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# Tail risk connectedness in the Australian National Electricity Markets: The impact of rare events

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ABSTRACT

The tail risks can exhibit different and important features than average measures of risk in interconnected electricity markets. This paper examines the interconnectedness of tail risks within the regionally interconnected Australian National Electricity Market. We use the Conditional Autoregressive Value-at-Risk (CAViaR) and time-varying parameter vector autoregression (TVP-VAR) connectedness approach. Analysing historical data between 01 January 2006 and 04 February 2024. The results show significant levels of connectedness for both negative and positive tail risks, highlighting the dynamic and interdependent nature of these markets. Notably, we identify asymmetries in the transmission of tail risks and their key drivers, including oil market volatility and global geopolitical risks. Our findings show that some regions play a pivotal role in the risk dynamics across the regions of the network and the influence of energy source diversity on risk profiles. The study underscores the complexity of managing the expected increase in tail risks in interconnected electricity markets, emphasizing the need for adaptive, forward-thinking strategies tailored to evolving global and local conditions.

## 1. Introduction

The electricity markets increasingly grapple with the inherent challenges of highly limited storage, inelastic demand, and supply constraints as energy transition deepens. Therefore, understanding the dynamics of risk transmission becomes paramount, especially in an interconnected framework where regional shocks can propagate with significant economic and operational implications (Pesaran and Pick, 2007; Newbery et al., 2016). This study presents an in-depth exploration of the tail risk spillover effects in the Australian National Electricity Market (NEM), using a Conditional Autoregressive Value at Risk (CAViaR) and Time-Varying Parameter Vector Autoregression (TVP-VAR) model to dissect the nuances of time-varying connectedness and its determinants.

Tail risk in the electricity market refers to extreme events—such as natural disasters, sudden fuel price changes, regulatory shifts, or technological failures—that can cause massive price spikes. Although infrequent, these events are increasing and can disproportionately impact market stability and the overall economy. Tail risk connectedness illustrates how these extreme risks are linked and transmitted across physically interconnected electricity markets like the NEM. For example, an extreme event in one market (like the 2016 tornadoes in South Australia that destroyed 23 transmission towers) can affect other regional markets.

However, a low level of connectedness isn't always desirable. While it might indicate resilience to localized shocks, it can also suggest a fragmented or dysfunctional system, undermining the goal of an integrated electricity market. Conversely, high connectedness isn't necessarily unfavourable. Although it can make the system more vulnerable to widespread disruptions from a single tail risk event, it also allows for rapid sharing of information and resources, enabling quicker responses to emerging risks. Therefore, understanding tail risks and their level of connectedness is crucial for effective risk management in electricity markets and for ensuring efficient operation of the entire system.

The NEM's unique structure, enabling electricity trade across five directly interconnected regions, offers a compelling case for studying interconnectedness and its impact on market stability and efficiency. While prior research has explored volatility spillovers, skewness, and

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kurtosis within the NEM (Clements et al., 2015; Manner et al., 2019; Do et al., 2020), these studies often lack a comprehensive analysis of tail risks and their asymmetric behaviour under different market conditions—such as during the COVID-19 pandemic, geopolitical tensions, and regulatory changes like market suspension and fuel price caps. By employing the CAViaR and TVP-VAR models, this paper aims to provide a detailed understanding of how extreme risks are transmitted across the NEM's interconnected regions, contributing to the literature on electricity market integration and risk management strategies.

Spillover effects refer to the impact that disturbances or crises in one region can exert on another through external connections (Diebold and Yilmaz, 2012). In financial contexts, these effects are predominantly marked by the spread of significant price fluctuations and volatility. In the electricity sector, analysing these spillover phenomena is crucial, particularly for entities engaged in multiple electricity markets, due to the associated risks of concurrent price surges and heightened volatility. Our study is centred on the Australian National Electricity Market (NEM), a cohesively integrated network with robust connections among its constituent regions.[1] It operates on a spot market basis, where the alignment of supply and demand in real-time establishes the pricing for each region. The NEM transitioned from a 30-min average to a 5-min single period settlement price since October 2021. The impact of this rule change on the transmission of tail risks also needs to be examined. Electricity transmission between these regions is facilitated by interconnectors, which are high-voltage lines linking neighbouring markets, enabling the importation of electricity from regions with lower prices to those with higher prices.

The examination of tail risk spillover effects garners significant interest within the Australian electricity markets. First, spot prices in the NEM are notably more volatile and prone to spikes than those observed in similar markets elsewhere (Higgs and Worthington, 2008; Mayer and Trück, 2018), with simultaneous occurrences of price spikes across various regions (Clements et al., 2015; Ignatieva and Trück, 2016). Therefore, scrutinizing tail risk spillovers could unveil deeper understanding into the mechanisms behind the spread of extreme price events. Moreover, an overarching goal of the NEM is to evolve into a unified market featuring consistent prices throughout the states (Australian Energy Market Commission, 2013). Second, the regions within the NEM remain somewhat segregated, as evidenced by notable price disparities across markets (Higgs, 2009; Apergis et al., 2017; Nepal and Foster, 2016; Do et al., 2020; Naeem et al., 2022). Concerns regarding potential underinvestment in interconnectors have been voiced, making the analysis of tail risk spillovers essential to evaluate the current effectiveness of market interconnections and the NEM's capacity for achieving broader integration (Ciarreta and Zarraga, 2015).

Building on this background, we examine the transmission of tail risk and its drivers across five Australian regional electricity markets from January 1, 2006, to February 4, 2024. We first employ the Conditional Autoregressive Value-at-Risk (CAViaR) model by Engle and Manganelli (2004) to measure daily positive and negative tail risks for each market. Then, we quantify tail risk spillover effects using the time-varying parameters vector autoregression (TVP-VAR) model from Antonakakis et al. (2020). The TVP-VAR approach offers advantages over traditional connectedness methods (Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012) by avoiding loss of observations and being insensitive to selected rolling windows. This method has been used in recent studies on energy market spillovers (Naeem and Arfaoui, 2023; Siddique et al., 2023; Wang et al., 2024). Using the estimated time-varying tail risk connectedness indices, we investigate the impacts of global risk factors and domestic determinants on tail risk transmission from 2006 to 2024. We carefully segment this period to analyse the drivers of connectedness during key crises, including the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict.

Our study yields several key results. First, the CAViaR model quantifies the magnitude of tail risk for each regional electricity market. Among the five markets, South Australia exhibits the highest levels of both positive and negative tail risk, while New South Wales shows the lowest levels. Second, we observe significant tail risk spillover effects across markets, with average negative and positive tail risk Total Connectedness Indices (TCIs) of 27.13 % and 29.97 %, respectively. This 11 % difference suggests an asymmetry in tail risk spillover within the NEM, indicating that positive tail risks are more interconnected than negative ones. Third, regarding the specific roles of each regional market in the tail risk network, Victoria and South Australia emerge as the most crucial net transmitters of both negative and positive tail risk over the sample period. Conversely, New South Wales and Tasmania are the primary absorbers of negative and positive tail risk, respectively.

Our time-varying analyses provide further insights into tail risk connectedness within Australian regional markets. We find that the magnitude of tail risk spillover effects is highly volatile over time, fluctuating between 10 % and 80 %. Notably, significant increases in both positive and negative tail risk TCIs occur during the middle of the COVID-19 pandemic and at the onset of the Russia-Ukraine conflict. Using the frequency connectedness approach by Baruník and Křehlík (2018) to decompose tail risk connectedness, we highlight that long-term spillover effects are the predominant drivers of overall connectedness.

Given that TCIs are time-varying, we investigate the determinants of tail risk spillover using a comprehensive set of explanatory variables. Over the full sample period, our results indicate that global uncertainties—such as crude oil volatility, global geopolitical risk, and risk aversion indicators—significantly impact tail risk connectedness. Additionally, the Australian term spread, reflecting the country's economic outlook, considerably influences the transmission of tail risk among regional electricity markets.

Our study contributes to the literature in several ways. First, we are the first to explore the dynamics of tail risk spillover effects among Australian regional electricity markets using the Conditional Autoregressive Value at Risk (CAViaR) model. Previous studies on the NEM have focused on volatility connectedness (Apergis et al., 2017; Han et al., 2020; Naeem et al., 2022), high-moment spillover effects (Do et al., 2020), and dependence structures (Higgs, 2009; Nepal and Foster, 2016; Apergis et al., 2020; Manner et al., 2019). Given the inherent volatility of Australian electricity prices (Higgs and Worthington, 2008; Mayer and Trück, 2018), examining tail risk spillover and its dynamics is essential. While Do et al. (2020) explored the transmission of extreme events (skewness) and their occurrence (kurtosis) within the NEM, our study advances this by using CAViaR to measure tail risk, providing a more nuanced and direct assessment of potential financial impacts. Specifically, our approach allows us to investigate both negative and positive tail risks, highlighting asymmetries in tail risk spillover. This precise quantification of worst-case financial outcomes under extreme market conditions offers actionable insights crucial for effective risk management and policy formulation.

Second, our research enhances understanding of tail risk connectedness in the NEM by examining the temporal evolution of connectedness indices. We uncover significant fluctuations in tail risk spillovers linked to NEM events like operational changes, regulatory updates, and external shocks. This analysis highlights the dynamic nature of risk spillovers and provides crucial insights into market interconnectedness over time. These findings are vital for energy sector stakeholders, aiding in the development of adaptive risk management strategies that can respond to evolving market risks and regulatory changes. Such strategies are particularly important in light of events like the introduction of the 5-min settlement rule and fuel price caps, which have significantly impacted market dynamics and risk perceptions.

Third, because existing literature rarely addresses the determinants

[1] The Australian Energy Regulator (2017) defines the National Electricity Market (NEM) as consisting of five regional markets: New South Wales (NSW), Queensland (QLD), South Australia (SA), Tasmania (TAS), and Victoria (VIC).

of interconnectedness, our research extensively analyses these factors over the sample and crisis periods. We find that global uncertainties—such as crude oil volatility, geopolitical risks, and risk aversion—significantly impact tail risk connectedness among Australian regional markets. This deepens our understanding of how external economic forces influence risk dynamics in interconnected electricity markets. Furthermore, our study reveals that the Australian term spread, a key domestic economic indicator, substantially affects tail risk transmission across regional markets. By highlighting the term spread as a barometer of the country's economic outlook, we illuminate the link between macroeconomic indicators and energy sector-specific risk factors. This underscores how national economic health shapes the risk landscape of sectoral markets, offering a novel perspective on the interconnectedness between broader economic conditions and sector-specific risk profiles.

Finally, our study sheds light on the drivers of tail risk connectedness during crises. By analysing global and domestic factors such as the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict, we identify elements that intensify risk transmission across Australian regional electricity markets. Our analysis reveals that crude oil volatility, global geopolitical risks, and changes in the national economic outlook—particularly term spreads—significantly elevate tail risk connectedness. This understanding enables policymakers and market operators to pinpoint vulnerabilities and tailor risk management strategies effectively, ensuring mitigation efforts are targeted and adaptive to evolving economic conditions. Thus, we contribute to the literature on energy market dynamics during crisis periods (e.g., Banerjee et al., 2024; Naeem and Arfaoui, 2023; Abdullah et al., 2023a, 2023b; Akyildirim et al., 2022).

The paper is structured as follows: Section 2 reviews the relevant literature. Section 3 outlines the methodology employed in this study. Section 4 presents the data. Section 5 discusses the empirical results derived from the analysis. Section 6 provides policy implications of the findings and concludes the paper.

## 2. Literature review

Established in 1998, the NEM is a wholesale electricity market covering the eastern and south-eastern states of Australia, including Queensland, New South Wales, the Australian Capital Territory, Victoria, South Australia, and Tasmania. It operates on a market-based system, facilitating the efficient generation, transmission, and distribution of electricity across the interconnected regional markets. Electricity markets within the NEM exhibit heightened volatility compared to other financial or commodity markets (Han et al., 2020; Evelyn Chanatásig-Niza et al., 2022). Han et al. (2020) emphasize the significance of physically interconnected markets in driving volatility spillovers and relate dynamic spillover patterns to specific short-term market events and long-term changes in renewable energy shares and regulatory mechanisms. Evelyn Chanatásig-Niza et al. (2022) highlight the importance of realized variances and covariances in accurately capturing volatility spillovers across different regions within the NEM.

Long-term structural changes—such as shifts in renewable energy shares, fuel mix compositions, and the implementation of regulatory mechanisms like the Carbon Pricing Mechanism, price settlement rules, or fuel price caps—significantly impact risk dynamics within the NEM (MacGill, 2010; Han et al., 2020; Ignatieva and Trück, 2016; Gonçalves and Menezes, 2022a, 2022b; Simshauser, 2023; Pourkhanali et al., 2024; Csereklyei and Khezr, 2024). MacGill (2010) discusses policy changes aimed at integrating wind power into the NEM and their implications for market dynamics. Ignatieva and Trück (2016) find positive price dependence between markets connected via interconnector lines, using copula models to capture dependence structures across regional electricity spot prices. Pourkhanali et al. (2024) discover that fuel price caps lowered wholesale electricity prices in Queensland and New South Wales but not in Victoria, highlighting the uneven efficacy of regulatory measures across different regions. Csereklyei and Khezr (2024) reveal that transitioning from a 30-min average to a 5-min settlement in October 2021 led to up to 4.9 % lower prices due to changes in strategic bidding behaviour.

Efforts to integrate the NEM face challenges in efficient resource allocation, network losses, and constraints across interregional interconnectors (Nepal and Foster, 2016; Apergis and Lau, 2015). Nepal and Foster (2016) analysed market integration using econometric techniques on daily electricity spot prices, highlighting significant network losses and interconnector constraints that hinder efficiency. Apergis and Lau (2015) investigated electricity price stability across Australian states, finding market instability due to structural breaks and carbon policy changes. Anderson et al. (2007) examined forward contracts and risk management practices in the Australian electricity market, revealing significant gaps between academic assumptions and actual market practices. Understanding contracting processes and risk management strategies is crucial for effective risk mitigation and market operation.

Recent studies have used advanced econometric and network analysis techniques to examine market dynamics within the NEM (Yan and Trück, 2020; Apergis et al., 2020; Do et al., 2020). Yan and Trück (2020) applied dynamic network analysis to regional spot electricity prices, uncovering significant dependencies among interconnected markets. Apergis et al. (2020) used regular vine copula techniques to explore the dependence structure of state-level electricity prices over different periods, enhancing understanding of risk management practices. Do et al. (2020) quantified the interconnectedness of higher moments within the NEM using a fractionally integrated VAR model. Together, these studies provide a comprehensive view of price interactions and risk dependencies, informing strategies for managing market volatility and enhancing stability.

While studies on NEM market dynamics cover volatility, risk transmission, policy changes, market integration challenges, forward contracts, and methodological advancements—offering valuable insights for enhancing market efficiency and stability—they have limitations that highlight the need for tail risk measures like the Conditional Autoregressive Value at Risk (CAViaR) model and dynamic connectedness techniques to fully quantify tail risk spillovers. Research by Han et al. (2020) and Evelyn Chanatásig-Niza et al. (2022) often fails to capture extreme tail events crucial for assessing market stability under severe conditions. Methods used by Anderson et al. (2007) and Apergis et al. (2020) may oversimplify interconnectedness, potentially underestimating tail risk connectedness. Do et al. (2020) utilize skewness and kurtosis to assess extreme events but do not directly quantify potential financial losses. In contrast, Value-at-Risk (VaR) provides actionable data by quantifying potential losses within specific confidence intervals and timeframes, aiding better decision-making in volatile markets. Furthermore, the literature lacks exploration into the determinants of tail risk connectedness—a gap this paper addresses by offering insights into the drivers of risk dynamics within the NEM. Addressing these limitations with advanced methodologies enables more accurate risk assessments and informs more effective risk management strategies for stakeholders.

## 3. Methodologies

### 3.1. Conditional autoregressive value-at-risk (CAViaR)

To quantify the time-varying value-at-risk (VAR) of the NEM, we employ the conditional autoregressive value-at-risk (CAViaR) model developed by Engle and Manganelli (2004). Unlike traditional approaches that estimate value-at-risk (VaR) by first deriving the distribution of returns and then inferring quantiles indirectly, the slope CAViaR method allows direct estimation of VaR and offers enhanced flexibility (Abdullah et al., 2023a, 2023b). This method also accounts for asymmetric effects, an important feature not accommodated by the symmetric absolute value method or the indirect GARCH(1,1) approach. Furthermore, the asymmetric slope CAViaR model imposes an autoregressive process on the VaR of a specific quantile, as described mathematically as

$$VaR_{\alpha,t}(\beta) = \beta_0 + \beta_1 VaR_{\alpha,t-1}(\beta) + \beta_2 x^{+}_{t-1} + \beta_3 x^{-}_{t-1} \tag{1}$$

where $VaR_{\alpha,t}$ denotes the VaR at the confidence level $(1-\alpha)$[2] in day $t$; $\beta_0$ is the intercept of the model; $\beta_1$ indicates the weights of lagged VaRs; $VaR_{\alpha,t-1}(\beta)$ represents lagged VaRs; and $\beta_2$ and $\beta_3$ show the impacts of positive and negative returns (i.e., $x^{+}_{t-1}$ and $x^{-}_{t-1}$) on the VaR, respectively.

### 3.2. TVP-VAR connectedness

To explore the dynamic transmission of tail risk among the Australian regional electricity markets, we employ the methodology outlined in Antonakakis et al. (2020). Antonakakis et al. (2020) propose a dynamic connectedness approach based on time-varying vector autoregressions (TVP-VAR) initially developed by Koop and Korobilis (2012). Compared to the traditional connectedness framework by Diebold and Yilmaz (2012), the results of TVP-VAR based connectedness approach are not influenced by the size of the rolling window. Furthermore, the TVP-VAR based connectedness framework does not cause loss of observations and is suitable for low frequency datasets. Given these advantages, this approach has been utilized in recent studies exploring the interconnectedness network in global financial markets (e.g., Bouri et al., 2021a, 2021b; Benlagha et al., 2022; Ali et al., 2023; Polat et al., 2024).

Based on the Bayesian Information Criterion (BIC), we utilize a stationary TVP-VAR(1), specified as follows,

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \varepsilon_t \sim N(0, S_t) \tag{2}$$

$$\beta_t = \beta_{t-1} + v_t v_t \sim N(0, R_t) \tag{3}$$

$$Y_t = A_t \varepsilon_{t-1} + \varepsilon_t \tag{4}$$

where $Y_t$ denotes $Nx1$ vector of negative or positive tail risks of Australian electricity markets, measured by the CAViaR model; $\varepsilon_t$ and $v_t$ are $Nx1$ vectors. $A_t$, $S_t$, $\beta_t$ and $R_t$ are $NxN$ matrices. Eq. (4) represents the Wold decomposition of the system, where the time-varying coefficients of the vector moving average (VMA) form the basis of the connectedness index. This index was introduced by Diebold and Yilmaz (2012) utilizing the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD), concepts further developed by Koop et al. (1996) and Pesaran and Shin (1998). The focus of our study is specifically on the h-step error variance in the forecast of variable $i$ that arises due to shocks to variable $j$, which is mathematically expressed as follows:

$$\widetilde{\varphi}^{g}_{ij,t} = \frac{\sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}}{\sum\limits_{i=1}^{N} \sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}} \tag{5}$$

with $\widetilde{\varphi}^{g}_{ij,t}$ denotes the h-step ahead GFEVD, $\Psi^{g}_{ij,t}(h) = S^{-1/2}_{ij,t} A_{h,t} \Sigma_t \varepsilon_{ij,t}$, $\Sigma_t$ is the covariance matrix for the error $\varepsilon_{ij,t}$ and $\sum_{j=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h) = 1$, $\sum_{i,j=1}^{N} \widetilde{\varphi}^{N}_{ij,t}(h) = N$.Utilizing the GFEVD, we construct the Total Connectedness Index (TCI) which quantifies the degree of interconnectedness across the network, as delineated by:

$$TCI^{g}_{h}(h) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)}{\sum\limits_{j=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)} x100 \tag{6}$$

Initially, we focus on the spillover effects from variable $i$ to all others,[3] which we define as the total directional connectedness to others, defined as follows:

$$DSI^{g}_{i\rightarrow j}(h) = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\varphi}^{g}_{ji,t}(h)}{\sum\limits_{j=1}^{N} \widetilde{\varphi}^{g}_{ji,t}(h)} x100 \tag{7}$$

Secondly, we calculate the spillover effects from all variables to variable $i$,[4] which is referred to as the total directional connectedness from others, specified as follows:

$$DSI^{g}_{j\rightarrow i}(h) = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)}{\sum\limits_{i=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)} x100 \tag{8}$$

Third, we determine the net spillover index (*NSI*) by calculating the differences between the total directional connectedness to others and from others. The *NSI* is defined as follows:

$$NSI^{g}_{i,t}(h) = DSI^{g}_{i\rightarrow j}(h) - DSI^{g}_{j\rightarrow i}(h) \tag{9}$$

The sign of the net spillover index indicates whether a variable acts as a net transmitter of shocks to network ($NSI^{g}_{i,t}(h) > 0$) or a net recipient of shocks from the network ($NSI^{g}_{i,t}(h) < 0$). This distinction helps in identifying the directional influence of the variable within the overall network dynamics.

## 4. Data and preliminary analysis

### 4.1. Sample and data

To explore the tail risk connectedness among Australia's regional electricity markets, daily data on price series for Victoria (VIC), South Australia (SA), New South Wales (NSW), Queensland (QLD), and Tasmania (TAS) were collected from the NEM website between 1st January 2006 and 4th February 2024. The research period is chosen based on data availability and covers significant events related to global economy and energy markets, such as the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine war. The daily market price data was transformed into log-differenced daily returns.[5] As Australian prices are subject to monthly seasonality (Naeem et al., 2022), we adjusted the daily log return for monthly seasonality using seasonal adjustment method of daily time series by Ollech (2021).

Fig. 1 illustrates the adjusted daily returns of the chosen markets, highlighting the substantial volatility of regional electricity markets, aligning with the findings of Han et al. (2020). Furthermore, these markets witnessed pronounced fluctuations between 2020 and 2024, a period marked by the COVID-19 pandemic and the onset of the conflict between Russia and Ukraine.

### 4.2. Descriptive statistics

Table 1 summarizes key statistics for the adjusted return series. Daily average returns for electricity prices vary across the states, with positive returns observed in New South Wales (NSW), Queensland (QLD), while negative returns are seen in South Australia (SA), Victoria (VIC), Tasmania (TA). South Australia (SA) has the lowest daily average return of

[2] In our study, $\alpha = 5\%$ is used for negative tail risk and $\alpha = 95\%$ is used for positive tail risk.

[3] The values of *To* row in the connectedness table presented in Section 5.

[4] The values of *From* column in connectedness tables presented in Section 5.

[5] The daily log returns are displayed in Appendix A1.

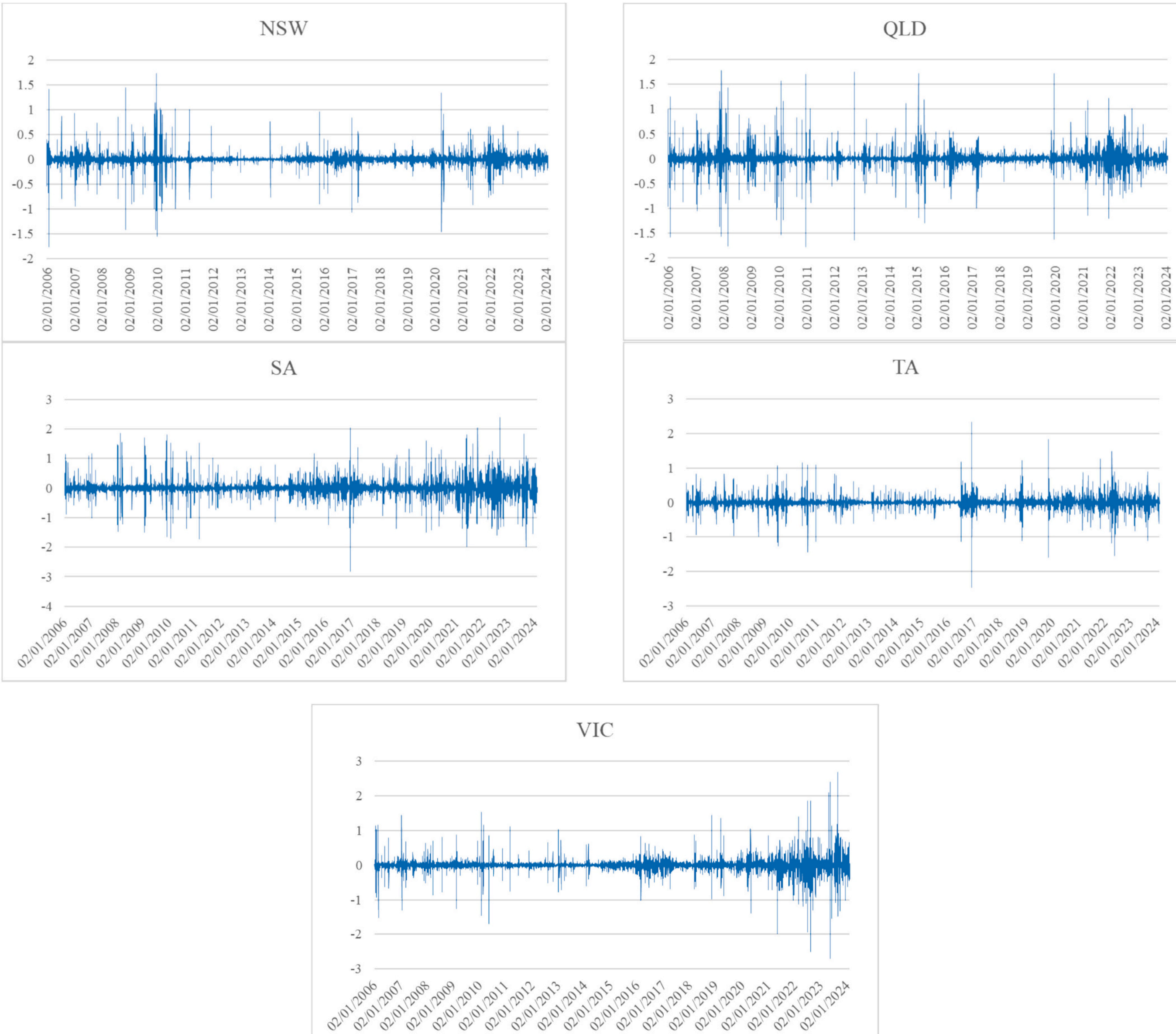



**Fig. 1.** Seasonally adjusted return series of electricity prices across Australian regions.
Note: This graph shows the seasonally adjusted return series of the selected regional electricity markets in Australia for the period between 01 January 2006 and 04 February 2024.

**Table 1**
Descriptive statistics of adjusted return series.

| | NSW | QLD | SA | VIC | TA |
|---|---|---|---|---|---|
| Mean | 0.0001 | 0.0001 | −0.005 | −0.001 | −0.003 |
| Variance | 0.018 | 0.03 | 0.074 | 0.028 | 0.04 |
| Skewness | −0.595 | −0.042 | −0.124 | −0.323 | −0.347 |
| Kurtosis | 40.496 | 29.395 | 14.166 | 30.816 | 36.865 |
| JB | 429478*** | 226093*** | 52526*** | 248590*** | 355744*** |
| ERS | −2.988*** | −11.012*** | −8.445*** | −22.306*** | −8.548*** |
| Q(10) | 529*** | 638*** | 106*** | 471*** | 205*** |
| Q(20) | 1033*** | 1074*** | 1318*** | 1391*** | 946*** |

Note: This table reports the descriptive statistics of seasonally adjusted daily return series of Australian regional electricity markets between January 01, 2006, to February 04, 2024. LB-Q(10) and LB-Q(20) represent the Ljung-Box Q-statistics up to the 10th and 20th order autocorrelation. Jarque-Bera statistics indicate the test for the normality of sample data. ERS test represent the Elliott et al. (1996) unit root test. *** denotes the cases where the null hypothesis of no autocorrelation (for LB Q test), and normal distribution (for JB test), and a presence of a unit root (for ERS test) is rejected at the 1 % significance level.

−0.005. Additionally, return variance reveals that South Australia (SA) exhibits the highest volatility. Tasmania (TA) and Queensland (QLD), show higher price volatility, while Victoria (VIC) and New South Wales (NSW) demonstrate the lowest volatility.

Table 1 shows that all regional markets exhibit a negative skewness, indicating a tendency towards extreme negative returns across the board. There is a noticeable variation in skewness across the markets, with substantial disparities. Moreover, the presence of high kurtosis values over 3 for each market highlights the frequent appearance of extreme returns, pointing to a leptokurtic distribution. This suggests the importance of implementing a tail risk connectedness approach for examining spillover effects in Australian regional markets. The diagnostic tests presented in the last four rows of Table 1 verify the non-normality, stationarity, and autocorrelation within the return series for the markets under study. The Jarque-Bera test outcomes refute the possibility of a normal distribution, while Elliott-Rothenberg-Stock (ERS) tests ascertain stationarity, and Ljung-Box Q statistics reveal significant autocorrelation at both 10 and 20 lags.

## 5. Empirical results and discussion

### 5.1. CAViaR estimation results

Based on the adjusted return series, we estimate the negative and positive tail risk using 95 % and 5 % Conditional Autoregressive Value-at-Risk (CAViaR) (Engle and Manganelli, 2004). The negative and positive tail risks of all return series are plotted in Figs. 2 and 3, respectively. The figures show a similar upsurge in tail risk during the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict, implying the magnifying impacts of these events on both negative and positive tail risk connectedness among Australian regional electricity markets.

Table 2, Panels A and B, detail the summary statistics for negative and positive tail risks, respectively, revealing significant insights into the tail risks within Australian regional electricity markets. Notably, South Australia (SA) exhibits the most pronounced tail risks among the markets analysed, with the highest negative and positive tail risks recorded at −0.312 and 0.324, respectively. This is followed closely by Victoria (VIC) with values of −0.201 for negative tail risk and 0.238 for positive tail risk. Conversely, New South Wales (NSW) shows the least tail risk across the periods studied, with −0.138 for negative tail risk and 0.141 for positive tail risk.

Furthermore, the variability of tail risk in SA, with variances of 0.061 for negative and 0.09 for positive tail risks, stands out when compared to other regions. This suggests a more pronounced fluctuation in tail risk within the South Australian market. Additionally, the skewness of the tail risk variables indicates that negative tail risks are generally negatively skewed, while positive tail risks tend to be positively skewed. The kurtosis values highlight that all tail risk measures exhibit a fat-tailed distribution, suggesting a higher likelihood of extreme outcomes. Lastly, the application of the Elliott-Rothenberg-Stock (ERS) unit-root test across all variables confirms their stationarity.

Figs. 4 reveals correlations in negative and positive tail risks within Australian regional markets. Fig. 4a shows that negative tail risks are positively correlated, indicating simultaneous movements across markets, but with varying strengths. The lowest correlations are between Tasmania (TA) and Queensland (QLD) at 0.06, and Tasmania (TA) and New South Wales (NSW) at 0.14. In contrast, the highest correlations are between Victoria (VIC) and South Australia (SA) at 0.56, and Victoria (VIC) and Tasmania (TA) at 0.35. Similarly, Fig. 4b shows linkages of positive tail risks, with the weakest correlation between Tasmania (TA) and Queensland (QLD) at 0.07, and the strongest between South Australia (SA) and Victoria (VIC) at 0.6. These varying correlation magnitudes across both negative and positive tail risks highlight the complex risk dynamics and interdependencies within Australia's regional electricity markets.

Estimating tail risk using the 5 % and 95 % Conditional Autoregressive Value-at-Risk (CAViaR) model highlights the urgent need to examine tail risk connectedness in Australian regional electricity markets, especially following global events like the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict. Our analysis reveals significant regional variations in risk exposure, with South Australia and Victoria notably more vulnerable, and intricate risk correlation patterns emphasizing the importance of understanding these dynamics. These findings underscore the necessity of adopting advanced risk management strategies to handle the complexities of tail risk connectedness. Strategies include dynamic hedging to adapt to market fluctuations and using tailored financial instruments like weather derivatives or catastrophe bonds to mitigate sector-specific risks such as natural disasters. Additionally, employing stress testing and scenario analysis can help utilities prepare for potential crises, while incorporating machine learning for predictive analytics enhances the detection and management of emerging risks.

### 5.2. Averaged tail risk connectedness

In this section, we employ the Time-Varying Parameter Vector Autoregression (TVP-VAR) approach to analyse the connectedness of tail risks within the Australian regional electricity markets over our sample period. The analysis, as detailed in Tables 3 and 4, reveals the average measures of connectedness for both negative and positive tail risks. The Total Connectedness Indices (TCIs) for negative and positive tail risks are found to be 27.13 % and 29.97 %, respectively. These results suggest a significant level of interconnectedness, where, on average, 27.13 % of a market's negative tail risk and 29.97 % of its positive tail risk can be attributed to historical variations in the tail risks of other markets in the network. This highlights the notable influence of past tail risk events across the markets, underscoring the importance of considering the dynamic and interdependent nature of risk factors in the regional electricity market landscape.

Total Connectedness Indices (TCIs) reveal an asymmetry in the transmission of positive and negative tail risks across the network. The TCI for positive tail risk is 29.87 %, about 11 % higher than the negative tail risk TCI at 27.13 %. This suggests that significant spikes in electricity prices are more readily transmitted throughout the network than significant drops. This asymmetrical transmission has important implications for risk management and policy formulation. It indicates that market infrastructure and regulations may more efficiently propagate upward price pressures rather than mitigate them, potentially leading to increased volatility and risk exposure during price surges. Understanding this asymmetry is crucial for developing balanced risk management strategies that address both sharp price increases and decreases. This insight underscores the need for targeted interventions and adaptive policies to ensure market stability and protect against the asymmetric propagation of tail risks.

The detailed analysis of tail risk connectedness among Australian regional electricity markets uncovers significant heterogeneity in the extent of spillover effects across different regions. Through Tables 3 and 4, it becomes evident that the interconnectedness of tail risks varies markedly from one market to another, indicating the asymmetrical impact of risk factors across the network. Specifically, Tasmania (TA) stands out for its lower level of connectedness within the network. Tables 3 and 4 quantitatively demonstrate this by showing that only 17.24 % (21.35 %) of Tasmania's negative (positive) tail risk is attributable to historical fluctuations in the negative tail risks of other markets. Furthermore, Tasmania's contribution to the network total negative (positive) tail risk is similarly modest, at 16.43 % (17.77 %). This suggests that Tasmania's market is relatively isolated in terms of negative tail risk spillovers, implying a degree of resilience or decoupling from broader market dynamics.

Tasmania's minimal dependency on fossil fuels significantly contributes to its lower connectivity with other Australian states regarding

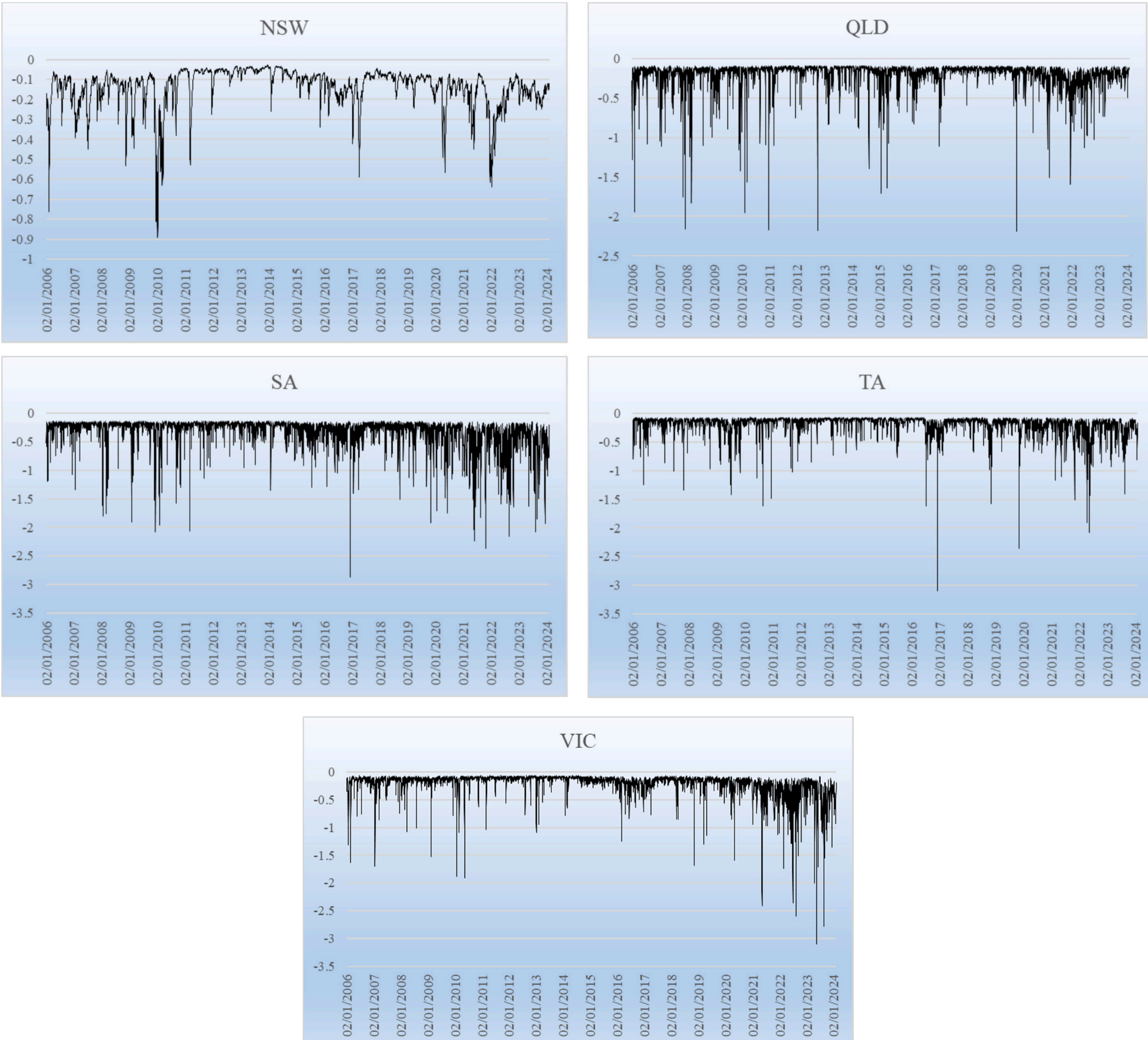



**Fig. 2.** Value-at-risk (5 %) (Negative tail risk) using CAViaR approach.
Note: This graph shows the time-varying negative tail risks of the selected regional electricity markets in Australia for the period between 01 January 2006 and 04 February 2024.

tail risk transmission in the energy market.[6] Tasmania's minimal reliance on fossil fuels contributes to its lower tail risk connectivity with other Australian states in the energy market, primarily due to its dependence on renewable hydropower. Firstly, Tasmania is insulated from global oil and gas price volatility caused by geopolitical tensions and supply disruptions. Regions reliant on fossil fuels are more exposed to these risks, but Tasmania's renewable infrastructure reduces its susceptibility to such economic shifts, lowering its tail risk interconnectedness with other regions. Secondly, hydropower offers stable and predictable energy generation, leading to fewer extreme price spikes or dips that could transmit tail risk to other states. In contrast, fossil fuel-dependent regions may experience abrupt cost increases when global fuel prices rise, resulting in higher tail risk spillovers due to synchronized price shocks. Lastly, Tasmania's geographic isolation and the limited capacity of the Basslink interconnector decouple its market dynamics from mainland Australia. While the interconnector facilitates energy trade, Tasmania's self-sufficiency reduces the need for substantial imports or exports, limiting its exposure to market fluctuations in other states and further reducing potential tail risk transmission.

Furthermore, the absence of a robust electricity futures market for Tasmania significantly contributes to its lower tail risk connectivity with other Australian states.[7] Unlike other regions, Tasmania lacks a well-developed platform for trading electricity futures and forward

[6] See Appendix 2A for the power generation by fuel sources of different Australian regions.

[7] In Australia, ASX Electricity Derivatives (including futures) are listed for trading on the Australian state regions of NSW, VIC, QLD and SA. See, https://www.asx.com.au/markets/trade-our-derivatives-market/overview/energy-derivatives/electricity

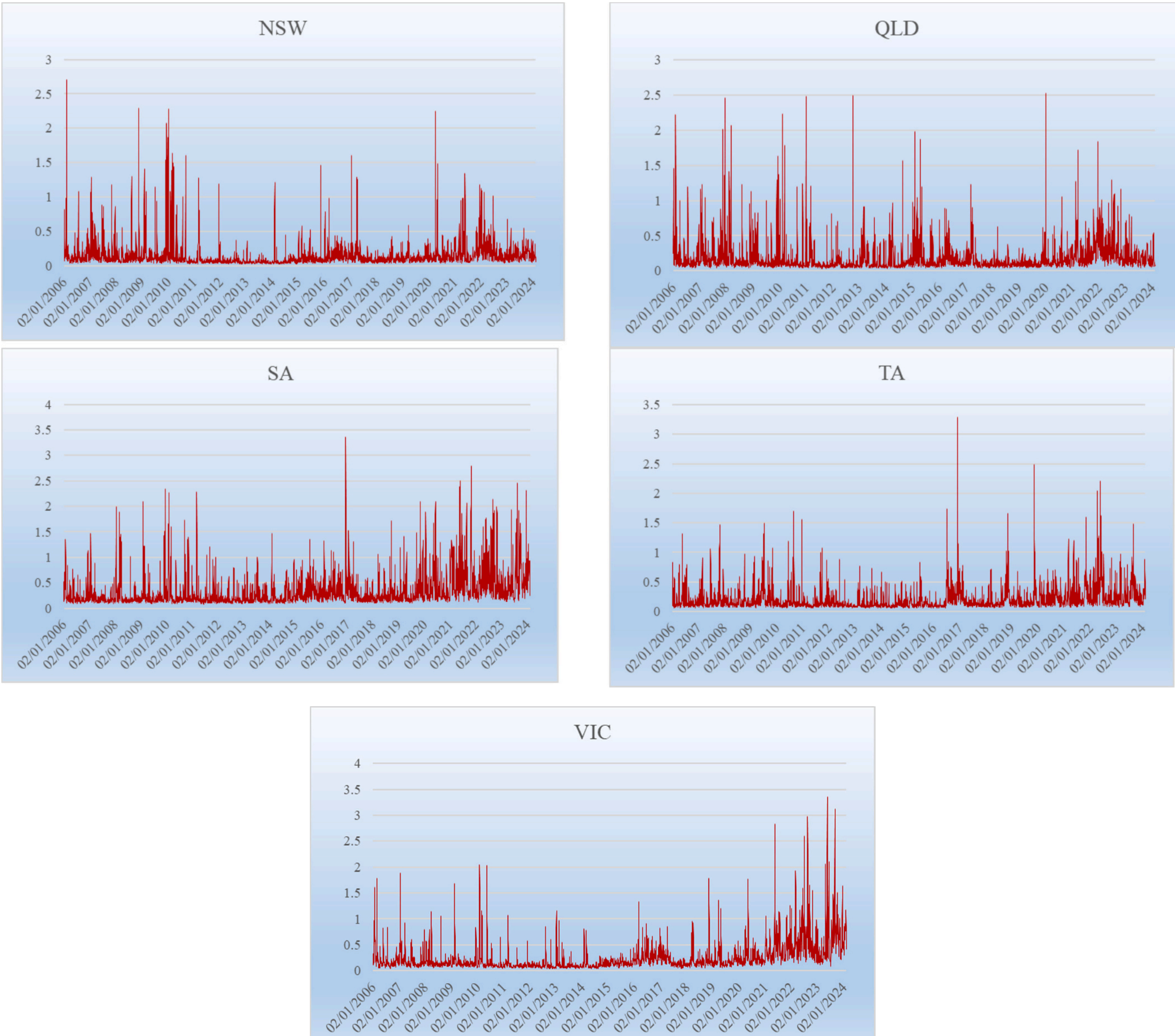



**Fig. 3.** Value-at-risk (95 %) (Positive tail risk) using CAViaR approach.
Note: This graph shows the time-varying positive tail risks of the selected regional electricity markets in Australia for the period between 01 January 2006 and 04 February 2024.

contracts. This deficiency limits the ability of market participants to hedge against future price fluctuations, reducing speculative trading and financial interconnectedness with other states.

In regions where electricity futures markets are active, such as Queensland, Victoria, and New South Wales, these financial instruments enable participants to manage risk by locking in prices for future delivery.[8] This activity not only facilitates greater liquidity but also fosters a network of financial relationships among market participants across different states. Consequently, any significant market event or price shock can propagate through these financial channels, increasing the likelihood of tail risk spillovers.

Tasmania's lack of an electricity futures market means that its energy transactions are predominantly confined to the spot market and long-term bilateral agreements. These arrangements are typically localized and involve fewer external parties, limiting the state's exposure to the broader national market's financial dynamics. The absence of forward contracts and hedging opportunities makes it less attractive for external retailers and generators to enter the Tasmanian market due to the higher risk associated with unhedged price volatility.

In stark contrast, Victoria (VIC) exhibits the highest degree of interconnectedness with the rest of the market network. According to Tables 3 and 4, a substantial 36.1 % (39.66 %) of Victoria's negative (positive) tail risk originates from other markets, and it contributes an even larger 40.26 % (42.43 %) to the network's aggregate negative (positive) tail risk. This prominent role underscores Victoria's significant influence on, and vulnerability to, the broader market's risk landscape. Other states such as New South Wales (NSW) and South Australia (SA) display high levels of integration in terms of negative tail risk spillovers. NSW, for instance, sees 34.89 % (33.85 %) of its negative tail risk stemming from the network, while contributing 27.1 % (34.09 %) back to it. SA's figures are similarly telling, with 27.88 % (32.25 %) of its negative (positive) tail risk coming from the network and a significant

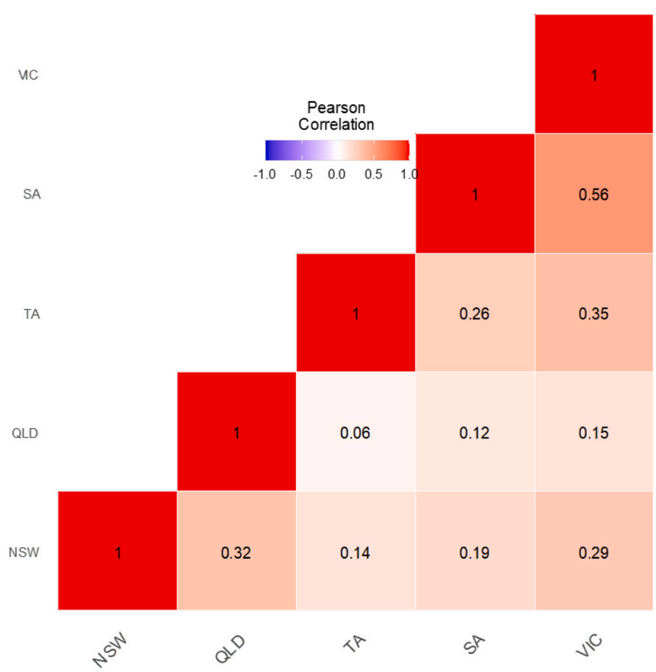
[8] See Australian Electricity Market Overview: Energy Derivative Financial Year 2023: https://www.asxenergy.com.au/products/electricity_futures

**Table 2**
Descriptive statistics of value-at-risk series.

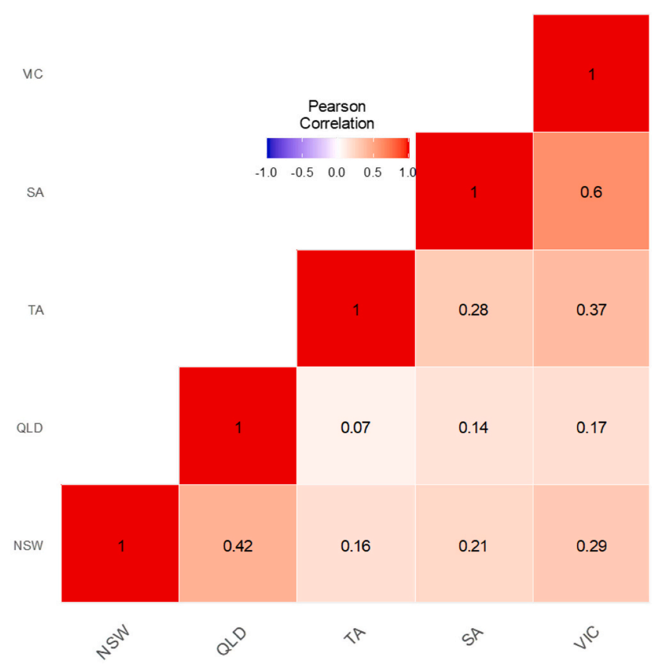
| Panel A. Negative tail risk (CAViaR 5 %) | | | | | |
|---|---|---|---|---|---|
| | NSW | QLD | SA | VIC | TA |
| Mean | −0.138 | −0.202 | −0.312 | −0.201 | −0.191 |
| Variance | 0.01 | 0.029 | 0.061 | 0.042 | 0.03 |
| Skewness | −2.45 | −4.63 | −3.34 | −4.74 | −4.47 |
| Kurtosis | 8.39 | 31.80 | 15.20 | 34.92 | 35.22 |
| JB | 24715*** | 287060*** | 72232*** | 342654*** | 345634*** |
| ERS | −8.472*** | −25.10*** | −19.46*** | −18.96*** | −17.63*** |
| Q(10) | 28868*** | 4879*** | 6085*** | 8008*** | 7446*** |
| Q(20) | 25671*** | 2162*** | 3581*** | 3125*** | 3257*** |

| Panel B. Positive tail risk (CAViaR 95 %) | | | | | |
|---|---|---|---|---|---|
| | NSW | QLD | SA | VIC | TA |
| Mean | 0.141 | 0.178 | 0.324 | 0.238 | 0.2 |
| Variance | 0.032 | 0.042 | 0.09 | 0.068 | 0.037 |
| Skewness | 5.197 | 4.369 | 3.031 | 3.837 | 4.204 |
| Kurtosis | 38.64 | 28.56 | 12.60 | 22.24 | 30.73 |
| JB | 419124*** | 233529*** | 51171*** | 144909*** | 265728*** |
| ERS | −23.09*** | −23.509*** | −19.88*** | −15.96*** | −19.38*** |
| Q(10) | 6887*** | 6011*** | 9357*** | 13985*** | 9267*** |
| Q(20) | 2868*** | 2432*** | 5427*** | 6617*** | 4202*** |

Note: This table reports the descriptive statistics of negative and positive tail risks of Australian regional electricity markets between January 01, 2006, to February 04, 2024. Negative and positive tail risks are computed based on the CAViaR model with the confidence level of 95 % ($\alpha = 5\%$) and 5% (($\alpha = 95\%$), respectively. LB-Q(10) and LB-Q(20) represent the Ljung-Box Q-statistics up to the 10th and 20th order autocorrelation. Jarque-Bera statistics indicate the test for the normality of sample data. ERS test represent the Elliot, Rothenberg, and Stock's (1996) unit root test. *** denotes the cases where the null hypothesis of no autocorrelation (for LB Q test), and normal distribution (for JB test), and a presence of a unit root (for ERS test) is rejected at the 1 % significance level.




*a. CAViAR (5%)*




*b. CAViaR (95%)*

**Fig. 4.** Correlation matrix of CAViAR.
Note: This graph shows the matrix of pair-wise Pearson correlation coefficients between the negative (positive) tail risks of the selected regional electricity market in Australia for the period between 01 January 2006 and 04 February 2024.

31.82 % (33.33 %) contribution to the network's total negative (positive) tail risk. These disparities in tail risk connectedness underscore the complex web of risk interdependencies within Australian regional electricity markets. Markets like VIC, NSW, and SA act as key nodes in the network's risk dynamics, significantly impacting the overall tail risk landscape due to their high degree of connectedness. Conversely, Tasmania's relatively isolated position regarding risk spillovers reveals unique characteristics and suggests different risk management needs within the network.

The results in Tables 3 and 4 highlight the intricate dynamics of

**Table 3**
Averaged connectedness table of negative tail risk.

| | NSW | QLD | SA | VIC | TA | *From* |
|---|---|---|---|---|---|---|
| NSW | 65.11 | 14.83 | 4.79 | 11.36 | 3.9 | 34.89 |
| QLD | 12.46 | 80.47 | 2.83 | 2.52 | 1.72 | 19.53 |
| SA | 3.39 | 1.86 | 72.12 | 18.66 | 3.97 | 27.88 |
| VIC | 8.1 | 1.96 | 19.2 | 63.9 | 6.84 | 36.1 |
| TA | 3.16 | 1.36 | 5 | 7.72 | 82.76 | 17.24 |
| *To* | 27.1 | 20.01 | 31.82 | 40.26 | 16.43 | |
| **NSI** | −7.78 | 0.48 | 3.95 | 4.17 | −0.81 | |
| **TCI** | 27.13 | | | | | |

Note: This table reports the averaged connectedness indices across the selected electricity markets, estimated based on TVP-VAR connectedness approach using negative tail risk series. NSI denotes Net Spillover Index. TCI indicates Total Connectedness Index.

**Table 4**
Averaged connectedness table of positive tail risk.

| | NSW | QLD | SA | VIC | TA | *From* |
|---|---|---|---|---|---|---|
| NSW | 66.15 | 14.06 | 5.06 | 10.98 | 3.76 | 33.85 |
| QLD | 13.92 | 77.26 | 3.45 | 3.33 | 2.05 | 22.74 |
| SA | 4.96 | 2.95 | 67.75 | 19.77 | 4.57 | 32.25 |
| VIC | 9.94 | 3.05 | 19.28 | 60.34 | 7.39 | 39.66 |
| TA | 5.26 | 2.19 | 5.55 | 8.35 | 78.65 | 21.35 |
| *To* | 34.09 | 22.24 | 33.33 | 42.43 | 17.77 | |
| **NSI** | 0.23 | −0.5 | 1.08 | 2.77 | −3.58 | |
| **TCI** | 29.97 | | | | | |

Note: This table reports the averaged connectedness indices across the selected electricity markets, estimated based on TVP-VAR connectedness approach using positive tail risk series. NSI denotes Net Spillover Index. TCI indicates Total Connectedness Index.

pairwise tail risk spillovers among Australian regional electricity markets, revealing significant variability in the strength of these connections across different states.[9] Understanding the underlying factors contributing to this variability is crucial for interpreting the risk landscape and developing targeted risk management strategies. The most notable relationship exists between South Australia (SA) and Victoria (VIC), where they exhibit the highest levels of mutual tail risk spillover. Historical data shows that Victoria's negative tail risk variations account for 18.66 % of SA's negative tail risk, with a reciprocal contribution of 19.2 % from SA to Victoria. For positive tail risks, 19.77 % of SA's positive tail risk is influenced by Victoria, and SA impacts Victoria's positive tail risk by 19.28 %. This significant two-way connection underscores a deep interdependency between these markets, which can be attributed to several key characteristics.

First, SA and VIC are physically interconnected through high-capacity transmission lines, notably the Heywood and Murraylink interconnectors. This physical connectivity allows substantial electricity flow between the two states, meaning that disruptions or shocks in one market can directly impact the other, leading to synchronized risk profiles. The ease of electricity transfer facilitates immediate responses to supply and demand fluctuations, making both markets highly sensitive to each other's operational conditions.

Second, both SA and VIC underwent early privatization of their electricity sectors—VIC between 1995 and 1997 and SA in 1999.[10] This shift introduced private ownership and a more commercially driven approach to electricity generation and supply, fostering competitive market environments. The competitive pressures may lead to similar investment decisions, pricing strategies, and risk management practices. As market participants in both states respond to comparable incentives and market signals, this can contribute to higher tail risk connectedness.

Third, both states have aggressive renewable energy targets and have integrated significant amounts of wind and solar power into their grids. This reliance on renewable energy sources, which are variable and weather-dependent, can introduce volatility into the electricity supply. Policy changes or external factors affecting renewable energy can simultaneously impact both states, amplifying the spillover of tail risks. For instance, a sudden drop in wind generation due to weather changes can affect supply levels in both markets, leading to price spikes and increased market stress.

Lastly, several energy companies operate in both SA and VIC, meaning that financial or operational issues within these companies can affect both markets.[11] Corporate strategies, investment decisions, and risk exposures are thus more likely to have cross-border impacts. If a major energy provider faces financial difficulties, the repercussions can resonate in both states, influencing market confidence and stability.

The interaction between New South Wales (NSW) and Queensland (QLD) also demonstrates significant cross-market tail risk transmission, albeit to a lesser extent than the SA-VIC pair. Negative tail risk spillovers from NSW influence QLD's risk profile by 12.46 %, with QLD reciprocating at 14.83 %. For positive tail risks, NSW contributes 13.92 % to QLD, and QLD impacts NSW by 14.06 %. Factors contributing to this risk transmission include their reliance on similar energy sources. Both states heavily depend on black coal for electricity generation, alongside substantial investments in rooftop solar and large-scale solar farms. Shared exposure to coal price fluctuations, supply chain disruptions, and solar generation variability due to weather conditions can lead to synchronized risk profiles.[12]

Additionally, NSW and QLD are connected through the Queensland–New South Wales Interconnector (QNI), facilitating electricity flow between the states. This interconnection allows market shocks or stresses in one state to propagate to the other. Operating under comparable regulatory frameworks and market rules within the National Electricity Market (NEM), both states may respond similarly to policy changes, affecting market stability and risk. For example, a policy shift affecting coal-fired power stations could simultaneously impact electricity prices and supply in both NSW and QLD.

In contrast, the lowest levels of tail risk transmission are found between QLD and other states such as TAS, SA, and VIC. These interactions exhibit minimal tail risk spillover, indicating a degree of isolation or decoupling. Reasons for this reduced interconnectedness include geographical separation and limited physical interconnections. QLD is geographically distant from SA and TAS, with no direct transmission lines connecting them. The absence of physical interconnections means that electricity cannot flow directly between these states, reducing the potential for immediate risk spillovers.

Moreover, differing energy mixes contribute to this decoupling. TAS is predominantly reliant on hydroelectric power and thus has an energy profile that is less susceptible to the same risks affecting QLD's coal and solar-based generation. SA and VIC, with higher proportions of wind and solar energy, face different operational challenges and market dynamics compared to QLD. Variations in state-specific regulations, renewable energy targets, and market incentives can lead to differing market behaviours. For instance, TAS operates under unique hydrological conditions affecting hydroelectric generation, which are not directly related to the coal and solar dynamics in QLD. Furthermore, fewer energy

[9] The off-diagonal elements for each column represent pairwise spillover to other variables, and the off-diagonal elements for each row represent pairwise spillover received from other variables. Pairwise spillover indicates how a shock causes many variations in the row variable's forecast error to the column variable.

[10] Victoria and South Australia are the only regions where electricity networks are 100 % privately owned. Source: https://www.energynetworks.com.au/resources/fact-sheets/guide-to-australias-energy-networks/

[11] For example, the "big three", including Origin Energy, AGL Energy and EnergyAustralia, are major electricity companies in both SA and VIC.

[12] See Appendix A2 for power generation by fuel sources in Australian regions.

companies operate across these state pairs, reducing the likelihood of corporate-level risks spilling over between markets.[13] The lack of overlapping market participants means that financial or operational issues are more contained within individual states, limiting cross-border impacts.

Fig. 5 visualizes the tail risk connectedness across Australian electricity markets, with Fig. 6a and b depicting networks for negative and positive tail risks, respectively. Node size reflects each market's overall contribution to net tail risk spillovers within the network. Node colour differentiates market roles: dark blue indicates net transmitters of shocks, while yellow represents net recipients. In Fig. 5a, Victoria (VIC), South Australia (SA), and Queensland (QLD) are key net transmitters of negative tail risk within the network, with VIC being the most influential, followed by SA. Conversely, New South Wales (NSW) and Tasmania (TA) are primary net recipients, with NSW serving as the main absorber of negative tail risk. The graphical representation highlights strong risk transmission channels between VIC and SA, and between NSW and QLD, confirming earlier analyses.

Transitioning to positive tail risk dynamics in Fig. 5b, a shift in roles among regional markets becomes apparent under the influence of extreme positive shocks. NSW, for instance, reverses its stance to become a net distributor of positive tail risks, marking a significant deviation from its previous position as a net recipient. Conversely, QLD shifts towards becoming a net recipient, diverging from its role as a transmitter. Remarkably, Tasmania (TA) assumes the position of the most pronounced net receiver of positive tail risks within this context. Consistently, VIC maintains its role as the foremost distributor of positive tail risks, underscoring its critical influence across both spectrums of tail risk connectedness.

This persistent role of Victoria (VIC) as the most crucial net transmitter of both negative and positive tail risks can be linked to its highly liquid electricity futures market.[14] The liquidity in VIC's futures market attracts a diverse array of market participants, including generators, retailers, and financial institutions, who engage in active trading and hedging activities. This vibrant trading environment not only facilitates efficient price discovery and risk management but also enhances the transmission of shocks—both adverse and favourable—throughout the National Electricity Market (NEM). The abundance of futures contracts allows participants to swiftly adjust their positions in response to market developments, which can amplify the spread of tail risks to other regions.

### 5.3. Dynamics of tail risk connectedness

Building on our previous analysis of averaged tail risk connectedness in Australian regional electricity markets, we now examine their dynamics over time. Fig. 6 illustrates the dynamic Total Connectedness Indices (TCIs) for negative and positive tail risks within the National Electricity Market (NEM), depicted by blue and orange lines, respectively. The TCIs are highly variable, diverging from the average levels of 27.13 % (negative) and 29.97 % (positive), and fluctuate between approximately 13 % and 77 % over the observed period, starting at about 55 % in January 2006. This wide range indicates substantial volatility in the market's risk environment. Key observations include a general synchronicity in the movement of the indices, suggesting that both types of tail risks often mirror each other's behaviour, reflecting a cohesive risk landscape within the NEM. However, notable divergences occur during periods like 2012 to 2018 and early 2021, where the gap between positive and negative TCIs widens. These intervals highlight times of heightened differentiation in market sentiment or external influences that affect the perception and manifestation of risk differently.

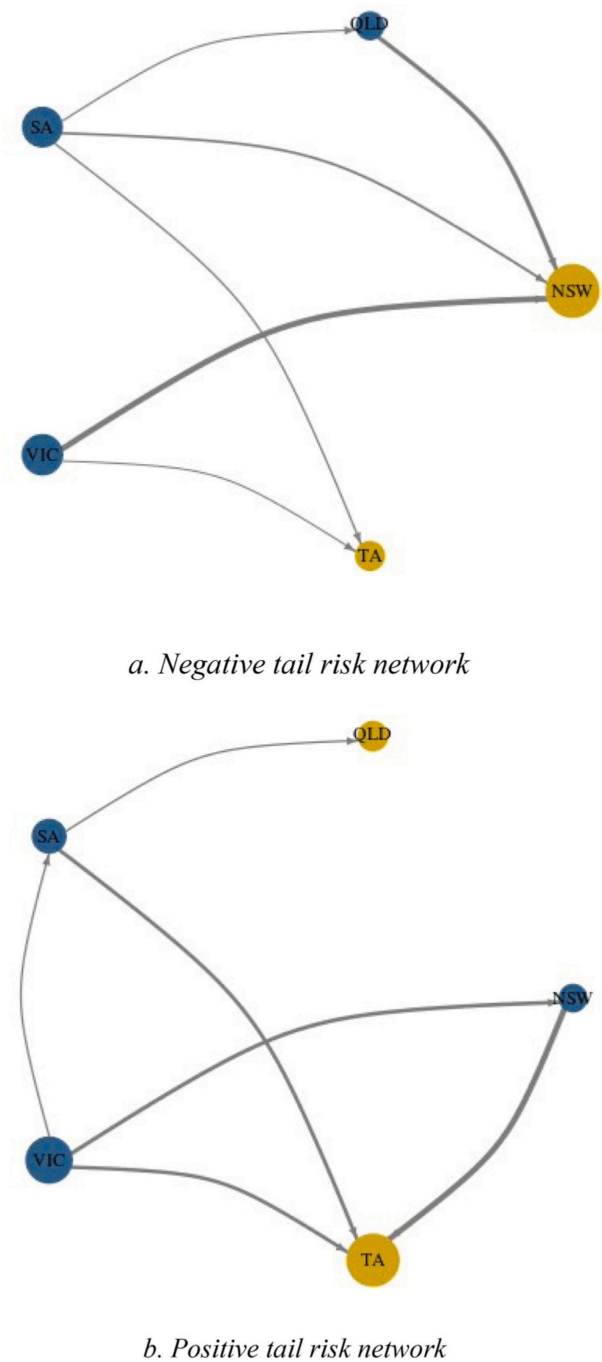



**Fig. 5.** Networks of tail risk connectedness.
Note: These graphs illustrate the network connectedness across the selected electricity markets. Fig. 5a and b describes the network connectedness for negative and positive tail risks, respectively. The node colour represents the role of net transmitter (dark blue)/ receiver (yellow) of tail risks. The node size is determined by the magnitude of the net tail risk spillover of each asset. The thickness of the arrow edge indicates the strength of pairwise directional spillover. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[13] For instance, AGL Energy has substantial generation assets and retail operations in New South Wales (NSW), Victoria (VIC), and South Australia (SA), but its presence in QLD is more focused on retail, with minimal generation assets, and it has little to no operations in TAS. See, chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.agl.com.au/content/dam/digital/agl/documents/about-agl/investors/2022/220819-agl-energy-annual-report-2022.pdf.

[14] Trading volume of electricity futures in Queensland was the highest among regional states. See, https://www.aer.gov.au/industry/registers/charts/quarterly-base-futures-prices-and-volume-traded.

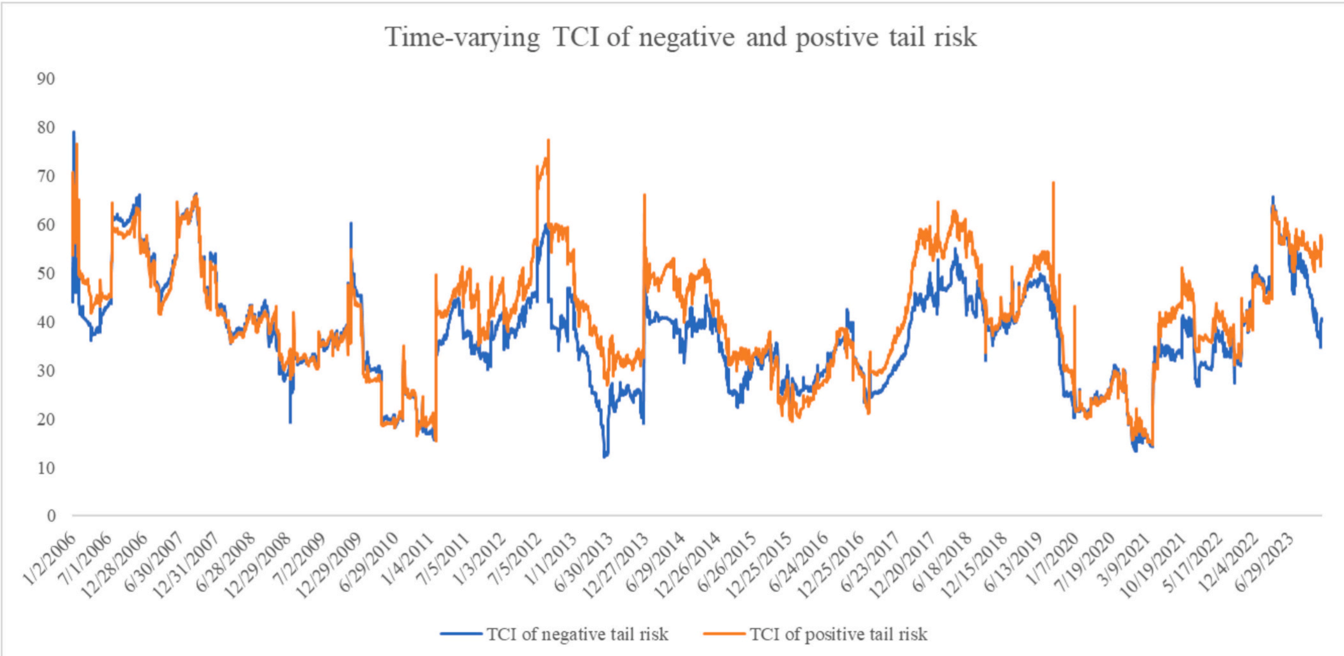



**Fig. 6.** Time-varying connectedness index of negative and positive tail risks.
Note: This figure shows the time-varying Total Connectedness Index (TCI) for negative (blue) and positive (orange) tail risks, during the research period.

Outside these periods, the distinctions between positive and negative tail risks diminish, indicating a return to a more uniform risk transmission profile.

In addition, the analysis of the time-varying TCIs reveals that fluctuations in the connectedness indices are intricately linked to a myriad of domestic and international occurrences. Specifically, events that are unique to a country—highlighted by the Australia Energy Regulator as involving unusually high demands for energy, bottlenecks in interconnector capacities, or significant power generation shortfalls—have a pronounced effect on these indices.[15] Examination of spillover plots distinctly shows a reactive pattern where the TCIs exhibit noticeable surges in response to these critical market events. This reaction signals an amplified risk of simultaneous significant price fluctuations in various regional electricity markets, indicating a heightened state of inter-market interconnectedness. Instances like the pronounced TCI spikes at the end of 2009, which corresponded with operational challenges and strategic bidding by generators in New South Wales (NSW), exemplify this correlation. Similarly, the elevated TCI levels witnessed in the early part of 2023 can be attributed to key events such as the negative weekly pricing in Victoria (VIC) or the phasing out of Liddell from the NEM operations.[16]

Two recent regulatory changes within the National Electricity Market (NEM)—namely, the 5-min settlement rule implemented in October 2021 and the introduction of fuel price caps in December 2022—have triggered noticeable responses in the time-varying Total Connectedness Index (TCI) for negative and positive tail risks. The 5-min settlement rule was introduced to enhance market efficiency by aligning the financial settlement interval with the operational dispatch interval, aiming for more accurate price signals and improved market performance. The fuel price caps were introduced to mitigate the impact of escalating fuel costs on electricity prices, aiming to protect consumers and ensure stability within the market.

The implementation of the 5-min settlement rule significantly impacted both negative and positive tail risk TCIs. Initially, the negative tail risk TCI rose due to uncertainty as market participants adapted to the new mechanism, indicating heightened volatility. Over time, it stabilized as confidence improved and volatility reduced. The positive tail risk TCI also saw an immediate increase as participants exploited more precise price signals for gains, followed by a gradual decline as the market adjusted and initial opportunities diminished.

The introduction of fuel price caps in December 2022 led to significant changes in both TCIs. Contrary to expectations, the negative tail risk TCI sharply increased due to concerns over potential supply constraints and market distortions from capped prices, leading to heightened uncertainty and volatility. Simultaneously, the positive tail risk TCI also increased, indicating that participants found new opportunities for gains within the constrained price environment. The sustained elevation suggests participants effectively navigated the new regulatory landscape, adjusting strategies to capitalize on the new conditions.

In summary, regulatory changes within the NEM, specifically the 5-min settlement rule and fuel price caps, have had distinct impacts on negative and positive tail risk TCIs. The 5-min settlement rule initially increased volatility but eventually led to a more stable market as participants adapted. Conversely, fuel price caps resulted in an immediate and sustained increase in both tail risk TCIs, highlighting complex market responses to such interventions. These developments underscore the dynamic nature of the NEM and the need for continuous monitoring and adaptation to regulatory changes to understand and manage evolving market risks.

Extending beyond the confines of domestic market incidents, the analysis also draws attention to the global landscape, where significant international crises have left their mark on the energy markets. Events of global magnitude, including the Global Financial Crisis (GFC), the sweeping COVID-19 pandemic, and the tumultuous Russia-Ukraine conflict, are mirrored in the fluctuations observed in the TCI readings. These periods are characterized by noticeably elevated TCIs, which are indicative of the far-reaching impacts these crises have had on the

[15] The full list of critical events in the NEM from 2006 to 2023 is synthetized from the State of Energy Market reports issued by Australia Energy Regulator from 2006 to 2023. It is presented in Appendix AX.

[16] Australia Gas Light Company (AGL) closed Liddell Power Station, a large coal-burning power stations in April 2023. This closure has pushed up energy prices in Australia. Source: https://reneweconomy.com.au/energy-oligopoly-turns-screws-on-customers-after-liddell-exit-and-renewable-pause/.

dynamics of energy supply, demand, and pricing. The GFC, despite not plunging the Australian economy into a recession, had far-reaching negative effects across various sectors, including the pivotal energy sector.[17] The narrative further unfolds with the onset of the COVID-19 pandemic and the Russia-Ukraine conflict, during which there was a pronounced intensification in the transmission of tail risk, evidenced by a sharp rise in TCIs during the second quarter of 2021, coinciding with a surge in COVID-19 cases and the implementation of lockdown measures by regional governments.[18] The early stages of 2022, marked by the escalation of the Russia-Ukraine war, also saw TCI levels remaining at elevated levels, highlighting the significant disruption caused by geopolitical conflicts on global energy markets and, by extension, the transmission of tail risk within the NEM.

Overall, the analysis of time-varying TCIs highlights the NEM's vulnerability to tail risk transmission due to shifts in local market conditions and global geopolitical and economic factors. This examination underscores the NEM's sensitivity to various disturbances and illuminates the complex interplay governing its risk dynamics. It emphasizes the necessity for adaptive, forward-thinking risk management strategies, urging stakeholders to consider a wide spectrum of potential impacts.

Our analysis extends to the dynamic net spillover indices across regional markets within the NEM. Fig. 7 illustrates temporal fluctuations of total net spillover indices for each of the five regions, corresponding to the "NSI" row from Tables 3 and 4. This visualization yields several key insights. Firstly, the intensity and flow of net tail risk spillovers are dynamic and vary over time. For instance, while average connectedness analysis shows Victoria (VIC) predominantly as a net source of both negative and positive tail risks, the time-varying plot reveals that VIC alternates between being a net recipient and a net distributor. This shifting role is consistent across all regions, highlighting the fluid nature of risk transmission within the NEM and underscoring the critical role each state plays in both distributing and absorbing tail risk spillovers, emphasizing the network's interconnectedness and mutual reliance. Secondly, despite short-term variances between the net spillover indices (NSIs) for negative and positive tail risks, there is a noticeable alignment in their long-term trends. This alignment suggests a deeper structural similarity in how these tail risks are assimilated across the network over time. It indicates that, despite immediate differences in responses to specific risk types, the regional markets within the NEM eventually converge towards a unified approach in handling both negative and positive risk spillovers.

### 5.4. Frequency decomposition of tail risk connectedness

To deepen our understanding of how tail risk is transmitted among Australian regional electricity markets across various time scales, we employ the frequency connectedness approach by Baruník and Křehlík (2018). This method enables us to dissect the time-varying total connectedness indices (TCI) depicted in Fig. 6 into distinct time horizons, specifically targeting short-, medium-, and long-term effects. The resulting analysis, illustrated in Fig. 8, categorizes these effects into periods of 1 day for short-term, 2 to 5 days for medium-term, and over 5 days for long-term connectedness. This frequency-domain connectedness analysis is crucial as it reveals the dynamics of tail risk spillover across different temporal scales, providing insights into the persistence and propagation of risks within the market. Understanding these temporal dynamics is essential for developing suitable risk management strategies that are effective at mitigating impacts over varying durations, thereby enhancing the resilience of the electricity market infrastructure against potential disruptions.

Fig. 8 delineates the time-frequency analysis of the Total Connectedness Indices (TCI) for negative and positive tail risks across Australian regional electricity markets, as shown in panels A and B respectively. This analysis yields several notable observations that enrich our understanding of the dynamics of tail risk connectedness. Primarily, it is observed that the long-term TCI consistently represents the largest component of the total TCI, suggesting that the spillover of tail risk has a more pronounced and sustained impact over longer durations (e.g., longer than a week). This is followed by medium-term TCI, with short-term TCI contributing the least. This pattern persists throughout the entire research period, highlighting a characteristic tendency for risks in these markets to be more deeply interconnected over extended periods rather than day-to-day fluctuations.

Moreover, the analysis reveals that long-term TCI exhibits the highest level of volatility, oscillating significantly over the observed period. Specifically, for negative tail risks (Fig. 8a), the long-term TCI fluctuates between 5 and 45, while for positive tail risks (Fig. 8b), it ranges from 7 to 57. This volatility underscores the variable nature of long-term risk transmission across Australian regional electricity markets, likely influenced by broader economic cycles, policy changes, or significant external events. In contrast, the medium-term TCI exhibits less volatility, with values ranging between 1.5 (1) and 15 (19) for negative (positive) tail risks, suggesting a moderate level of fluctuation that reflects more transient market conditions. The short-term TCI shows the least variability, ranging from 0.3 (0.1) to 5 (4.5) for negative (positive) tail risks, indicating that immediate tail risk spillover effects are relatively minor and less impactful on the overall risk landscape.

These observations indicate that tail risk connectedness in Australian regional electricity markets varies significantly across time horizons and market conditions. The predominance and volatility of long-term connectedness highlight the importance of structural market characteristics and external economic influences. Policymakers and market operators must adopt long-term strategic planning and risk management to address prolonged risk exposures, while also implementing responsive practices for shorter-term spillovers. A dynamic, comprehensive risk management approach across various time scales is essential to ensure the resilience and stability of the electricity market against both immediate and prolonged challenges, supporting efficient operation and sustainable development amid evolving conditions.

### 5.5. Drivers of the connectedness indices

#### 5.5.1. Analysis for the whole sample period

Given the observed significant fluctuations and volatility in tail risk connectedness measures, it's imperative for participants in the NEM to closely monitor their tail risk through these pivotal drivers. To delineate the factors influencing these connectedness indices, we implement the model as outlined below:

$$TCI_t = \beta + \gamma X_{t-1} + \varepsilon_t \tag{10}$$

where $TCI_t$ is the dynamic total connectedness index (TCI), which is computed for the negative and positive tail risks; $\beta$ denotes the intercept; $\varepsilon_t$ represents the error term; and $X_{t-1}$ demonstrates a vector of five explanatory variables.

[17] Numerous effects of the Global Financial Crisis (GFC) on Australia's economy have been recorded. These include a significant depreciation of the Australian dollar, dropping from 0.98 USD in July 2008 to 0.6 USD by October 2008. Additionally, there was a sharp decline in the total value of household assets, ranging between 13 % and 14 %. The period also saw a reduction in household consumption and a rise in unemployment rates. Source: https://www.aph.gov.au/binaries/house/committee/itrdlg/financialcrisis/report/gfc%20final%20report.pdf.

[18] Victoria announced a state-wide lockdown on 26 May 2021, followed by Greater Sydney and parts of New South Wales on 25 June 2021, Greater Melbourne and parts of Victoria on 15 July 2021. Source: https://www.aph.gov.au/Parliamentary_Business/Committees/Senate/COVID-19/COVID19/Report/section?id=committees%2Freportsen%2F024920%2F79485.

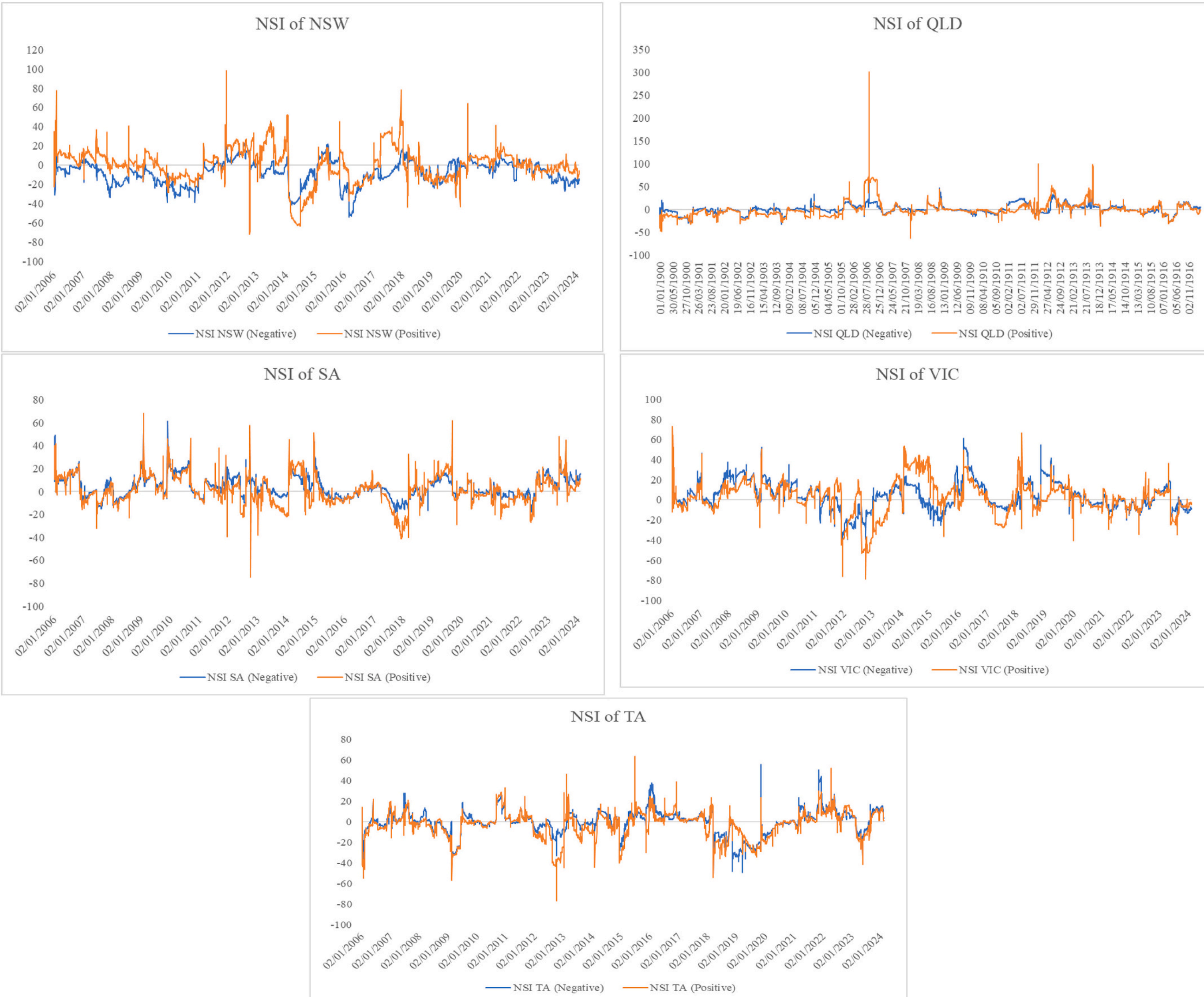


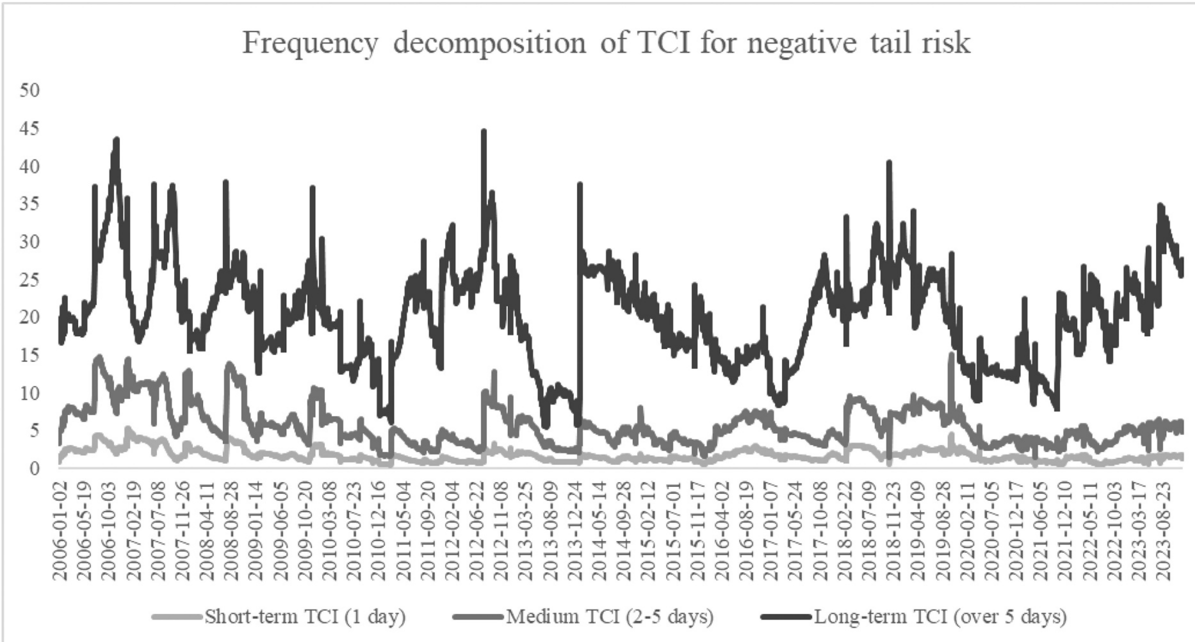

**Fig. 7.** Net Spillover Index of Tail Risks.
Note: This figure shows the time-varying Net spillover index (NSI) of each regional market, during the research period with blue (orange) line indicates the NSI for negative (positive) tail risk. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The explanatory variables include daily frequency of both country-specific factors and global determinants. They are: (1) the implied volatility of the crude oil market measured by the CBOE[19] Crude Oil Volatility Index (*OVX*); (2) the index of global geopolitical risk (GOPRX), developed by Caldara and Iacoviello (2022); (3) the risk aversion index (RAI) as a sentiment indicator (Bekaert et al., 2022); (4) the implied volatility of the Australian stock market measured by the S&P/ASX 200 VIX (*ASV*); and the Australian term spread as the difference between the yield of Australian 10-year Treasury note and that of the 2-year Treasury note (*TERMSPR*).[20]

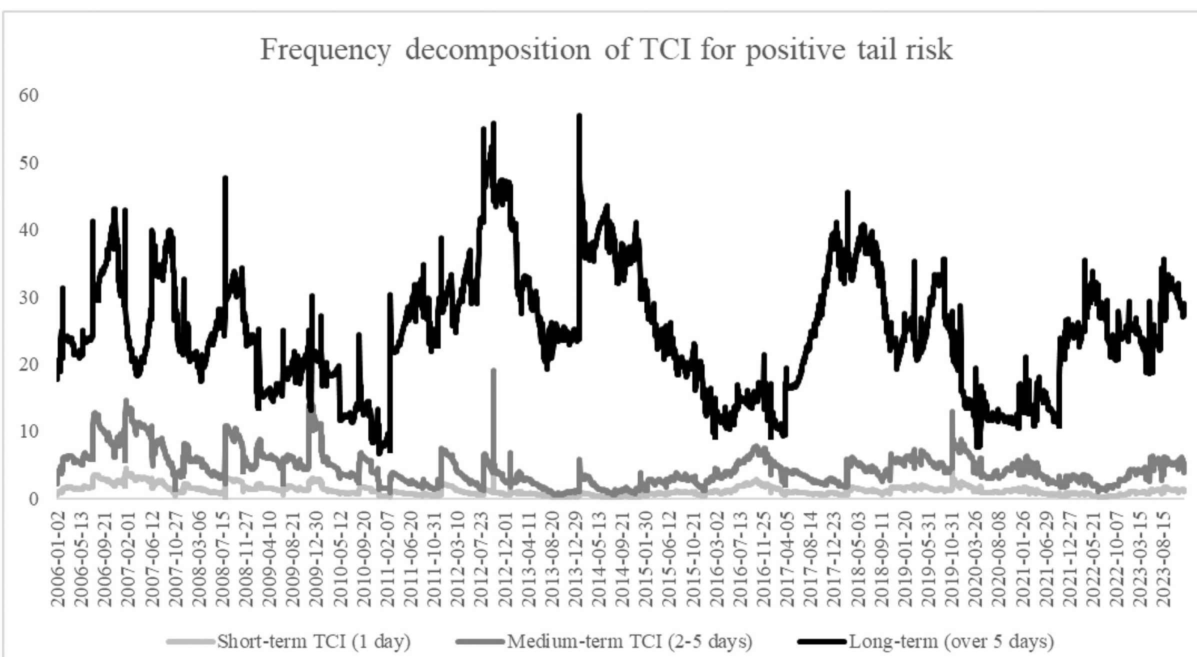
Research has identified key variables affecting volatility and interconnectedness in energy and electricity markets, particularly global uncertainties (Karali and Ramirez, 2014; Dutta et al., 2020; Abdullah et al., 2023a, 2023b). The implied volatility of crude oil (OVX) is crucial for forecasting oil market volatility and serves as a general indicator of uncertainty in energy markets. Dutta et al. (2020) note that energy market uncertainty increases with higher OVX levels, and Zhang et al. (2023) show that rising OVX strengthens connections between clean energy, electricity, and energy metals. Gong and Xu (2022) find that global geopolitical risks (GOPRX) significantly enhance linkages among commodities. The Risk Aversion Index (RAI), a global sentiment measure recognised by Bekaert et al. (2022), is positively associated with risk connectedness in European electricity markets (Abdullah et al., 2023a, 2023b). These global uncertainty indices are expected to similarly influence tail risk connectedness across Australian regional markets.

In addition to global factors, our model in Eq. (10) includes two country-specific macroeconomic variables: the implied volatility of the Australian stock market (ASV), identified by Tang and Yan (2010) as reflecting the broader business climate, and the term spread (TERMSPR), the slope of the Australian government yield curve, a critical economic indicator. Positive term spreads generally indicate economic expansion, while negative spreads signal potential downturns. Given the strong correlation between electricity demand and economic performance (Stern, 1993; Lorde et al., 2010; Gurgul and Lach, 2012), shifts in economic conditions can significantly influence market

[19] Chicago Board Options Exchange (CBOE).
[20] We use logarithmic forms of OVX, GOPRX, RAI, and ASV.




*a. Frequency decomposition of TCI for negative tail risk*




*b. Frequency decomposition of TCI for positive tail risk*

**Fig. 8.** Time-frequency decomposition of TCI.

dynamics, affecting demand, pricing, and volatility. Monitoring economic indicators is thus essential for anticipating and managing potential impacts on the electricity market. Karali and Ramirez (2014) also reveal that energy commodities tend to experience increased volatility as the term spread contracts, highlighting the interconnectedness of economic indicators with energy market behaviour.

We apply Ordinary Least Squares (OLS) estimation to Eq. (10)

following Bouri et al. (2021a, 2021b), Ji et al. (2019), Tan et al. (2020), Abdullah et al. (2023a, 2023b).[21] The results, adjusted for heteroscedasticity using Newey and West's (1987) robust standard errors, are detailed in Table 5, offering noteworthy insights into the dynamics of tail risk transmission. Overall, the significant adjusted R-squared values, which range from 13.01 % for the TCI of negative tail risk to 17.71 % for the TCI of positive tail risk, underscore the explanatory power of the independent variables in accounting for TCI fluctuations. The robust F-statistics further validate the model's selection of independent variables.

For positive tail risk connectedness (Column 2), the implied oil volatility (OVX) has a significant and strong influence, with a positive and significant coefficient of 13.60. This indicates that fluctuations in the global crude oil market play a crucial role in amplifying extreme positive price movements in the Australian electricity markets. The significance of OVX aligns with the interconnectedness of global energy markets, where increases in oil price volatility can lead to higher production costs and, consequently, higher electricity prices. The global geopolitical risk index (GOPRX) also shows a significant positive effect on positive tail risks, as evidenced by a coefficient of 2.70. This suggests that heightened geopolitical tensions contribute to increased uncertainty and risk in the electricity markets, potentially due to concerns over energy security and supply chain disruptions. In addition, the risk aversion index (RAI) exhibits a pronounced impact on positive tail risk connectedness, with a coefficient of 17.03. This underscores the role of global investor sentiment in driving extreme positive price movements, where increased risk aversion leads to higher demand for energy commodities as safe assets, pushing prices upward.

For negative tail risk connectedness (Column 1), the influence of global factors like OVX is not statistically significant, implying that international oil market volatility does not play a significant role in negative tail risk transmissions within the NEM. Similarly, the effects of GOPRX and RAI, while significantly positive, are less pronounced for negative tail risks. GOPRX has a coefficient of 2.48, and RAI has a coefficient of 10.86. The less pronounced impacts might be explained by the fact that negative tail risks in the NEM are primarily driven by domestic factors, particularly structural oversupply and low net system demand events. The increasing penetration of inflexible base load plants and renewable energy sources like solar photovoltaic (PV) and wind power leads to periods of excess supply, especially during times of low demand (Mwampashi et al., 2021; Gonçalves and Menezes, 2022a, 2022b).

Regarding domestic economic indicators, the implied volatility of the Australian stock market appears to have no significant effect on the tail risk connectedness indices, suggesting that domestic stock market volatility does not directly impact the transmission of tail risks within regional markets. However, the term spread (TERMSPR) yields significant insights; its negative coefficients in both models indicate that a narrowing term spread, which often signals a deteriorating economic outlook, markedly intensifies the transmission of tail risks across regional markets. This observation implies that economic conditions play a crucial role in the dynamics of risk transmission within the sector, with worsening economic forecasts potentially exacerbating the spread of tail risks.

In summary, these findings provide a comprehensive view of how global uncertainties, geopolitical risks, investor sentiment, and domestic economic conditions collectively influence the transmission of tail risks in the energy sector, offering valuable insights for policymakers, investors, and market participants in developing strategies to mitigate these risks.

**Table 5**
Determinants of tail risk connectedness.

| | TCI for negative tail risk (1) | TCI for positive tail risk (2) |
|---|---|---|
| OVX | 4.63 | 13.60*** |
| | (2.83) | (2.44) |
| GOPRX | 2.48*** | 2.70** |
| | (0.63) | (0.83) |
| RAI | 10.86*** | 17.03*** |
| | (0.94) | (2.13) |
| ASV | −3.41 | −6.03 |
| | (2.13) | (2.71) |
| TERMSPR | −6.37*** | −5.18** |
| | (1.71) | (1.64) |
| Intercept | 39.45*** | 74.00*** |
| | (11.03) | (12.77) |
| R-squared | 0.1301 | 0.1771 |
| F-statistics | 182.57 | 320.20*** |

Note: This table presents the regression results of Eq. (10) to investigate the effects of various global and domestic factors on the Total Connectedness Index (TCI) among Australian regional electricity markets for the whole research period. Eq. (10) is estimated using OLS estimation with t-statistics computed using Newey and West's (1987) robust standard errors. ***, **, and * indicate statistical significance at 10 %, 5%, and 1% level, respectively.

*5.5.2. Heterogeneous impacts of drivers across different crisis periods*

In this subsection, we extend the analysis of the drivers of tail risk connectedness indices by investigating their impacts over different crisis periods, including the Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine war. Extending the analysis of the drivers of tail risk connectedness indices in Australian regional electricity markets to include different crisis periods is essential for multiple compelling reasons. First, each crisis brings unique challenges and impacts on energy markets. The GFC highlighted financial and economic vulnerabilities, COVID-19 exposed the effects of global health emergencies on supply and demand, and the Russia-Ukraine conflict underscores geopolitical risks. Second, understanding the impact of various crises on tail risk connectedness enables policymakers and market operators to gauge the resilience of the energy sector. It provides insights into how prepared the market is for managing unforeseen shocks and stresses, guiding improvements in risk management practices and infrastructure resilience. Third, Insights from crisis period analyses can inform the development of regulatory frameworks and policies tailored to safeguarding against the specific types of risks each crisis presents. Lastly, given the increasing integration of global markets, understanding the impact of international crises on Australian energy markets is crucial. It sheds light on global interdependencies and how external shocks can ripple through the energy sector, affecting supply, demand, and prices.

Following Abdullah et al. (2023a, 2023b), we choose the periods associated with the crisis periods as follows: the Global Financial Crisis from 18 July 2006 to 31 December 2011; the COVID-19 crisis from 01 January 2020 to 31 December 2021; and the Russia-Ukraine conflict from 01 January 2022 to 16 March 2023. Panels A, B, and C of Table 6 give the estimation results of the Eq. (10) for the specified periods. The results show a heterogeneous impact over the sub-samples.

In Panel A, during the GFC, the analysis reveals that the implied volatility of crude oil (OVX) played a significant role in both negative and positive tail risk connectedness, with a notably stronger impact on positive tail risks. This period coincided with the rise of coal seam gas development in Australia, leading up to the LNG export industry around 2014 (Simshauser and Nelson, 2015). The anticipation of LNG exports and increasing investment in coal seam gas heightened the sensitivity of the Australian energy markets to global oil price volatility, as reflected

[21] To address potential endogeneity issues, we confirmed low multicollinearity (all independent variables have VIF values around 3 or lower; see Table 2R) and included lagged dependent variables in Eq. (10) to minimize reverse causality. Reverse causality is unlikely, as tail risk transmission in the National Electricity Market (NEM) does not influence global factors like OVX, GOPRX, RAI, Australian stock market volatility, or interest rates.

**Table 6**
Determinants of tail risk connectedness across crisis periods.

| | *Panel A. During GFC* | | *Panel B. During COVID-19* | | *Panel C. During war* | |
|---|---|---|---|---|---|---|
| | NTCI (1) | PTCI (2) | NTCI (3) | PTCI (4) | NTCI (5) | PTCI (6) |
| OVX | 9.51*** | 16.05*** | −0.01 | 0.31 | 15.45*** | 2.27* |
| | (1.47) | (1.60) | (0.71) | (0.85) | (1.35) | (1.12) |
| GOPRX | 0.01 | 0.87 | 1.53*** | 2.11*** | 0.91 | 1.30* |
| | (0.68) | (0.73) | (0.35) | (0.35) | (0.62) | (0.58) |
| RAI | 3.15* | 1.71 | 0.97 | 3.73*** | 0.56 | −12.43** |
| | (1.41) | (1.47) | (0.59) | (0.89) | (2.85) | (3.92) |
| ASV | 8.09*** | 3.30* | 2.69* | 7.12*** | 2.84* | 2.07 |
| | (1.37) | (1.45) | (1.12) | (1.31) | (1.53) | (1.88) |
| TERMSPR | −2.70*** | −4.57*** | −1.82*** | −1.48** | −0.22 | 0.27 |
| | (0.40) | (0.41) | (0.48) | (0.49) | (0.23) | (0.23) |
| Intercept | −23.25*** | −35.97 | 23.66*** | 29.97*** | 94.05*** | 46.94 |
| | (4.88) | (5.25) | (2.49) | (3.02) | (3.79) | (3.08) |
| Adj. R-squared | 0.2142 | 0.2471 | 0.0536 | 0.1531 | 0.3385 | 0.0996 |
| F-statistics | 63.86*** | 78.19*** | 9.03*** | 17.86*** | 62.16*** | 7.38*** |

Note: This table presents the regression results of Eq. (10) to investigate the effects of various global and domestic factors on the Total Connectedness Index (TCI) among Australian regional electricity markets for sub-sample periods (i.e., crisis periods) including Global Financial Crisis (GFC), COVID-19, and Russia-Ukraine war. NTCI and PTCI stands for the TCI of negative tail risks, respectively. Eq. (10) is estimated using OLS estimation with t-statistics computed using Newey and West's (1987) robust standard errors. ***, **, and * indicate statistical significance at 10 %, 5 %, and 1% level, respectively.

in OVX. This suggests that oil market volatility was a critical factor in driving tail risk spillovers in Australian electricity markets during this period.

Interestingly, global geopolitical risk (GOPRX) had minimal impact, indicating that the crisis' effects were more directly tied to market volatility rather than geopolitical uncertainties. The Risk Aversion Index (RAI) and Australian stock market volatility (ASV) both significantly contributed to tail risk connectedness, particularly for negative tail risks, highlighting the influence of domestic market sentiment and stock market fluctuations. The negative association with the term spread (TERMSPR) across both types of tail risks suggests that economic expectations and interest rate differentials were also key factors in shaping risk transmission during the GFC.

Throughout the COVID-19 pandemic, the determinants of tail risk connectedness exhibited different patterns compared to the GFC as evidenced in Panel B. OVX had an insignificant impact, highlighting that crude oil volatility was not a primary driver of tail risk spillovers during the pandemic. This can be attributed to low oil prices during this period, which led to low LNG and domestic gas prices. Additionally, there was high coal plant availability and rising renewable energy market shares, contributing to a stable domestic energy supply and reducing the sensitivity to global oil market volatility.[22] Instead, GOPRX was a significant factor for both types of tail risks, reflecting the heightened impact of geopolitical risks in a globally interconnected crisis. RAI's strong association with positive tail risks underscored the pandemic's influence on investor sentiment, marking a shift from the GFC where risk aversion uniformly affected both tail risks. ASV remained influential, especially for positive tail risks, indicating ongoing sensitivity to domestic stock market volatility. The negative effect of TERMSPR, though less pronounced than during the GFC, continued to highlight economic outlook considerations.

In Panel C, during the Russia-Ukraine conflict, the OVX significantly affected negative tail risk connectedness, marking a stark contrast to its negligible influence during the COVID-19 pandemic. This period was notable in the NEM for an uncharacteristically high level of coal generation plant failures, including prolonged outages at Kogan Creek, Loy Yang, and Bayswater power stations, and the partial closure of Liddell.[23] Additionally, a La Niña weather event led to low solar output, resulting in an over-reliance on natural gas.[24] Domestic gas prices, linked to global LNG markets in crisis due to the conflict, increased significantly. These factors heightened the sensitivity of the Australian electricity markets to global crude oil volatility, as reflected in OVX, thereby influencing negative tail risk connectedness.

GOPRX's impact was observed mainly on positive tail risks, differing from its broad influence during the pandemic, indicating specific geopolitical risk perceptions affecting market optimism or pessimism. RAI's mixed effects, particularly its negative association with positive tail risks, reveal complex investor sentiment dynamics during the war. The influence of ASV was more balanced across tail risks compared to its stronger effect on negative tail risks during the GFC and on positive tail risks during the pandemic. TERMSPR's negligible impact marks a departure from its significant negative association in previous crises, suggesting changing dynamics in how economic expectations influenced tail risk connectedness.

Across all panels, the variation in determinants' significance and impact on tail risk connectedness during different crises highlights the dynamic interplay between external shocks, market volatility, geopolitical risks, and investor sentiment. While crude oil volatility (OVX) and domestic stock market fluctuations (ASV) consistently emerge as pivotal factors, the influence of global geopolitical risks (GOPRX) and risk aversion (RAI) varies, reflecting the unique contexts of each crisis. These insights underscore the complexity of tail risk transmission mechanisms in Australian regional electricity markets and emphasize the need for crisis-specific risk management and policy interventions.

### 5.6. Robustness checks

To ensure the robustness of our analysis, we employed both 1 % CAViaR ($\alpha = 1\%$) and 99 % CAViaR ($\alpha = 99\%$) to measure negative and positive tail risks, respectively. Subsequently, we recalculated the time-varying Total Connectedness Indices (TCIs) using these metrics to confirm the stability and reliability of our findings across different measures of tail risk. The recalculated TCIs, alongside those obtained using 5 % CAViaR and 95 % CAViaR from our baseline analysis, are presented in Appendix A4. The comparative figures in the appendix demonstrate a strong correlation between the newly computed TCIs and

[22] See, https://www.aer.gov.au/industry/registers/charts/gas-market-prices.
[23] See, https://www.reuters.com/business/energy/australias-agl-energy-extends-victoria-power-station-outage-by-month-oct-2022-09-12/.
[24] https://climateextremes.org.au/large-scale-climate-drivers-in-australia-2022/#:~:text=La%20Ni%C3%B1a%20conditions%20first%20began,persisted%20through%20early%20winter%202022.

the original ones, affirming the reliability of our tail risk connectedness estimates.

As an additional robustness check, we applied the quantile connectedness approach by Ando et al. (2022) to the adjusted electricity price returns over the entire period, using $\tau = 90$ % for positive tail risk and $\tau = 10$ % for negative tail risk with a 100-day forecast horizon. The results in Appendix A1 largely confirm our baseline findings. First, the overall connectedness indices (TCIs) at the lower and upper quantiles closely match those estimated using the TVP-VAR models. Second, we observe a slight asymmetry, with the upper-tail TCI being higher than the lower-tail TCI. Third, the roles of net receivers and transmitters among regions generally align with our previous analysis, except for QLD in Panel A and SA in Panel B. These discrepancies may stem from differences in the econometric methodologies of the TVP-VAR and quantile connectedness approaches.

## 6. Conclusion and policy implications

This paper analyses how tail risk is transmitted across Australian regional electricity markets using the Conditional Autoregressive Value-at-Risk (CAViaR) model and the time-varying parameter vector autoregression (TVP-VAR) connectedness approach. Focusing on both global and domestic influences, we examine the evolution and drivers of connectedness indices over time. The key insights from our findings are summarised as follows:

First, there is significant interconnectedness within the National Electricity Market (NEM), with Total Connectedness Indices (TCIs) for negative and positive tail risks at 27.13 % and 29.97 %, respectively. This substantial spillover suggests that events in one market can impact others, emphasizing the need for comprehensive risk management strategies that account for the network's interconnected nature. Policies should address both local and network-wide risk factors by implementing real-time risk monitoring, developing regional risk pools, utilizing advanced analytical tools for forecasting, and ensuring coordinated regulatory practices across markets.

Second, the observed asymmetry in the transmission of positive and negative tail risks—where positive risks are more transmissible—highlights vulnerabilities in handling price surges. This could lead to increased volatility affecting consumers and suppliers during spikes. Policymakers may need to implement measures to balance the management of both risk types, such as revising market regulations, enhancing infrastructure to better absorb positive tail risks, introducing automated trading halts or price caps during volatility spikes, and investing in energy storage technologies to smooth out price fluctuations.

Third, Tasmania's lower levels of tail risk connectedness illustrate the benefits of energy diversification and reduced reliance on fossil fuels. Its emphasis on renewable energy sources, primarily hydropower, minimizes risk exposure to global oil and gas market volatility and serves as a model for sustainable energy production. Encouraging similar renewable energy investments and diversification in other regions could reduce vulnerability to external shocks and enhance the overall stability of the national energy market.

Fourth, Victoria's significant interconnectedness and role in tail risk spillover point to its pivotal position in the network's risk dynamics. This necessitates targeted risk management strategies to prevent localized risks from escalating into network-wide issues. Implementing advanced forecasting tools, enhancing regulatory oversight, investing in resilient infrastructure, fostering interstate cooperation, and establishing rapid-response protocols can mitigate widespread disruptions and protect against cascading failures.

Lastly, the heterogeneity in tail risk connectedness across different regions and crisis periods underscores the complexity of the Australian electricity markets' risk landscape. Each crisis—from the Global Financial Crisis to the COVID-19 pandemic and the Russia-Ukraine war—has uniquely influenced the markets, reflecting the interplay between global events, domestic economic conditions, and market-specific factors. Policymakers and market participants must employ dynamic and flexible risk management approaches tailored to evolving risks to safeguard the stability and integrity of the energy market in the face of future crises.

Limitations of this study include the exclusion of evolving market mechanisms and the granularity of data. The current approach may not fully capture market intricacies such as demand-side management, distributed generation, and the increasing penetration of renewable energy sources, which significantly shape market dynamics and risk profiles. Future research could delve into micro-level mechanisms, incorporating the effects of consumer behaviour shifts, renewable integration, digitalization, and smart technologies. Investigating the role of policy innovations and market reforms in enhancing system resilience against tail risks presents a promising avenue for mitigating systemic risks amid rapid sectoral transformations.

## CRediT authorship contribution statement

**Son Duy Pham:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Hung Xuan Do:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Rabindra Nepal:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Tooraj Jamasb:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108123.

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