PRINCIPAL ECONOMICS

The standardised super-peak hedge product

Volumes and bid-ask spread for market making

REPORT TO

Electricity Authority Te Mana Hiko

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Executive summary

The Electricity Authority commissioned Principal Economics to evaluate the appropriate minimum trading volumes and maximum bid-ask spreads for market-making on a standardised super-peak hedge contract. This study is pivotal in refining regulatory options to enhance price transparency, improve market liquidity, and secure enduring consumer benefits. By modelling the costs and advantages of distinct regulatory scenarios, the analysis is designed to support the Authority's efforts in outlining well-calibrated interventions that effectively address market challenges.

The findings of this report will directly contribute to an upcoming consultation that seeks to explore and validate potential implementations of market-making mechanisms on both over-the-counter and exchange platforms. The goal is to create a robust framework that ensures the sustainability and efficiency of hedge contract trading in the electricity market. Through a robust and transparent analysis, this report aims to:

- Enhance the resilience and reliability of the super-peak hedge contract market.
- Support greater price stability and predictability for consumers.
- Encourage active participation from market-makers by providing equitable incentives.

We adopt an optimal frontier approach, striking a balance between market liquidity and market-maker incentives.

The optimal frontier approach uses spread caps and minimum depth obligations as variables. It helps quantify the minimum compensation needed for market-makers to provide liquidity, identifies inefficient policy options, and evaluates whether liquidity-promoting interventions are socially justified. This evidence-based framework supports the Authority's objective of balancing private market-maker benefits with broader system efficiency, ensuring cost-effective liquidity provision without overcompensation or unnecessary distortions in price discovery.

Using regression analysis, we quantified how bid-ask spreads vary with volatility and quote depth, and simulated net benefits to market makers under different regulatory scenarios.

Empirical analysis of super-peak auction log data revealed that relative bid-ask spreads are typically tight under normal conditions — the **median spread percentage (S%) was 3%**. However, spreads widen markedly during stress periods, with the 90th percentile exceeding 5% and the 95th percentile reaching up to 9–10%. To keep the cap both practical and responsive, we recommend a clear two-tier policy:

- a base cap of **3.5%** under normal conditions; and
- an elevated cap of up to **8%** when the trailing 30-day volatility exceeds **0.15**, or during designated stress events.

This structure balances cost-effective market-making with dependable liquidity and price transparency for hedge-takers in the electricity futures market.

Observed Net Benefit Peaks Around 10–15 MW of Quote Depth

Our results suggest that at any given quote depth, net benefit increases with volatility. Additionally, we identify depth as a more significant factor in the spread than volatility. Across both average and high-volatility conditions, **net benefit to market makers peaks between 10 and 15 MW** of quoted volume. Beyond this range, marginal net benefit declines and eventually turns negative, suggesting **diminishing returns to additional depth**.

Estimated Spread Elasticities Differ Sharply by Price Regime

Regression results indicate that during high-price days, a 1% increase in volatility increases bid-ask spreads by ~0.37%, whereas in other periods, the effect is negligible (−0.02%). Similarly, quote depth has a **negative elasticity of −0.08**, implying that doubling depth reduces spreads by ~8%.

Typical Relative Spread Is Around 3.7% (Median), Up to 9.5% (95th Percentile)

Analysis of Intraday ASX market data shows that the **median S% is 3**, with the 95th percentile at 9.5%. This distribution supports setting **a spread cap of about 3.5% in normal conditions**, **with an allowance for a higher cap — up to 8%** — during periods of increased volatility or market stress.

Simulated Scenarios Confirm Optimality of Intermediate Settings

We investigated the impact of four benchmark scenarios:

- Low vol / high depth (Scenario B) yields the highest daily revenue: **~$406/day**.
- High vol / high depth (Scenario D) yields **~$890/day** but also incurs higher cost.

The results confirm that tight spreads with low depth or wide spreads with high depth are suboptimal.

Break-Even Social Benefit Required to Justify Tighter Spread Caps

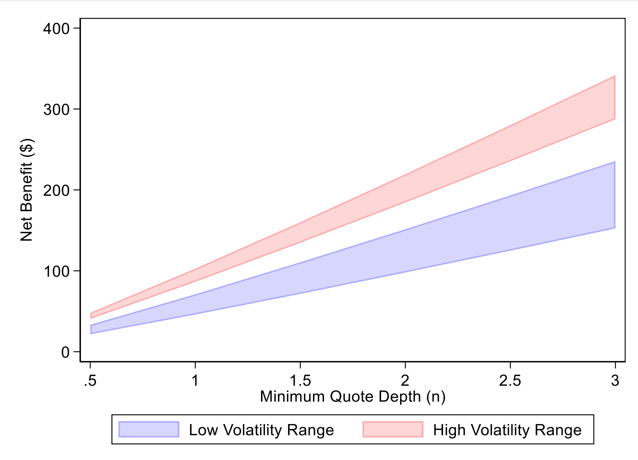
A break-even analysis indicates that to support a S% cap of 2–3% under high-volatility conditions, a social benefit of approximately **$1.5 per MWh** would be required to offset private losses.[1] This benchmark helps assess whether tighter caps are justified on **the grounds of public interest**. Beyond that, private benefits decline, while costs rise. For a **2% cap**, the social benefit would need to be **at least 1.56 times the private benefit to break even**.

Based on trailing 30-day volatility estimates, the analysis supports a **tiered S% cap**:

- ~3–3.5% for low-volatility days (e.g. vol < 0.10)
- ~4–5% for moderate volatility (0.10–0.15)
- ~7–9% for high volatility (e.g. vol > 0.15–0.20)

This aligns market-maker compensation with risk exposure while preserving liquidity.

This chart illustrates how the net benefit to market makers varies with the minimum quote depth (n) under two different volatility regimes. Accordingly, Net benefit increases linearly with quote depth in both low- and high-volatility conditions. However, at every level of depth, net benefit is substantially higher under high volatility, reflecting wider allowed spreads and greater risk compensation. The shaded bands represent the range of outcomes from low to high fitted spreads under each volatility band, illustrating the sensitivity of incentives to market conditions.



This supports the use of volatility-responsive quoting rules. During high-volatility periods, higher spread caps and/or quoting incentives may be justified to maintain participation. The optimal range of net benefit can be benchmarked to avoid under- or over-compensation.

The private net benefit peaks at spread caps around 0.5% to 2%.

We improve the usefulness of our report by considering the required social benefit increases for specific spread caps. While private net benefit captures the financial incentive for market makers, it does not account for potential external

[1] This threshold defines the minimum public value required to make the policy socially worthwhile.

or social benefits resulting from improved market liquidity. The net private benefit is highest at the tightest caps and remains relatively stable up to about 2–3%, before declining at higher caps.

Limitations and topics for future investigation

While this report uses the best available information and methodology, there are a range of limitations as follows:

- **No direct super-peak transaction data**: Analysis relies on proxies (high-price periods and auction logs), as real-time super-peak contract trading is limited.
- **Unobserved contract positions**: Market-maker risk exposures (e.g. generator-retailer hedges) are not visible, limiting precision in incentive modelling.
- **Simplified cost function**: Inventory cost is based on volatility and depth, but omits behavioural strategies (e.g. quote withdrawal, position hedging).
- **Social welfare impacts not quantified**: While private net benefit is modelled, broader system-wide effects (e.g. on competition or end-user prices) are not included.
- **No dynamic strategy modelling**: The analysis does not capture potential strategic behaviour under different quoting frequencies or cap structures.

Below is a list of topics for future research:

- **Empirical testing with super-peak implementation data**, if/when contracts are actively traded.
- **Integration of physical capacity constraints** to account for system stress effects on liquidity and pricing.
- **Incorporation of risk-aversion and strategic quoting models**, using agent-based or game-theoretic frameworks.
- **Social CBA extension** to measure transparency, competition, and downstream consumer impacts.
- **Behavioural and timing dynamics** using Granger causality or high-frequency event study methods.
- **Instrumental variable approach** to infer causal impacts.

We should also note that once an S% cap is defined, e.g. 8%, market makers may anchor their quotes at or near the cap, even when tighter spreads would be feasible. The Authority should accompany implementation with **monitoring tools** to detect clustering around the cap and **reassess cap calibration** as market behaviour evolves.

Abbreviations and acronyms

Abbreviations	Definition
ASX	Australian Stock Exchange Limited
CBA	Cost-benefit analysis
EOD	End-of-Day
HF	High-Frequency
MMO	Market Making Obligation
MW	Megawatts
NZ	New Zealand
SPF	Standardised flexibility product

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1 Introduction

Electricity Authority (the Authority) commissioned Principal Economics to provide analysis and advice on appropriate minimum trading volumes and maximum bid-ask spreads for market making of a standardised super-peak hedge contract. This work aims to model the costs and benefits of different regulatory settings under a range of market conditions, helping the Authority to identify arrangements that support price transparency, market liquidity, and long-term consumer benefit. The findings will inform an upcoming consultation on options for implementing market-making on both over-the-counter and exchange platforms.

The objective of this project is to provide scenario modelling of economic costs and benefits. We modelled net benefits to market makers across four regulatory scenarios (narrow/wide spreads × low/high depth), estimating benefits and risk-adjusted costs using observed market behaviour. We take a platform-agnostic analysis by avoiding embedding platform-specific assumptions, treating spread, volume, and volatility drivers as generic across trading venues.

1.1 Policy context

New Zealand's wholesale electricity market was put under sharp stress in August 2024 when low gas reserves, poor hydro inflows and weak wind output combined to create a sudden fuel shortage. Spot prices spiked, forcing some industrial users on pass-through contracts to absorb extreme costs even though most households, insulated by fixed retail tariffs, were left untouched (Commerce Commission, 2024; Electricity Authority, 2025a). The episode exposed how fragile the security of supply can be when the generation mix leans heavily on weather-dependent resources and highlighted gaps in the tools available for managing peak-hour price risk.

In response, the Electricity Authority and Commerce formed the Energy Competition Task Force with two linked objectives: to enable new generators and independent retailers to enter and compete more effectively in the market, and to provide more options for end-users of electricity. The introduction of standardised flexibility products (SFP)[2] is one of four initiatives being considered by the Task Force under Package One to support the entry and competitiveness of new generators and independent retailers. Hence, the new standardised super-peak hedge contract has been developed in this context (Electricity Authority, 2024).

The Electricity Authority's two service-level levers, the maximum full-width bid-ask spread (S) and the minimum displayed trading volume (n lots), pull liquidity in opposite directions, so they must be calibrated together. A tighter spread lowers the half-spread that every hedge-taker pays and therefore sharpens the forward price signal, but each one-tick squeeze also removes gross margin from market-makers and can prompt them to widen elsewhere or withdraw altogether (Ho & Stoll, 1981). Requiring larger displayed volume at the best price raises market depth and lets hedge-takers execute most or all of their order immediately, but each extra lot enlarges the position that market-makers must carry between the seller's trade and the arrival of offsetting buyers. Grossman and Miller (1988) show that this bigger temporary inventory increases the variance of the market-maker's wealth and therefore the compensation (via price concessions or spread) that the maker must charge for providing immediacy. For the new super-peak contract, identifying the (S, n) pair that minimises all-in execution cost for hedge-takers without pushing maker profitability below break-even is therefore the central design challenge and the focus of the modelling that follows.

As the Co-design Group's primary recommendations focus on further developing the recently launched standardised super-peak product and implementing brokered trading events to support market liquidity (Electricity Authority, 2025b), this study is centred on the insights of the liquidity and the trade-offs between the maximum bid-ask spread

[2]Details: https://www.ea.govt.nz/documents/6196/Product_specification_of_standardised_flexibility_product_2025.pdf

and minimum trading volume. It compares the economic costs of four spread-and-volume scenarios and recommends the settings most likely to deliver long-term benefits to consumers. The findings also have the potential to inform the Authority's regulated market-making scheme, which could require designated participants to maintain a minimum market depth and keep bid–ask spreads within a defined cap in future.

1.2 Scope of this report

This analysis focuses on estimating the economic costs and benefits of potential market-making obligations for a standardised super-peak electricity hedge product. Specifically, it models how combinations of bid-ask spread caps and minimum quote volumes affect expected revenue and risk-adjusted costs for market makers. The study uses regression-based estimates derived from ASX and auction log data, simulates multiple policy scenarios under varying volatility conditions, and constructs an optimal frontier to identify efficient regulatory settings. The analysis is platform-agnostic and aims to inform the Authority's design of market-making obligations that deliver sufficient liquidity at least cost, using transparent and replicable methods.

We have applied best-practice methods and used all available data sources to inform this analysis; the caveats of our analysis are highlighted in Chapter 5.

1.3 The report structure

This report is structured as follows:

- Chapter 2 provides a brief literature review and explains the usefulness of an optimal frontier approach.
- Chapter 3 describes our data and the modelling approach.
- Chapter 4 presents regression results and discusses the implications of the findings.
- Chapter 5 provides a concise conclusion, highlights limitations and topics for future investigation.

2 Literature Review

2.1 Liquidity and risk premium

A growing body of empirical work reviews the relationship between the **liquidity conditions** in electricity futures markets and **risk premiums**. Understanding this link is essential for our research because the Authority must show that any obligations it imposes on market makers will translate into lower hedge costs and, ultimately, lower consumer prices. Bessembinder and Lemmon (2002) show that forward prices in electricity markets embed risk premia that arise from skewed and volatile spot prices, especially under non-storability and supply inflexibility. Their equilibrium framework implies that both volatility and higher-order moments (e.g., skewness) play a critical role in shaping optimal hedge positions and forward price levels. In this context, bid-ask spreads can be interpreted as compensation for risk exposure, particularly under volatile or asymmetric conditions. Fiuza and Daglish (2016) further highlight the transmission of market power from spot markets into hedge products, suggesting that spread behaviour may reflect strategic bidding or dominance by vertically integrated firms. Accordingly, the analysis allows for structural breaks (e.g. policy changes or supply shocks) and includes interaction terms to test for time-varying effects.

New Zealand evidence demonstrates that liquidity drives **risk premia** and **reacts to spread caps**. Bevin-McCrimmon et al. (2018) provide empirical evidence from the New Zealand market that bid-ask spreads and risk premia are jointly influenced by liquidity conditions, seasonal effects, and trading incentives. Importantly, they find that regulatory settings such as spread caps and market-making obligations can alter market behaviour, but that liquidity improvements may not always follow from mandatory policies. This informs the current study's regression design, which explicitly models spread as a function of volatility and depth—two key proxies for market risk and liquidity—and tests these relationships across structural regimes using break analysis. Simulation work for Colombia indicates that introducing a regulated market-maker who quotes at a tight 0.21¢/kWh spread and boosts trading volume could have lowered retailers' extreme-event procurement costs by about 13¢/kWh, underscoring the scale of consumer gains that follow from higher liquidity (Arias et al., 2024). Incorporating such liquidity-premium elasticities into our model can help us translate alternative minimum-volume and maximum-spread settings into quantified consumer-surplus estimates, which can then be weighed against the inventory and capital charges borne by market-makers.

Additionally, Peña and Rodriguez (2022) show that the **forward premium** in European electricity futures largely reflects a **liquidity premium** earned by market makers for absorbing short-run imbalances between producer and retailer hedging. Using French, German, Spanish and Nordic contracts from 2008 to 2017, they find the premium turns negative in episodes where retailers rush to buy protection and market makers must take the opposite short side, while it becomes less negative or even positive when producers dominate selling. Crucially, the premium shrinks as the number of active market makers rises, confirming that greater competition lowers the cost of immediacy. Their panel estimates, which control for fuel and carbon prices, spot-price variance and skewness, equity-market movements and (in the Nordic market) reservoir levels, attribute a statistically significant share of day-to-day futures returns to this liquidity effect. For the super-peak hedge product, this study provides a transferable mechanism: tightening spread obligations or raising minimum quote volumes should compress the liquidity premium embedded in forward prices, thereby reducing hedge costs for retailers and yielding measurable consumer-surplus gains, which is exactly the benefit side required in our model.

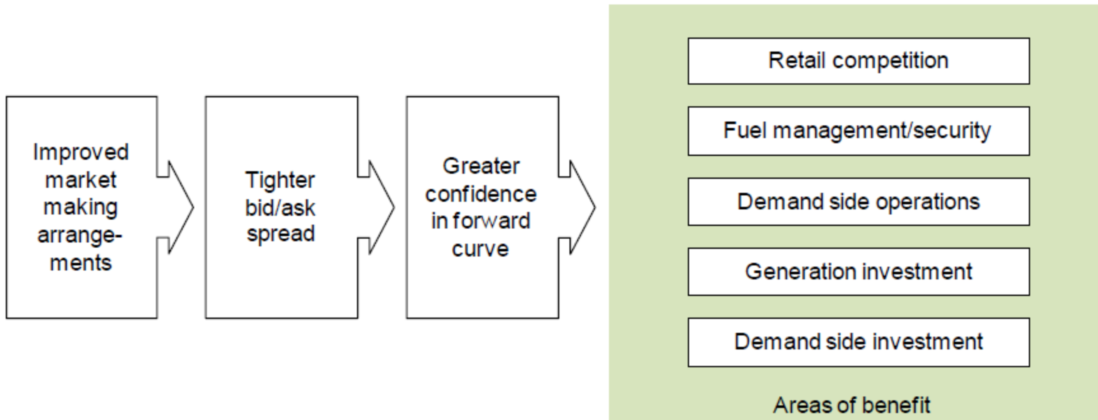
Arias et al. (2024) quantify the welfare trade-off that arises when a designated market maker injects liquidity into an illiquid electricity-futures market. They calibrate a Colombian case in which the market maker would quote around a 0.212¢/kWh bid–ask gap, which is based on observed quote adjustments and commit to standing in a minimum volume. **Treating that spread as compensation** for **inventory risk** and **operational overheads**, they simulate spot-price paths with a bootstrap method and compare three hedging mixes: 95 %, 50 % and 5 % coverage with futures. Under extreme price shocks, the additional liquidity cuts retailers' procurement costs by roughly 13 ¢/kWh, whereas even modest execution growth (about 7 % more trades and 10 % extra energy coverage) is sufficient to deliver the benefit. Because the saving accrues to regulated customers through lower tariff volatility, while the market maker's cost is limited to holding risk within the quoted spread, the net surplus is strongly positive. This explicit pairing of an inventory-type cost with a participant benefit highlights that by inserting New Zealand spot-volatility estimates and alternative spread and volume settings into the same cost-versus-benefit structure, we can translate each candidate super-peak market-making obligation into a monetised consumer gain for our approach.

Taken together, the studies reviewed above establish an empirically grounded link between tighter spreads, larger displayed quote volumes and lower forward premia. They also show that the magnitude of any premium reduction depends on both market volatility and the number of active liquidity providers. The next step is to translate these qualitative findings into a quantitative framework that can guide policy. To do so, we decompose the analysis into two parts. First, we identify and parameterise the costs that a regulated market maker must bear when obliged to quote at prescribed spread and volume levels. Secondly, we measure the corresponding benefits to market participants and, by extension, to end-use consumers if possible.

2.2 Costs and benefits to be considered

We noted that the Authority's 2011 cost–benefit analysis of Market-Making Obligations summarises the link between market making and economic benefits (see Figure 2.1).

Figure 2.1 Linkage between market-making and economic benefits



Source: Electricity Authority (2011, p. 7)

Additionally, the Authority identified two categories of cost sources for mandatory market making:

- Direct costs: these are costs that the affected parties would incur to provide a mandatory market-making service of the proposed form.
- Dynamic efficiency effects: other costs that arise as a result of placing the market-making obligation in the Code (as opposed to retaining a voluntary approach).

We will use this report as the starting point to further investigate the components for benefits side for market making of SFP.

We also reviewed the recent Ofgem published paper 'GB Wholesale Power Market Liquidity: Options Assessment[3]' (Ofgem, 2020). This report is to inform Ofgem's review of liquidity policy in the GB wholesale electricity market, evaluating alternative interventions after the Secure and Promote market making obligation was suspended. It analyses whether different market-making options can sustain tight bid-offer spreads and adequate traded volumes

[3] https://www.ofgem.gov.uk/sites/default/files/docs/2020/01/nera_report.pdf

so that forward prices remain a reliable guide for generators suppliers and consumers. This report focuses on costs and benefits of a tendered MMO that delivers the same level of liquidity (by bid-ask spread) as the S&P MMO against three counterfactual levels of liquidity that may prevail in the market with “no intervention”, i.e., high liquidity counter-factual, historical (2009-2013), and low liquidity counter-factual. To estimate the benefits, the study runs Monte Carlo simulations for every pairing of calibrated bid-ask spread and retailer hedge ratio, smoothing the volatility in inputs such as wholesale power prices. For each spread it selects the hedge that maximises net benefit, defined as risk-capital savings minus transaction costs, and expresses this gain on a £ per MWh basis. That unit benefit is then scaled by the sum of total generated volume and the portion previously left unhedged to obtain the aggregate market benefit of the market-making obligation. Generator gains are captured by the extent to which the chosen hedges raise the minimum price they receive over a 12-month horizon, thereby reducing the capital they must hold against adverse price movements. Also, their study estimates costs in three clear steps. It begins with Ofgem’s set up and ongoing cost categories for one market maker, then replaces those assumptions with the fixed and variable amounts that firms actually reported after the scheme was in place. Using the lowest observed annual cost of 0.7 million pounds and the highest of 8.5 million pounds to define a range, it scales these figures across the six obligated firms to obtain a market total. A further allowance of half a million pounds is added for Ofgem’s own expense in running a competitive tender. This produces an annual cost band that can be compared directly with the simulated benefits.

The Ofgem report shows that any regulated market-making obligation should first be justified by a clear market-failure test, then evaluated by net consumer benefit rather than by liquidity targets alone. It measures benefits by tracing how tighter bid-ask spreads cut hedging transaction costs and let participants adopt cheaper risk-capital positions, while setting costs in two layers: market-maker outlays and the regulator’s own administration. It also highlights the value of flexible design, such as wider spreads or reduced quoting volumes during price shocks and of early stakeholder engagement to calibrate practical parameters like clip size and availability. Framing the Electricity Authority’s super-peak analysis around these principles will keep scenario modelling platform-neutral, capture all relevant costs, and show where any intervention genuinely improves welfare.

Our scenario analysis is grounded in these insights. The four modelled cases: combinations of tight vs wide spreads and low vs high depth. All these scenarios reflect trade-offs between market-maker cost, risk compensation, and the hedging benefit to participants. The model thus provides a practical tool to estimate the net benefit of different market-making settings, aligned with both equilibrium theory and observed behaviour in real-world electricity futures markets.

2.3 Optimal Frontier Approach and Its Policy Relevance

In this report, the concept of an **optimal frontier** is used to identify efficient trade-offs between **market maker incentives** and **market liquidity outcomes** under different regulatory settings. Specifically, we estimate the **net benefit** to a market maker — defined as the difference between expected revenue (spread × volume) and the risk-adjusted cost of participation — across a range of plausible spread caps and minimum depth obligations. These net benefit values are then plotted to form an **efficiency frontier**, analogous to a production frontier in microeconomic theory.

2.3.1 Theoretical Foundation

The frontier represents the set of **non-dominated scenarios**, where for any given level of liquidity (depth), no alternative regulatory setting delivers a higher net benefit to the market maker. In production theory, such frontiers are used to evaluate technical efficiency — identifying points at which output is maximised for a given input. Here, we reverse the logic: the Electricity Authority seeks to **minimise the required incentive (cost) to achieve a given liquidity target**.

By constructing this frontier, we provide a framework to:

- Quantify the **minimum compensation** required to induce a market maker to provide a specified level of liquidity.
- Identify **policy options that lie off the frontier**, and are thus **inefficient** — i.e., they require more incentive for the same liquidity, or deliver less liquidity at the same cost.
- Support **cost-effectiveness analysis**: among feasible market-making settings, which provide "just enough" liquidity for the lowest regulatory cost?

We also recognise that the regulator's interest is not only in private incentives, but in the **broader social benefit of market liquidity**. While tighter spreads and greater depth are often assumed to improve hedge access and pricing efficiency, this may not hold in all contexts — particularly in electricity hedge markets where **gentailers already absorb most super-peak price risks within their own portfolios**, and wider hedge market access may support participants with higher systemic costs. The **social benefit of liquidity is therefore not guaranteed to be positive**, and must be critically evaluated – this is beyond the scope of our report.

To operationalise this uncertainty, we apply a **break-even social benefit analysis**. For each point on the frontier, we estimate how much **additional social benefit** (e.g., from increased competition or reduced price volatility) would be required to justify spread caps higher than the private optimum. For example, if the privately optimal spread were roughly 0.8%, imposing a 2% cap would require the social benefit to exceed 1.5× the private benefit — a high bar unless compelling externalities can be demonstrated.

2.3.1.1 Implications for Electricity Authority

For the Electricity Authority, this approach directly aligns with its statutory objective of promoting **efficient and reliable electricity markets**. By identifying the optimal combinations of bid-ask spread caps and minimum quote depth that lie on the efficient frontier, the Authority can set market-making obligations that:

- Prevent overcompensation of market makers
- Avoid excessive tightening of spread or volume rules that are costly and deliver diminishing returns
- Ensure sufficient liquidity for hedge users (particularly in super-peak periods), without distorting price discovery or undermining voluntary participation
- Critically assess whether **liquidity-promoting interventions** are socially justified, based on measurable thresholds.

In summary, the frontier represents a set of **evidence-based, economically rational regulatory choices**, and supports the Authority's goal of achieving **minimum necessary liquidity provision at least cost**. Figure 2.2 illustrates an **optimal frontier of market-making scenarios**, with holding the fixed spread. Each point represents a combination of **minimum quote depth (n)** and its associated **net benefit to a market maker**, calculated as expected revenue minus risk-adjusted cost.

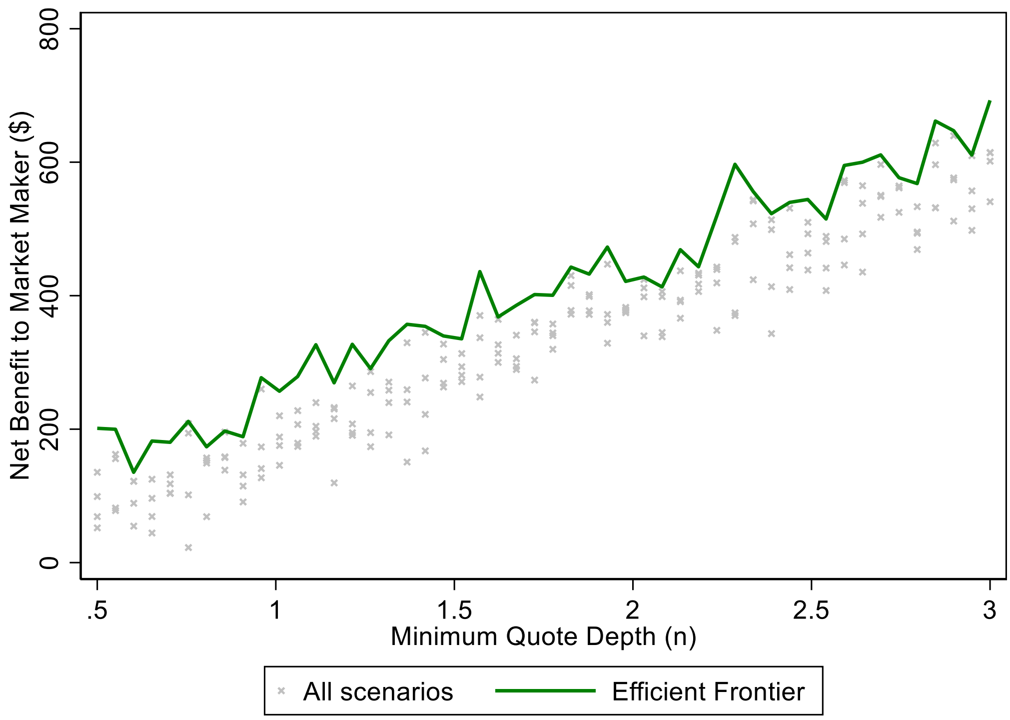
- The **green line** connects the **efficient scenarios** — those where no other setting yields a higher net benefit for the same or lower depth.
- These represent **optimal trade-offs** from the regulator's perspective: scenarios where **liquidity is maximized for the minimum necessary compensation**.

For the Authority, this frontier helps identify:

- **How much liquidity (depth) can be obtained for a given cost**
- Where further increases in depth require **disproportionate compensation**
- Settings **off the frontier** that are inefficient (i.e., same depth but higher cost or lower benefit)

This framework enables **transparent and accountable spread cap setting**, while ensuring that policy interventions are **justified by either private sustainability or demonstrable public benefit** — a crucial distinction in thin, high-risk products like super-peak hedge contracts.

Figure 2.2 Illustrative optimal frontier

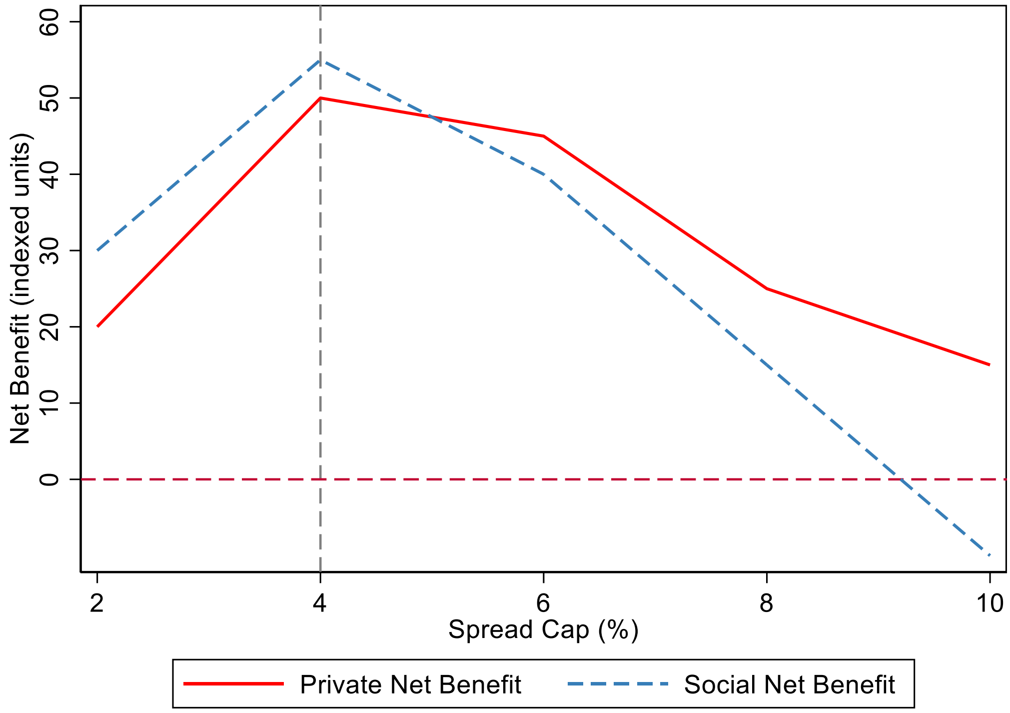


Source: Principal Economics

Figure 2.3 provides an illustrative comparison of **private vs. social net benefit** across different spread cap levels:

- **Private net benefit** peaks around a 4–6% spread cap, where market makers are best compensated.
- **Social net benefit** rises initially but declines beyond 4–6%, reflecting potential inefficiencies (e.g., subsidising weak retail models, misaligned incentives).
- This illustrates that **optimal policy must balance market-maker incentives with broader system outcomes**, and not just liquidity for its own sake.

Figure 2.3 Contrasting private versus social benefits



Source: Principal Economics

3 Data and methodology

This chapter provides a description of the key variables and our methodology. We provide discussions of the implications of the observed patterns for the results, which will provided in the next chapter.

3.1 Data sources: ASX electricity futures data provides a credible empirical foundation

We used three data sources with complementary features to improve confidence in our findings.

3.1.1 ASX End-of-Day Futures Data ("ASX EOD Data")

- **Description**: Daily settlement data for electricity futures contracts traded on the Australian Securities Exchange (ASX), including bid-ask spreads, traded volumes, mid-prices, and contract expiry information.
- **Usage**:
    - Formed the **basis of the regression model** linking bid-ask spreads to depth and 30-day volatility.
    - Used to **estimate average S% (relative spread)** across contracts.
    - Provided input for scenario-based simulation of market maker incentives under varying spread cap and depth settings.
- **Why**: Offers **stable, contract-level pricing and liquidity metrics** — ideal for modelling policy-relevant spread cap settings over time.

Although the super-peak hedge contract is new or lightly traded, the **ASX electricity futures** (especially **peak load contracts**) are:

- **Standardised, exchange-traded contracts**
- Used by the same participants (gentailers, large buyers)
- Reflective of **price discovery and liquidity behaviour** in the NZ hedge market

This makes ASX Information Services dataset the **best available analogue** for modelling spreads, volumes, and volatility effects. ASX data includes Bid-ask spreads, quoted volumes (contracts), and Market volatility (via return variation). Hence, the ASX dataset provides information about the variables needed to estimate **how market makers price risk**, and how depth affects spreads.

The caveats of using the ASX data are as follows:

- ASX does not include Super-peak contracts. The super-peak contract differs in **duration and demand risk profile**
- Some extrapolation is required to reflect **scarcer liquidity**
- Scenario testing should account for **greater volatility and uncertainty**
- **The End-of-Day data is after the trading has been completed**. If the market makers have exhausted their volumes their bids and offers are no longer present.
- The **ASX data series goes back to 2009**. Market making settings have changed over that duration.

These are **mitigated** by:

- Stress testing with higher volatility levels. In particular, to deal with the lack of super-peak contracts in ASX, we take two approaches. First, we distinguish between the high-price day[4] and the other days. We use this strategy to test how the estimated parameters may differ for the high-price days.
- Using scenario-specific assumptions for the super-peak contract.
- We use complementary data sources, such as high-frequency ASX data to validate our findings and compared with the End-of-Day data results.
- We undertake time-series structural break tests to identify changes in market-making settings that matter to our statistical analysis.

Our dataset covers the period from July 2009 to June 2025. Appendix A: provides a list of the variables in ASX and describes them. Table 3.1 provides a list of the derived variables and their formula.

Table 3.1 Derive variable definitions

Derived variables	Formula
Mid Price	$MidPrice_t = \frac{(AskDollarsPerMWh_t + BidDollarsPerMWh_t)}{2}$
30-Day Rolling Volatility	$\text{Volatility}_{30d,t} = \text{StdDev}(\log(MidPrice_{t-29}) \dots \log\text{Volatility}_{\{30d,t\}}$ $= \text{StdDev}(\log(MidPrice_{\{t-29\}}) \dots \log(MidPrice_t))\text{StdDev}\big(\log(MidPrice_{t-29}) \dots \log(MidPrice_t)\big)$
Bid-ask Spread (the Spread)	$\text{SpreadDollarsPerMWh}_\text{t} = \text{AskDollarsPerMWh}_\text{t} - \text{BidDollarsPerMWh}_\text{t}$
Relative Spread	$\text{RelativeSpread}_\text{t} = \frac{(\text{AskDollarsPerMWh}_\text{t} - \text{BidDollarsPerMWh}_\text{t})}{AskDollarsPerMWh_t}$
Quote Depth (n)	$\text{n}_\text{t} = \text{BidDepthMW}_\text{t} + \text{AskDepthMW}_\text{t}$
Net (Private) Benefit	$NetBenefit = Revenue - Cost$

Source: Principal Economics

3.1.2 ASX High-Frequency Data ("ASX HF Data")

- **Description**: Intraday market snapshots including bid/ask quotes, order book depth, and volumes, captured at millisecond resolution across trading days.
- **Usage**:
  - Used to build a **high-resolution intraday regression model** of spread behaviour, capturing dynamic relationships between volatility, depth, and quote imbalance.
  - Enabled **real-time estimation of fitted S%** and net benefit across thousands of quote events.
  - Informed the **construction of empirical frontiers** by volatility regime and allowed visualisation of marginal effects across market conditions.

[4] A day is marked as a **high price day** if the Mid-Price exceeds the **90th percentile (P90)** of the Mid-Price distribution across all observations.

- **Why**: Provides **granular behavioural evidence** on market-making in volatile conditions, which is essential for modelling real-time quoting incentives and stress scenarios.

3.1.3 Super-Peak Forward Auction Log Data ("SPF Data")

- **Description**: Historical auction log data for the NZ super-peak contract, including individual bid/offer events, pricing, and depth across contract periods.
- **Usage**:
    - Offered the **only direct evidence of market pricing behaviour** for super-peak hedge products.
    - Used to derive **empirical S% benchmarks** and compare with the modelled ASX results.
    - Helped validate the relevance of ASX models to the NZ context, and to calibrate parameters for policy testing.
- **Why**: Captures the **actual market conditions for the policy target instrument**, and is essential for aligning spread cap advice with NZ-specific realities.

3.2 Data description

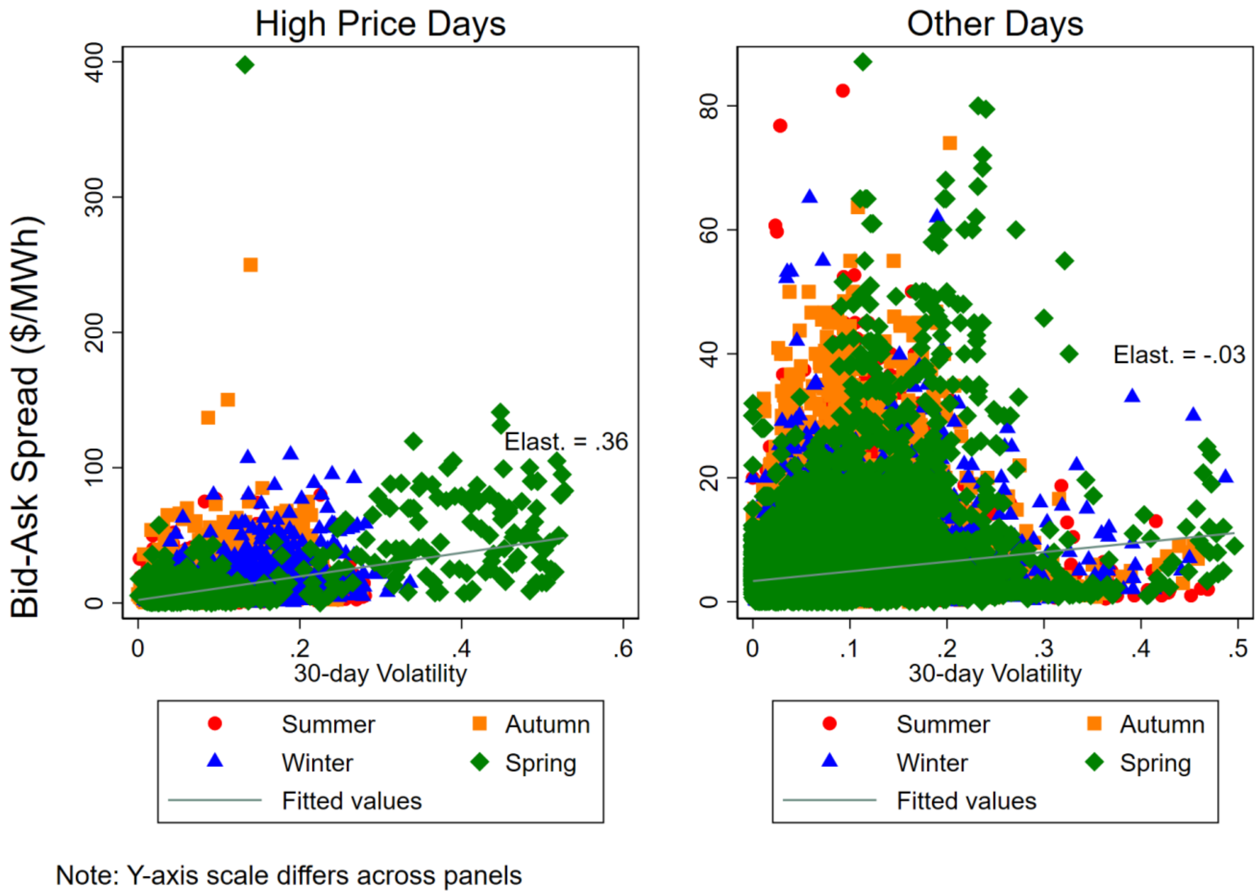
Figure 3.1 presents two scatter plots comparing the relationship between 30-day volatility and bid-ask spread ($/MWh) across **high price days** (left panel) and **other days** (right panel) in the ASX data. Points are colour- and symbol-coded by season. The fitted lines reflect the estimated elasticity from a log–log model. In the left panel, spreads during high-price days range from nearly $0 to over $400/MWh. The estimated **elasticity of 0.36** indicates a moderate positive association between volatility and spreads. This suggests that in high-volatility, high-price regimes, market makers widen spreads to manage increased risk exposure. While seasonal clustering is evident, particularly for Spring and Winter, the general spread-volatility relationship is more important for market design. In contrast, the right panel (other days) shows spreads typically below $80/MWh, with most clustered between $0 and $20/MWh. The estimated **elasticity is slightly negative at −0.03**, implying that volatility has virtually no explanatory power for spread variation during normal trading conditions.

Figure 1.2 compares this relationship using **the SPF data for super-peak contracts**, matched to ASX-derived volatility for each period. Spreads are visibly higher and more dispersed (ranging from near $0 to above $200/MWh), and the estimated **elasticity is 0.47**, higher than ASX results. This indicates that **modest increases in volatility are associated with disproportionately large increases in spread under super-peak conditions**.

In summary, the **auction-based elasticity (0.47)** reinforces the idea that **super-peak products embed larger risk premiums** and are more sensitive to market uncertainty. The ASX figures show that **spread–volatility relationships are regime-dependent**: only meaningful during high-price periods. This supports a differentiated regulatory approach: **spread caps and quote requirements should account for price regime and product class**, with looser caps or higher incentives justified for super-peak conditions.

Figure 3.1 Spread versus volatility by season and price level

ASX End-of-Day data 2009q3-2025q2



Source: ASX Information Services; Principal Economics analysis.

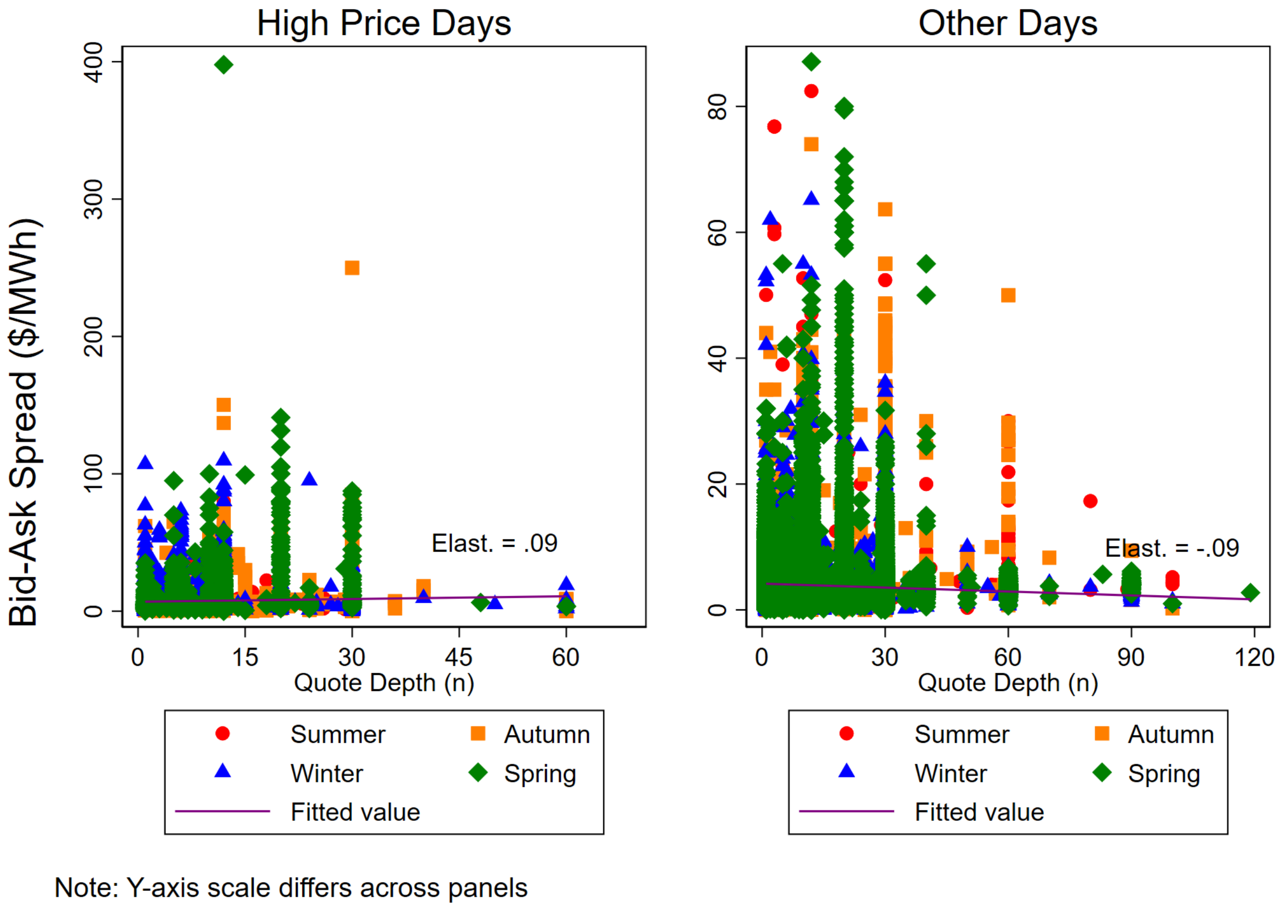
Figure 3.2 presents scatter plots showing the relationship between **quote depth** (a proxy for market liquidity) and **bid-ask spread** under two pricing regimes: **high price days** (left panel) and **other days** (right panel), with points color-coded by season. The fitted lines represent log–log elasticities.

In the **high price panel**, spreads range up to $400/MWh and are most concentrated at low depth levels (under 15) – **note that 1 lot is equal to 0.1 MW strip**. The estimated **elasticity is 0.09**, indicating a weak and slightly positive association between depth and spread. This is counterintuitive and likely reflects the dominance of volatility and uncertainty over liquidity during stress periods. In other words, market makers widen spreads due to risk, regardless of how much volume is posted at the top of the book.

- In the **other days panel**, spreads are lower (mostly below $80/MWh), and the estimated **elasticity is –0.09**, showing a weak negative relationship between depth and spread. This aligns with standard market microstructure theory, i.e., greater depth modestly improves liquidity and narrows spreads.

Figure 3.2 Spread versus volatility by season and price level

ASX End-of-Day data 2009q3-2025q2

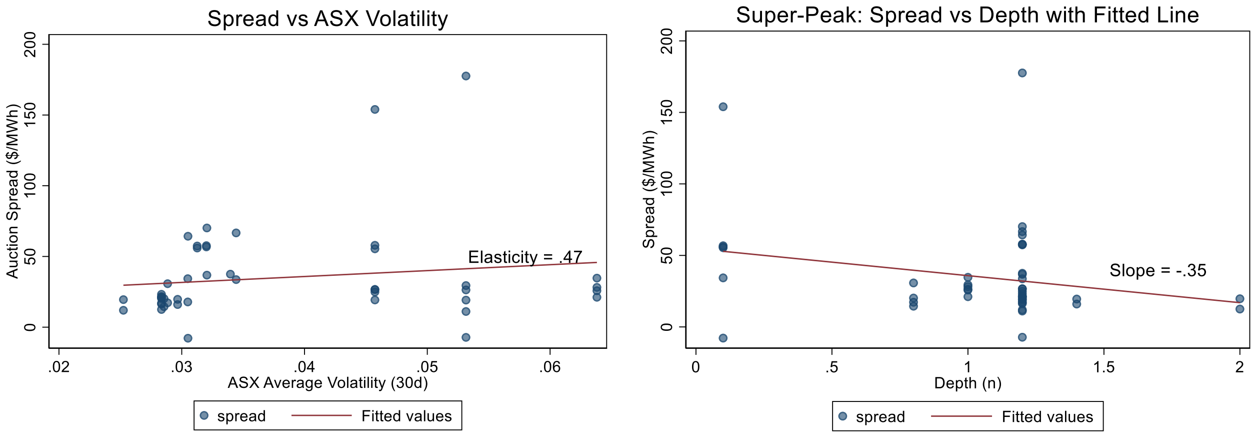


Source: ASX Information Services; Principal Economics analysis.

The right-hand side panel in Figure 3.3 focuses on auction log data for **super-peak contracts**, which are not covered by ASX. The spread-depth relationship is plotted using matched bid and offer quotes. The estimated **slope is −0.35**, meaning that a one-unit increase in quote depth (n) is associated with a $0.35/MWh decrease in the bid-ask spread. This slope is modest in magnitude, and given the low depth variation (clustered around 1.0–1.2), it suggests that **super-peak spreads are only weakly sensitive to liquidity**. This supports the interpretation that these spreads primarily reflect **structural risk premiums** associated with tight supply, extreme demand, or super-peak timing — rather than being driven by immediate market depth.

Figure 3.3 Super-peak spread versus volatility by season and price level

SPF data 2025q1-2025q2



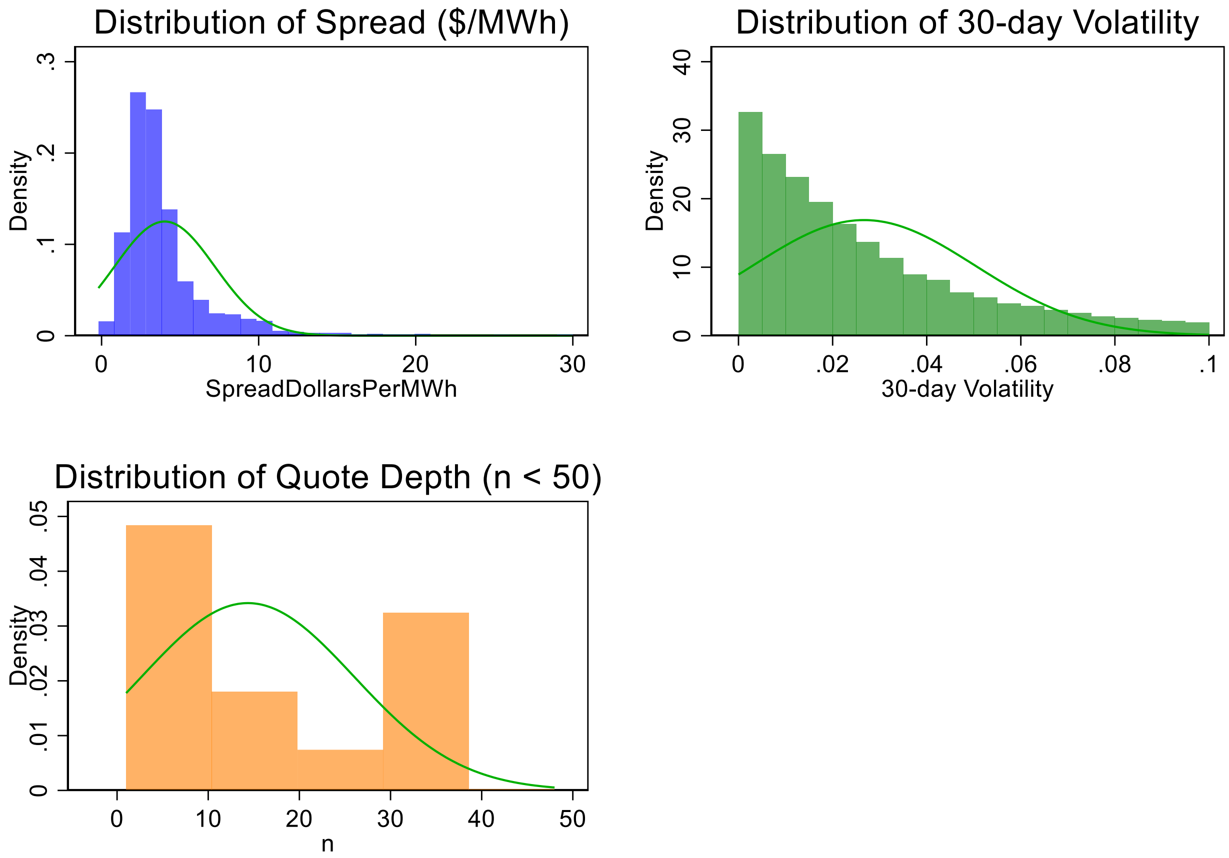
Source: SPF data; Principal Economics analysis.

As shown in Figure 3.4, the spread and volatility are both right-skewed.[5] For quote depth, some fatness in tails indicates limited market participation in certain periods or products. Given the strong right-skewness in both spread and volatility, a log transformation can improve model performance and interpretability.

[5] Density refers to the relative frequency of observations across the range of a variable (e.g., spread, volatility, or depth). It represents how concentrated or dispersed the data are at each value. Unlike a histogram that counts raw frequencies in bins, the density function is scaled so that the total area under the curve equals one, allowing easy comparison of distributions regardless of sample size.

Figure 3.4 Distribution of key variables

ASX End-of-Day data 2009q3-2025q2



Source: Principal Economics analysis

Table 3.2 contrasts the raw auction log spreads with the fitted intraday spread distribution. While the raw posted spread can reach a median of ~13% and exceeds 35% at the 95th percentile, the fitted effective spread — which accounts for executable volume and prevailing liquidity — shows a median of ~3% and a 95th percentile around 9–10%. The recommended spread caps are based on the fitted distribution, which better represents the true market-making cost and liquidity available to participants.

Table 3.2 Relative spreads using the SPF data

Percentile	Relative Spread (%)	Fitted Effective Spread (%)
50th (Median)	**12.9%**	~3.0%
75th	18.6%	~4.0%
90th	25.7%	~5.7%
95th	36.7%	~9–10%
99th	47.0%	~9–10% (trimmed tail)

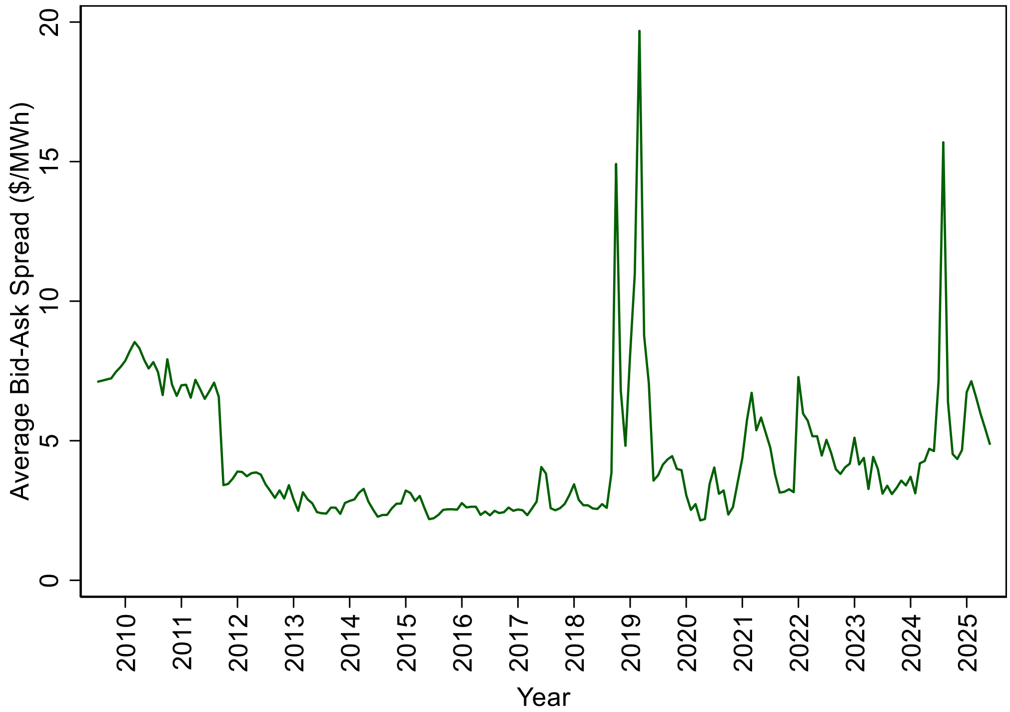
Source: Principal Economics analysis

Note: The relative spread pct (%) column shows the spread between the best bid and best offer *without filtering* for stale orders or depth; can be very wide if there are only placeholder offers. The fitted effective spread (%) column smooths spreads using actual depth, volatility, and imbalance; reflects realistic conditions a hedge-taker would face for tradeable volume.

Figure 3.5 shows average monthly spread over time. Accordingly, we observe structural breaks, due to various reasons.[6] Using the Chow test, the breaks in December 2011 and May 2019 are identified as statistically significant. Hence, we add period dummies to our regression analysis.

Figure 3.5 Average spread over time

ASX End-of-Day data 2009q3-2025q2

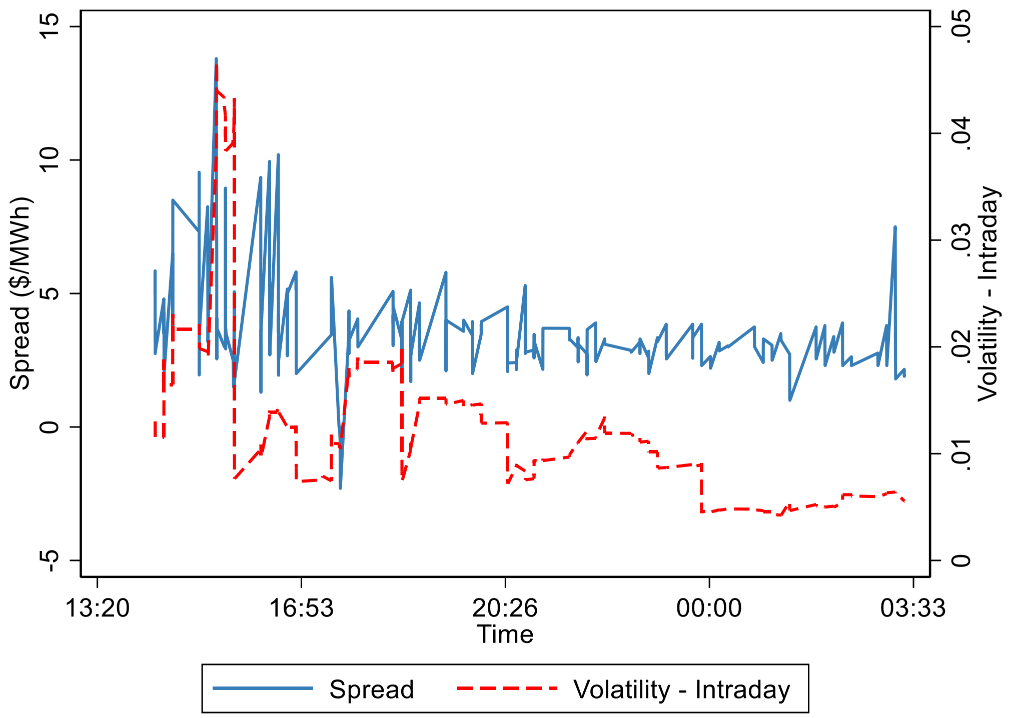


Source: ASX Information Services; Principal Economics analysis.

[6] Note that the purpose of this illustration is to identify structural breaks. For policy purposes, a relative spread illustration provides more useful information.

Figure 3.6 Intraday Pattern of Spread and Volatility

ASX High-Frequency data 2018q2-2025q2



Source: ASX Information Services; Principal Economics analysis.

3.3 Methodology

Technically, our methodological approach builds on established theoretical and empirical insights from the electricity futures literature.

We estimate the economic implications of different market-making scenarios for a super-peak hedge contract by modelling the determinants of bid-ask spreads, calculating relative spreads, and simulating the net benefit to market makers under varying volume and spread cap conditions. The methodology combines panel regression analysis with scenario-based forecasting, guided by theoretical models of forward pricing and empirical literature on electricity market liquidity and risk premia.

We estimate how **spread** behaves in relation to:

- **Volatility** (volatility_30d) — higher uncertainty → wider spreads
- **Quote depth** (n) — more volume offered → may narrow spreads (or increase risk exposure)

We model the dollar spread between the best ask and bid prices as a function of market volatility and liquidity:

$$\log\left(Spread_{it}\right) = \alpha_i + \beta_1 \cdot \log\left(Volatility_{it}\right) + \beta_2 \cdot \log\left(n_{it}\right) + \epsilon_{it} \qquad \text{(Equation 3.1)}$$

- $Spread_{it}$: Bid-ask spread ($/MWh) for contract ii at time t

- $Volatility_{it}$: 30-day rolling standard deviation of the log mid-price
- n_{it}: Quote depth, measured as the sum of bid and ask volume at the best price
- α_i: Contract fixed effect
- ε_{it}: Cluster-robust error term

Estimated coefficients indicate that spreads are **positively related to volatility** (risk premium) and **negatively related to depth** (liquidity effect). Structural break tests confirm that these relationships vary across time, especially post-2019. Regression intuition:

- If **$\beta_2 < 0$** → more quoted depth compresses spreads (suggests competition/liquidity)
- If **$\beta_2 > 0$** → quoting more contracts increases risk → wider spreads

To account for price levels and allow comparison across contracts and periods, we estimate the relative spread:

$$Relative\ Spread_{it} = \frac{Spread_{it}}{Mid\ Price_{it}} \quad \text{(Equation 3.2)}$$

This dimensionless measure captures transaction cost as a proportion of the contract price. It is used in scenario modelling to compare market conditions independent of price scale. $Mid\ Price_{it}$ is the average of bid and ask prices.

To evaluate the attractiveness of different market-making scenarios, we compute the expected net benefit to the market maker:

$$\begin{aligned} Net\ Benefits &= Benefit_s - Cost_s \\ Benefit_s &= \mathrm{Spread}_s \cdot \mathrm{Volume}_s \end{aligned} \quad \text{(Equation 3.3)}$$

The **spread** and **relative spread** are predicted using the regression models, based on input values for volatility and depth defined in each scenario (e.g., low/high volatility, low/high depth). The benefits formula reflects the **potential revenue per quote event**, assuming one unit is transacted at the quoted spread. In high-frequency contexts, this is akin to a **quote-adjusted gross margin**. What this benefit includes is:

- **Compensation for risk exposure**, especially in high-volatility environments.
- **Reward for liquidity provision** — tighter spreads and deeper quotes help improve market functioning.
- An **incentive-compatible return** for complying with market-making obligations.

But the benefit excludes Operational costs (e.g. trading infrastructure, staffing), Inventory holding costs beyond the capital-at-risk (covered in the "cost" term), Multi-quote matching or execution risk under low fill conditions (due to lack of fill probability data). It is critical to note that:

"The benefit estimate used in our net benefit calculation reflects the private incentive for market makers. This is a lower bound on total benefit, as it does not include the broader social gains from improved market liquidity. For regulatory purposes, these external benefits should be considered when interpreting the optimal spread cap."

For a complete cost-benefit analysis aligned with the Electricity Authority's public interest mandate, we suggest further consideration of social benefits of liquidity. Social benefits are considered beyond the scope of this report.

Costs reflect the market maker's exposure to price risk under each setting, proxied by contract price and volatility. For the cost function, we assume price is equal to the mid-price, for which we use the high-price observations in the ASX dataset.

Our cost function is based on the notion of *inventory-holding cost*, and aligns with the Electricity Authority's 2011 CBA report (Electricity Authority, 2011), though the implementation differs in methodology and level of specificity. Both our analysis and the 2011 CBA recognise that tighter bid-ask spreads improve price discovery but come at a cost to market makers. Our cost function assumes that tighter spreads require higher capital commitments, which aligns with the Authority's reference to trading risks, staff systems, and financial capital requirements under Section 4.2 of the report. The CBA report states that market makers incur **real costs** when forced to quote tighter spreads, including holding risk positions and liquidity exposure. Similarly, our cost function translates these costs into a simplified inventory model (Bessembinder & Venkataraman, 2009; Ho & Stoll, 1981; Stoll, 1989):

$$Cost = \frac{1}{2} \cdot s \cdot V \cdot P \cdot r_w \qquad \text{(Equation 3.4)}$$

where:

- s is the relative spread,
- V is the quote volume,
- P is the mid-price (used as value of inventory),
- r_w is the cost of capital.

Our approach empirically calibrates spread, volume, and volatility, estimating actual parameter sensitivity, rather than assuming fixed margins as the CBA did. This allows for scenario-specific marginal cost estimation. The introduction of the *optimal frontier* in our work adds an economic production framework—mapping feasible combinations of spreads and volumes to maximize net benefit—an enhancement beyond the linear benefit-cost assessment in the 2011 CBA. We distinguish between market regimes (high-price, super-peak), which allows us to reflect real-world asymmetries in risk and cost that the 2011 CBA only discussed qualitatively.

The cost component in our net benefit analysis incorporates a **risk weight (r_w)** to reflect the capital exposure faced by market makers when quoting in volatile market conditions. We assume a value of r_w=0.04, or 4%, representing the share of quote value that must be covered as capital at risk over a 30-day period. This aligns with the logic of **inventory-holding cost models** commonly used in market microstructure theory.

While the Treasury's revised guidance on discount rates recommends a **2% real social rate of time preference (SRTP)** for evaluating non-commercial public investments (with lower rates applied over longer horizons), this rate reflects **society's valuation of deferred consumption**, not the **commercial opportunity cost of capital** or the **risk-adjusted return required by market participants**. As such, it provides a **lower bound** for discounting but is not appropriate for modelling commercial risk exposure. Our assumed 4% risk weight corresponds approximately to an **annualised commercial rate of 8–10%**, consistent with common assumptions about **required returns on capital** in financial markets. This approach ensures the cost estimates remain conservative and grounded in the financial economics of market making.

In low-volume, high-volatility scenarios, net benefits are often negative, reflecting insufficient spread to compensate for risk. High-volume settings with moderate volatility yield the highest net benefit, suggesting that regulatory design should target sufficient depth and flexible spread caps under stress conditions.

The implications of the statistical tests

As part of the modelling, we test stationarity. The results suggest that all series are stationary. Using Wooldridge test for autocorrelation in panel data, we identify first-order autocorrelation, and, hence, use robust standard errors. Testing for group-wise heteroskedasticity rejects the null hypothesis of equal variance across panels. Hence, we use cluster-robust standard errors. We use Hausman test to identify best panel regression method. The results suggested that the fixed effects panel is preferred.

All regressions are estimated using **fixed-effects panel models** with **cluster-robust standard errors** at the contract level. Variables are **log-transformed** to capture elasticity relationships and stabilize variance. **Structural breaks** (2011 and 2019) are identified via the Bai-Perron test and incorporated as interaction terms in extended models.

4 Results

Table 4.1 presents the relationship between the spread and the explanatory variables, for all days, high price days and other days, using the ASX data. The results suggest that:

- **Volatility has a large positive impact** on spreads during **high-price days** (**elasticity = 0.367**), but this relationship is **weak or even negative** on regular days. This reflects strong risk pricing under stress conditions.
- **Quote depth has a negative effect** in normal conditions (**–0.077**) — consistent with liquidity theory — but oddly turns positive in high-price regimes (**0.090**), possibly due to market maker aversion to being hit with large volume during uncertainty.
- The **R^2 is much higher in high-price regressions (0.165)**, suggesting that volatility and depth explain spreads far more effectively under stressed conditions than under normal market operation.

Table 4.1 Regression Summary: Determinants of Log Bid-Ask Spread

	(1) All Days	(2) High Price Days	(3) Other Days
Log(Volatility)	0.027 ***	0.367 ***	–0.018 ***
	(0.001)	(0.007)	(0.001)
Log(Depth)	–0.068 ***	0.090 ***	–0.077 ***
	(0.001)	(0.008)	(0.001)
Constant	1.455 ***	2.637 ***	1.231 ***
	(0.007)	(0.029)	(0.007)
Observations	~140,000	~14,000	~130,000
R-squared	0.016	0.165	0.028

Source: Principal Economics

Note: Standard errors in parentheses. *** $p < 0.01$.

We try to infer the implications for the super-peak product using these regression results and the earlier descriptive statistics, we suggest that **higher estimated elasticities are likely.** For Volatility Elasticity ASX regression results suggest an elasticity of 0.37 for high-price days and the SPF log log–log model suggested an elasticity of **0.236** (despite sparse data. Super-peak products are **inherently exposed to extreme price volatility**, often during system stress or scarcity pricing. This suggests **even greater sensitivity** of spreads to volatility in super-peak contexts. In fact, the true elasticity could **exceed 0.4 or 0.5**, especially if intraday or real-time volatility were observable. For **Depth Elasticity (Log(Depth))**, ASX under high price suggests and elasticity of **+0.09** — counterintuitive but possibly due to market makers quoting wider spreads when posting larger volume under risk. SPF log-log model suggested an elasticity of **–0.35 in levels**, but low variation in n. Super-peak depth elasticity is likely to be **weak**, **negative**, and **less stable** — as market makers may be reluctant to quote large volumes at fixed prices during peaks. Hence elasticity with respect to log(n) may **vary widely**, but it is less reliable than volatility in explaining spreads.

Figure 4.1 presents the **optimal net benefit frontier** for market-making across three scenarios, differentiated by assumed **Mid Price levels**:

- **Base (Mid Price = $130/MWh)** – reflects typical ASX contract pricing
- **High Price (Mid Price = $210/MWh)** – observed during elevated market stress
- **Super-Peak (Mid Price = $280/MWh)** – assumed to reflect future auction-based super-peak hedge markets

As **Mid Price increases**, the **cost of risk exposure rises**, especially at higher volatility and depth. The **super-peak curve shifts downward**: despite higher spread revenues, **costs grow faster**, lowering net benefit. **Optimal quote depths are scenario-dependent**: for super-peak settings, the efficient net benefit may flatten or decline beyond ~2.0 MW.

The Electricity Authority can use this framework to calibrate **market-making obligations** (spread caps, quote sizes) while accounting for **product-specific volatility and price levels**.

Figure 4.2 shows the **optimal net benefit ranges** for market makers under two volatility regimes. For the high volatility (red shaded bands) ranges between 0.30 and 0.45 and show net benefit ranges across volatility. The low volatility ranges between 0.05 and 0.2, for which net benefits are shown in blue. Minimum quote depth (n) is shown on the X-axis and net benefits ($) on the y-axis. The findings suggest that:

- At any given quote depth, **net benefit increases with volatility**, reflecting larger spreads and higher revenue opportunities — even after accounting for higher cost of risk.
- The vertical width of each band represents the **sensitivity of outcomes** within the volatility range.
- These bands define **policy-relevant envelopes**. These could be used to define **minimum and maximum sustainable quote depths** depending on prevailing market conditions. For example, under high volatility, net benefit remains positive even at higher depths.

Figure 4.1 Optimal frontier under varying mid-price assumptions

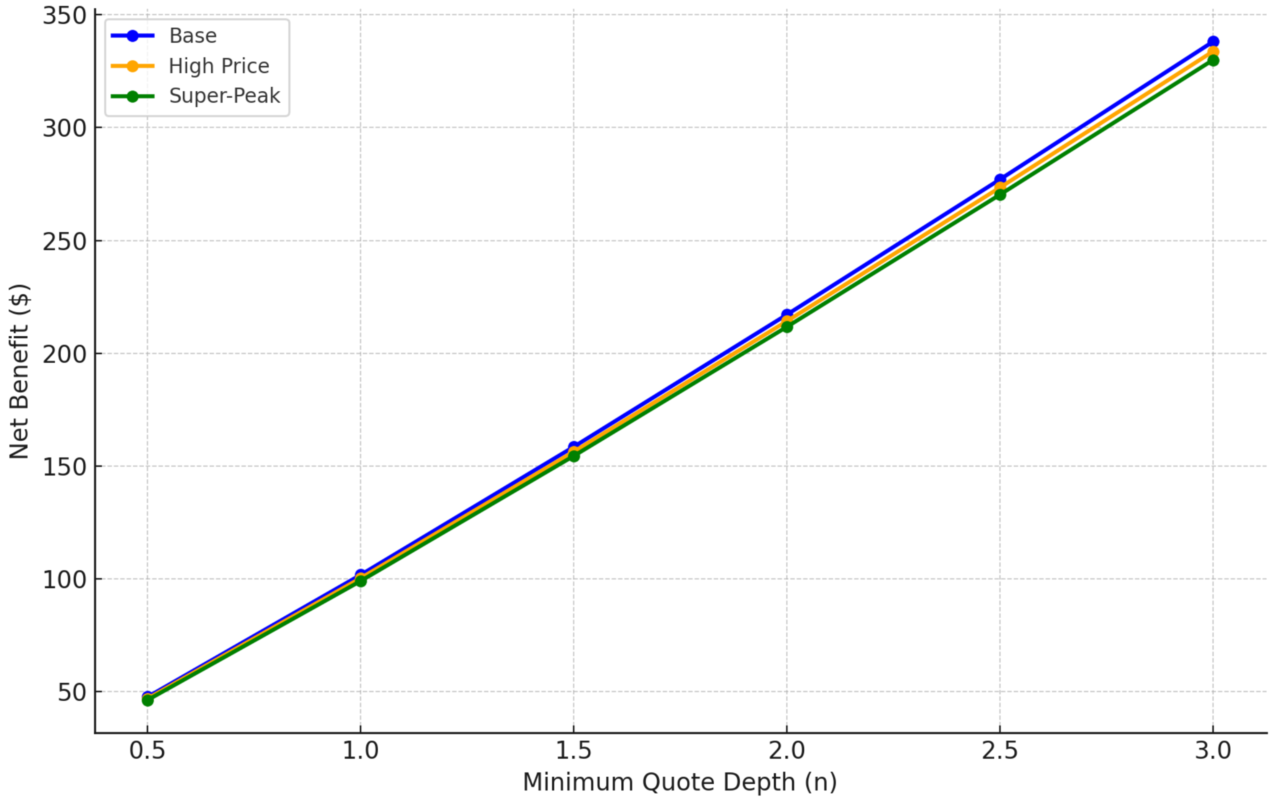
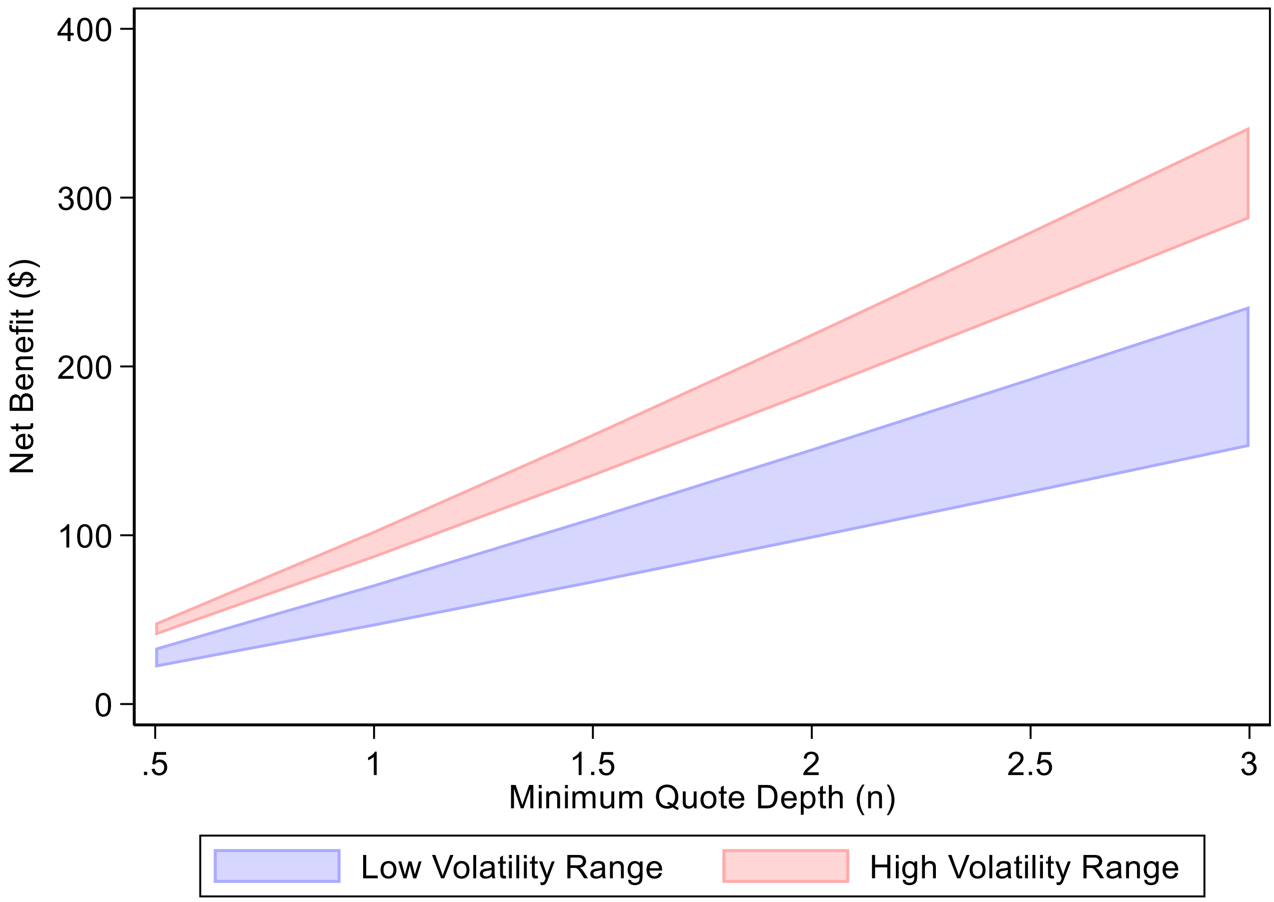


Figure 4.2 Optimal net benefit ranges by volatility



Implications for Liquidity Policy

Figure 4.2 shows that **net benefit to market makers increases with both quote depth and volatility**, but the **range of feasible and efficient depth obligations varies depending on the volatility regime**. The results suggest that:

1. **Liquidity can be increased when volatility is high — without excessive compensation**
   - In high-volatility regimes (red band), market makers can sustain **higher depth obligations** (i.e. more liquidity) **while remaining net-benefit positive**.
   - The Authority can **raise minimum quote depths or tighten spread caps** in stressed markets without deterring participation — because spreads are naturally wider and more profitable.
   - This supports **adaptive liquidity requirements**, rather than fixed caps across regimes.
2. **In low-volatility markets, liquidity targets must be cost-sensitive**
   - The blue band shows that, in stable conditions, the net benefit curve flattens quickly.
   - Pushing for excessive depth in low-volatility periods **risks negative or marginal returns**, undermining market-maker participation.
   - Liquidity requirements should therefore be **calibrated conservatively in calm markets** or supported with financial incentives.
3. Liquidity policy should reflect the trade-off between participation cost and benefit

  - The shaded regions define a **sustainability envelope** — depth requirements **inside the band** are feasible; outside, they're either underperforming (low benefit) or unsustainable (high cost).
  - This allows the Authority to **anchor minimum liquidity levels in observable volatility conditions**, maintaining market function without overregulating.

The Electricity Authority can use this framework to:

- Set depth and spread obligations that scale with observed volatility.
- Define dynamic liquidity corridors, ensuring that obligations are always within the feasible net benefit range.
- Support super-peak or stress products with **scenario-adjusted liquidity floors**, avoiding a one-size-fits-all approach.

This maintains **liquidity during stress** while avoiding excessive rents.

The ASX data excludes super-peak products, but shows price and spread behaviour during high-price periods for base and peak load futures. Therefore, the regression model is calibrated to **stress conditions** in standard contracts — **not true super-peak products**. Our **SPF data *does* cover super-peak contracts**, and that's where our empirical S% estimates (e.g. 3.66% median, 9.52% at the 95th percentile) are coming from. These values reflect **actual market quotes for the super-peak product**, even though the sample size is limited.

- The **regression model** (based on the ASX Information Services' dataset) reflects spread behaviour under **stress-like conditions** in **base/peak contracts**, but **not super-peak**.
- The **empirical S% distribution** (based on the SPF data) reflects **real super-peak market pricing**, and could **anchor the recommended spread caps**.
- Therefore, **our proposed policy tiers in Table** 4.4 **are grounded in actual super-peak quotes**, while the regression model supports extrapolation and cost-benefit simulations.

4.1 Testing the results using the high-frequency ASX data

Table 4.2 provides a summary of high-frequency regressions. Accordingly, the explanatory variables are both **statistically robust** and **highly informative** for understanding intraday spread behaviour.

Table 4.2 Regression results – High frequency ASX

Variable	Coefficient	Interpretation
log_vol30	**+0.09**	A 1% increase in short-term volatility raises spread by 0.09%
log_depth	**–0.58**	A 1% increase in depth reduces spread by 0.585% — **strong liquidity effect**
log_imbalance	**–0.05**	Slightly counterintuitive: greater order imbalance (absolute) reduces spread slightly — may reflect aggressive quoting or depth dominance
R^2 = 0.54		The model explains **54% of variation** in spreads — which is strong for microstructure data

Source: Principal Economics

This regression confirms the core structure of the earlier model (spread ↔ volatility + depth) using high-resolution data. This ensures the outputs are credible for **fine-tuning super-peak market-making settings**. The i**mplications are as follows:**

1. **Depth matters more than volatility**:
   - The elasticity of spread with respect to depth is large (–0.585), showing that depth is the **dominant driver** of spread compression intraday.

- This supports a cost-benefit argument for **spread caps that scale with observed depth**.

2. **Volatility has significant but more modest effect**:
   - Volatility sensitivity is lower than in the daily regression model (~0.36), which makes sense — intraday quotes adjust more incrementally.
   - This supports using **short-term volatility thresholds to adjust market-making rules**, but not overly reactive ones.
3. **We have empirical justification for r_w**:
   - These results let us **back out implied cost of spread** at different levels of volatility and depth — and validate or recalibrate our rw = 0.04 assumption using real-time quoting behaviour.

As show in Figure 4.3, the intraday analysis shows that:

- **Predicted spreads increase with volatility**, but the rise is **nonlinear** and flattens at higher volatility levels.
- **Greater quote depth significantly compresses spreads** — at any volatility level, quoting more volume reduces the required spread.
- The **impact of volatility is strongest at low depth**; at higher depths, spreads are more stable.

The implication of the finding is that fixed spread caps are more sustainable at higher depths. At low depths and high volatility, market makers require much wider spreads to cover risk — supporting the case for depth- and volatility-responsive market-making rules.

As shown in Table 4.3, based on intraday regression and outlier-trimmed estimates, the typical relative spread is approximately 3% of the ask price, with plausible stress conditions increasing this to 4–5.7%. Empirical spread distribution from intraday regression supports the proposed tiered S% caps by market condition and volatility bracket presented in Table 4.4.

Table 4.3 Empirical Distribution of Relative Spread (S%)

Percentile	S%	Interpretation
50th (Median)	2.96%	Most typical super-peak spread; a defensible base cap
75th	4.02%	Upper bound of normal market-making conditions
90th	5.67%	Starts to reflect stress/liquidity constraints
Min-Max	0.66-12.4%	
Mean	3.41%	Consistent with a slightly right-skewed distribution

Source: Principal Economics

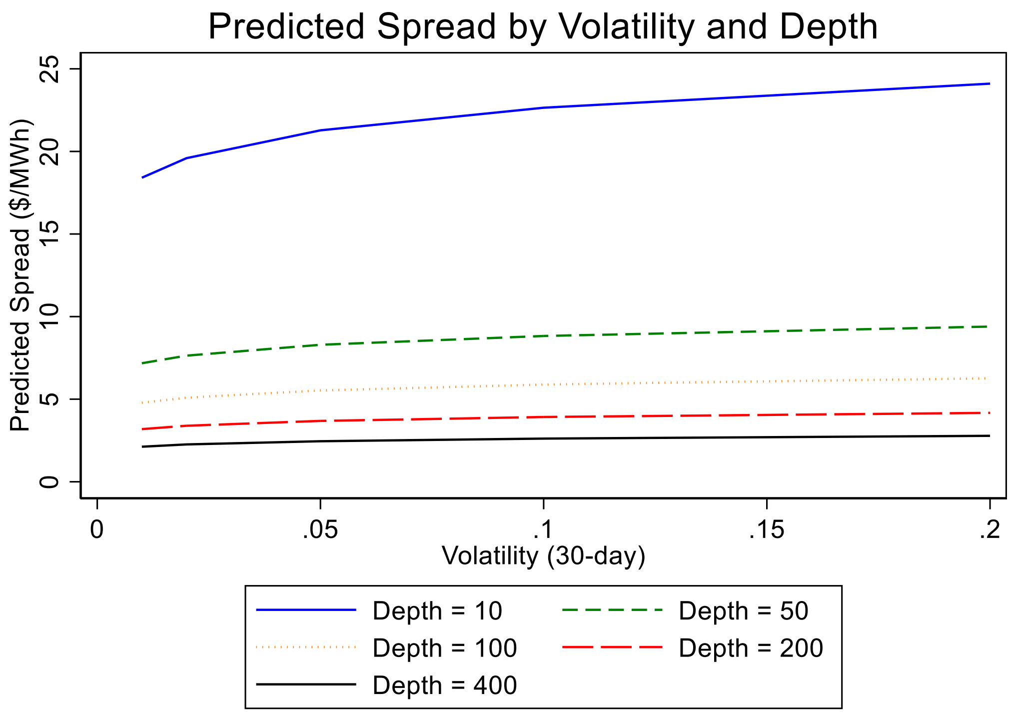
Table 4.4 Policy Recommendation Based on Results

Market Condition	Volatility Context	Recommended S% Cap
Normal Super-Peak	30-day vol < 0.10	**3.0–3.5%** (base cap)
Moderate Stress	0.10 ≤ vol < 0.15	**4–5%** (volatility-adjusted)
High Stress / Override	vol ≥ 0.15 or designated event	**up to 6-7%** (95th percentile cap)

Source: Principal Economics

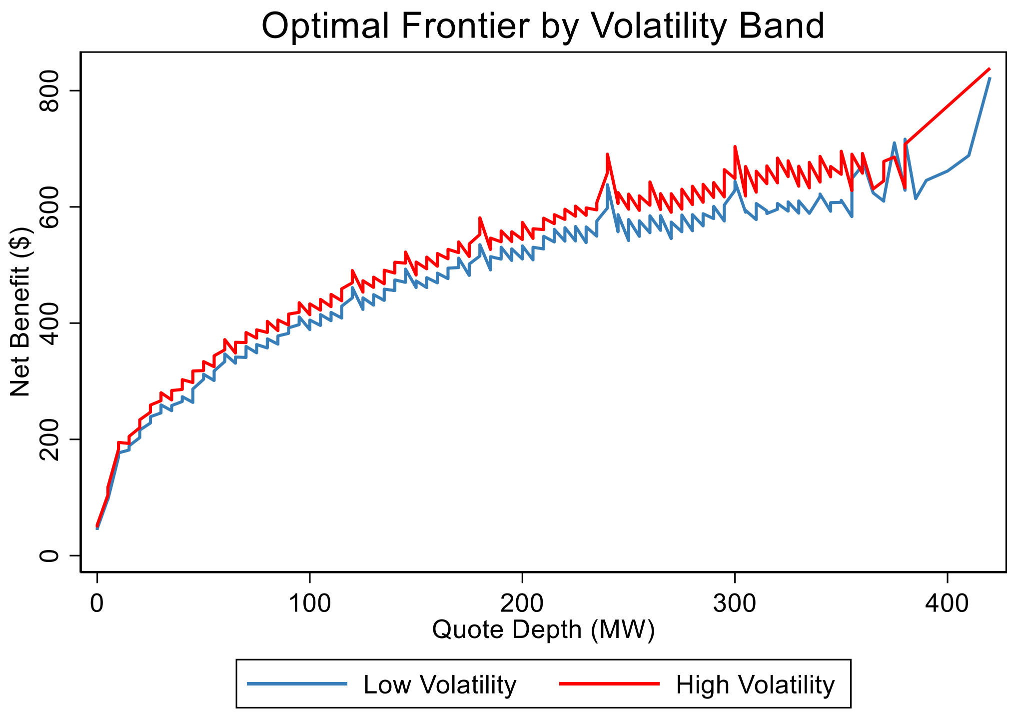
As shown in Figure 4.4, Net benefit increases with quote depth, but the gains flatten beyond ~300 MW. High-volatility conditions support higher net benefit across most depths, reflecting wider spreads. The frontier becomes jagged at higher depths due to data granularity or noise in the fitted values.

Figure 4.3 Predicted spread by volatility and depth



Source: Principal Economics

Figure 4.4 Optimal frontier by volatility band



Source: Principal Economics

4.2 The required social benefits for higher spread caps

While it's beyond the scope of our report to consider social benefits of liquidity, we improve the usefulness of our report by considering the required social benefit increases for specific spread caps. While private net benefit captures the financial incentive for market makers, it does not include potential **external or social benefits** from improved market liquidity — such as better hedge access for small retailers, smoother price discovery, and enhanced confidence in the hedge market. However, these benefits are difficult to observe directly.

Instead of assuming them, we **quantified how large the social benefit would need to be** for higher spread caps to be welfare-improving. This gives policymakers a defensible threshold: unless credible social value exceeds this threshold, tighter caps are economically preferable. To inform the Electricity Authority's decision on setting a spread cap (S%) for super-peak market making, we conducted a **break-even cost-benefit analysis** using fitted spread and depth values from the ASX Information Services' dataset. Specifically, we calculated:

- The **private benefit** to market makers from quoting at various spread levels, defined as Benefit = Spread × Depth.
- The corresponding **inventory holding cost**, based on mid-price, depth, volatility, and assumed capital cost (rw = 4%).
- The resulting **net private benefit** for each spread cap band.
- The **additional social benefit** that would be required at higher spread caps to match the private net benefit at the optimal (lowest-cost, highest-return) cap.
- A **"social multiplier"** showing how much additional benefit (as a proportion of private benefit) would need to exist to justify each cap.

Our results are presented in Table 4.5. The **private net benefit peaks at spread caps between 2% and 3%**. Beyond this range, private benefits decline while the break-even social benefit multiplier rises steadily. For a 3% cap, the required social benefit needs to be **about 0.73× the private benefit** to break even. At 4–5%, the multiplier increases to around 1.0–1.2×, and for caps above 6%, it **exceeds 1.5×** — implying that significantly higher social benefits are needed to justify looser spread caps under stress conditions.

The private net benefit is highest at tight spread caps and remains relatively stable up to around 2–3%, before declining at wider caps. To strengthen this analysis, we also consider how much additional social benefit would be needed to justify allowing higher spread caps. While the private net benefit reflects the direct financial return to market makers, it does not capture wider market benefits from deeper liquidity and reduced risk premiums. Quantifying this trade-off ensures that any relaxation of the cap remains justified by broader market outcomes.

Table 4.5 The required social benefits for different spread caps (S%)

Spread cap (S%)	Benefit ($)	Cost ($)	Net private Bft	Break-even SBft	Break-even Social M.
1%	538.57	13.68	524.88	313.76	0.60
1.5%	517.53	11.46	506.07	332.58	0.67
2%	507.93	9.02	498.91	339.74	0.71
2.5%	506.87	7.18	499.70	338.95	0.72
3%	508.61	5.86	502.76	335.89	0.73
3.5%	496.82	5.12	491.71	346.94	0.78
4%	476.52	4.60	471.92	366.73	0.85
4.5%	452.70	4.40	448.29	390.35	0.96
5%	430.21	3.98	426.23	412.41	1.07
5.5%	403.97	4.25	399.72	438.93	1.22
6%	383.55	4.26	379.29	459.35	1.35

Source: Principal Economics

Note: Spread cap is the rounded spread cap (S%) i.e., predicted relative spread band. Benefit is the estimated private benefit = spread_hat × depth — i.e., what a market maker earns from quoting at this spread. Cost is the estimated inventory holding cost using midprice × depth × volatility × r_w. Net_private Bft is the Net private benefit = benefit – cost, i.e. the amount a market maker keeps after covering cost. Break-even social benefit (SBft) is needed to make this spread cap as good as the best private scenario (i.e. max net private). Break-even Social Multiplier = required_social_benefit / benefit. This tells you how much uplift (as a % of private benefit) is needed to justify this S% cap socially.

5 Conclusion

This project developed an evidence-based framework to advise the Electricity Authority on appropriate bid-ask spread caps (S%) and minimum quote depths for market-making obligations on the standardised super-peak hedge contract. Our approach combined econometric analysis of ASX base and peak load futures with observed pricing behaviour from auction log data for super-peak products.

Using regression models, we quantified how bid-ask spreads vary with volatility and quote depth, and simulated net benefits to market makers under different regulatory scenarios. At the heart of the analysis is the construction of an **optimal frontier**—a boundary that defines the maximum achievable net benefit across combinations of quote depth and spread. This frontier provides a rigorous basis for identifying policy settings that balance market-maker incentives with the Authority's objective of ensuring liquidity.

Empirical analysis of the auction log data revealed that typical relative spreads for super-peak contracts are tight under normal conditions—median S% was 3%. However, spreads widen markedly during stress periods, with the 90th percentile exceeding 5% and the 95th percentile reaching up to 9–10%. To keep the cap both practical and responsive, we recommend a clear two-tier policy:

- a base cap of **3.5%** under normal conditions; and
- an elevated cap of up to **8%** when volatility exceeds a defined threshold or during designated stress events.

This structure balances cost-effective market-making with dependable liquidity and price transparency for hedge-takers in the electricity futures market.

5.1 Limitations and recommendations for future investigation

While we have applied best-practice methods and used all available data sources to inform this analysis, the following caveats apply. This section provides a summary of the caveats and encourages future work on these topics.

- The consideration of the social benefits of liquidity is beyond the scope of our report.

  We suggest that while **greater liquidity** (i.e. tighter spreads and deeper markets) is often assumed to improve market function, the **social benefit of increased liquidity** depends on:
  - **Who benefits** from improved liquidity (e.g. small retailers, large gentailers, industrial users).
  - **Whether lower hedge costs** for buyers are passed through to **final consumers**.
  - **The structure of the market** — particularly in NZ, where **gentailers internalise generation and retail risk**, possibly leading to **efficient hedging via vertical integration** rather than financial market making.
  - **The marginal cost of achieving that liquidity** — e.g., costs imposed on market makers (possibly gentailers), which could reduce incentives for long-term investment or distort risk allocation.

  Improved access to hedging may reduce retail price volatility for some participants, but it may also encourage entry of less efficient retailers, distort investment signals, or duplicate the risk management already internalised by vertically integrated gentailers. The implication of this for the Authority is that the **social benefit of liquidity is context-dependent**, and **not necessarily positive**. In some cases, **excess liquidity could redistribute risk inefficiently**, or **support market entrants** whose participation leads to **higher system costs** (e.g. through volatility amplification or overreliance on financial hedging). Hence, we suggest a future project to investigate the social value of liquidity. That study should use a general equilibrium approach to capture impacts across markets.

- **Lack of directly observed super-peak data**: The ASX Information Services' dataset does not include actual super-peak contracts, requiring the use of high-price proxies and supplemental the SPF auction data. This limits precision when extrapolating to super-peak conditions.
- **Limited visibility of contract positions**: Contractual exposure, such as physical generation hedges or portfolio obligations, can materially affect market-making behaviour. These positions are not observable in the available data and were therefore excluded, but warrant further investigation.
- **Omission of supply-side constraints**: The analysis does not explicitly account for physical capacity constraints during peak periods, which may influence both pricing and quoting behaviour. This could be explored through integrated market simulation or dispatch models in future work.
- **Exponential risk pricing under stress**: Extreme market conditions may result in nonlinear pricing dynamics (e.g. jump diffusion, regime shifts). While we incorporate volatility in our cost modelling, additional work using disaster or rare-event modelling could enhance robustness.
- **Social benefit estimation is simplified**: The analysis quantifies private net benefit to market makers. Broader social welfare impacts — such as price transparency, risk-sharing, or retailer competition — are acknowledged but not modelled. These require value judgments and assumptions beyond this report's scope.
- **Trading frequency and behavioural effects not directly modelled**: While we distinguish between daily (exchange) and fortnightly (OTC) regimes, strategic behaviours (e.g. quote fading, market timing) are not explicitly modelled, and could influence real-world performance.

5.2 Further discussion of the implications of the limitations

While the analysis is grounded in robust data and modelling, several limitations were acknowledged. These limitations do not invalidate the findings but help frame their **appropriate interpretation and use** for policy development. In this section, we further explore the potential impacts of the limitations on our findings and recommendations.

1. Lack of actively traded super-peak contract data

- **Implication**: Spread and depth estimates for super-peak products rely on auction log data and proxies (e.g. high-price ASX contracts), not continuous market observations.
- **Effect on findings**:
    - The estimated **S% range (3.7% median, 9.5% at 95th percentile)** reflects indicative behaviour rather than observed liquidity during active trading.
    - The proposed **tiered spread cap structure** (e.g. 4%, 6–8%, up to 10%) provides **scenario-based** evidence and should be further empirically calibrated from live markets.
    - Policy should allow **flexibility for refinement** once trading data becomes available.

2. Unobserved contract positions and internal hedging

- **Implication**: Market-makers may already be hedging super-peak exposures internally (e.g. via vertical integration), which reduces the need for quoting compensation.
- **Effect on findings**:
    - Net benefit and cost simulations may **overstate required incentives**, particularly for gentailers.
    - The **optimal frontier** is still informative but should be interpreted as a **ceiling of required compensation**, not a minimum.

- Break-even social benefit thresholds (e.g. $1.5/MWh) may be **conservative estimates** of what's needed.

3. Simplified cost structure (inventory risk only)

- **Implication**: The model assumes spread costs arise from inventory risk based on volatility, midprice, and depth, but excludes:
  - Operational constraints
  - Strategic behaviour (e.g. quote shading or cancellation)
- **Effect on findings**:
  - The calculated **marginal net benefit curves** are directionally correct but may **underestimate tactical quoting incentives**.
  - The identified **efficient quote depth range (10–15 MW)** may shift slightly once operational factors are accounted for.

Further refinement of the market-making cost function could draw on sector-specific input price escalation forecasts, such as those provided in Principal Economics Limited (2024). This would ensure that future adjustments to spread caps remain aligned with evolving cost structures for liquidity provision.

4. No quantification of downstream social welfare effects

- **Implication**: While we estimate private net benefit, broader impacts on competition, hedge accessibility, or consumer pricing are not modelled.
- **Effect on findings**:
  - The **break-even social benefit analysis** (e.g. $1.5/MWh to justify a 2–3% S% cap under high volatility) provides a **threshold**, not a full CBA.
  - Any decision to set tighter caps must be backed by **external evidence** of market or consumer benefit.

5. No endogenous modelling of market behaviour

- **Implication**: The model treats volatility, depth, and spreads as inputs, not jointly determined by strategic interaction among traders.
- **Effect on findings**:
  - The recommended spread caps are structurally sound, but **not equilibrium-tested** in a dynamic setting.
  - This suggests the need for **ongoing monitoring and potential re-calibration**.

These limitations do not undermine the usefulness of the results but indicate that the findings provide a strong initial calibration for spread caps and quoting obligations. They should be implemented with flexibility and sunset provisions, and re-evaluated as live super-peak trading data becomes available. The Authority should consider this project as a first-stage cost-benefit screen, with further development focused on empirical validation and social welfare quantification.

References

Arias, S., Santa-Alvarado, A. M., & Salazar, H. (2024). The Impact of a Market Maker in an Electricity Market. *Energies*, *17*(16), 4042. https://doi.org/10.3390/en17164042

Bessembinder, H., & Lemmon, M. L. (2002). Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. *The Journal of Finance*, *57*(3), 1347–1382. https://doi.org/10.1111/1540-6261.00463

Bessembinder, H., & Venkataraman, K. (2009). *Bid-Ask Spreads: Measuring Trade Execution Costs in Financial Markets*.

Bevin-McCrimmon, F., Diaz-Rainey, I., McCarten, M., & Sise, G. (2018). Liquidity and risk premia in electricity futures. *Energy Economics*, *75*, 503–517. https://doi.org/10.1016/j.eneco.2018.09.002

Commerce Commission. (2024, August 28). *Energy Competition Task Force set up to improve electricity market performance*. https://comcom.govt.nz/news-and-media/media-releases/2024/energy-competition-task-force-set-up-to-improve-electricity-market-performance

Electricity Authority. (2011). *Information Paper: Cost Benefit Analysis – Market-Making Obligations*.

Electricity Authority. (2024, December 20). *Super-peak hedge contract to trade in January*. https://www.ea.govt.nz/news/general-news/super-peak-hedge-contract-to-trade-in-january/

Electricity Authority. (2025a). *Energy Competition Task Force*. https://www.ea.govt.nz/projects/all/energy-competition-task-force/

Electricity Authority. (2025b, January 31). *Standardised Flexibility Co-design Group recommendations published*. https://www.ea.govt.nz/news/general-news/standardised-flexibility-co-design-group-recommendations-published/

Fiuza de Bragança, G. G., & Daglish, T. (2016). Can market power in the electricity spot market translate into market power in the hedge market? *Energy Economics*, *58*, 11–26. https://doi.org/10.1016/j.eneco.2016.05.010

Grossman, S. J., & Merton H., M. (1988). *Liquidity and Market Structure*. http://links.jstor.org/sici?sici=0022-1082%28198807%2943%3A3%3C617%3ALAMS%3E2.0.CO%3B2-G

Ho, T., & Stoll, H. R. (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics*, *9*(1), 47–73. https://doi.org/10.1016/0304-405X(81)90020-9

Ofgem. (2020, January 30). *Update – Liquidity Policy Review: Publication of NERA Economic Consulting Options Assessment Report | Ofgem*. https://www.ofgem.gov.uk/publications/update-liquidity-policy-review-publication-nera-economic-consulting-options-assessment-report

Peña, J. I., & Rodriguez, R. (2022). Market Makers and Liquidity Premium in Electricity Futures Markets. *The Energy Journal*, *43*(2), 91–110. https://doi.org/10.5547/01956574.43.2.jpen

Principal Economics. (2024). *Sector-specific input price escalation forecasts for Electricity Distribution Businesses (EDBs)*. https://principaleconomics.com/reports/sector-specific-input-price-escalation-forecasts-for-electricity-distribution-businesses-edbs/

Stoll, H. R. (1989). *Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests*. https://www.acsu.buffalo.edu/~keechung/MGF743/Readings/Stoll%201989.pdf

Appendix A: The ASX Dataset

The table below provides a brief list of the variables available in the ASX electricity futures data.

Table A.1 Variables in ASX and their description

Variable	Description
country_cd	Country code of the contract (e.g., NZ)
conloc_cd	Contract location code (e.g., Otahuhu, Benmore)
con_cd	Unique identifier for the contract
com_cd	Commodity code (e.g., ELEC for electricity)
comtype_cd	Commodity type (e.g., futures or options)
duration_cd	Contract duration (e.g., quarterly, monthly)
expiryyear, expirymonth, expirydate	Contract expiry information
shortlongdated_ind	Indicates if the contract is short- or long-dated
settlementdate	Date of settlement
settlement_dp_mwh	Final settlement price ($/MWh)
tradedcons	Number of contracts traded that day
bid_dp_mwh, ask_dp_mwh	Bid and ask prices ($/MWh)
bidcons, askcons	Number of contracts quoted at bid and ask
open_dp_mwh, last_dp_mwh	Opening and last traded price ($/MWh)
low_dp_mwh, high_dp_mwh	Daily low and high prices ($/MWh)
MidPrice	Average of bid and ask prices
SpreadDollarsPerMWh	Bid-ask spread in $/MWh
RelativeSpread	Spread as a percentage of mid price
BidDepthMW, AskDepthMW	Implied volume at bid/ask prices (contracts × 0.1 MW)
DepthRatio	Ratio of bid to ask depth
ContractDate	Trading date
log_midprice	Natural log of mid price
log_return	Daily return based on log midprice