The Interplay of Carbon Offset, Renewable Energy Certificate and Electricity Markets in Australia

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ABSTRACT:

Having the world's first renewable energy certificate (REC) market and a large and diverse (by project types) government-backed carbon offsets (ACCUs) market, Australia provides an interesting context to study the interplay of the offset, REC, and electricity market. We investigate the existence, extent, and direction of the connectedness in prices among these three markets in Australia during May 2018- June 2023 and back-test the implications of the results using a portfolio approach. Our results highlight: 1) an insignificant connectedness between the ACCU and REC markets, implying that the landfill gas offset projects, as a potential linking channel, do not appear to distort either pricing mechanism and that ACCU's and REC's are viable portfolio diversification assets; 2) that the national electricity market (NEM) is a net risk receiver from the ACCU and the REC markets, largely due to the regional electricity market (REM) in South Australia (SA); and 3) that the cost to effectively hedge the risk channeled from the SA market is very expensive, likely reflecting the high penetration of 'new' (wind and solar) renewable electricity in SA.

KEYWORDS: Green Certificate, Carbon Offset, Electricity, Renewable Energy, Climate Policy

JEL Classification: G11; G14; G18; Q28; Q52; Q54

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1 Introduction

Energy transition is prioritized in the global greenhouse gases (GHG) emissions reduction agenda as the energy sector accounts for nearly 75% of the GHG emissions in 2021 (World Resources Institute, 2022). Subsequently, various climate-related pricing instruments have been created for reducing GHG emissions in the energy sector – this can disincentivize a negative externality (e.g. pricing carbon emission) or incentivize a positive externality (e.g. lower emissions via renewables or energy efficiency). These climate-related pricing instruments can be categorized into direct pricing mechanism, including carbon tax, emissions trading scheme (ETS) and carbon crediting, and indirect mechanisms, including the renewable energy standards, energy saving mandates, and fossil fuel taxes or (removal of) subsidies for renewables (fossil fuels). The implementation of the ETS, carbon crediting, renewable energy standards, and energy saving targets are mainly facilitated by the market mechanism where the climate-related certificates are traded as financial commodities. This class of financial asset consists of carbon allowances traded in an ETS, carbon credits (or the offsets) in an offset market, renewable energy certificates (RECs) in a REC market (Green Certificate Market), and energy efficiency certificate (or White Certificate Market) in an energy efficiency market. Carbon allowances are tradable permits to emitting, often subject to regulatory compliance, whereas carbon credits are tradable credits generated for often voluntary emissions reductions activities. Arguably, in terms of history, trading volume and standardization level, the ETSs, with the first one established in the EU in 2008, and the REC markets, with the first being set-up in Australia in 2001, are the more matured tradable certificates markets.

While the ETS and the REC market have obtained a degree of maturation, the offsets market seems to be in an accelerated growth stage, a pathway set under the Kyoto Protocol and Paris Agreement Article 6 (World Bank, 2023) and as a result of to the growth of voluntary carbon markets and associated corporate 'net-zero' commitments. In 2015, after the Kyoto Protocol, international offset projects sprang into being. This included the Clean Development Mechanism (CDM) leading to certified emissions reductions (CER), Joint Implementation (JI) projects resulting in emissions reduction units (ERU), and the land use, land-use change and forestry (LULUCF) projects generating removal units (RMU). Additionally, facing the reality of meeting climate change goals, more and more jurisdictions are setting up net-zero targets and considering creating government-backed offsets (e.g. the California Compliance Offset Program and Australia's Emissions Reduction Fund) to fulfil their international emissions reduction commitment. Moreover, pressured by investors and increasingly stringent climate policies, corporations are seeking solutions to decarbonize their businesses and 'net' their emissions at the same time, resulting in a robust demand for offset credits. This demand has incentivized many carbon crediting businesses to create voluntary offset projects and issue offset credits that are backed by third parties. The most well-known voluntary offsets are the Verified Carbon Units (VCU), issued under Verra's verified carbon standard, and the Verified Emission Reduction (VER) credit, under the Gold Standard. On the one hand, the offset credits have drawn much interest as they become a "safety valve" for meeting the net-zero target if the marginal carbon abatement costs are too high and excessively affect profits and economic stability. On the other hand, they have been scrutinized and criticized given concerns around additionality, permanence and double counting issues and other unintended consequences such as the rising land price due to land conversion for offset projects (Anderson, 2012; Calel et al., 2021; Jaraitė et al., 2022).

A fundamental proposition for pricing carbon is that if the price of emissions is higher, emissions should be lower (Best et al., 2020). This proposition implies that for the market pricing mechanism to be effective in incentivizing emissions reduction, the pricing of the market instruments should be sufficiently high and robust. However, with a variety of pricing mechanisms which can be concurrently implemented (we call this a 'pricing network'), how each one interacts with another critically underpins the success of achieving emissions reduction. With the offset crediting businesses booming in recent years, how do offset markets, which are aimed at net emissions, interact with other climate-related pricing mechanisms, which are aimed at gross emissions reduction? Will the offset prices enhance or "counteract" the robustness of other (gross) emissions reduction pricing tools?

This issue is especially relevant for the landfill gas offset projects in Australia. Macintosh (2022) pointed out, most landfill gas offset projects registered under the national offset scheme receive ACCUs but can also receive revenues from selling RECs and electricity. This implies that the landfill gas offset projects provide a linking channel to connect the offset, REC and electricity markets together. Thus, it is possible that, a shock to one market may be transmitted to another, distorting the other market's pricing efficiency in achieving the climate targets. For instance, rising electricity and REC prices could incentivize more offsets to be created from landfill gas projects, thereby pushing downward pressure on offset prices. A lower offset price may lower the carbon cost for the generators, which in turn encourages more electricity generation. Increased electricity generation could increase demand, and the prices of RECs and offsets (if the energy source is largely nonrenewable) and also lower electricity prices. Thus, although seemingly an initial higher electricity and REC price may reduce energy consumption and generation emissions, if the linkage exists and is significant, the offsets could dampen the electricity prices as a feedback effect, providing a channel for more energy consumption and emissions. To identify the dynamics in prices among the three markets, our study addresses the research question; are there spillovers in prices among offset, REC, and electricity markets? If so, how large and in what direction do the spillovers occur?

Literature on overlapping climate policies and instruments has mainly investigated renewable energy interventions and emissions trading schemes (Amundsen & Bye, 2018; Koch et al., 2014; Liao et al., 2023; Schusser & Jaraitė, 2018), but has not explored the overlapping effects related to the offset markets. In fact, analyses of carbon offsets are principally focused on the environmental effectiveness, i.e. whether offset programs are associated with emissions reduction (Calel et al., 2021; Jaraitė et al., 2022), rather than from a pricing efficiency/ linkage perspective, i.e. whether adding another pricing mechanism such as the offset market strengthens or undermines the entire climate-related pricing network? Thus, our study contributes to filling this literature gap. Further, we enrich the literature on carbon pricing (Best et al., 2020; Deryugina et al., 2021; Medema, 2020) with new empirical evidence of an important and rapidly evolving carbon offset market.

From a practical perspective, our study contributes to the discussion on the issues that are associated inherently with offsets market (e.g. the additionality, permanence, and double counting issues), as well as to how offsets market interacts with other established climate-related pricing mechanisms. For instance, does the offsets market erode the environmental integrity of the climate-related pricing network (e.g. green certificate, carbon and electricity markets)? For regulators, it provides empirical evidence for the effectiveness and efficiency of the use of several market instruments at the same and sheds light on possible improvements to be made in the legislative framework and market design.

Further our results provide insights for offset and renewable energy providers into the pricing signals of the various markets and assists their decision-making in developing new projects. Also, if channels exist to establish the linkage among the three markets, offsets may become another hedging tool for the electricity traders to diversify their risk profile.

We estimate a VAR-X model for a dataset covering a period from May 2018 to June 2023 that computes the connectedness matrix over the full period, and over 200-day rolling windows. We further back-test the implications of the results using a portfolio approach. We investigate the three markets in the Australian context for several reasons.[1] First, Australia has the longest experience with a REC market, which commenced in 2001 and is among a few countries which have government-backed carbon offsets, the Australian Carbon Credit Units (ACCUs), traded in a national scheme since 2012 (World Bank, 2023). Thus, as more jurisdictions are considering creating their own government-backed credits to be traded in a national scheme, a study in the Australian context is relevant to the global context as other jurisdictions explore such moves, e.g. South Africa. Second, our study in Australia contributes to the empirical evidence on offset pricing within the southern hemisphere, an area that is notably underexplored despite its expansive ocean serving as a significant carbon 'sink' with immense potential for carbon offsets (Mikaloff-Fletcher, 2015). Third, Australia is establishing the national carbon exchange market, starting with the incorporation of ACCUs and progressing with international units, large-scale generation certificates (LGCs), and small-scale technology certificates (STCs) (Clean Energy Regulator, 2023b). Once established, it can promote standardization and improve transparency and liquidity of the offset market. If simultaneous trading of other climate-related assets becomes available in the exchange, risk transmission across different markets will likely increase. Thus, this paper provides an *ex-ante* assessment of the likely interplay of the market instruments before the exchange is formally set up. Moreover, this can enlighten other countries who are also considering establishing a carbon exchange with various climate-related certificates.

This paper documents, firstly, that the total connectedness among the ACCU, REC, and electricity markets is trending downward. This seems to suggest that the potential climate policy overlapping effect is decreasing as the three markets are operating more and more independently. Secondly, there is an insignificant connectedness between the ACCU and REC markets. This implies that these two markets can operate independently despite the fact that the landfill gas offset methodology provides a potential linking channel to distort both pricing mechanisms. Moreover, evidenced by portfolio back testing, REC and ACCU are shown to be viable risk hedging tools. Thirdly, there is a significant connectedness between the national electricity market (NEM) and the ACCU market.[2] Over the full period, a shock to the NEM (ACCU) price transmits 0.95% (2.34%) risk to the ACCU (NEM) price, making the ACCU

[1] Our dataset starts in May 2018 as this is the earliest offset pricing data we can obtain from the third party. It ends in June 2023 because from July 2023, the Safeguard Mechanism Certificate (SMC), another type of carbon pricing certificate, was created and thus would impact the Australian carbon pricing network.

[2] The NEM includes the regional electricity markets in New South Wales (NSW), Australian Capital Territory (ACT), Queensland (QLD), South Australia (SA), Victoria (VIC) and Tasmania (TAS). Nevertheless, we follow Nazifi et al. (2021) and refer the NEM to the totality of the regional markets in NSW, QLD, SA, and VIC.

market a net risk transmitter to the NEM with a net balance in transmitted risk of 1.39% by ACCUs. Lastly, there is a significant connectedness between the NEM and the REC market. Over the full period, a shock to the NEM (REC) price transmits 0.6% (1.2%) of its risk to the REC (NEM) price, making the REC market a net risk transmitter to the NEM with a net transmission of 0.6%. When we look into the regional electricity markets (REMs), we find that South Australia's (SA) REM is the main contributor to the net risk transmission to the NEM respectively from the ACCU and the REC markets. Lastly, we find that it is very expensive to effectively hedge the risk of price volatility in the SA market. In fact, if any hedging operation was executed, the cumulative returns yield to be negative. This is likely due to its high penetration of 'new' (wind and solar) renewable electricity in SA.

The remainder of this paper is organized as follows: Section 2 provides background information for the ACCU scheme, REC market, and the NEM. Section 3 reviews the literature and develops the hypotheses. Section 4 describes the data and methodology. Section 5 reports and interprets the results. Lastly, Section 6 concludes the paper.

2 Australian Context

2.1 The Australian National Carbon Offset Scheme

The Australian national carbon offset scheme, also known as the Australian Carbon Credit Units (ACCUs) Scheme, was initiated under the Emissions Reduction Fund (ERF) in 2014, which was established by the Carbon Credits (Carbon Farming Initiative) Act 2011 (Carbon Credits (Carbon Farming Initiative) Act 2011, 2011). It is a national voluntary carbon offset scheme where eligible projects can be granted with the amount of ACCUs, which is equivalent to the amount of tonnes of carbon dioxide equivalent (tCO2-e) stored or avoided. Both the industry and the land sectors are eligible to participate in the Scheme by operating projects under the eight major method types namely, carbon capture and storage, energy efficiency, landfill and alternative waste treatment, mining, oil and gas, transport, agricultural, savanna fire management, and vegetation. (Clean Energy Regulator, 2023a). Moreover, various sub-class methods are specified, nesting under each type. Specifically, the Human-Induced Regeneration of a Permanent Even-Aged Native Forest (HIR) method (under the Vegetation type), and the landfill gas methods each accounts for roughly 28% of all ACCUs generated as of December 2021 (Macintosh, 2022). The ACCUs are issued by the Clean Energy Regulator to the project holder's account in the Australian National Registry of Emissions Units (ANREU). The ACCUs generating projects are thus the suppliers of the ACCUs trading market. The demand side of the ACCUs comes from the federal government via the Emissions

Reduction Fund reverse auctions, facilities obligated under the Safeguard Mechanism, and the voluntary demand from the corporates, and state and territory governments.[3] In addition to the ERF contract auctions, which are the predominant demand source and effectively set the price floors of ACCUs, the secondary over-the-counter market, which became active in the latter half of 2018, facilitates the trading of ACCUs in the spot market.[4]

Common to nearly all the offset schemes, the integrity of the ACCUs is challenged. Scholars specifically highlighted measurement and additionality issues of the ACCUs. Related to landfill gas projects, while regulatory additionality is addressed at least partially (via a baseline), controls for financial additionality are absent (Macintosh 2022). Macintosh (2022, Page 11) define regulatory additionality as "whether abatement would occur anyway because there is a mandatory legal obligation to undertake the abatement activity" and financial additionality as "whether abatement would occur anyway because the abatement activity is profitable without ACCUs". Macintosh (2022) exposed ACCU's lack of financial additionality as most generation projects also receive revenues from selling LGCs and electricity. This criticism is the basis of the linkage theory among the ACCU, REC, and electricity markets.

2.2 The Australian Renewable Energy Certificate (REC) Market

The Australian REC market is the oldest REC market in the world having been functioning since 2001 (Andrews, 2001) and is operated under a mandatory scheme, which is initiated by the Mandatory Renewable Energy Target (MRET) under the Renewable Energy (Electricity) Act 2000 and the Renewable Energy (Electricity) Act 2000 (the Act). Since 2011, the MRET has been split into a Large-scale Renewable Energy Target (LRET), which is to achieve 33,000 gigawatt hours (GWhs) by 2020, and a Small-scale Renewable Energy Scheme (SRES). LRET mandated a Renewable Power Percentage (RPP), and SRES a small-scale technology percentage (STP). These standards determine the number of large-scale generation certificates (LGCs) and the small-scale technology certificates (STCs) for which an electricity retailer is liable. One LGC or STC is equivalent to one megawatt-hour (MWh) of renewable energy generated by the accredited renewable energy power station. It is celebrated that on August 30th, 2019, Australia achieved its capacity for 2020 LRET's 33,000 GWhs ahead of

[3] Safeguard mechanism commenced in 2016 and was reformed in 2023. To limit emissions, this mechanism legislates gradually phase-down emissions baselines for the largest industrial facilities, which emit more than 100,000 tonnes of CO2-e per year. To manage excess emissions, facilities can: 1) apply for a new baseline - calculated baseline or production adjusted baseline; 2) surrender ACCUs or Safeguard Mechanism Credit units (SMCs); 3) apply for a multi-year monitoring period to allow additional time to reduce net emissions (2-3yrs); and 4) apply for an exemption where excess emissions are due to exceptional circumstances such as a natural disaster or criminal activity.

[4] https://tfsgreen.com.au/australian-environmental-markets/carbon-markets/

schedule and in January 2021, it met its MRET of 33,000 gigawatt hours on a 12-month rolling basis (DCCEEW, 2023).

2.3 The Australian National Electricity Market (NEM)

The Australian NEM was established in December 1998 and has one of the world's longest interconnected power systems, with approximately 40,000km of transmission lines and cables (Nazifi et al., 2021). It covers New South Wales (NSW), Australian Capital Territory (ACT), Queensland (QLD), South Australia (SA), Victoria (VIC) and Tasmania (TAS) by Australian Energy Market Operator (AEMO). It is a central system, pooling together the electricity generated and dispatching it to the retailers every 5 minutes at a particular price. Before October 1st, 2021, the settlement price is the average of the six 5-minute dispatch prices during every 30 minutes. Within each 5-minute interval, bids of supply are ranked in ascending order, and the dispatch price is the last bid in the queue that can meet the demand within that 5-minute interval. Since October 1st, 2021, the settlement price has been revised to "five-minute settlement (5MS)" (AEMC, 2017). There are regional prices within the NEM, namely for NSW, QLD, SA, TAS, and VIC.

Similar to other electricity markets around the world, strong seasonality and volatility are apparent, in fact Australia is one of the most volatile markets with the spot price floor being -1000 and the price cap being 15500 AUD/MWh for FY 2022-2023 (AEMC, 2022; AEMO, 2023). The volatility can be attributed to a sudden change in demand, extreme weather events, and equipment failure or network congestion. An interesting feature of the electricity market is that at times generators are willing to offer the electricity at negative wholesale prices. Table 1 displays the electricity source mix of each state and highlights that black coal is powering 70% of the electricity of NSW and 75% of QLD respectively, brown coal 67% of VIC, a mix of wind and gas powers 61%, and 30% of SA and a mix of hydro and wind powers 81% and 19% of TAS during the period of November 2022- November 2023.

[INSERT TABLE 1 HERE]

3 Literature Review and Hypotheses Development

Literature on the interplay between various climate-related pricing mechanisms and the electricity market can be grouped into two stands, namely on pricing interrelationship and environmental effectiveness.

Specifically, on pricing interrelationship, Amundsen & Mortensen (2001) theorize that higher carbon price is associated with lower REC price because higher carbon price makes it more costly to generate dirty electricity compared to clean electricity, and consequently, more clean electricity and thus more RECs are generated, resulting in lower REC prices. However, the empirical findings are divided on the negative relationship between carbon prices and REC prices. While Amundsen & Nese (2009) find that higher carbon prices lead to lower REC prices regardless of whether the markets are linked or not, Schusser & Jaraitė (2018) found the opposite. Nazifi, Trück, & Zhu (2021) identified a high carbon pass-through rate in Australia during the implementation of the carbon pricing mechanism, resulting in higher electricity prices. Cotton & De Mello (2014) found that REC prices have little effect on electricity prices. Liao et al., (2023) found that in a highly renewable context, higher electricity prices lead to lower carbon prices. Lastly, there is also ample empirical literature on the spillovers in prices among carbon and stock markets (Suleman et al., 2023). However, we have not seen relevant research on the offset market.

Moreover, the strand of literature on environmental effectiveness investigates the effectiveness of climate-related certificates in reducing GHG emissions or reaching other environmental targets such as higher renewable energy penetration rates. The theoretical paper by Amundsen & Bye (2018) suggests that 'black', 'green', 'white', certificate markets and electricity markets can coordinate well to meet current renewable energy and energy efficiency targets but it is impossible to judge whether they will lead to a change in consumption of black, green, or white electricity. Best et al. (2020) provide empirical evidence that carbon pricing, including carbon taxes and ETS, reduce the average annual growth rate of CO-2e emissions globally. Calel et al.(2021) and Jaraitė et al. (2022) suggest that offset certificate markets seem to increase rather than decrease GHG gross emissions.

Drawing on the preceding literature and the Australian context (see section 2), it can be hypothesised that the relationship between the REC and ACCU prices could go in two plausible directions. On one hand, a higher ACCU price could encourage more landfill gas electricity generation, and thus more REC supply, resulting in lower REC prices. On the other hand, a higher REC price could lead to more landfill gas electricity generation and thus more ACCU supply, thereby reducing the ACCU prices. Accordingly, we formulate our first hypothesis as follows.

H1: There is a mutual weakening effect in prices between REC and ACCU markets, such that:

H1a: a higher ACCU price leads to a lower REC price.

H1b: a higher REC price leads to a lower ACCU price.

When it comes to the mutual relationship between electricity and ACCU prices, the relationship is not straightforward. First, on the effect of rising electricity price on the ACCU price, a higher electricity price encourages both gas and coal-fired and clean electricity generation, including sourced from landfill gas. On the one hand, more gas and coal-fired power increase ACCU demand, especially for NSW, QLD, and VIC where these generating sources are dominant, resulting in higher ACCU price. On the other hand, more landfill gas generation increases ACCU supply, depreciating the ACCU price. Second, on the reverse relationship, i.e. between the ACCU price and the electricity price, a higher ACCU price can 1) incentivize more landfill gas electricity generation, depreciating the electricity prices, and 2) make it more costly for states like NSW, QLD, and VIC to offset their emissions, thus passing the cost to the consumers resulting in a higher electricity price. This is similar to the effect of a carbon price on electricity prices (Nazifi et al., 2021). Despite the complexity that may affect the mutual relationship, we hypothesize H2 as follows.

H2: There is a mutual weakening effect between electricity and ACCU markets.

H2a: a higher electricity price leads to a lower ACCU price.

H2b: a higher ACCU price leads to a lower electricity price.

Similar complexity applies to the mutual relationship between the electricity price and the REC price. First, a higher electricity price encourages both gas and coal-fired and clean electricity generation, including sourced from landfill gas. More gas and coal-fired electricity generation leads to a higher REC demand, but more landfill gas electricity generation results in a higher REC supply. Thus, there is not a straightforward answer to the direction of the effect. Second, a higher REC price can 1) incentivize more landfill gas electricity generation, depreciating the electricity prices, and 2) make it more costly for states like NSW, QLD, and VIC to reach the mandatory renewable energy percentage, thus passing the cost to the end user and resulting a higher electricity price. Despite the complexity that may affect the mutual relationship, we nevertheless hypothesize H3 as follows.

H3: There is a price offsetting between electricity and REC markets.

H3a: a higher electricity price leads to a lower REC price.

H3b: a higher REC price leads to a higher electricity price.

Lastly, according to the large empirical literature on energy and carbon pricing (see Diaz-Rainey & Tulloch, 2018), exogenous variables such as coal, oil, gas, and international carbon prices can affect domestic climate-related certificate prices. Therefore, we adopt them as exogenous variables in our statistical analyses so that we can focus on the interaction within the endogenous system, similar to the idea of Cushman & Zha (1997).

4 Data and Methodology

4.1 Data

We sourced the LGC spot prices (in AU$/MWh) as a proxy for REC prices, New Zealand Unit (NZU) spot prices (in AU$/ton), Arabian Dubai Fateh crude spot index oil prices (in AU$/barrel), and Coal future prices (in AU$/ton) from Bloomberg over the period from May 1st, 2018 to June 30th, 2023. [5] We sourced and collated the daily average declared wholesale gas market price (in AU$/gigajoule) and NSW, QLD, SA, TAS, and VIC daily average electricity spot prices (in AU$/MWh) from the Australian Energy Market Operator (AEMO). We sourced daily ACCU spot prices) (in AU$/ton) from Jarden, a leading spot and forward carbon broker, and daily European Union Allowance (EUA) futures close prices (in AU$/ton) from the S&P Capital IQ database. [6]

4.2 Empirical Methods

4.2.1 Variable Definitions

Since there are missing data points in LGC and ACCU spot prices due to inactive trading days, we backfilled the missing values with the previous available prices. Additionally, to control for potential structural shifts in the pricing series (see Diaz-Rainey & Tulloch, 2018; Liao et al., 2023), we test their unit roots with a single structural break following Clemente, Montañés, & Reyes (1998) and attempt to coalign the archived news to validate the identified breakpoint. If a breakpoint exists, we regress the corresponding price series over the breakpoint dummy variable to extract residuals as our filtered price proxy for the models to remove the compounding effect from such structural shifts. [7]

Another issue in our data is outliers, especially in electricity prices. To treat the outliers in electricity prices, which are reported as either negative or above 300 AU$/MWh, we adopt a recursive model approach with a polynomial model specified in Equation (1) following Nazifi, Trück, & Zhu (2021).

$$Elec_t = \alpha_t + \beta_{1,t}D_t + \beta_{2,t}D_t^2 + \beta_{3,t}D_t^3 + \epsilon_t \tag{1}$$

Here $Elec_t$ is the daily average electricity spot price series of each NSW, QLD, SA, TAS, and VIC states on day t, and D_t is the corresponding daily average electricity demand. We replace identified outliers with the predicted price from Equation (1). Furthermore, we de-

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[5] We use Arabian Dubai Fateh crude spot because in 2021, Australia imported 34% of refined oil from Singapore, its biggest exporter, and Singapore imported over two-thirds of its crude oil from UAE, Saudi Arabia, and Kuwait (EIA, 2021; OEC, 2023).

[6] Jarden website: https://www.jardengroup.com.au/our-services

[7] We conducted the unit root with a single structural break on both the raw and the imputed pricing series and found the results are consistent.

seasonalize and linearly de-trend all numerical variables to eliminate potential confounding effects due to deterministic time series characteristics, that may cause spurious regressions.

4.2.2 Empirical Model

To address the first research question, i.e. whether spillovers exist among the three markets, we estimate a VAR-X model illustrated in Equation (2) following (Nicholson et al., 2017), and test H1, H2 and H3.[8]

$$Y_t = B_0 + \Sigma_{i=1}^{P} B_{1,i} Y_{t-i} + \Sigma_{j=0}^{Q} B_{2,j} X_{t-j} + \mathrm{E}_t \tag{2}$$

Here Y_t is the vector of stationary endogenous variables, B_0 is the constant vector, $B_{1,i}$ is the matrix of coefficients corresponding to Y_{t-i}. Further, we introduce a set of distributed lags of selected stationary exogenous variables, X_{t-j} and $B_{2,j}$ is the corresponding coefficient matrix. P and Q are the appropriate lag orders of endogenous and exogenous variables, respectively, determined by the AIC criterion and post-estimation serial correlation test jointly. E_t is the random error vector.

4.2.3 Connectedness Analysis

To address our second research question, i.e. how large and in what direction are the price risk spillovers, we follow the connectedness approach in Diebold & Yilmaz (2012, 2014) (DY hereafter) as follows. First, with the estimated VAR-X model in Equation (2), we obtain the residual matrices and compute the generalized forecast errors by applying the generalized impulse response function (GIRF) in Equation (3) following Koop, Pesaran, & Potter (1996) and Pesaran & Shin (1998).

$$GI_Y(H, \delta_j, \Omega_{t-1}) = \mathrm{E}(Y_{t+H} | \epsilon_{j,t} = \delta_j, \Omega_{t-1}) - \mathrm{E}(Y_{t+H} | \Omega_{t-1}) = \mathrm{A}_H \mathrm{E}(\epsilon_t | \epsilon_{j,t} = \delta_j) \tag{3}$$

Here GI_Y is the GIRF of the endogenous vector, Y, which is a function of the horizon H, a shock to variable j (δ_j), and the free-of-shock condition at time $t-1$ (Ω_{t-1}). $\mathrm{E}(Y_{t+H} | \epsilon_{j,t} = \delta_j, \Omega_{t-1})$ is the conditional expectation of Y_{t+H} given a shock δ_j on the error term, $\epsilon_{j,t}$ of variable j while $\mathrm{E}(Y_{t+H} | \Omega_{t-1})$ is the corresponding expected value without such a shock. A_H is the coefficient matrix of the residuals corresponding to the VAR-X model in Equation (2).

Further, we decompose the H-step generalized forecast errors following DY as specified in Equation (4),

[8] As our preliminary diagnosis reveals that only the logarithmic coal and NZU price series are stationary after the first difference, whereas the rest variables are stationary at (log) level, we do not expect any cointegration relationship among these variables.

$$d_{ij}^{H} = \frac{\sum_{h=0}^{H-1}\left[GI_Y\left(h, \delta_j, \Omega_{t-1}\right)_i\right]^2}{\sum_{h=0}^{H-1}\sum_{j=1}^{n}\left[GI_Y\left(h, \delta_j, \Omega_{t-1}\right)_i\right]^2} \tag{4}$$

and compute the directional connectedness from market j to market i as in Equation (5).

$$C_{i\leftarrow j}^{H} = d_{ij}^{H} \tag{5}$$

such that $C_{i\leftarrow j}^{H} \neq C_{j\leftarrow i}^{H}$. Thus, the net pairwise directional connectedness (i.e. the "NPDC" measure) can be specified as $C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H}$.

Hence, the total directional connectedness from all other markets to market i (i.e. the "FROM" measure) is specified in Equation (6).

$$C_{i\leftarrow\cdot}^{H} = \sum_{\substack{j=1\\ j\neq i}}^{Y} d_{ij}^{H} \tag{6}$$

The total directional connectedness from market i to all other markets (i.e. the "TO" measure) is specified in Equation (7).

$$C_{\cdot\leftarrow i}^{H} = \sum_{\substack{i=1\\ i\neq j}}^{Y} d_{ij}^{H} \tag{7}$$

Moreover, the total net directional connectedness (i.e. the "NET" measure) can be specified as $C_{i}^{H} = C_{\cdot\leftarrow i}^{H} - C_{i\leftarrow\cdot}^{H}$.

Lastly, the total connectedness of the entire network ("TC" measure) can be specified as in Equation (8).

$$C^{H} = \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{Y} d_{ij}^{H} \tag{8}$$

4.2.4 Portfolio Back Testing

Following the analysis on the extent of connectedness between the selected assets, we can draw an implication on an effective risk hedging strategy. To validate such a strategy, we adopt a dynamic portfolio back testing approach by constructing the minimum-variance portfolio (MVP) in Markowitz (1959), and calculate the corresponding weights specified in Equation (9).

$$\boldsymbol{w}_t^{*} = \frac{\boldsymbol{H}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}^{T}\boldsymbol{H}_t^{-1}\boldsymbol{I}} \tag{9}$$

where $\boldsymbol{w}_t^*$ is an m × 1 dimensional portfolio weight vector at time t, $\boldsymbol{I}$ is an m-dimensional indicator vector, $\boldsymbol{H_t}$ is m×m dimensional conditional variance-covariance matrix of asset returns in a period t and $\boldsymbol{H}_t^{-1}$ is the corresponding inverse matrix. [9]

Moreover, as the connectedness analysis in section 4.2.3 unveils the primary net risk channel, i.e. the particular regional electricity market, through which the NEM largely receives the net risk from REC or ACCU, we quantify how costly it may be to hedge one-dollar long position in the primary risk channel to the NEM using bivariate portfolios and calculating the dynamic hedge ratios following Kroner & Sultan (1993). A hedge ratio, β_{ijt} illustrated in Equation (10) indicates that in order to hedge one-dollar long position in asset i, the dollar position in asset j needs to be short.

$$\beta_{ijt} = \frac{h_{ijt}}{h_{jjt}} \tag{10}$$

Here h_{ijt} is the conditional covariance of asset i and j; h_{jjt} is the conditional variance of asset j and β_{ijt} can be considered as the dynamic hedging cost.

To evaluate the portfolio performance of both the multivariate and bivariate portfolios, we adopt two criteria, namely, the hedging effectiveness in Ederington (1979) and the cumulative returns. The hedging effectiveness of a portfolio can be specified in Equation (11).

$$HE = 1 - \frac{Var(r_{hedged})}{Var(r_{unhedged})} \tag{11}$$

where $Var(r_{hedged})$ is the variance of a hedge portfolio, which is constructed according to the dynamic hedge ratios; and $Var(r_{unhedged})$ the variance of the unhedged position.

5 Results

5.1 Descriptive Statistics

Figure 1 depicts REC, ACCU, electricity, energy, EUA and NZU prices. Firstly, as highlighted in Figure 1, structural breaks are statistically significant in ACCU price series on October 7th, 2021, and in EUA prices on May 17th, 2021. The structural break found in the ACCU pricing series is probably due to the imbalance between an unexpectedly high demand and a supply shortage occurred at the same time as major polluters were in an offset buying frenzy before the February compliance deadline (Reuters, 2021). The structural break found in

[9] For robustness, we also constructed two-, three- and four-asset minimum-variance portfolios. All portfolio sets include REC and ACCU with the remaining asset(s) being the regional electricity prices.

EUA prices is likely due to the impact of the European Parliament's resolution vote on "a WTO-compatible EU carbon border adjustment mechanism" on March 10, 2021 (IISD, 2021). Secondly, consistent with the observation that all pricing series (except for coal and NZU prices) revert to a mean level, the unreported but available upon request Dicky-Fuller unit-root tests reveal that only the logarithmic coal prices and NZU prices are non-stationary at logarithmic levels, and stationary after first differenced, whereas the rest of the price series are stationary at logarithmic levels. One thing noteworthy is that ACCU and EUA prices are stationary after we control for their respective structural breakpoints. Thirdly, electricity prices present strong seasonality and high volatility with many spikes, which is a unique feature of the electricity market (see Section 2.3).

Table 2 presents summary statistics of the detrended and de-seasonalized variables, which are adopted for our analysis for the sample period of May 1st, 2018 - June 30th,2023. It shows that: 1) while oil, EUA and NZU prices are approximately symmetric, all other pricing series are highly right-skewed, and 2) while the oil price is approximately mesokurtic, EUA and NZU are platykurtic, and the rest are leptokurtic, i.e. with a higher peak and fatter tails. Moreover, among the five regional electricity markets, NSW and QLD (TAS) have the highest (lowest) average electricity prices, and SA has the most volatile prices. QLD's prices are the most right-skewed and central-peaked with fat tails. [10]

[INSERT FIGURE 1 HERE]

[INSERT TABLE 2 HERE]

5.2 VAR-X Model

Table 3 presents an excerpt of the significant results obtained from the VAR-X model in Equation (2) (at various lags) to answer the first research question on the existence of the spillovers. Moreover, Table A1 presents the detailed results of the estimated VAR-X indicating short-run relationships among REC, $ACCU$, $Elec_{nsw}$, $Elec_{qld}$, $Elec_{sa}$ and $Elec_{vic}$, having controlled for the exogenous effects from $EUA,\ NZU,\ Elec_{tas},\ Coal,\ Oil\ and\ Gas$. Cumulative effect for a 5-workday lagged period is tested. Firstly, in Table 3, we do not find spillovers from the ACCU to the REC markets and vice versa, rejecting H1a and Hb (in yellow colour), respectively. This signals that the ACCU and REC markets can operate independently from each other regardless of the potential linkage depicted in the landfill gas methodology.

[10] Since the backfilled REC, ACCU, EUA and NZU values account for only 6%, 4.3%, 1.3% and 0.3% of its respective complete dataset, the summary statistics of the treated values present similar statistical properties as that of the raw data. Moreover, as the electricity price outliers account for roughly 5% of the NSW, QLD, TAS and VIC electricity data and 10% for the SA electricity data, the treated electricity prices remain to be highly right skewed and leptokurtic while data noises are filtered.

Secondly, on the mutual relationship between the electricity and ACCU markets tested in H2 (in peach colour), we find that there is a spillover effect from NSW (within 3 days), QLD (within 2 days) and TAS (instantly) but not from SA, VIC electricity markets, to the ACCU market and therefore H2a is accepted partially. Furthermore, there is a spillover effect from the ACCU market to QLD (within 4 days) and SA (within 1 day) electricity markets but not to NSW and VIC markets, accepting H2b partially. Lastly, related to H3 (in purple colour) on the mutual relationship between the electricity and REC markets, we find a spillover effect from SA (within 3 days), VIC (within 5 days), and TAS (instantly) electricity markets to the REC market but not from NSW and QLD markets, accepting H3a partially. Also, there is a spillover from the REC market to VIC (within 1 day) electricity markets but not to NSW, QLD and SA markets, and hence, H3b is accepted partially.

When we delve in further by looking at the signs of the significant relationships, particularly related to H2 and H3, we obviously find that the results are aligned with our conjecture (see Section 3). Specifically, the direction of the effects of regional electricity prices on the ACCU and REC prices, and the effects of the ACCU and REC prices on the regional electricity prices vary with dynamics. For instance, while (3 day prior) NSW electricity prices are positively related to the ACCU prices, likely due to an increased demand for the ACCUs from coal-fired power generation, QLD electricity prices change from a negative (3 day prior) to a positive (the following day) relationship with the ACCU prices. The dynamics shown in QLD are likely because higher QLD electricity prices increase both landfill gas and coal-fired power generation, resulting in both increased supply and demand of the ACCUs.

[INSERT TABLE 3 HERE]

5.3 Connectedness Analysis

5.3.1 Static connectedness matrix

Table 4 presents the results of the static connectedness measures illustrated in Equation (5)-(8) over the full period with a 10-day predictive horizon, which answers our second research question on the extent (in percentage) and direction of spillovers from a long-run perspective. Firstly, Panel A of Table 4 shows that the entire network's connectedness (TC) is approximately 20%, mainly dominated by the connectedness among the four regional electricity markets overall. Secondly, the "TO" and "FROM" measures reveal that the extent of the spillover effect among the ACCU, REC and NEM is very small, being less than 3%, though the spillovers among the REMs are fairly high. Specifically, 1) a shock to ACCU (REC) price on a day will transmit 0.07% (0.25%) of its risk to REC (ACCU) price during the following 10 days that corresponds to H1a (H1b); 2) a shock to the regional electricity markets (ACCU) price(s) on a day collectively transmit 0.95% (2.34%) to the ACCU (the regional electricity markets) price(s) during the following 10 days supporting H2a (H2b); and 3) a shock to the REM (REC) price(s) on a day collectively transmit 0.6% (1.2%) of its risk to the REC (the REM) price(s) during the following 10 days supporting H3a (H3b). Lastly, in equilibrium over the full period, from the NET spillover measure, we observe that the REC, ACCU, NSW electricity markets are net risk transmitters, whereas the QLD, SA, and VIC electricity markets are net receivers. The weak connectedness between the ACCU and the REC markets is consistent with our VAR-X results in Section 5.2 on the insignificant relationship between these two markets. This finding may suggest that both ACCU and REC can be considered in an investment portfolio for risk diversification.

Panel B presents an excerpt of the NPDC measure of each pair. The results show that: 1) ACCU market is a net risk receiver from REC market with a net balance of 0.18%; 2) ACCU market is a net risk transmitter to the regional electricity markets as a whole with a net balance of 1.39%, which is composed of the risk transmitted to the NSW (0.23%), SA (0.99%) and VIC (0.28%) electricity markets and the risk received from the QLD (0.11%) electricity market; and 3) REC market is a net risk transmitter to all the regional electricity markets with a total connectedness of 0.6%, which is composed of the risk transmission to NSW (0.09%), QLD (0.18%), SA (0.21%), and VIC (0.12%). In conclusion, the static connectedness matrix over the full period suggests that the linkage between the ACCU market and the NEM in price is the strongest among the three pairs, followed by that between the REC and NEM and that SA is the primary risk channel, through which the NEM is a net risk receiver from both ACCU and REC markets.

[INSERT TABLE 4 HERE]

5.3.2 Dynamic connectedness indices

Table 5 presents the summary statistics of the results of the connectedness indices, which are computed using Equations (5)-(8) based on a 10-day predictive horizon for 200-day rolling windows. While Table 4 shows a relatively low connectedness level among the three markets in price over the full sample period, Table 5 sheds light on the dynamic behaviour of connectedness within 200-day rolling windows. Table 5 shows that within the entire network, the mean of total connectedness (TCI) is 32% with a standard deviation of 5%. The minimum of 23% occurs on 26/12/2022, and the maximum of 48% on 26/04/2019, which is the early stage of the index (the TCI starts on February 4th, 2019). The 1st percentile lies during

December 2022- March 2023, and the 99th percentile lies in April 2019. Jointly with Figure 2, the results in Table 5 unveil a downward trend of the connectedness among the three markets. This implies that as the markets mature, especially with the ACCU market, each can act more independently from the other. One noteworthy finding is that there was a spike on October 7th, 2021 at 46% (see Figure 2), which coincides with the identified structural break point of ACCU (see Section 5.1).[11] The shock to the entire system dissipated within three days, and the total connectedness returned to pre-shock level on the fourth day following the event. This shows that when the ACCU market was most stressed, the risk transmission within the network was intensified, particularly to the SA and VIC electricity markets (see Figure 3 and Figure 4). The amplified transmission fades away within 3 days, however, implying that the entire network can absorb the idiosyncratic market risk well.

Moreover, the averages of the TO and FROM connectedness measures show that the energy market transmits to, and receives from the network the most. The NET connectedness measure shows that, on average, the REC and the energy markets (especially with the NSW and VIC REM) are net risk transmitters to the network, while the ACCU market is the net risk receiver from the network. As the NET measure can be decomposed into NPDC measures, we observe from Table 5 and Figure A1 that REC is mainly a risk transmitter to the QLD electricity market, and ACCU mainly receives risk from all the regional electricity markets. Additionally, we can see that the directional connectedness between the REC and ACCU markets seems to offset each other on average. This may explain the insignificant relationship between the REC and ACCU prices in Table 3, rejecting H1. Related to H2 on the bilateral connectedness between the ACCU and the NEM energy market, the ACCU market is a net risk receiver by an average sum of 5%. Related to H3, on average, the REC market only presents as a net risk transmitter to the QLD electricity market by 3%.

[INSERT TABLE 5 HERE]

[INSERT FIGURE 2-5 HERE]

5.4 Portfolio Analysis

Table 6 presents the summary statistics of the results of the dynamic MVP with dynamic portfolio weights computed in Equation (9) and the hedging effectiveness in Equation (11). On average, in a five-asset portfolio, REC (ACCU) asset weighs 30% (69%) in MVP,

[11] Although we removed the structural shift (due to the breakpoint event in Section 5.1) in the mean of the ACCU prices from the ACCU series to meet the stationarity requirement for estimating the VAR-X model, the shock to the ACCU market on this date is preserved in the treated data series for our connectedness analysis. The transmission of this shock in the ACCU market to the entire network is thus reflected here.

showing their significant role in minimizing portfolio volatility. This is consistent with the findings related to H1 about the insignificant existence and the low degree of connectedness between REC and ACCU. [12] Moreover, the limited allocation to REMs is sensible due to the fact that there is a significant existence and a strong degree of connectedness among the REMs. Furthermore, the results of the hedging effectiveness (HE) show that the volatility of each asset in this portfolio would be statistically significantly lowered by 81%, 24%, 95%, 96%, 98% and 98%, respectively. Lastly, the average of the cumulative portfolio returns is 14.48%. Figure 5 reveals the dynamic portfolio allocation in Panel A and the dynamic cumulative portfolio returns in Panel B of a multivariate portfolio. Consistent with Table 6, Figure 5 generally unveils the dominant weight of ACCU, followed by REC. However, such dominance experienced a period of drastic change. Specifically, a drastic shift in allocation took place after October 7th, 2021, where asset allocation to REC surged, whereas to ACCU plummeted. This shift coincides with the structural break of ACCU prices (see Section 5.1), showing that a shock to, i.e. the volatility of, ACCU price on that day could affect the asset allocation, i.e. the investing behavior, if a minimum-variance portfolio is pursued. Similarly, the drastic change is also reflected in Panel B which after the same date, the cumulative portfolio returns plummeted.

[INSERT TABLE 6 HERE]

[INSERT FIGURE 5 HERE]

Table 7 presents the summary statistics of the results of the dynamic bivariate portfolios following Kroner & Sultan (1993) with dynamic hedge ratios computed in Equation (10) and the corresponding hedging effectiveness in Equation (11). The average of the dynamic hedge ratios reveals that, firstly, REC and ACCU cannot hedge effectively with statistical significance. This corresponds to the finding in Section 5.3.1 that SA is the principal net risk channel from REC and ACCU to the NEM. Secondly, the effective hedge exists within the NEM with the cheapest hedge being QLD (54 cents), followed by VIC (78 cents) and NSW (95 cents). Thirdly, the hedging effectiveness shows that the volatility of the bivariate portfolio would be statistically significantly lowered by 24% in a long-SA-short-NSW portfolio (SA/NSW portfolio), 14% in SA/QLD portfolio and 42% in SA/VIC portfolio. Lastly, the cumulative portfolio returns of the effective hedge portfolio are negative. All the statistics show that it is very expensive to hedge the risk of the SA market. [13]

[12] Our two-, three- and four-asset minimum-variance portfolios report the similar results.

[13] Bivariate portfolio results for hedging the risk of the other regional markets are available upon request.

[INSERT TABLE 7 HERE]

6 Conclusion

We explore the interplay of the offset, REC, and electricity market in the interesting context of Australia by investigating the existence, extent, and direction of the spillovers in prices among the offset, REC, and electricity markets during May 2018- June 2023. Our results are relevant to the controversy about the absence of 'financial additionality' of some offsets (ACCUs), and concerns about electricity hedging strategies as more intermittent renewables are integrated into energy systems.

Firstly, our results show that the total connectedness among the offset, REC and electricity markets is trending downward based on the short-run 200-day rolling windows. This suggests that the potential climate policy overlapping effect is decreasing as the three markets are operating more and more independently. Moreover, there is an insignificant connectedness between the offset and REC markets over the full period, implying that these two markets can operate independently. Our findings thus provide evidence relating to the integrity of the ACCUs. On the one hand, Macintosh (2022) criticizes that the landfill gas offset methodology suffers from financial non-additionality and his team also exposed the measurement and integrity issues with the human-induced regeneration method (Macintosh, Butler, & Ansell, 2022; Macintosh, Butler, Ansell, et al., 2022). On the other hand, the review by Chubb, Bennett, Gorring, & Hatfield-Dodds (2022) concludes that the ACCU scheme is fundamentally sound. As Macintosh, Butler, Evans, Waschka, & Ansell (2023) point out, the latter review does not discuss in detail the landfill gas method. Our empirical findings do not suggest that the landfill gas method, being a potential linkage channel, is distorting other pricing mechanisms. On the contrary, our findings imply that although the argument of Macintosh (2022) may be sound, the effect of non-additionality may not be significant from a pricing perspective. Admittedly, our study uses the generic ACCU prices as a proxy rather than a specific landfill gas project-based ACCU price. Future analyses may be done with volumes of ACCUs generated from different methods, e.g. HIR, landfill gas, agriculture, etc. Further, as noted in Section 1, Australia is moving to establish the national carbon exchange market. Once the exchange is fully functional and trading various climate-related certificates simultaneously, it seems reasonable to expect that higher liquidity, standardization, and transparency would increase the spillovers among the certificate prices, reduce transaction cost, reduce the bid-offer spread, and increase pricing efficiency.

Secondly, we find a significant connectedness between the electricity market and the offset market. Over the full period, a shock to the regional electricity (ACCU) price(s) collectively transmits 0.95% (2.34%) risk to the ACCU (the regional electricity) price(s), making the ACCU market a net risk transmitter to the regional electricity markets as a whole with a net balance of 1.39%. What's more, there is a significant connectedness between the electricity market and the REC market. Over the full period, a shock to the regional electricity (REC) price(s) collectively transmits 0.6% (1.2%) risk to the REC (the regional electricity) price(s), making the REC market a net risk transmitter to the regional electricity markets as a whole with a net balance of 0.6%. The low level of risk transmission from the ACCU and REC markets to the regional electricity prices and the insignificant spillover between ACCU and REC markets suggest to electricity traders that ACCU and REC are both good hedging tools to diversify their portfolio risks.

Thirdly, when we look into the regional electricity markets, we find that South Australia's regional electricity market is the main contributor to the net pairwise directional connectedness between the national electricity market and the ACCU market and between the electricity market and the REC market. Moreover, we find that it is very expensive to effectively hedge the risk of price volatility in the SA market. In fact, if any hedging operation was executed, the cumulative returns yield to be negative. This may be explained by South Australia's high penetration of 'new' (wind and solar) renewable electricity. This finding suggests heterogeneity in hedging risk based on geography and energy mix. This highlights the need to develop effective hedging tools as more wind and solar energy generation is deployed in Australia and beyond.

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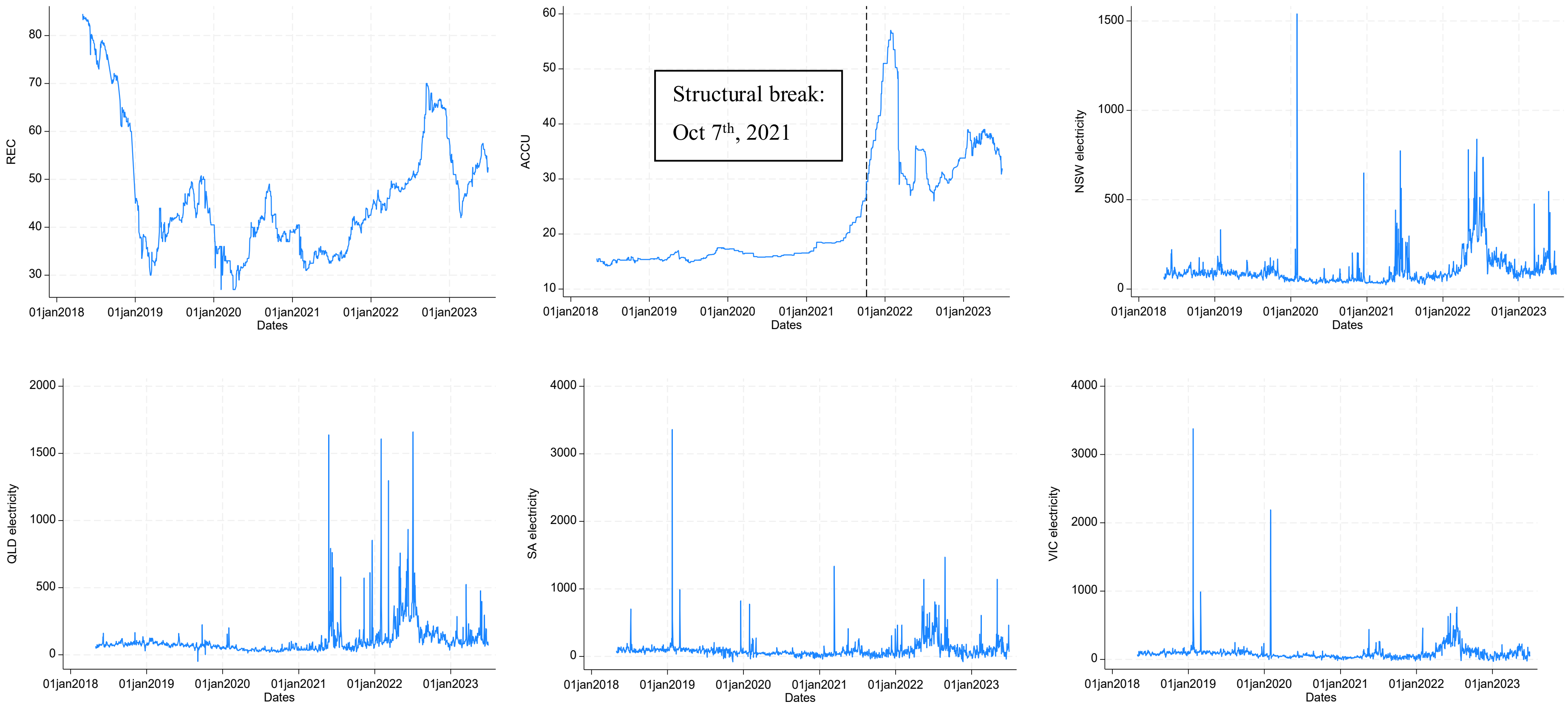

REC
Dates
ACCU
Structural break:
Oct 7th, 2021
NSW electricity
QLD electricity
SA electricity
VIC electricity
01jan2018
01jan2019
01jan2020
01jan2021
01jan2022
01jan2023

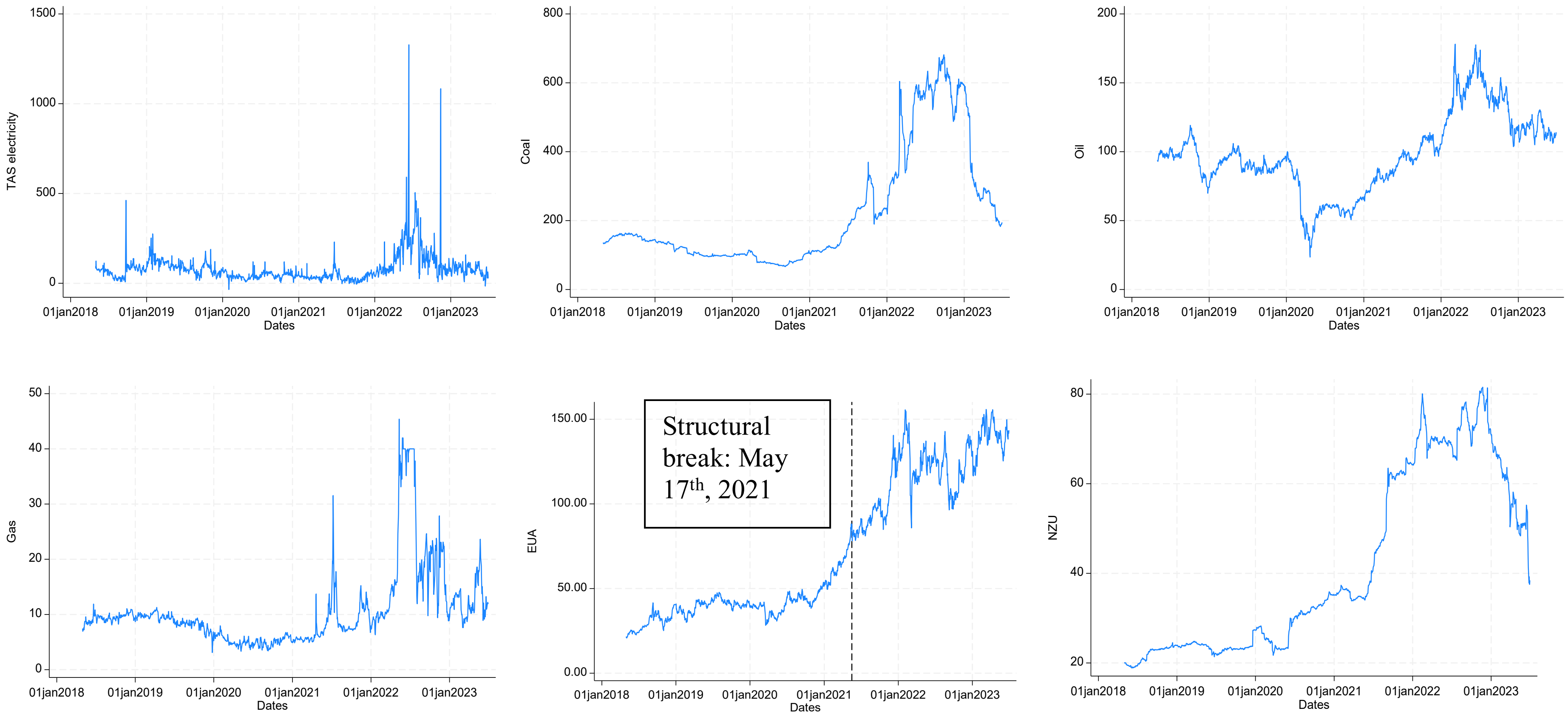


Figure 1: Prices of REC, ACCU, Electricity, Energy and International Carbon Markets

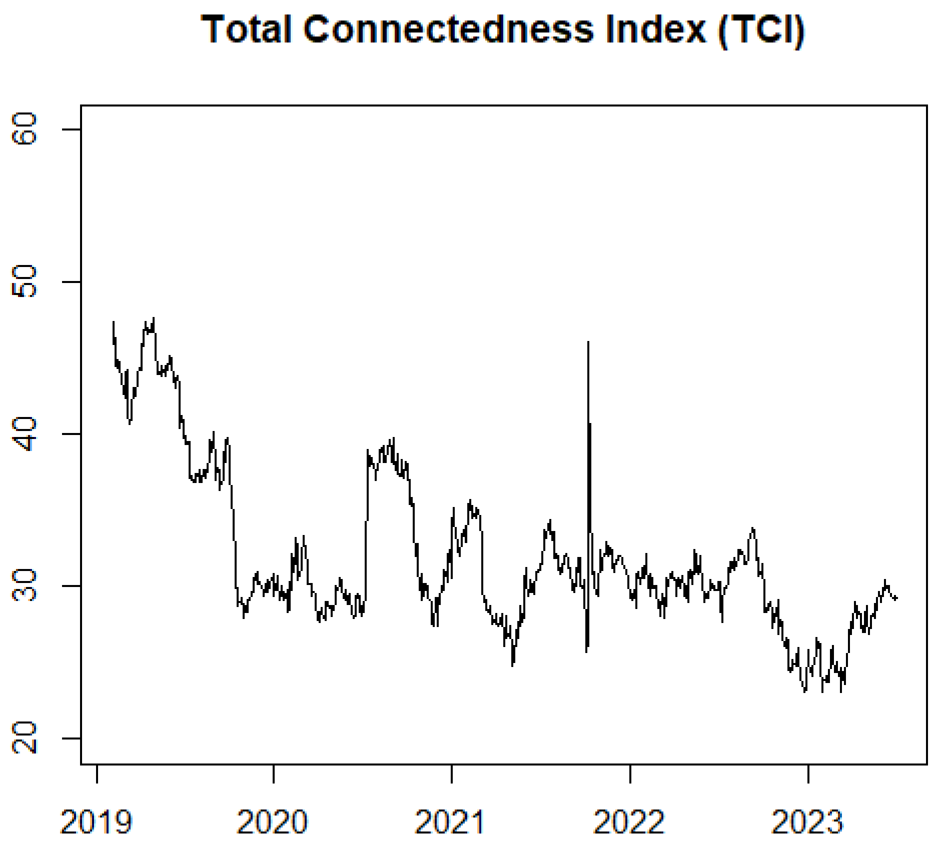


Figure 2: Dynamic Total Connectedness Index

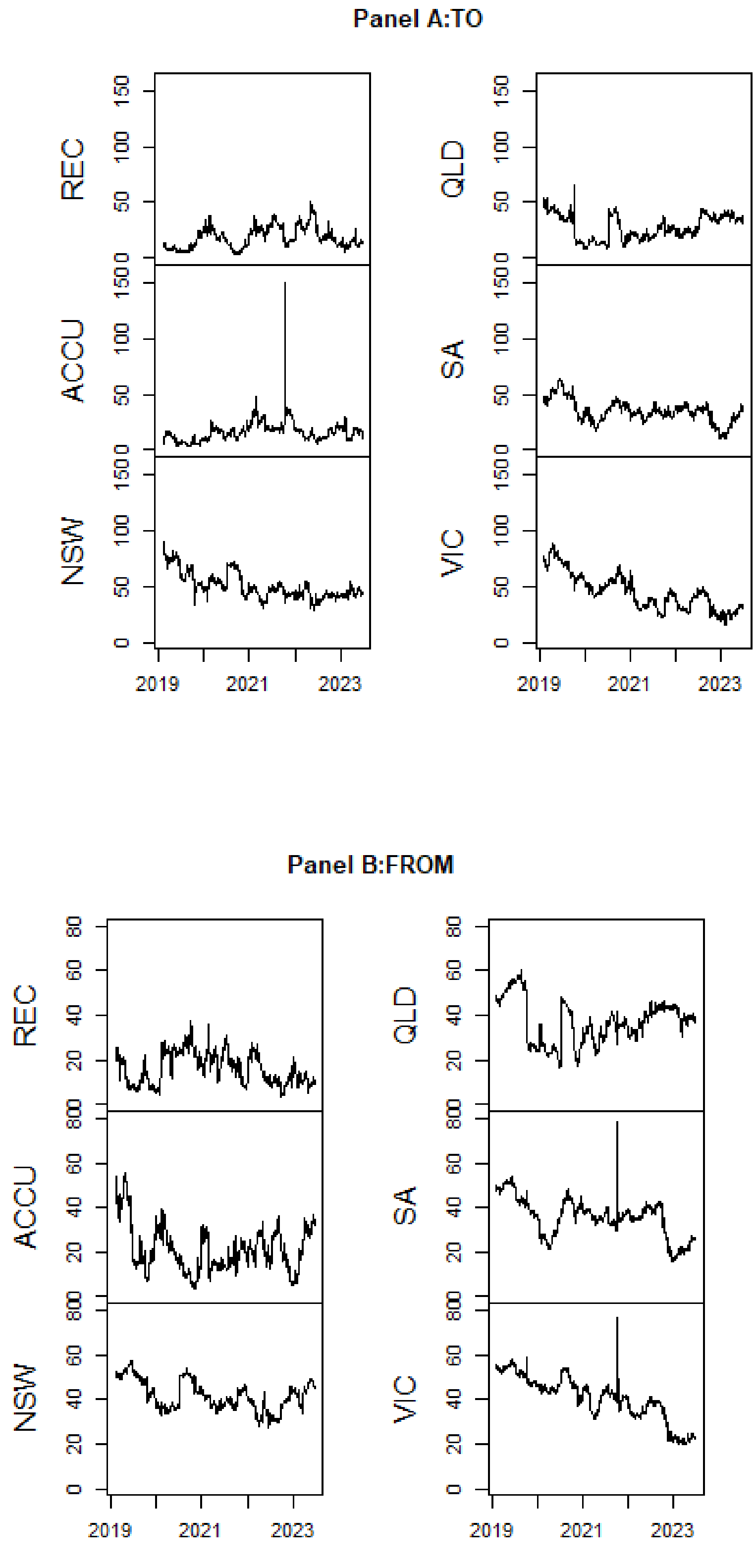


Figure 3: Dynamic TO and FROM Directional Connectedness

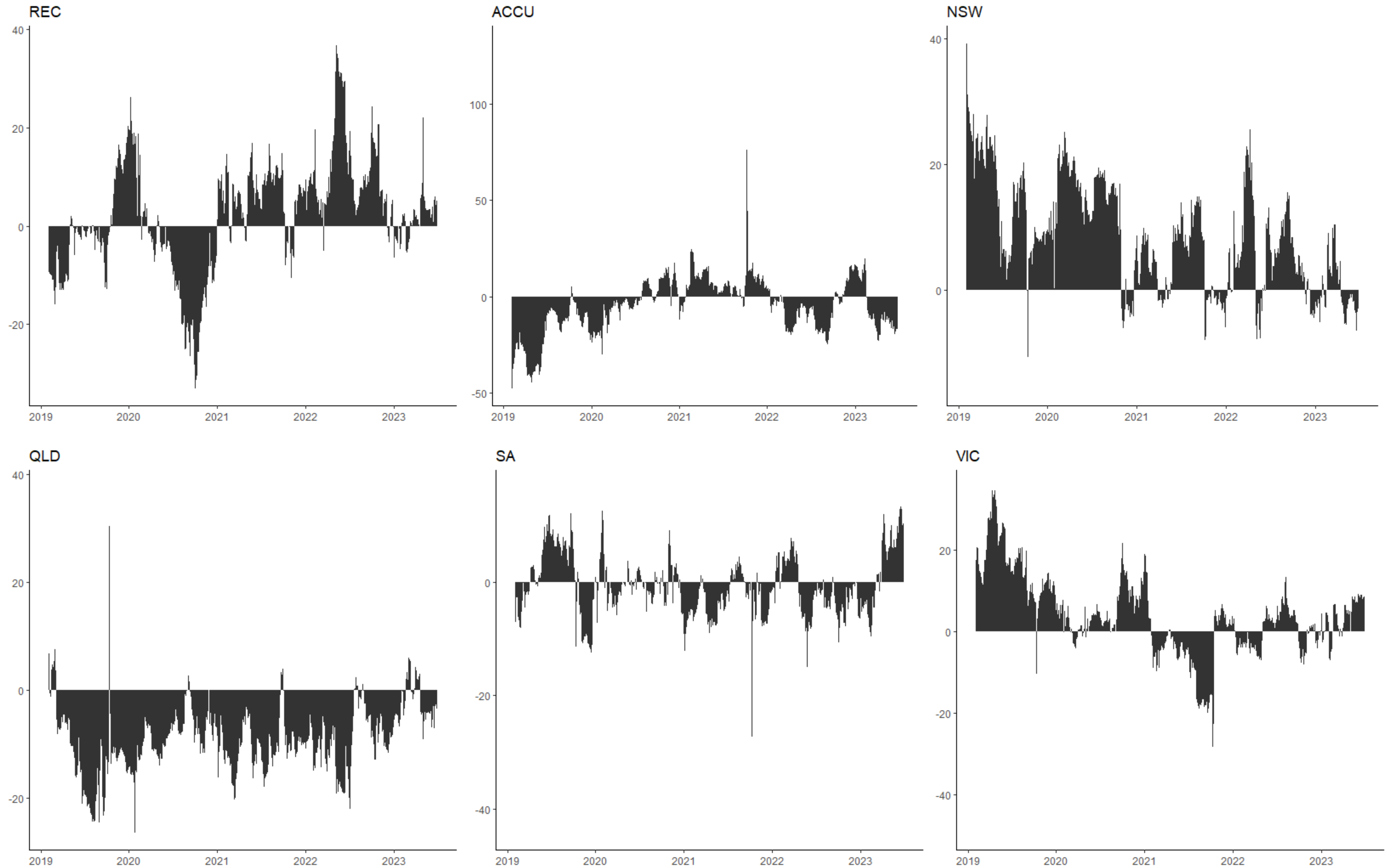
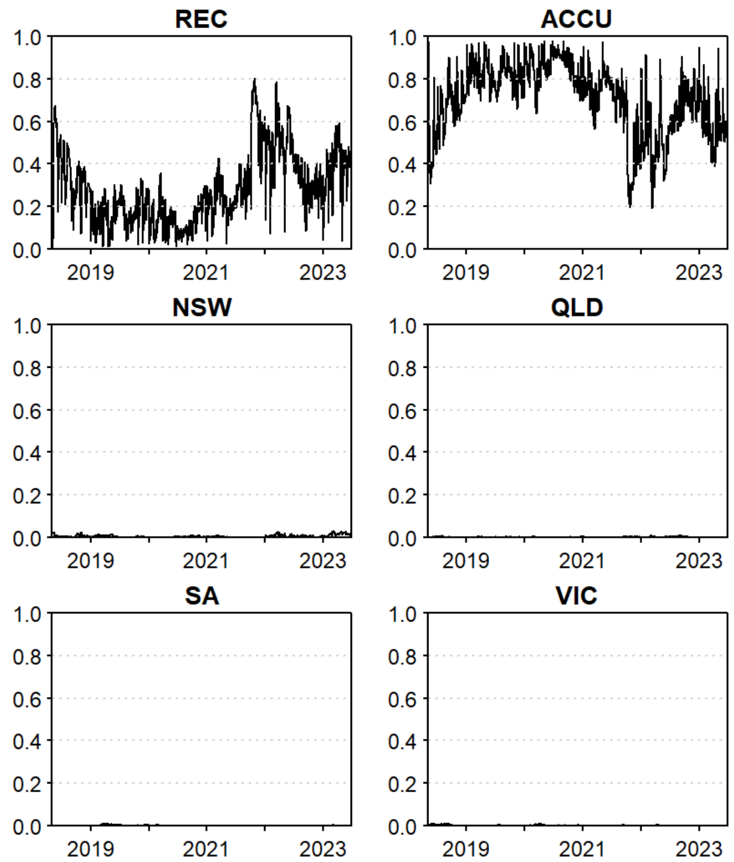


Figure 4: Dynamic Net Directional Connectedness

Panel A Dynamic Portfolio Allocation



Panel B Dynamic Cumulative Portfolio Returns

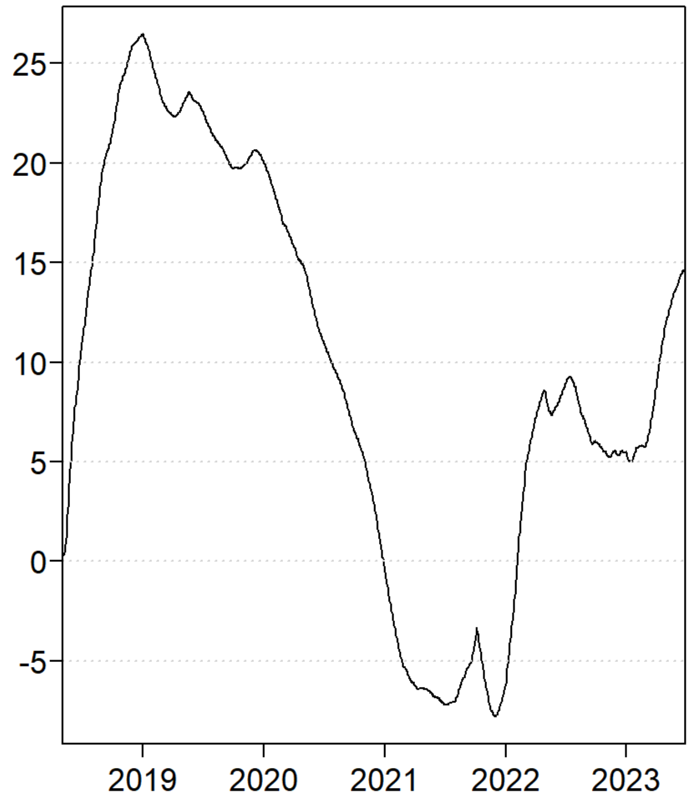


Figure 5: Dynamic Multivariate Portfolio

Table 1: NEM's Regional Electricity Market Electricity Source Mix and Targets

Location	Electricity Source Mix	Renewable Energy Target	Emissions Reduction Target
New South Wales	70% black coal 11% solar, 10% wind	NA	50% by 2030 (from 2005 levels) Net zero by 2050
Queensland	75% black coal, 10% solar, 8% gas	50% by 2030	30% by 2030 (from 2005 levels) Net zero by 2050
South Australia	61% wind, 30% gas	26% by 2020 (met) 75% by 2025 100% by 2030	50% by 2030 (from 2005 levels) Net zero by 2050
Victoria	67% brown coal, 23% wind	40% by 2025 50% by 2030	28-33% by 2025 (from 2005 levels) 45-50% by 2030 (from 2005 levels) Net zero by 2050
Tasmania	81% hydro, 19% wind	100% by 2022 (met) 200% by 2040	60% by 2050 (from 1990 levels) Net zero by 2030

Source: AEMO

Table 2: Summary Statistics

This table illustrates summary statistics of all variables for the sample period of May 1st, 2018 – June 30th,2023. REC is the LGC spot prices (in AU$/MWh). ACCU is the ACCU spot prices (in AU$/ton). $Elec_{nsw}, Elec_{qld}, Elec_{sa}, Elec_{vic}, Elec_{tas}$ are the daily average electricity spot prices (in AU$/MWh) in 5 states respectively. Coal is the future prices (in AU$/ton). Gas is the daily average declared wholesale gas market price (in AU$/gigajoule). Oil is the Arabian Dubai Fateh crude spot index oil prices (in AU$/barrel). EUA is the daily EUA futures close prices (in AU$/ton). NZU is the daily ACCU spot prices (in AU$/ton).

VARIABLES	N	mean	sd	skewness	kurtosis	min	p1	p5	p50	p95	p99	max
REC	1,349	46.926	13.314	1.029	3.297	27.000	29.000	32.000	43.550	76.000	83.300	84.500
ACCU	1,349	23.151	10.086	1.267	3.827	14.170	14.370	15.000	17.250	40.250	55.250	57.000
$\mathrm{Elec}_{\mathrm{nsw}}$	1,349	90.049	47.999	1.634	6.219	23.380	31.920	36.750	80.980	191.430	264.180	299.230
$\mathrm{Elec}_{\mathrm{qld}}$	1,349	86.127	50.979	1.751	6.673	1.470	22.880	31.330	75.830	192.020	285.030	296.500
$\mathrm{Elec}_{\mathrm{sa}}$	1,349	83.517	54.154	1.419	5.611	0.060	2.960	16.210	74.780	195.780	273.010	294.510
$\mathrm{Elec}_{\mathrm{vic}}$	1,349	80.923	51.182	1.337	5.298	0.180	5.820	18.180	72.950	184.000	257.520	290.650
$\mathrm{Elec}_{\mathrm{tas}}$	1,349	72.896	50.041	1.617	6.414	0.220	6.090	17.050	63.290	179.250	256.310	299.220
Coal	1,349	223.133	170.305	1.327	3.396	66.603	69.375	76.694	143.201	597.319	655.704	681.379
Gas	1,349	10.662	7.257	2.613	10.346	3.114	3.724	4.535	9.132	23.628	40.000	45.386
Oil	1,349	97.932	28.270	0.270	2.976	23.550	38.120	53.890	95.900	150.100	167.080	178.040
EUA	1,349	72.942	41.327	0.520	1.670	20.830	23.305	27.510	48.256	141.854	151.556	155.788
NZU	1,349	41.428	19.878	0.576	1.718	18.860	19.130	20.800	33.970	74.830	80.070	81.530

Table 3: VAR-X Results

This table presents results for short-run relationships among REC, ACCU and electricity prices for the period of May 1st, 2018 -June 30th, 2023. Vector autoregressions with exogenous variables (VAR-X) are run to test H1, H2, and H3. $Elec_{tas}$ is an exogenous variable and has a contemporaneous effect. "ns" means not significant. Variable definitions are available in Table 2. Extended results of this estimated model are illustrated in Appendix Table 1. *** significance at p < 0.01. ** significance at p < 0.05. * significance at p < 0.10

Hypotheses	from	to	lag1	lag2	lag3	lag4	lag5	lag0
H1a: -	$ACCU$	REC	ns	ns	ns	ns	ns	
H1b:-	REC	$ACCU$	ns	ns	ns	ns	ns	
H2a:-	$Elec_{nsw}$	$ACCU$	ns	ns	0.009***	ns	ns	
H2a:-	$Elec_{qld}$	$ACCU$	ns	0.008***	-0.009***	ns	ns	
H2a:-	$Elec_{sa}$	$ACCU$	ns	ns	ns	ns	ns	
H2a:-	$Elec_{vic}$	$ACCU$	ns	ns	ns	ns	ns	
H2a:-	$Elec_{tas}$	$ACCU$	ns	-0.006***	ns	ns	-0.002*	0.008***
H2b:-	$ACCU$	$Elec_{nsw}$	ns	ns	ns	ns	ns	
H2b:-	$ACCU$	$Elec_{qld}$	ns	ns	ns	0.967*	ns	
H2b:-	$ACCU$	$Elec_{sa}$	2.807***	-3.210***	ns	ns	ns	
H2b:-	$ACCU$	$Elec_{vic}$	ns	ns	ns	ns	ns	
H3a:-	$Elec_{nsw}$	REC	ns	ns	ns	ns	ns	
H3a:-	$Elec_{qld}$	REC	ns	ns	ns	ns	ns	
H3a:-	$Elec_{sa}$	REC	ns	ns	0.002*	-0.002*	ns	
H3a:-	$Elec_{vic}$	REC	ns	ns	ns	ns	-0.003*	
H3a:-	$Elec_{tas}$	REC	ns	ns	ns	ns	0.004**	-0.003*
H3b:+	REC	$Elec_{nsw}$	ns	ns	ns	ns	ns	
H3b:+	REC	$Elec_{qld}$	ns	ns	ns	ns	ns	
H3b:+	REC	$Elec_{sa}$	ns	ns	ns	ns	ns	
H3b:+	REC	$Elec_{vic}$	-1.255**	ns	ns	ns	ns	

Table 4: Static Connectedness Matrix

Panel A presents the connectedness among REC, ACCU and electricity markets. The "FROM" column shows the total directional connectedness from all other markets to i market. The "To" row shows the total directional connectedness from j market to all other markets. The "NET" row shows the total net directional connectedness (TO minus FROM). The bottom-right value (in bold) is the total connectedness of the entire network (TC). Panel B presents a breakdown of the "NET" values, i.e. a net pairwise directional connectedness (NPDC) from i market to j market. The connectedness measures are computed from our estimated VAR-X model via Equation (2) over a 10-workday horizon. The values are in percentages. Yellow colour refers to H1, peach colour H2, purple colour H3. Variable definitions are available in Table 2.

Panel A Connectedness network among REC, ACCU and electricity markets

From j / To i	REC	$ACCU$	$Elec_{nsw}$	$Elec_{qld}$	$Elec_{sa}$	$Elec_{vic}$	FROM
REC	99.33	0.07	0.07	0.01	0.10	0.42	0.67
$ACCU$	0.25	98.81	0.19	0.34	0.08	0.34	1.19
$Elec_{nsw}$	0.16	0.42	69.28	16.19	5.72	8.23	30.72
$Elec_{qld}$	0.19	0.23	25.18	70.15	2.36	1.89	29.85
$Elec_{sa}$	0.31	1.07	5.74	1.17	74.40	17.30	25.60
$Elec_{vic}$	0.54	0.62	11.47	1.90	15.97	69.50	30.50
TO	1.45	2.41	42.65	19.60	24.23	28.19	19.76 (TC)
NET	0.78	1.21	11.93	-10.24	-1.36	-2.31	

Panel B net pairwise directional connectedness

Hypotheses	From	To	NPDC
H1a: -	ACCU	REC	-0.18
H1b:-	REC	ACCU	0.18
H2a:-	NSW	ACCU	-0.23
H2a:-	QLD	ACCU	0.11
H2a:-	SA	ACCU	-0.99
H2a:-	VIC	ACCU	-0.28
H2b:-	ACCU	NSW	0.23
H2b:-	ACCU	QLD	-0.11
H2b:-	ACCU	SA	0.99
H2b:-	ACCU	VIC	0.28
H3a:-	NSW	REC	-0.09
H3a:-	QLD	REC	-0.18
H3a:-	SA	REC	-0.21
H3a:-	VIC	REC	-0.12
H3b:+	REC	NSW	0.09
H3b:+	REC	QLD	0.18
H3b:+	REC	SA	0.21
H3b:+	REC	VIC	0.12

Table 5: Summary Statistics of Dynamic Connectedness Indices

This table shows summary statistics of the total connectedness (TCI) in Equation (8), total "TO", "FROM" and "NET" indices. The results are based on a 10-day predicative horizon and 200-day rolling window. Yellow color refers to H1, peach H2, purple H3. The definition of connectedness measures is available in Table 4. Mean, min, p1, p5, p50, p95, p99 and max values are in percentage.

VARIABLES	N	mean	sd	skewness	kurtosis	min	p1	p5	p50	p95	p99	max
TCI	1,150	32	5	1.1	3.6	23	24	25	30	44	47	48
TO_REC	1,150	18	10	0.6	2.8	3	4	6	17	36	45	50
TO_ACCU	1,150	16	9	4.5	53	3	4	6	16	31	43	150
TO_NSW	1,150	50	12	1	3.1	28	32	36	47	75	79	90
TO_QLD	1,150	28	11	0.1	1.9	9	9	12	27	44	51	65
TO_SA	1,150	35	10	0.1	3.3	10	11	18	35	52	62	64
TO_VIC	1,150	45	16	0.6	2.6	16	19	23	43	76	86	89
FROM_REC	1,150	16	7	0.3	2.1	4	4	6	15	28	33	37
FROM_ACCU	1,150	21	10	0.9	3.7	3	5	7	19	43	53	55
FROM_NSW	1,150	42	7	0.2	2.2	28	29	31	41	53	56	57
FROM_QLD	1,150	37	10	0.2	2.3	16	18	23	37	55	57	60
FROM_SA	1,150	36	9	-0.2	3.1	16	17	20	36	51	53	78
FROM_VIC	1,150	41	10	-0.4	2.5	20	21	22	42	55	58	77
NET_REC	1,150	2	11	-0.1	3.7	-33	-27	-19	3	19	32	37
NET_ACCU	1,150	-5	15	0.6	10.6	-48	-41	-30	-4	15	23	132
NET_NSW	1,150	8	9	0.3	2.3	-16	-7	-4	8	23	28	39
NET_QLD	1,150	-9	6	0.6	6.7	-26	-24	-20	-9	2	6	38
NET_SA	1,150	-1	6	-0.3	6.4	-44	-12	-9	-1	9	12	17
NET_VIC	1,150	4	10	0.2	4.5	-49	-18	-11	3	22	32	35
NPDC_REC_ACCU	1,150	0	5	0.3	4.4	-23	-13	-8	0	10	15	20
NPDC_REC_NSW	1,150	0	4	0.8	6.7	-18	-10	-7	0	5	16	20
NPDC_REC_QLD	1,150	3	4	1.2	4.8	-7	-3	-2	2	10	16	17
NPDC_REC_SA	1,150	0	4	-1.5	6.5	-17	-13	-7	1	5	7	9
NPDC_REC_VIC	1,150	0	3	0.2	3	-10	-8	-6	0	5	9	10
NPDC_ACCU_NSW	1,150	-2	6	-1.2	5	-25	-23	-16	-1	7	10	13
NPDC_ACCU_QLD	1,150	-1	4	-1.1	4.7	-16	-14	-9	0	5	6	11
NPDC_ACCU_SA	1,150	-1	5	0.8	23.4	-21	-18	-12	0	5	5	58
NPDC_ACCU_VIC	1,150	-1	5	0.7	17.2	-17	-16	-9	0	5	7	50
NPDC_NSW_QLD	1,150	6	3	-0.3	5.1	-13	-3	-1	6	10	15	18
NPDC_NSW_SA	1,150	1	2	0	2.5	-4	-4	-3	1	5	6	7
NPDC_NSW_VIC	1,150	0	4	-0.4	2.2	-9	-8	-6	0	5	5	6
NPDC_QLD_SA	1,150	-1	2	0.3	5.3	-8	-6	-4	-1	2	5	10
NPDC_QLD_VIC	1,150	0	3	-0.4	5.4	-10	-10	-8	0	4	5	19
NPDC_SA_VIC	1,150	-2	2	-0.6	3.7	-10	-9	-6	-2	1	2	4

Table 6: Summary Statistics of Dynamic Multivariate Portfolios

This table presents the summary statistics of the results of the dynamic MVP. Mean is the average of the dynamic weights of the portfolio. HE is hedging effectiveness and CR is cumulative portfolio returns.

	Mean	Std.Dev.	5%	95%	HE	p-value	CR
REC	0.30	0.17	0.08	0.67	0.81	0.00	14.48
ACCU	0.69	0.17	0.32	0.91	0.24	0.00	14.48
NSW	0.01	0.01	0.00	0.02	0.95	0.00	14.48
QLD	0.00	0.00	0.00	0.01	0.96	0.00	14.48
SA	0.00	0.00	0.00	0.01	0.98	0.00	14.48
VIC	0.00	0.00	0.00	0.01	0.98	0.00	14.48

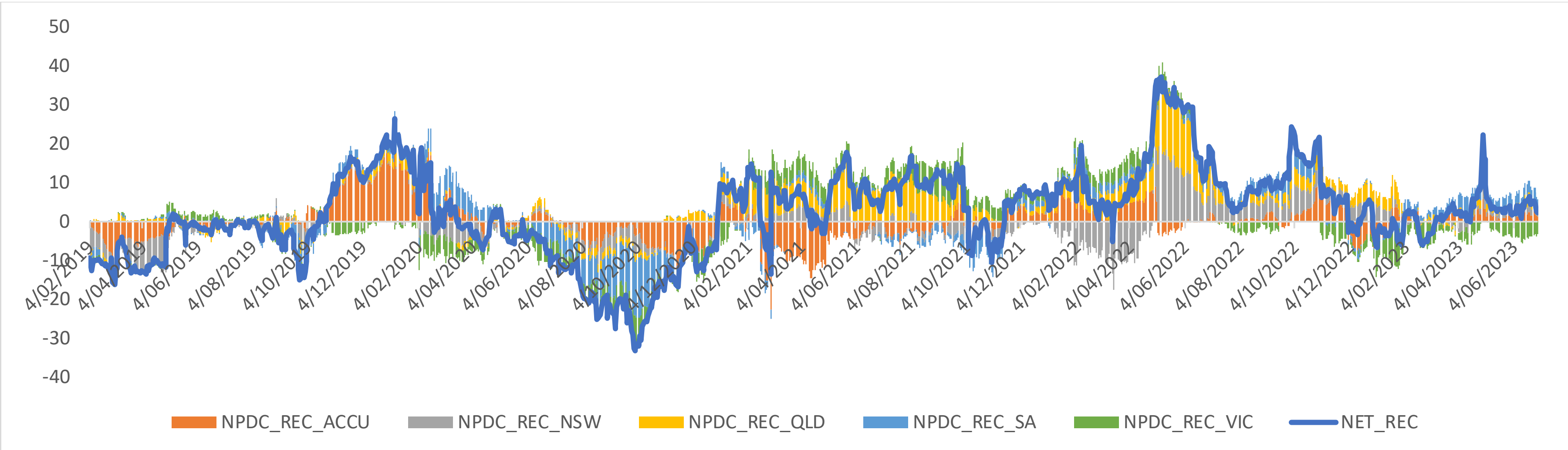
Table 7: Summary Statistics of Dynamic Bivariate Portfolios

This table presents the summary statistics of the results of the dynamic bivariate portfolios following Kroner & Sultan (1993). Mean is the average of the dynamic hedge ratios, which is computed with Equation (10) while HE is the hedging effectiveness computed with Equation (11). p-value is the statistical significance of HE. CR is the cumulative returns.

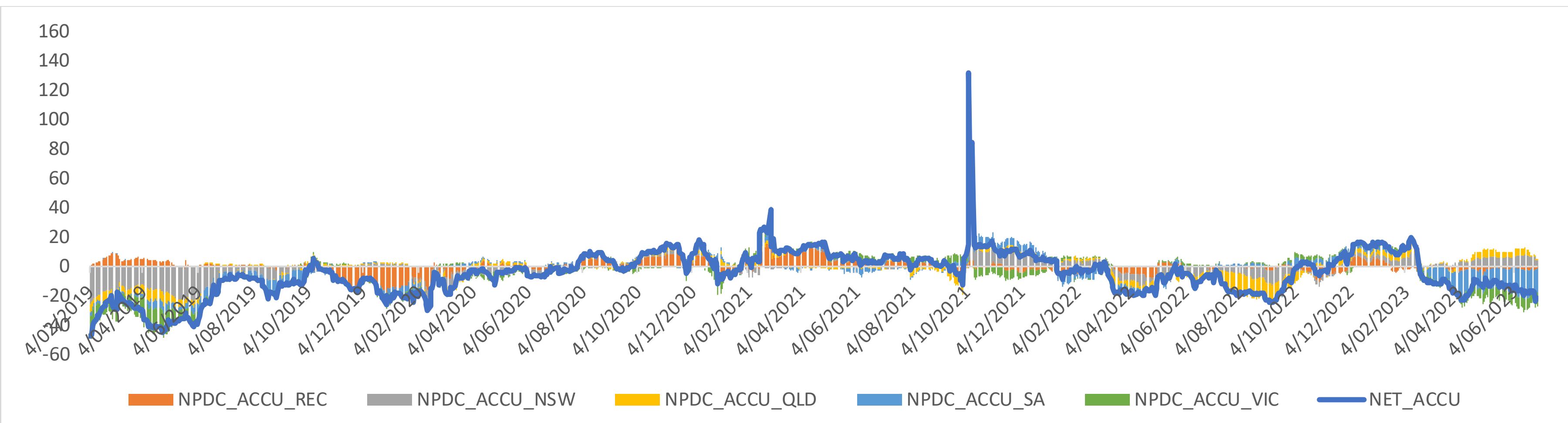
Long/Short	Mean	Std.Dev.	5%	95%	HE	p-value	CR
SA/REC	0.04	2.20	-3.04	3.77	-0.24	1.00	0.05
SA/ACCU	-0.37	3.21	-4.48	5.17	0.02	0.95	0.32
SA/NSW	0.95	0.32	0.49	1.52	0.24	0.00	-6.66
SA/QLD	0.54	0.25	0.12	0.94	0.14	0.00	-5.19
SA/VIC	0.78	0.19	0.45	1.07	0.42	0.00	-37.26

Appendices

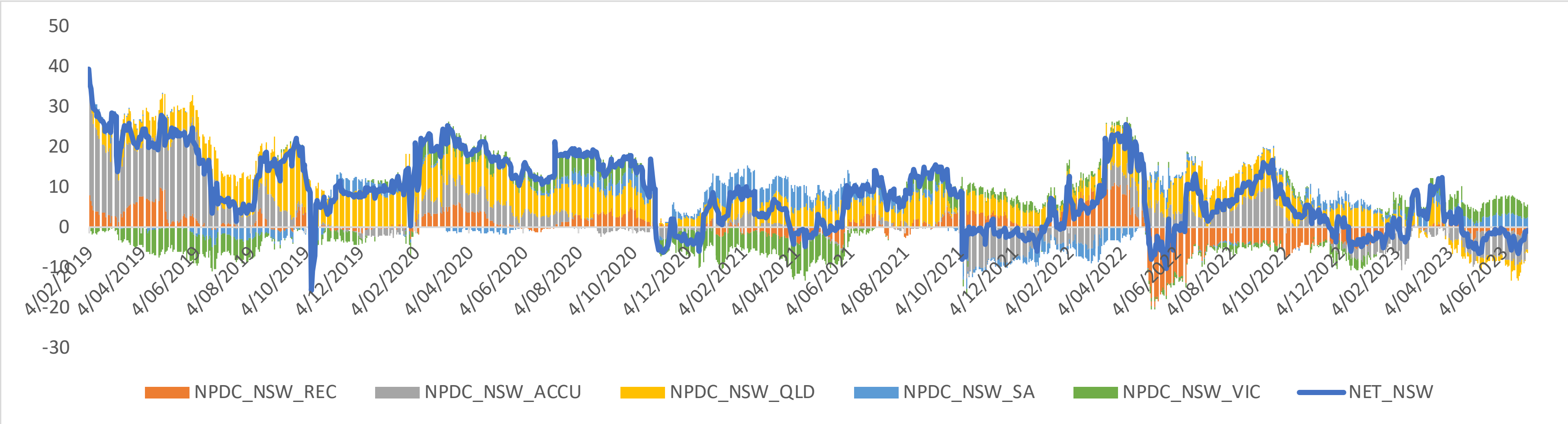
Panel A REC



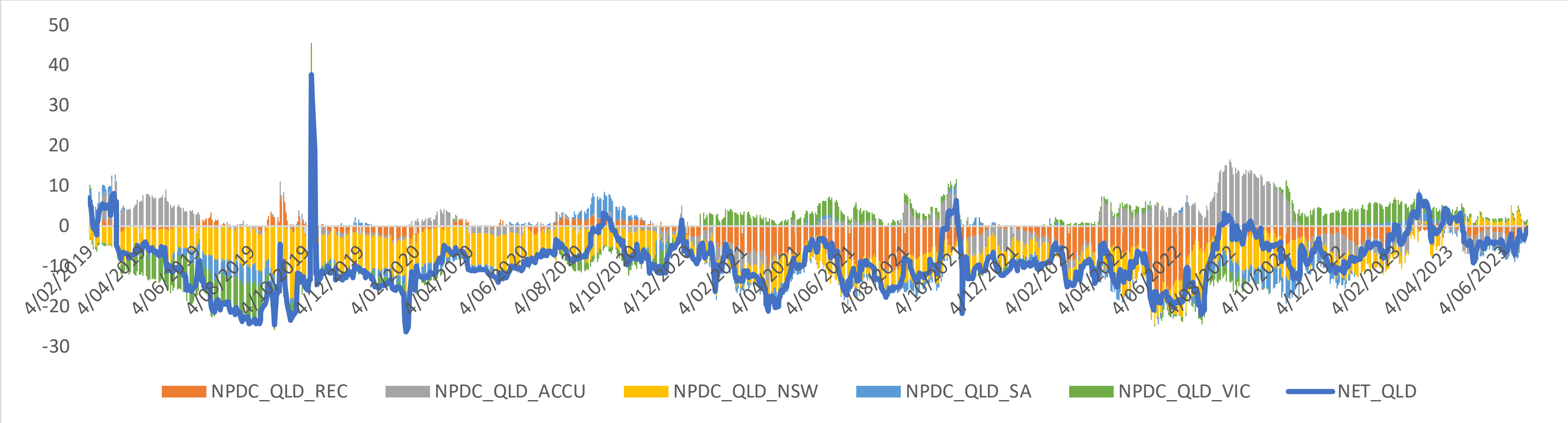
Panel B ACCU



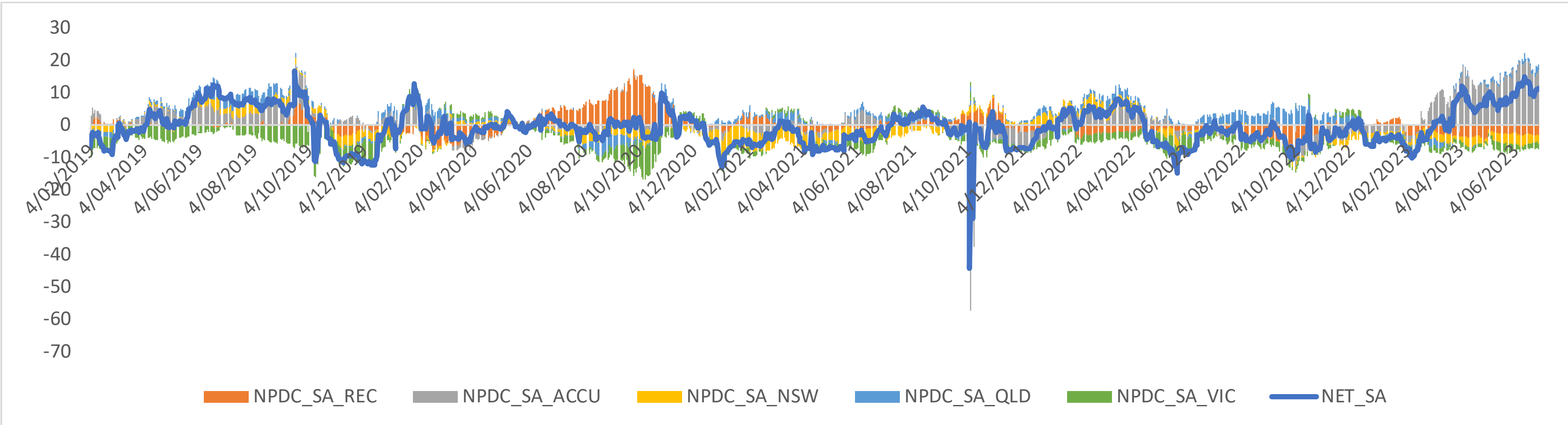
Panel C NSW



Panel D QLD



Panel E SA



Panel F VIC

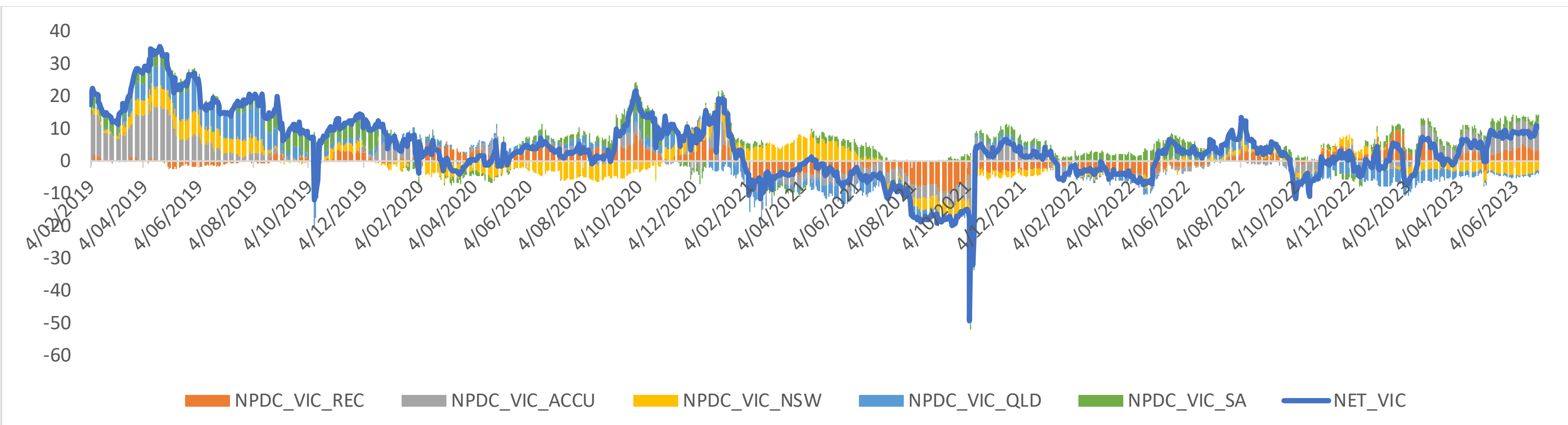


Figure A1: Total Net Connectedness Decomposition

Table A1: Short-run Relationships among REC, ACCU and Electricity Prices

This table presents results for short-run relationships among REC, ACCU and electricity prices for the period of May 1st, 2018 -June 30th, 2023. Vector autoregressions with exogenous variables (VAR-X) are run focusing our research hypotheses H1, H2, and H3. 5-workday lagged period is tested for hypothesized relationships. Standard errors are in parentheses. *** significance at p < 0.01. ** significance at p < 0.05. * significance at p < 0.10.

$VARIABLES$	REC_t	$ACCU_t$	$Elec_{nsw_t}$	$Elec_{qld_t}$	$Elec_{sa_t}$	$Elec_{vic_t}$
REC_{t-1}	0.914***	-0.011	0.128	0.374	-0.821	-1.255**
	(0.027)	(0.021)	(0.245)	(0.291)	(0.644)	(0.521)
REC_{t-2}	-0.009	0.027	-0.274	-0.356	0.259	0.804
	(0.037)	(0.029)	(0.331)	(0.394)	(0.870)	(0.704)
REC_{t-3}	0.031	-0.007	0.469	0.281	0.693	0.207
	(0.037)	(0.029)	(0.331)	(0.393)	(0.869)	(0.703)
REC_{t-4}	0.084**	-0.035	-0.384	-0.382	-0.718	-0.421
	(0.037)	(0.028)	(0.329)	(0.391)	(0.864)	(0.700)
REC_{t-5}	-0.034	0.021	0.121	0.087	0.591	0.644
	(0.027)	(0.021)	(0.243)	(0.289)	(0.639)	(0.517)
$ACCU_{t-1}$	0.056	0.957***	-0.176	-0.252	2.807***	0.812
	(0.035)	(0.027)	(0.316)	(0.375)	(0.830)	(0.672)
$ACCU_{t-2}$	-0.058	0.091**	-0.113	0.299	-3.210***	-0.503
	(0.048)	(0.037)	(0.434)	(0.516)	(1.141)	(0.924)
$ACCU_{t-3}$	0.004	-0.056	-0.055	-0.605	-1.349	-0.703
	(0.047)	(0.037)	(0.423)	(0.503)	(1.113)	(0.901)
$ACCU_{t-4}$	0.011	-0.112***	0.460	0.967*	1.030	-0.531
	(0.046)	(0.036)	(0.418)	(0.496)	(1.097)	(0.888)
$ACCU_{t-5}$	-0.006	0.104***	-0.148	-0.303	0.596	0.866
	(0.034)	(0.026)	(0.306)	(0.364)	(0.805)	(0.652)
$Elec_{nsw_{t-1}}$	0.001	-0.001	0.372***	0.232***	0.000	0.292***
	(0.004)	(0.003)	(0.032)	(0.038)	(0.084)	(0.068)
$Elec_{nsw_{t-2}}$	0.003	-0.003	0.123***	0.075*	0.142	0.049
	(0.004)	(0.003)	(0.034)	(0.040)	(0.088)	(0.071)
$Elec_{nsw_{t-3}}$	-0.005	0.009***	0.105***	0.115***	0.114	0.014
	(0.004)	(0.003)	(0.034)	(0.040)	(0.089)	(0.072)
$Elec_{nsw_{t-4}}$	0.000	-0.000	0.024	-0.028	-0.088	0.072
	(0.004)	(0.003)	(0.034)	(0.040)	(0.089)	(0.072)
$Elec_{nsw_{t-5}}$	0.001	-0.002	0.006	0.001	-0.030	-0.055
	(0.004)	(0.003)	(0.032)	(0.038)	(0.084)	(0.068)
$Elec_{qld_{t-1}}$	-0.001	0.001	0.081***	0.266***	-0.023	0.012
	(0.003)	(0.002)	(0.025)	(0.030)	(0.067)	(0.054)
$Elec_{qld_{t-2}}$	-0.001	0.008***	-0.028	0.039	-0.137**	-0.100*
	(0.003)	(0.002)	(0.026)	(0.031)	(0.068)	(0.055)
$Elec_{qld_{t-3}}$	0.001	-0.009***	0.027	0.042	0.009	-0.030
	(0.003)	(0.002)	(0.026)	(0.031)	(0.069)	(0.056)
$Elec_{qld_{t-4}}$	0.003	0.002	-0.037	-0.059*	0.122*	-0.074
	(0.003)	(0.002)	(0.026)	(0.031)	(0.069)	(0.056)
$Elec_{qld_{t-5}}$	-0.002	-0.003	0.045*	0.054*	-0.031	-0.023
	(0.003)	(0.002)	(0.025)	(0.030)	(0.067)	(0.054)

$VARIABLES$	REC_t	$ACCU_t$	$Elec_{nsw_t}$	$Elec_{qld_t}$	$Elec_{sa_t}$	$Elec_{vic_t}$
$Elec_{sa_{t-1}}$	0.000	0.002	0.027**	0.033**	0.116***	0.052**
	(0.001)	(0.001)	(0.012)	(0.014)	(0.031)	(0.025)
$Elec_{sa_{t-2}}$	0.001	0.001	0.003	0.008	0.031	-0.012
	(0.001)	(0.001)	(0.012)	(0.014)	(0.031)	(0.025)
$Elec_{sa_{t-3}}$	0.002*	-0.001	-0.016	-0.018	0.008	-0.009
	(0.001)	(0.001)	(0.012)	(0.014)	(0.031)	(0.025)
$Elec_{sa_{t-4}}$	-0.002*	-0.001	0.004	0.001	-0.031	0.037
	(0.001)	(0.001)	(0.012)	(0.014)	(0.031)	(0.025)
$Elec_{sa_{t-5}}$	-0.000	0.001	0.003	0.014	0.013	0.026
	(0.001)	(0.001)	(0.012)	(0.014)	(0.031)	(0.025)
$Elec_{vic_{t-1}}$	0.001	0.001	0.011	-0.021	0.124***	0.081**
	(0.002)	(0.001)	(0.015)	(0.018)	(0.039)	(0.032)
$Elec_{vic_{t-2}}$	-0.003	0.000	-0.037**	-0.046***	-0.009	0.032
	(0.002)	(0.001)	(0.015)	(0.018)	(0.039)	(0.032)
$Elec_{vic_{t-3}}$	0.001	-0.002	0.004	-0.017	0.010	0.006
	(0.002)	(0.001)	(0.015)	(0.018)	(0.039)	(0.032)
$Elec_{vic_{t-4}}$	0.001	-0.001	-0.015	-0.023	0.021	-0.034
	(0.002)	(0.001)	(0.015)	(0.018)	(0.039)	(0.032)
$Elec_{vic_{t-5}}$	-0.003*	0.001	-0.000	-0.009	0.023	0.071**
	(0.002)	(0.001)	(0.015)	(0.018)	(0.039)	(0.032)
EUA_t	-0.036	0.020	-0.444**	-0.198	-1.067**	-0.606
	(0.023)	(0.018)	(0.203)	(0.242)	(0.534)	(0.432)
EUA_{t-1}	0.051	0.022	0.156	0.161	0.445	0.062
	(0.031)	(0.024)	(0.280)	(0.333)	(0.737)	(0.597)
EUA_{t-2}	-0.013	-0.010	0.183	0.141	0.907	0.483
	(0.031)	(0.024)	(0.282)	(0.336)	(0.742)	(0.601)
EUA_{t-3}	0.001	-0.020	-0.153	-0.147	-0.366	0.305
	(0.031)	(0.024)	(0.283)	(0.336)	(0.742)	(0.601)
EUA_{t-4}	0.005	-0.039	0.283	-0.160	0.094	0.730
	(0.031)	(0.024)	(0.280)	(0.333)	(0.736)	(0.596)
EUA_{t-5}	-0.013	0.034*	-0.081	0.150	-0.103	-0.745*
	(0.023)	(0.018)	(0.204)	(0.243)	(0.536)	(0.434)
NZU	0.060	0.164***	0.127	-0.227	0.522	-0.252
	(0.049)	(0.038)	(0.439)	(0.522)	(1.154)	(0.935)
NZU_{t-1}	-0.084*	0.000	-0.327	-0.206	1.646	1.124
	(0.049)	(0.038)	(0.444)	(0.527)	(1.166)	(0.944)
NZU_{t-2}	0.121**	0.061	0.530	0.895*	-0.082	-0.234
	(0.049)	(0.038)	(0.444)	(0.528)	(1.168)	(0.945)
NZU_{t-3}	-0.038	-0.055	0.049	-0.001	-1.889	-0.692
	(0.050)	(0.039)	(0.447)	(0.531)	(1.174)	(0.950)
NZU_{t-4}	-0.025	0.010	0.315	-0.087	-0.267	0.078
	(0.050)	(0.039)	(0.447)	(0.531)	(1.174)	(0.951)
NZU_{t-5}	-0.051	-0.027	0.089	0.143	-0.573	-0.001
	(0.050)	(0.038)	(0.446)	(0.530)	(1.172)	(0.949)
$Elec_{tas}$	-0.003*	0.008***	0.058***	0.011	0.238***	0.344***
	(0.002)	(0.001)	(0.016)	(0.019)	(0.042)	(0.034)
$Elec_{tas_{t-1}}$	0.001	0.001	0.010	-0.016	-0.037	0.033
	(0.002)	(0.002)	(0.018)	(0.021)	(0.048)	(0.038)

$VARIABLES$	REC_t	$ACCU_t$	$Elec_{nsw_t}$	$Elec_{qld_t}$	$Elec_{sa_t}$	$Elec_{vic_t}$
$Elec_{tas_{t-2}}$	-0.002	-0.006***	-0.006	-0.020	-0.071	-0.032
	(0.002)	(0.002)	(0.018)	(0.021)	(0.047)	(0.038)
$Elec_{tas_{t-3}}$	0.003	-0.002	-0.002	0.026	0.018	-0.048
	(0.002)	(0.002)	(0.018)	(0.021)	(0.047)	(0.038)
$Elec_{tas_{t-4}}$	0.000	0.001	-0.002	0.000	0.028	0.024
	(0.002)	(0.002)	(0.018)	(0.021)	(0.047)	(0.038)
$Elec_{tas_{t-5}}$	0.004**	-0.002*	-0.005	-0.002	-0.065	-0.058*
	(0.002)	(0.001)	(0.016)	(0.019)	(0.043)	(0.034)
$Coal$	0.095***	-0.032	-0.435*	-0.104	-0.041	0.266
	(0.025)	(0.020)	(0.227)	(0.269)	(0.595)	(0.482)
$Coal_{t-1}$	-0.023	0.100***	-0.294	-0.346	-0.771	0.109
	(0.025)	(0.020)	(0.229)	(0.272)	(0.602)	(0.487)
$Coal_{t-2}$	-0.037	-0.133***	0.282	0.336	0.388	0.878*
	(0.025)	(0.020)	(0.228)	(0.271)	(0.600)	(0.486)
$Coal_{t-3}$	0.017	0.004	-0.299	-0.030	0.945	0.651
	(0.026)	(0.020)	(0.232)	(0.275)	(0.608)	(0.493)
Oil	0.030	0.026	0.081	0.397	0.713	0.602
	(0.024)	(0.019)	(0.220)	(0.262)	(0.578)	(0.468)
Oil_{t-1}	-0.020	-0.068***	-0.276	-0.852**	-1.199	-1.132*
	(0.034)	(0.026)	(0.305)	(0.363)	(0.802)	(0.649)
Oil_{t-2}	0.000	0.040**	0.234	0.736***	0.657	0.416
	(0.025)	(0.019)	(0.221)	(0.262)	(0.580)	(0.470)
Gas	0.011	-0.006	0.401***	0.483***	0.538***	0.750***
	(0.009)	(0.007)	(0.079)	(0.094)	(0.208)	(0.168)
Gas_{t-1}	-0.023*	0.004	-0.010	-0.156	0.366	-0.060
	(0.012)	(0.010)	(0.112)	(0.134)	(0.295)	(0.239)
Gas_{t-2}	0.009	0.004	-0.265***	-0.145	-0.562***	-0.315*
	(0.009)	(0.007)	(0.081)	(0.096)	(0.212)	(0.171)
$Constant$	-0.000	-0.000	0.000	0.000	0.001	0.003
	(0.001)	(0.001)	(0.007)	(0.008)	(0.018)	(0.015)
$Observations$	1,343	1,343	1,343	1,343	1,343	1,343