TRANSITION 3NERGY
Renewal, Resilience, Reliability

Electricity markets around the world

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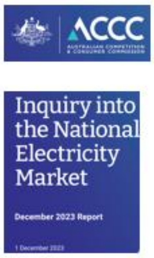
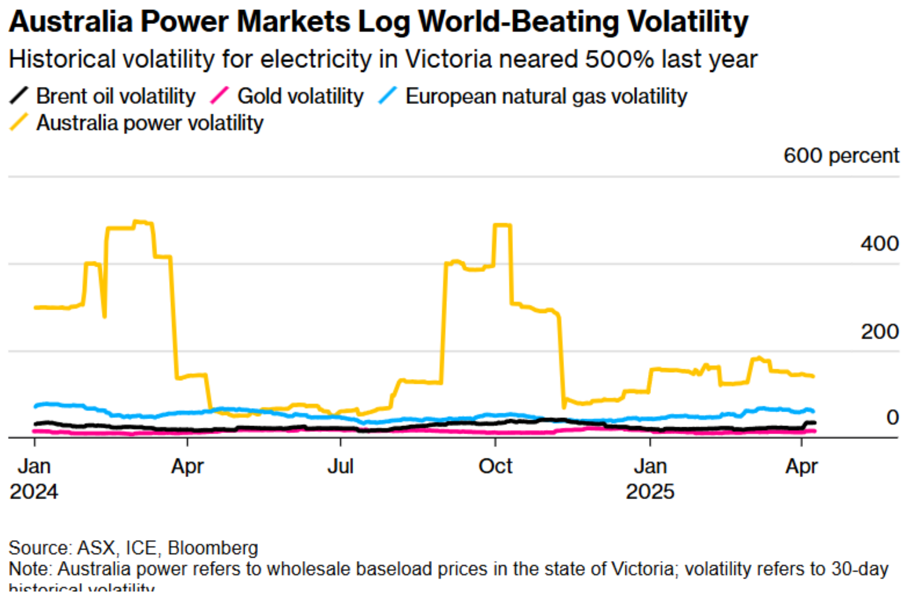
The amount of electrical energy or power specified in a hedging contract is important, as it determines how much the retailer's or generator's spot-market risk is reduced. In this report, we use 'volume' as a general term to describe either the amount of energy or power. Some examples of how volume can be specified (or not specified) in different categories of contracts include:

- Fixed-volume hedging contracts where the total amount of energy over the contract period is agreed in advance. The power output at certain times of the day or week may also be specified. In this report, we use the term 'firm' to describe contracts where the power output is specified in the contract and the term 'flat' to refer to contracts where the same power output and strike price apply at all times of the day or week. Flat swaps are the most common type of hedging contract in the NEM.
- Load-following contracts, where a fixed price is paid per unit of energy, but the volume is not agreed in advance. Instead, the volume of electricity that is settled under the hedging contract depends on (or 'follows') the load of the buyer of the hedging contract. These contracts provide the greatest reduction in risk for retailers as the volume risk is transferred to the generator.
- Generation-following contracts, where a fixed price is paid per unit of energy, but the volume is not agreed in advance. This is similar to a load-following contract, however, in this instance, the amount of electricity settled under the contract depends on (or 'follows') the power output of the seller of the contract. These contracts provide the greatest reduction in risk to the generator but transfer the volume risk to the retailer. A common example is a power purchase agreement, executed between a retailer and a renewable energy project.



Percentage of flat swap contracts (of total volume purchased) purchased from 2021 to 2023

Time period	Total volume purchased (MWh)	Total volume of flat swaps purchased (MWh)	Percentage of swaps (%)



Price volatility in Australia's wholesale electricity markets, particularly in the National Electricity Market (NEM), is deeply damaging across **political, economic, social, and technological** dimensions. The high frequency and magnitude of price swings create uncertainty, which directly impacts **affordability, competition, and sustainability** for all major stakeholders.

🏛️ Political Impacts

Volatile wholesale prices create a challenging and often reactive political environment.

- **Policy Instability:** Sudden price spikes and threats to supply reliability lead to **government intervention** (e.g., price caps, market suspension, targeted subsidies), which can undermine long-term market certainty and investment signals.
- **Public Pressure and Trust:** High and volatile household and business energy bills generate **significant public dissatisfaction** and political pressure, damaging consumer trust in the market, regulators, and energy policy directions.
- **Decarbonisation Risk:** Political infighting and frequent policy changes around the energy transition (e.g., the pace of coal retirement and renewable energy targets) are often exacerbated by volatility, slowing down the **orderly and efficient shift to sustainable energy**.

💰 Economic Impacts

The core damage of volatility is economic, impacting the financial viability and investment decisions of market participants.

- **Users (Businesses & Households):**
  - **Affordability:** High wholesale costs flow through to higher retail prices, increasing the **cost of living and doing business**. This is especially punitive for energy-intensive industries and low-income households, increasing energy debt.
- **Retailers:**
  - **Financial Risk:** Retailers typically sell power on fixed or capped price contracts but must buy from the volatile wholesale spot market. Volatility makes **hedging risk** more expensive and complex, threatening the financial viability of smaller, asset-light retailers and **reducing competition**. Retailer failures lead to increased market concentration.
- **Generators:**
  - **Investment Uncertainty:** Volatility makes revenue streams unpredictable. **Dispatchable (firming) generators** like batteries and gas plants rely on price spikes for revenue, but extreme volatility makes it difficult to model and finance new long-term investments. **Renewable generators** face revenue risk from periods of negative pricing.
- **Transmission/Distribution (Networks):**
  - **Investment Difficulty:** While their revenues are largely regulated and stable, volatility increases the **risk premium** for investors in new network infrastructure (like interconnectors and Renewable Energy Zones), which are crucial for grid stability and transporting cheaper renewable power.

👫 Social Impacts

Volatility directly translates into social inequity and stress.

- **Affordability and Equity:** Increased prices disproportionately affect **vulnerable and low-income users**, leading to energy poverty, disconnection risk, and mental stress.
- **Business Viability:** Volatile costs can force energy-intensive businesses to **reduce operations or close down**, leading to job losses and regional economic instability.
- **Consumer Choice:** The complexity and opacity of volatile wholesale costs make it harder for consumers to **compare offers and engage** effectively with the market, potentially leading to poorer outcomes and higher bills.

🔬 Technological Impacts

Volatility complicates the required technological transition towards a reliable, sustainable grid.

- **Storage and Firming:** High volatility is intended to incentivise investment in **fast-response, firming technologies** (like batteries and pumped hydro) that can arbitrage price differences. However, **extreme and unpredictable volatility** makes the business case for these long-term assets harder to lock in, slowing down their essential deployment.
- **Sustainability Goal Hindrance:** The inability to manage volatility effectively can lead to **inadequate investment in transmission** and storage, which is needed to integrate large-scale, intermittent renewables (solar and wind), ultimately hindering the **sustainability** goal of deep decarbonisation.
- **System Reliability:** Volatility often spikes during periods of **supply scarcity** (e.g., extreme weather events, generator breakdowns). This stress tests the system, increasing the risk of **technical failure, market intervention, or blackouts**.

Stakeholder Group	**Key Damage from Volatility**	**Impact on Affordability, Competition & Sustainability**
Users (Customers)	Higher, unpredictable bills and debt risk.	**Affordability** severely compromised.
Retailers	Higher hedging costs, increased financial failure risk.	**Competition** reduced, higher final prices.
Generators	Unpredictable long-term revenue, difficulty financing new projects.	Hinders **sustainability** transition and long-term reliability.
Networks	Increased risk premium on essential transmission investment.	Delays in infrastructure critical for **sustainability** and lower long-term costs.
Political/Regulators	Policy inconsistency, public loss of trust, reactive intervention.	Undermines stability needed for all three—**affordability, competition, and sustainability**.

The Recommended Method: GARCH Modelling

The **GARCH model** is superior to simple measures like Standard Deviation because it accounts for a key feature of electricity markets: **volatility clustering**. This means large price changes (positive or negative) are likely to be followed by more large price changes, and small changes by small changes.

1. Data Preparation and Baseline (Returns)

The first step is to transform the raw spot price data (e.g., NEM 5-minute or 30-minute interval prices) into **logarithmic returns (r_t)**. This standardizes the data and makes it stationary, which is necessary for time-series analysis.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where P_t is the price at time t. The **mean** of these returns can be modelled using an Autoregressive Moving Average (ARMA) model, but the focus is on the variance.

2. The GARCH(1,1) Model

The GARCH(1,1) model is the most common and robust specification for measuring and forecasting volatility. It separates the total variance into a long-run mean variance, past squared errors (ARCH term), and past conditional variance (GARCH term).

The model consists of two equations:

A. Mean Equation

The mean return at time t (μ_t) is modelled:

$$r_t = \mu_t + \epsilon_t$$

Where ϵ_t is the error term, and μ_t is often assumed to be constant or zero, but can be an ARMA process.

B. Variance Equation (The Volatility Measure)

The conditional variance (σ_t^2) at time t is the measure of volatility. This is estimated simultaneously with the mean equation:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

- **σ_t^2 (Conditional Variance):** This is the **baseline volatility** measure. It represents the expected price volatility for the next period, given all current information.
- **ω (Constant Term):** The long-run, stable component of variance (the "long-run average volatility").
- **α (ARCH Term):** Measures the impact of **news** (i.e., the error squared, ϵ_{t-1}^2) from the previous period on current volatility. A high α means volatility responds quickly to market shocks.

- **β (GARCH Term):** Measures the **persistence** of volatility; how much of the previous period's forecasted variance (σ_{t-1}^2) carries over to the current period. A high β indicates that volatility shocks take a long time to decay.

3. Baseline Establishment

The estimated **σ_t^2 series** generated by the GARCH model provides the statistically sound, time-varying baseline volatility.

- **Measuring Volatility:** The current σ_t (the conditional standard deviation) is the **direct measure** of volatility for a given period.
- **Against Which to Measure:** Any **deviation** from the expected path of the GARCH-forecasted σ_t can be flagged as an unusual or extreme volatility event. The estimated parameters (ω, α, β) define the market's **structural relationship** with volatility, against which the impact of new policies, major network events, or generator retirements can be measured.

💡 Why GARCH is Best for Electricity Markets

Feature	Importance to Electricity Markets
Volatility Clustering	Price spikes are concentrated due to generation outages, network constraints, or high demand events that often persist for hours/days. GARCH specifically models this clustering.
Mean Reversion	The NEM spot price is highly mean-reverting (it rarely stays at $\$15,500/\text{MWh}$ or $-\$1,000/\text{MWh}$ for long). The ω term in GARCH captures this tendency toward a long-run stable variance.
Forecasting Power	The GARCH model is a powerful tool for forecasting the **expected range of prices** in the short term, which is crucial for retailers' hedging decisions and generators' bidding strategies.
Asymmetry (EGARCH/GJR-GARCH)	Variants like the **Exponential GARCH (EGARCH)** are useful because electricity markets exhibit **leverage effects**: negative shocks (e.g., a large generation unit trip) may increase future volatility *more* than positive shocks of the same magnitude (e.g., a sudden drop in demand).