration counts *l*, max iterations L
Resource update loop: **while** $|U^G| > \epsilon_1$ **and** $k < K$ **do:**
    $r^* \leftarrow \arg\max \Gamma_{r(k)} \;\; \forall r \in \mathcal{R}$
    $P_{r*(k)} = P_{r*(k-1)} + \Delta$
    solve (ED_ω), $\forall \omega \in \Omega$
    initialise $\lambda^F \leftarrow \lambda^{F*}$
    tatonnement loop **while** $|v^D - v^G| > \epsilon$ **and** $l < L$ **do:**
        $v^G \leftarrow$ solve (GEN)
        $v^D \leftarrow$solve (CON)
        $\lambda^F_{(l+1)} = \lambda^F_l + \delta(v^D - v^G)$
        $l \leftarrow l + 1$
    end
    end
    return

Appendix B: Percentile Scatter and Conditional Probability Plots

Figure B1: Percentile scatter plots for fuel commodities – coal, natural gas, and diesel

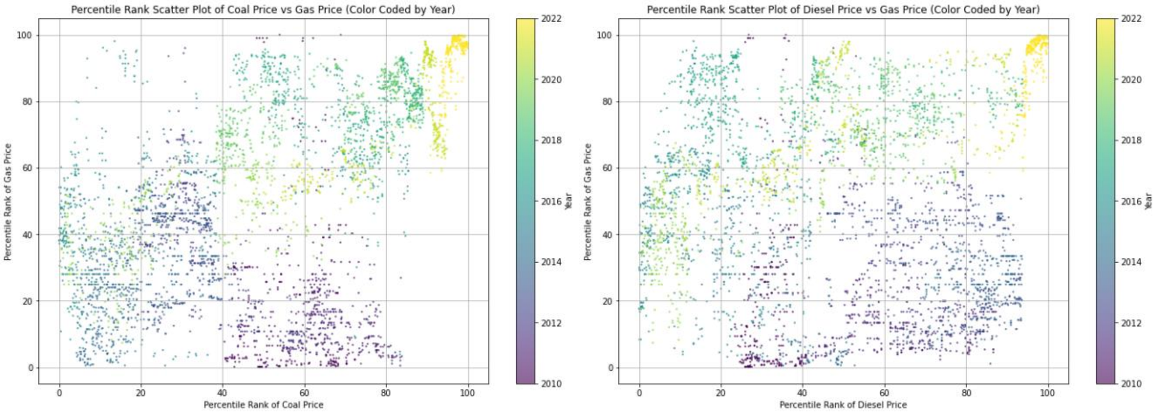
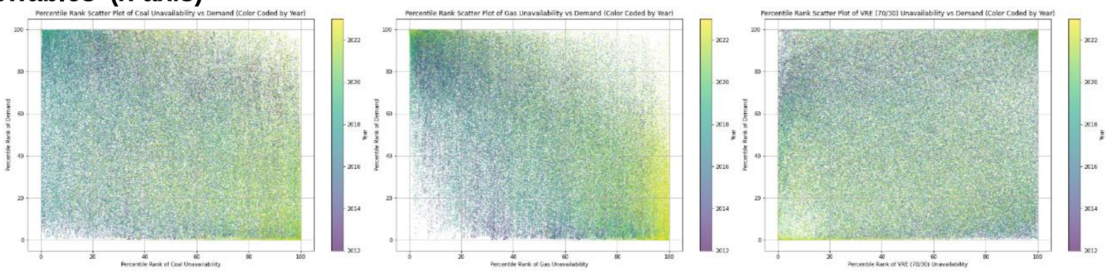
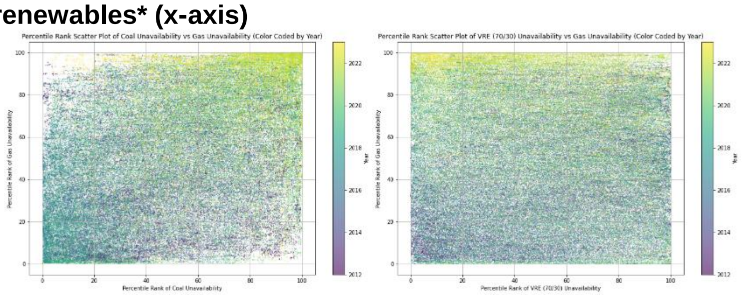


Figure B2: Percentile scatter plots for demand (y-axis) against – coal, natural gas, and variable renewables* (x-axis)



* Variable renewables availability based on a combined 70/30 wind-solar portfolio

Figure B3: Percentile scatter plots for gas generation unavailability (y-axis) against coal and variable renewables* (x-axis)



* Variable renewables availability based on and a combined 70/30 wind-solar portfolio

Figure B4: Conditional probability plot for gas prices against coal and diesel prices (daily)

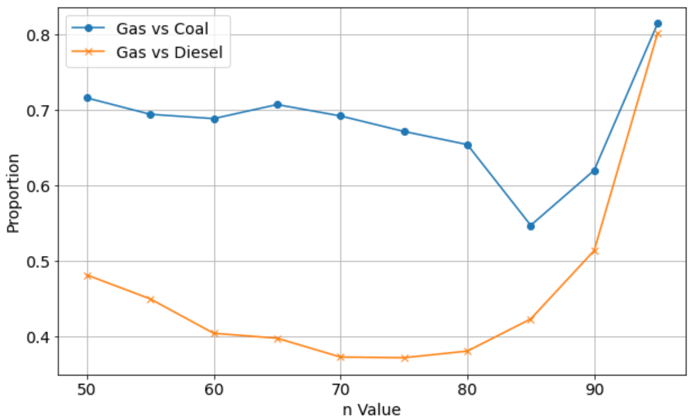


Figure B5: Conditional probability plot for gas prices against coal and diesel prices (monthly aggregation)

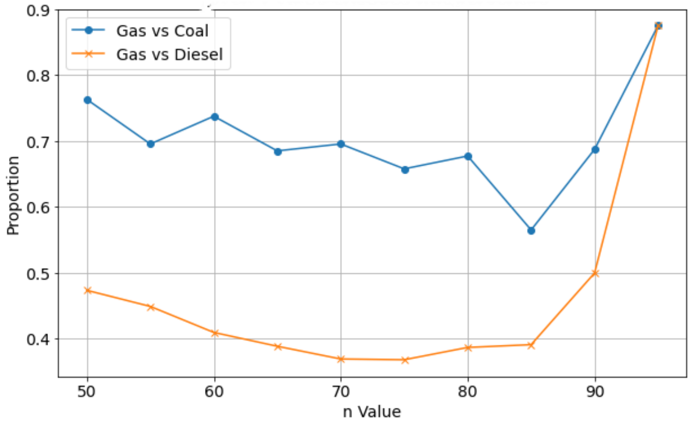


Figure B6: Conditional probability plot for demand against gas, coal and variable renewables availability (dispatch interval)

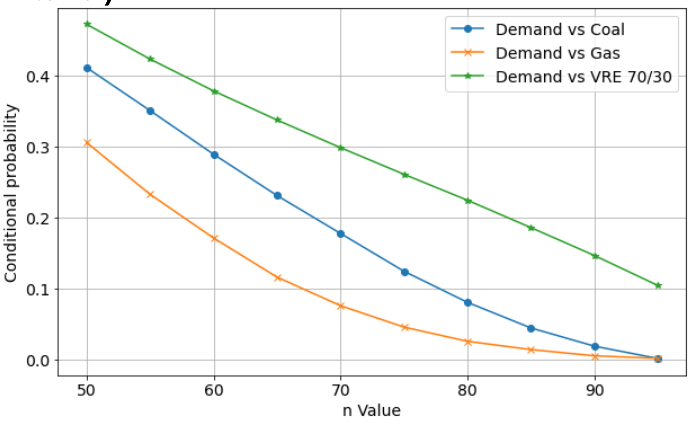
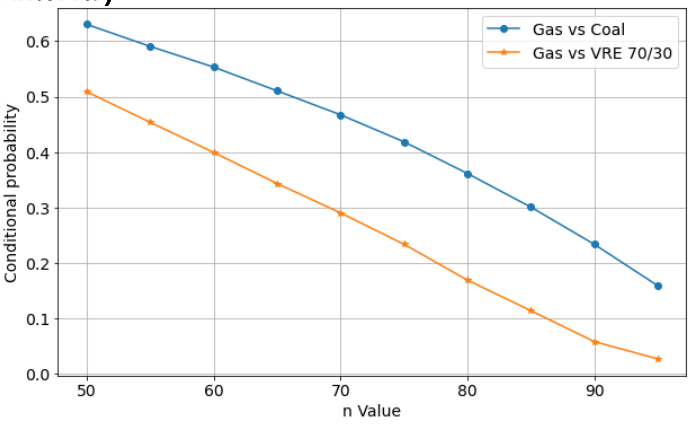


Figure B7: Conditional probability plot for gas availability against coal and variable renewables availability (dispatch interval)



Appendix C: Calculation of Minimum Hedge Contract Price under Full Contracting

Given a fixed set of resource capacities and solution to $ED_{\omega} \forall \omega \in \Omega$, setting contract volumes as a fixed parameter ($v^{G} = 1$) the dual of GEN can be written as a convex LP:

$$DUAL\ GEN_{v^G=1}: \min_{a_\omega, b_\omega} \sum_{\omega \in \Omega} \left[\left(1 - \beta^{G}\right) \pi_\omega + a_\omega \right] \Psi_\omega^{G} \quad \text{s.t} \qquad \text{(C1.1a)}$$

$$\sum_{\omega \in \Omega} a_\omega = \beta^{G} \qquad [VaR^{G}] \qquad \text{(C1.1b)}$$

$$\frac{\beta^{G}}{\alpha^{G}} \pi_\omega = a_\omega + b_\omega \quad \forall \omega \in \Omega \qquad [\varrho_\omega^{G}] \qquad \text{(C1.1c)}$$

It can be seen that the term $\left(1 - \beta^{G}\right)\pi_\omega + a_\omega$ in (C1.1a) represents the risk adjusted probability weighting ascribed to scenario ω. At the optimum objective value and under perfect competition, the supplier will seek a minimum contract price $\lambda^{F(min)}$ that ensures a risk-averse utility of *zero*.

$$\lambda^{F(min)} \in \arg\min U^{G} = 0 \qquad \text{(C1.1d)}$$

Substituting (A.1a) and (A.1c) into (A1.1d), at the optimum the minimum contract price is:

$$\lambda^{F(min)} = -\frac{\sum_{\omega \in \Omega} \left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega \right] \left(\Psi_\omega^{M} - \sum_{t \in \mathcal{T}} \lambda_{t\omega}^{E} p_{rt\omega}^{D}\right)}{\sum_{\omega \in \Omega} \left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega \right] \sum_{t \in \mathcal{T}} p_{rt\omega}^{D}} \qquad \text{(C1.1e)}$$

The iterative process for calculating $\lambda^{F(min)}$ is set out in Algorithm A1.

Algorithm A1: Iterative Calculation of $\lambda^{F(min)}$

Input: Fixed resource capacity, $P_r \forall r \in \mathcal{R}$ Output: Value of $\lambda^{F(min)}$			
1	set parameters for iterative loop iteration counts *k*, error tolerance ϵ		
2	solve (ED_ω), $\forall \omega \in \Omega$		
3	set $k = 0, \lambda_k^{F(min)} = 0$		
4	**while** $\lvert U^{G} \rvert > \epsilon$ **do:**		
5		$a_{\omega(k)}, b_{\omega(k)}, U^{G} \leftarrow$ solve (GEN)	# estimate of a_ω at iteration *k*
5		$\Delta\lambda_k^{F(min)} = -\frac{\sum_{\omega \in \Omega} \left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega \right] \left(\Psi_\omega^{G}\right)}{\sum_{\omega \in \Omega} \left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega \right] \sum_{t \in \mathcal{T}} p_{rt\omega}^{D}}$	# increment to estimate of $\lambda_k^{F(min)}$
6		$\lambda_{k+1}^{F(min)} = \lambda_k^{F(min)} + \Delta\lambda_k^{F(min)}$	# updated estimate of $\lambda^{F(min)}$
7		$k \leftarrow k + 1$	
8	**end**		

After preliminaries in lines 1 and 2, to iteratively calculate the value of $\lambda^{F(min)}$ we begin in line 3 by setting an initial value at $\lambda_k^{F(min)} = 0$ and running GEN, which obtains initial estimates of a_ω and b_ω. An incremental improvement to the estimate of $\lambda^{F(min)}$ is calculated in lines 5 and 6. Successive iterations converge to the final value of $\lambda^{F(min)}$, which is confirmed when the zero-utility condition is reached $\lvert U^{G} \rvert \leq \epsilon$.

Appendix D: Derivation of Total Inframarginal Rents and Contribution Factor Γ_r

The dual of ED_ω is calculated as below:

$$dual\ ED_\omega: \quad \max \sum_{r\in G}(\overline{\boldsymbol{\mu}^G_{r\omega}} \cdot \mathbf{A}^{\mathbf{G}}_{\mathbf{r}\omega} + \overline{\boldsymbol{\delta}^G_{r\omega}}\, R^{\uparrow} + \underline{\boldsymbol{\delta}^G_{r\omega}}\, R^{\downarrow}).\overline{\mathbf{1}P_r} + \sum_{r\in S}(\overline{\boldsymbol{\mu}^{G+}_{r\omega}} + \overline{\boldsymbol{\mu}^{G-}_{r\omega}} + \overline{\boldsymbol{\mu}^{S}_{r\omega}} e_r).\,\mathbf{1}\overline{P_r} + \overline{\boldsymbol{\mu}^D_{r\omega}} \cdot \overline{\mathbf{P}^{\mathbf{D}}_{\omega}} \tag{D1a}$$

$$C^{vc}_{rt\omega} - \lambda^E_{t\omega} + \overline{\mu^G_{rt\omega}} - \underline{\mu^G_{rt\omega}} + \overline{\delta^G_{rt\omega}} - \underline{\delta^G_{rt\omega}} - \overline{\delta^G_{r,t+1,\omega}} + \underline{\delta^G_{r,t+1,\omega}} = 0 \quad \forall r \in \mathcal{G}, t \in \mathcal{T}/\{1,T\}, \omega \in \Omega \quad [p^G_{rt\omega}] \tag{D1b}$$

$$C^{vc}_{r1\omega} - \lambda^E_{1\omega} + \overline{\mu^G_{r1\omega}} - \underline{\mu^G_{r1\omega}} - \overline{\delta^G_{r,2,\omega}} + \underline{\delta^G_{r,2,\omega}} = 0 \quad \forall r \in \mathcal{G},\ t = 1, \omega \in \Omega \quad [p^G_{rt\omega}] \tag{D1c}$$

$$C^{vc}_{rT\omega} - \lambda^E_{T\omega} + \overline{\mu^G_{rT\omega}} - \underline{\mu^G_{rT\omega}} + \overline{\delta^G_{rT\omega}} - \underline{\delta^G_{rT\omega}} = 0 \quad \forall r \in \mathcal{G},\ t = T, \omega \in \Omega \quad [p^G_{rt\omega}] \tag{D1d}$$

$$-C^{voll}_{t\omega} + \overline{\mu^D_{t\omega}} - \underline{\mu^D_{t\omega}} + \lambda^E_{t\omega} = 0 \quad \forall t \in \mathcal{T}, \omega \in \Omega \quad [p^D_{t\omega}] \tag{D1e}$$

$$-\lambda^E_{t\omega} + \overline{\mu^{G-}_{rt\omega}} - \underline{\mu^{G-}_{rt\omega}} - \frac{\mu^{Soc}_{rt\omega}}{q^-_r} = 0 \quad \forall r \in \mathcal{S}, t \in \mathcal{T}, \omega \in \Omega \quad [p^{G-}_{rt\omega}] \tag{D1f}$$

$$\lambda^E_{t\omega} + \overline{\mu^{G+}_{rt\omega}} - \underline{\mu^{G+}_{rt\omega}} + q^+_r \mu^{Soc}_{rt\omega} = 0 \quad \forall r \in \mathcal{S}, t \in \mathcal{T}, \omega \in \Omega \quad [p^{G+}_{rt\omega}] \tag{D1g}$$

$$\overline{\mu^S_{rt\omega}} - \underline{\mu^S_{rt\omega}} - \mu^{Soc}_{rt\omega} + \mu^{Soc}_{r,t+1,\omega} = 0 \quad \forall r \in \mathcal{S}, t \in \mathcal{T}/\{T\}, \omega \in \Omega\ [S_{rt\omega}] \tag{D1h}$$

$$\overline{\mu^S_{rT\omega}} - \underline{\mu^S_{rT\omega}} - \mu^{Soc}_{rT\omega} + \mu^{Soc}_{r1\omega} = 0 \quad \forall r \in \mathcal{S}, t \in \{T\}, \omega \in \Omega \quad [S_{rt\omega}] \tag{D1i}$$

The Karush-Kahn Tucker complementarity conditions of ED_ω are:

$$\mathbf{0} \le (\mathbf{A}^{\mathbf{G}}_{\mathbf{r}\omega}\overline{P_r} - \mathbf{p}^G_{r\omega}) \perp \overline{\boldsymbol{\mu}^G_{r\omega}} \ge 0 \quad \forall r \in \mathcal{R},\ \omega \in \Omega \tag{D2a}$$

$$\mathbf{0} \le \mathbf{p}^G_{r\omega} \perp \underline{\boldsymbol{\mu}^G_{r\omega}} \ge 0 \quad \forall r \in \mathcal{R},\ \omega \in \Omega \tag{D2b}$$

$$0 \le \left(\overline{\mathbf{P}^{\mathbf{D}}_{\omega}} - \mathbf{p}^{\mathbf{D}}_{\omega}\right) \perp \overline{\boldsymbol{\mu}^D_{\omega}} \ge 0 \quad \forall t \in \mathcal{T}, \omega \in \Omega \tag{D2c}$$

$$\mathbf{0} \le \mathbf{p}^{\mathbf{D}}_{\omega} \perp \underline{\boldsymbol{\mu}^D_{\omega}}, \ge 0 \quad \forall t \in \mathcal{T}, \omega \in \Omega \tag{D2d}$$

$$0 \le (\overline{P_r}\, R^{\uparrow} - p^G_{rt\omega} + p^G_{r(t-1)\omega}) \perp \overline{\delta^G_{rt\omega}} \ge 0 \quad \forall r \in \mathcal{G}, t \in \{\mathcal{T}/1\},\ \omega \in \Omega \tag{D2e}$$

$$0 \le (p^G_{rt\omega} - p^G_{r(t-1)\omega} + \overline{P_r}\, R^{\downarrow}) \perp \underline{\delta^G_{rt\omega}} \ge 0 \quad \forall r \in \mathcal{G}, t \in \{\mathcal{T}/1\},\ \omega \in \Omega \tag{D2f}$$

$$\mathbf{0} \le (\mathbf{A}^{\mathbf{G}}_{\mathbf{r}\omega}\overline{P_r} - \mathbf{p}^{G+}_{r\omega}) \perp \overline{\boldsymbol{\mu}^{G+}_{r\omega}} \ge 0 \quad \forall r \in \mathcal{S},\ \omega \in \Omega \tag{D2g}$$

$$\mathbf{0} \le \mathbf{p}^{G+}_{r\omega} \perp \underline{\boldsymbol{\mu}^{G+}_{r\omega}} \ge 0 \quad \forall r \in \mathcal{S},\ \omega \in \Omega \tag{D2h}$$

$$\mathbf{0} \le (\mathbf{A}^{\mathbf{G}}_{\mathbf{r}\omega}\overline{P_r} - \mathbf{p}^{G-}_{r\omega}) \perp \overline{\boldsymbol{\mu}^{G-}_{r\omega}} \ge 0 \quad \forall r \in \mathcal{S},\ \omega \in \Omega \tag{D2i}$$

$$\mathbf{0} \le \mathbf{p}^{G-}_{r\omega} \perp \underline{\boldsymbol{\mu}^{G-}_{r\omega}} \ge 0 \quad \forall r \in \mathcal{S},\ \omega \in \Omega \tag{D2j}$$

$$\mathbf{0} \le (e_r\overline{P_r} - \mathbf{S}_{\mathbf{r}\omega}) \perp \overline{\boldsymbol{\mu}^S_{r\omega}} \ge 0 \quad \forall r \in \mathcal{S},\ \omega \in \Omega \tag{D2k}$$

$$\mathbf{0} \le \mathbf{S}_{\mathbf{r}\omega} \perp \underline{\boldsymbol{\mu}^S_{r\omega}} \ge 0 \quad \forall r \in \mathcal{S},\ \omega \in \Omega \tag{D2l}$$

By combining equations (D1b-d) with (D2a-f) it can be observed that the total gross margin of a generation resource across a scenario ω (the gross revenues net off variable costs) $\sum_{t\in\mathcal{T}}(\lambda^E_{t\omega} - C^{vc}_{rt\omega}).p^G_{rt\omega}$ is equivalent to $\overline{\overline{\boldsymbol{\mu}^G_{\mathbf{r}\omega}}}$. Thereby, the following term $\Delta\overline{\overline{\boldsymbol{\mu}^G_{\mathbf{r}\omega}}}$ reflects the unit contribution of resource to total supplier profits in scenario ω.

$$\Delta\overline{\overline{\boldsymbol{\mu}^G_{\mathbf{r}\omega}}} = \overline{\overline{\boldsymbol{\mu}^G_{\mathbf{r}\omega}}}/\overline{P_r} = \overline{\boldsymbol{\mu}^G_{r\omega}}.\mathbf{A}^{\mathbf{G}}_{\mathbf{r}\omega} + R^{\uparrow} \cdot \overline{\boldsymbol{\delta}^G_{r\omega}} + R^{\downarrow} \cdot \underline{\boldsymbol{\delta}^G_{r\omega}} \tag{B3}$$

Similarly, for storage resources the equations (D1f-i) can be combined with (D2g-l) to indicate the unit contribution of a storage resource to total supplier profits in scenario ω as:

$$\Delta\overline{\overline{\boldsymbol{\mu}_{r\omega}^{S}}} = \overline{\overline{\boldsymbol{\mu}_{r\omega}^{S}}}/\overline{P_r} = \overline{\boldsymbol{\mu}_{r\omega}^{G+}} \cdot \mathbf{A}_{\mathbf{r}\boldsymbol{\omega}}^{\mathbf{S}} + \sum_{t\in\mathcal{T}} \overline{\boldsymbol{\mu}_{r\omega}^{G-}} \cdot \mathbf{A}_{\mathbf{r}\boldsymbol{\omega}}^{\mathbf{S}} + e_r \mathbf{1}\, \overline{\boldsymbol{\mu}_{r\omega}^{S}} \qquad \text{(B4)}$$

The dual of GEN can be written as:

$$\min_{a_\omega, b_\omega} \sum_{\omega\in\Omega}\left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega\right]\Psi_\omega^{M} \qquad \text{(B5a)}$$

$$\sum_{\omega\in\Omega} a_\omega = \beta^{G} \qquad [VaR^{G}] \qquad \text{(B5b)}$$

$$\frac{\beta^{G}}{\alpha^{G}}\pi_\omega = a_\omega + b_\omega \qquad \forall\omega\in\Omega \qquad [\varrho_\omega^{G}] \qquad \text{(B5c)}$$

$$\sum_{\omega\in\Omega}\sum_{t\in\mathcal{T}}\left[\pi_\omega\left(\beta^{G}-1\right)\left(\lambda^{F}-\lambda_{t\omega}^{E}\right)p_{rt\omega}^{D} - a_\omega\left(\lambda^{F}-\lambda_{t\omega}^{E}\right)p_{rt\omega}^{D}\right] = 0 \qquad [v^{G}] \qquad \text{(B5e)}$$

The vector $\left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega\right]$ represents the risk-weighted probability of each scenario $\omega\in\Omega$ (Shu & Mays, 2023). Thus, the marginal contribution factor of generation and storage resources to the supplier's risk-adjusted utility is represented as per equations B6a and B6b.

Generation: $\Gamma_r = \left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega\right].\Delta\overline{\overline{\boldsymbol{\mu}_{r\omega}^{G}}} - C_r^{I} \qquad \forall r\in\mathcal{G}$ (B6a)

Storage: $\Gamma_r = \left[\left(1-\beta^{G}\right)\pi_\omega + a_\omega\right].\Delta\overline{\overline{\boldsymbol{\mu}_{r\omega}^{S}}} - C_r^{I} \qquad \forall r\in\mathcal{S}$ (B6b)

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