Energy market connectedness: A tale of two crises

Abstract

From 2020 to 2023, energy markets faced significant turbulence. The COVID-19 demand shock in 2020 caused major declines in oil, coal and natural gas prices. By mid-2021, supply shocks led to record highs in natural gas and coal prices and soaring oil prices, marking the first global energy crisis (GEC). Our study examines intra- and intermarket connectedness of oil, coal and natural gas during the COVID-19 crisis and GEC. Energy market connectedness is driven by major events, with substantial but brief spikes during the COVID-19 crisis and more sustained, synchronised connectedness during the GEC. Oil consistently leads in transmitting spillovers to coal and natural gas, although its influence diminished during the pandemic, while natural gas took a more prominent role. Coal exhibited little variation. Brent crude and West Texas Intermediary oil prices and Title Transfer Facility and National Balancing Point natural gas prices are central to price discovery. The natural gas market is more integrated than oil or coal markets, strengthening during the COVID-19 crisis but weakening during the GEC. In contrast, oil and coal market intra-connectedness rose during the GEC. These findings are vital for firms, portfolio managers and policymakers.

1. Introduction

Energy markets experienced a tumultuous period from 2020 to 2023. The economic stagnation following the implementation of lockdowns to curb the spread of the COVID-19 virus led to a sharp fall in oil prices (Alam et al., 2023). This was further fuelled by Saudi Arabia flooding the oil market because of a disagreement with Russia regarding a proposal to reduce oil supply. This increased supply caused the oil price to fall by more than 30% on 8 March 2020, the largest one day drop since the Gulf War (Iyke, 2020). Natural gas prices also declined due to reduced demand, with Asian and European benchmarks reaching all-time lows in February and May 2020 respectively (Meredith, 2020). United States (U.S.) natural gas prices were more resilient and increased in the second half of 2020 attributable to the reduction in shale gas output which accompanied the reduction in oil output (in response to lower demand) as the two are extracted simultaneously (Finley & Mikulska, 2020), demonstrating the interconnectedness between energy commodities. However, demand for natural gas was less impacted than any other fossil fuel due to its limited exposure to the transport sector (International Energy Forum (IEF), 2020). Coal prices fell more than 30% during the first half of 2020 as countries reduced coal usage in response to the demand shock. Coal-fired power stations stood idle in the United Kingdom (U.K.) and Portugal, with some countries such as Austria and the U.S. permanently shutting stations and others, including Sweden, bringing forward planned closures (Watts & Ambrose, 2020). Energy prices stabilised somewhat in the second half of 2020 as market participants adapted to the prevailing conditions.

From mid-2021, however, energy prices soared because of a variety of factors including increased demand due to the rapid post-COVID-19 pandemic economic rebound. Additionally, there was low renewable energy power generation arising from adverse weather conditions (a cold northern hemisphere winter; droughts in parts of Europe, Asia and the Americas; and a wind drought in Europe) (Gilbert et al., 2021; Pescatori & Stuermer, 2022). Reduced natural gas flows from Russia to Europe from mid-2021 and concerns over a possible Russian incursion into Ukraine pushed natural gas prices to record highs. Russia’s subsequent invasion pushed energy markets into a full-blown energy crisis (International Energy Agency (IEA), 2022). The event caused oil prices to rocket, with West Texas Intermediary (WTI) prices rising 15% in the week following the invasion, reaching its highest level since 2008. Coal prices almost doubled due to the confluence of events (Pescatori & Stuermer, 2022). The Dutch Title Transfer Facility (TFF), a benchmark for European natural gas prices, reached a record high of €269 per mega-watt hour on 7 March 2022 (Gajdzik et al., 2024). Subsequent sanctions on Russian energy exports, reduced deliveries to Europe by Russia in retaliation to the sanctions and gas leaks in the Nord Stream pipelines which made them inoperable intensified energy market vulnerabilities (Meredith, 2022; Gajdzik et al., 2024). In response, Europe increased liquified natural gas (LNG) imports from the U.S., Qatar, Nigeria, Algeria and Norway, amongst others (European

Council and Council of the European Union, 2023). The rising global demand for LNG resulted in suppliers prioritising high-paying markets, notably in Europe, which led to acute shortages in countries such as Pakistan and Bangladesh in late 2022 (Sullivan, 2022). Additionally, to fill the natural gas power gap some European countries delayed the planned decommissioning or reopened coal-fired power stations fuelling demand for coal (Nagel & Temaj, 2022). Due to limited coal stock, many countries in the region sourced coal from other markets such as China, Colombia, South Africa and Australia spurring spillovers across regional benchmarks (Saul, 2022; Wehrmann, 2023). India could not bridge its coal deficit via imports due to the exorbitant cost of coal. European countries also sourced oil from the U.S. and Angola to meet previous Russian supplies (Ghantous, 2023). Collectively, these events culminated in energy supply shortages and surging oil, natural gas and coal prices worldwide.

The IEA (2022) highlights that while this crisis shares some similarities with the oil shocks of the 1970s, there are two key differences. First, this crisis involves all fossil fuels not only oil and second, the global economy and energy markets are much more interlinked than in the 1970s, exacerbating the impact. Countries were forced to seek alternative suppliers and/or turn to alternative sources of fossil fuel which, according to Gilbert et al. (2021), Pescatori and Stuermer (2022), the IEA (2023), Yanguas-Parra et al. (2023) and Gajdzik et al. (2024), contributed to increased integration within and across energy markets. Hence, this crisis has become known as the first truly global energy crisis (GEC).

Prior studies investigate inter- and intra-energy market integration in terms of price co-movement and return and volatility connectedness. For example, Neuman et al. (2006), Li et al. (2010), Ji and Fan (2016), Batten et al. (2019) and Chatziantoniou et al. (2023) find integration between oil price benchmarks, coal price benchmarks and European natural gas price benchmarks. Nick and Thoenes (2014), Ma et al. (2021) and Rizvi et al. (2022) observe inter-energy market integration with strengthening relationships during the Global Financial Crisis (GFC) and European debt crisis. Similarly, Asadi et al. (2022) finds connectedness increases across energy markets during the COVID-19 pandemic, but the increase is short-lived. Chen, Wang and Zhu (2022) and Papież et al. (2022) observe a decline in integration among natural gas price benchmarks during the COVID-19 crisis which they attribute to the demand shock. Szafranek et al. (2023) document the decoupling of the U.K. gas price and heightened interdependence among other European natural gas benchmarks during Russia's invasion of Ukraine.

We undertake a comprehensive investigation of changing return connectedness between oil, coal and natural gas price benchmarks over two crisis periods – COVID-19 and the GEC. Given the unique nature of the crisis, we use multiple regional pricing benchmarks allowing us to fully study intra- and inter-market spillovers over the crisis period which we designate 1 June 2021 to 15 August 2023 (at the time of writing).[1] We also analyse the immediately preceding COVID-19 crisis (January 2020 to 31 May 2021) and a pre-COVID-19 period (1 October 2017 to 31 December 2019) allowing us to compare connectedness during two unprecedented crises and further investigate relationships during COVID-19 that have not been examined. We utilise the Time-Varying Parameter Vector Autoregression (TVP-VAR) model with heteroscedastic variance-covariances of Antonakakis et al. (2020) and Chatziantoniou and Gabauer (2021) to model total connectedness, net connectedness and pairwise connectedness. We then go on to examine the determinants of connectedness including both fundamental factors (such as commodity prices and economic conditions) and non-fundamental factors (such as uncertainty). We also undertake several robustness tests, including the use of mutual information.

Results show that energy market connectedness is heavily influenced by major events, experiencing sharp but short-lived increases during the COVID-19 crisis and more prolonged, coordinated connectedness during the energy crisis. Oil remains the primary driver of return spillovers to coal and natural gas across crises, though its impact lessened during the pandemic. Natural gas became more influential in the price discovery process during this period. Coal remained a net receiver of return spillovers, with little variation across crises. Price benchmarks like Brent, WTI, Title Transfer Facility and National Balancing Point are crucial in energy market price discovery. Network diagrams reveal strong intra- and intermarket spillovers. The natural gas market is most integrated, particularly during COVID-19, but this weakened during the energy crisis, whereas oil and coal markets became more connected during the energy crisis.

Oil, natural gas and coal account for 33.1%, 27% and 24.3% of global energy supply (Ritchie et al., 2022). As such, understanding the market dynamics between and within these energy sources is critical for market participants to anticipate and respond to price changes. For industrial companies, energy is a critical input and knowledge of market dynamics for these commodities will enable better risk management strategies to be developed. The increased financialisation of commodities means that spillovers across fossil fuels also have implications for portfolio management (Lin & Su, 2021). For policymakers, knowledge of energy market connectedness sheds light on market responses to demand and supply shocks (during the two crises) and aids in identifying vulnerabilities to develop strategies to ensure uninterrupted energy supply and minimise harmful effects of energy price shocks on consumers (Urbano et al., 2023). Energy market connectedness also has significant geopolitical implications due to the weaponisation of energy supplies (Tertre, 2022). Finally, understanding fossil fuel energy market dynamics is critical as the transition to renewable energy will impact the demand for fossil fuels.

[1] Kemp (2023), writing in late November 2023, states that the crisis phase is over given that energy markets have adapted to the disruptions caused by the end of the pandemic and Russia's invasion of Ukraine, with prices reverting to long-term inflation adjusted-average prices and inventories stable.

Our study makes several important contributions. First, while there is a burgeoning literature on the effects of the Russia-Ukraine war on energy markets (such as Chen et al., 2023; Roy et al., 2023; Szafranek et al., 2023), far less attention has been given to the effects of the broader GEC. Only a few studies have explicitly considered the GEC such as Szczygielski et al. (2024a; b), who observe that uncertainty due to the energy crisis negatively effects global sector returns and triggers heightened volatility, Urbano et al. (2023) and Pollitt (2023) who both reflect on Europe's response to limit the effects of the price shocks on consumers and Gdajzki et al. (2024) who review the implications of the crisis on energy efficiency. To the best of our knowledge, no study (at the time of writing) has modelled and quantified the connectedness both across and within the three fossil fuel markets which has been discussed by international organisations, journalists and scholars (Gilbert et al., 2021; Pescatori and Stuermer, 2022; IEA, 2023; Yanguas-Parra et al., 2023; Gajdzik et al., 2024). By considering both inter- and intramarket spillovers we are better able to capture the dynamics of this crisis.

Second, we add to the wider body of knowledge in understanding inter- and intra-energy market spillovers. Most intermarket studies only examine natural gas and oil (and other oil-related products) (such as Ji et al., 2018; Ma et al., 2021) with coal being ignored. However, coal is a critical energy source and while its use in the production of electricity is being phased out in many countries around the world, governments saw coal as an easy short- and medium-term solution to the energy shortfall during the GEC (Mišík & Prachárová, 2023). Ignoring coal means that a full picture of the inter-energy market connectedness cannot be modelled. Additionally, when intermarket dynamics are considered, typically only a single price benchmark for each energy commodity is used. This approach overlooks important intra-market dynamics that contribute to intermarket spillovers, particularly in segmented energy markets like natural gas (Chiappini et al., 2019; Kim et al., 2020). Additionally, studies which do examine all three fossil fuels do so in the presence of stock market indices, currencies or renewable energy stocks and thus the 'true' energy market dynamics are not quantified but rather how the commodities interact with the stock or currency markets (Zolfaghari et al., 2020; Asadi et al., 2022; Zhang et al., 2023). Third, we build on the analysis of energy market connectedness during the COVID-19 crisis, such as that by Chen Wang and Zhu (2022) and Papież et al. (2022). However, in comparison to these studies, we obtain unique insights into intra-market connectedness due to the inclusion of multiple price benchmarks for each commodity and include coal which these studies do not consider.

Fourth, comparing spillovers across two unique crises – one characterised by an energy demand shock and the other by energy supply shocks – enables us to provide a broad understanding of energy market dynamics. Finally, we contribute to an understanding of the determinants of energy price connectedness. While several studies attribute time-varying energy market connectedness to specific events and crises (such as Chen, Wang and Zhu, 2022; Papież et al., 2022) there has been limited focus on quantifying the determinants in the studies focused only on energy markets. Ma et al. (2021), for example, evaluate the role of fundamental and non-fundamental determinants of connectedness between a broad sample of metal, agricultural and energy commodities. Drawing from Ma et al. (2021) and literature on determinants of connectedness in commodity futures by Bouri, Lucey et al. (2021) and cryptocurrencies by Bouri, Gabauer et al. (2021), among others, we explore the influence of fundamental and non-fundamental factors on energy market connectedness. Both categories of determinants are investigated as spillovers originate from real and financial linkages, and investor behaviour.

The remainder of this study is structured as follows: Section 2 provides an overview of the literature on the intra- and intermarket oil, coal and natural gas connectedness. Section 3 outlines the data and methodology employed to compute the spillovers across fossil fuel markets. Section 4 presents and analyses the results. Section 5 provides the implications of our findings and Section 6 concludes.

2. Literature review

The law of one price proposes that identical commodities traded in different markets should have the same price. However, Heckscher (1916) and Stigler and Sherwin (1985) point out that transport costs and variations in quality (e.g., differing crude oil grades) can cause price differentials. Price differentials across markets and/or commodities create opportunities for arbitrage for substitutable goods. According to Batten et al. (2019), cheaper commodities are shipped to other markets and sold at prices covering transaction and transportation costs, resulting in price convergence. Fattouh (2010) explains that in integrated markets, supply and demand shocks affecting prices in one market or region are transmitted to other markets. In contrast, in segregated markets, prices react to local market conditions and regional disturbances but remain unresponsive to shocks in other markets.

Market integration may similarly occur across energy commodities. Brown and Yücel (2008) and Zolfaghari et al. (2020) highlight that some energy commodity pairs, such as oil and natural gas, or natural gas and coal, are substitutable in the long run which limits price differences due to demand pressures. Moreover, McHich and Till (2020) indicate that the pricing of certain energy commodities is linked through contracts, such as natural gas which is frequently contractually priced using oil. Relatedly, Panagiotidis and Rutledge (2007) acknowledge that in monopoly-controlled markets, monopoly players adjust prices to match those of the only alternative fuels, raising price connectedness. Zolfaghari et al. (2020) also point out that the production processes of some energy sources (such as oil and natural gas) are shared (e.g., an oil well produces both natural gas and oil), so increased production of one translates into increased production of the other. Energy commodity prices are also driven by common fundamental factors; economic growth, inflation, global demand and supply shocks, the real interest rate, world stock market prices, the oil price, the U.S. dollar effective exchange rate and geopolitical events (Vansteenkiste, 2009; Kagraoka, 2016; Alquist et al., 2020). Additionally, several studies, such as Zolfaghari et al. (2020) and Szczygielski et al. (2023), find that non-fundamental factors such as sentiment or uncertainty play a role in driving commodity markets. Finally, Zhang (2018) underscores how commodity markets have become integrated with financial markets, a phenomenon known as financialisation, as investors increasingly view commodities as a core asset class. This financialisation affects energy market pricing and volatility, with information shocks from financial markets transmitted to commodities contributing to connectedness (Zhang & Broadstock, 2020; Ji et al. 2019; Lin & Su, 2021).

Early studies of market integration within or across energy markets, such as Neumann et al. (2006) and Brown and Yücel (2008) examine price co-movements. More recently, the focus has been on investigating return and/or volatility connectedness, including Batten et al. (2019) and Szafranek et al. (2023), among others. The latter approach provides insights into not only the extent of integration, but also the intensity and direction of return and risk transmission (Batten et al., 2019; Sayed & Charteris, 2022). According to Živkov et al. (2022), spillovers may occur between commodities due to real and financial relationships such as substitution or portfolio rebalancing by investors or informational asymmetries.

Bachmeier and Griffin (2006), Ji and Fan (2016) and Kuck and Schweikert (2017) report that global oil markets are integrated despite quality differences and graphical dispersion. Linkages are typically stronger between markets in proximity and increase in periods of higher global economic uncertainty. The Dubai price benchmark plays a leading role as a price setter, reflecting OPEC's pricing influence (Ji & Fan, 2016; Kuck & Schweikert, 2017). WTI is also an important benchmark, except during crisis periods when it responds to other oil price benchmarks. Chatziantoniou et al. (2023) report robust volatility connectedness between six crude oil benchmarks. Short-run spillovers dominate although market turbulence, such as the COVID-19 pandemic, corresponds with more pervasive long-run effects. Wei et al. (2022) observe Shanghai crude oil (SC) to be highly connected with WTI and Brent in both returns and volatility. According to Ren et al. (2022), the relationship between SC, Brent and WTI strengthened during the COVID-19 pandemic.

Examining coal markets, Wårell (2006) finds Japanese and European steam coal prices were cointegrated in the 1980s but decoupled during the 1990s. Li et al. (2010) observe that Australian, Chinese, Polish and South African coal prices are integrated but the Colombian and Indonesian markets are relatively segmented. According to Papież and Śmiech (2015), periods of higher integration in global coal markets correspond with lower freight costs and greater commodity market disruptions. Batten et al. (2019) document evidence of global coal market connectedness due to strong spillovers across markets although integration varies over time due to economic shocks. The Australian benchmark is the largest net transmitter of return spillovers and smallest net recipient of return and volatility spillovers suggesting it is the most dominant coal trading centre and least responsive to disturbances in other markets. Batten et al. (2019) attribute Australia's global leadership to the quality of the country’s coal. According to Li et al. (2019), Chinese coal prices transmit return spillovers to the Australian coal market, consistent with the country’s consumption of more than 50% of global coal.

Neumann et al. (2006), Broadstock et al. (2020), Chen, Wang and Zhu (2022) and Szafranek et al. (2023) find European natural gas markets are connected, with prices converging in the long run, and significant return and volatility spillovers, which have intensified over time. Moreover, connectedness occurs almost entirely at short horizons and generally increases during periods of market turbulence. According to Neumann et al. (2006) and Broadstock et al. (2020), increased integration has been driven by physical integration via the construction of pipelines between countries, European Union (EU) gas directives aimed at creating competition and enhancing market connections, and the move towards hub trading and gas-on-gas (GOG) pricing. Szafranek et al. (2023) report a decline in total price spillovers following Russia’s invasion of Ukraine, which they ascribe to a decoupling of the U.K. gas price. In contrast, prices across continental Europe remained strongly connected, attributable to Europe’s greater reliance on Russian natural gas. Chen, Wang and Zhu (2022) and Papież et al. (2022) report a decline in return and volatility connectedness in European natural gas markets during the COVID-19 pandemic, reflecting the demand shock resulting from lockdowns and shifting supply patterns. Several studies, including Broadstock et al. (2020), Papież et al. (2022) and Szafranek et al. (2023), find that the Dutch TTF and U.K. National Balancing Point (NBP) natural gas price benchmarks are dominant shock transmitters among European natural gas benchmarks although Papież et al. (2022) conclude that no single benchmark dominates the European natural gas market. Siliverstovs et al. (2005), Chiappini et al. (2019) and Kim et al. (2020), among others, show that European and Asian natural gas markets are integrated whereas U.S. markets are less integrated with other regions. European and Asian market integration is attributed to contracts linking natural gas prices to oil prices. Kim et al. (2020) highlight that Qatar’s increased role as an LNG supplier, along with its central location, has contributed to price connections in these regions. According to Nakajima and Toyoshima (2019), U.S. and Asian market returns are relatively independent but receive and transmit volatility spillovers from and to European gas markets over short-run horizons.

There is also evidence of inter-energy market integration. Bachmeier and Griffin (2006), Brown and Yücel (2008) and Mohammadi (2011) observe a strong long-run relationship between natural gas and oil prices with oil prices leading price discovery. This cointegration relationship is attributable to oil-indexed natural gas prices, monopoly markets and flexible facilities that can switch between the two energy sources. However, Nick and Thoenes (2014), Hulshof et al. (2016) and Wang et al. (2019) show that global natural gas and oil prices have decoupled due to factors such as natural gas market liberalisation, the promotion of GOG pricing and the U.S. shale gas revolution. Nevertheless, Panagiotidis and Rutledge (2007), Chevallier and Ielpo (2014), Nick and Thoenes (2014), Asche et al. (2017) and Rizvi et al. (2022) report a continuing long-run relationship between oil and natural gas, although its strength varies across regions and time.

Nick and Thoenes (2014) report a strong contemporaneous relationship between natural gas and coal prices in Europe, driven by competition between coal and gas carriers resulting in cross-price elasticity, and regional economic dynamics. Contrastingly, Bachmeier and Griffin (2006) and Hulshof et al. (2016) find coal prices have a negligible impact on natural gas prices. Several studies, including Bachmeier and Griffin (2006), Joëts and Mignon (2011), Mohammadi (2011) and Wang et al. (2020) report that coal and oil markets display weak or no integration. Mohammadi (2011) argues that coal prices are unaffected by oil due to long-term contracts between coal producers and buyers. Nevertheless, Zamani (2016) finds that oil impacts coal prices when accounting for oil supply and demand shocks, primarily due to the role of substitution.

Ma et al. (2021) find strong return and volatility connectedness among WTI, U.S. natural gas and other oil-linked commodities, with connectedness spiking during the GFC and weakening thereafter. Non-fundamental factors, specifically market sentiment and the extent of financialisation, have a more significant impact on energy market connectedness than fundamental factors such as macroeconomic conditions. Ji et al. (2018) identify substantial but diminishing return connectedness between oil and U.K. and U.S. natural gas prices, consistent with the findings of cointegration studies such as Panagiotidis and Rutledge (2007), Chevallier and Ielpo (2014) and Nick and Thoenes (2014). Crude oil is primarily a net transmitter whereas natural gas prices are net recipients. During the COVID-19 crisis from March to May 2020, Lin and Su (2021) observe a significant but temporary jump in return connectedness between oil, natural gas and other fuel commodities; attributed to increased panic arising from soaring COVID-19 cases. Lovcha and Perez-Laborda (2020) find time-varying volatility spillovers between oil and natural gas prices. Natural gas, rather than oil, is a net transmitter for substantial periods and connectedness occurs predominantly over long horizons. However, during periods of market turmoil, spillovers tend to occur more over short-term horizons. Li et al. (2019) report increased return spillovers between oil and coal markets during the GFC and in 2016 which was driven by limited steam coal supplies. The Chinese coal price shifted from being a net recipient of spillovers from oil to a net transmitter to oil after China became a net coal importer. Zhang et al. (2023) examine the return connectedness between the three fossil fuels over the period 2006 to 2022, where one price benchmark is used to proxy each energy source (WTI - oil, Rotterdam - coal and Henry Hub – natural gas). They confirm that crude oil is a net transmitter of return spillovers while coal and natural gas are net recipients of spillovers. They also document heightened spillovers after Russia's invasion of Ukraine and concerns about energy supply in early 2022.

When considering all three fossil fuel energy sources together with stock and currency markets, Zolfaghari et al. (2020) identify return and volatility spillovers from oil to natural gas and coal that far exceed those from coal and natural gas to oil. They attribute oil's dominance to its leading role in the pricing of other energy sources and overlapping oil well production. Asadi et al. (2022) find a strong relationship between oil and coal price volatility, with bidirectional spillovers of comparable magnitude.

Volatility spillovers also occur between oil and natural gas but there is negligible connectedness between natural gas and coal. The contrasting findings regarding oil's dominance in these two studies may result from different coal benchmarks (Australia versus U.S), varying time periods and other variables in the system (stock and currency markets). Asadi et al. (2022) go on to demonstrate that connectedness increases during the GFC, European debt crisis and COVID-19 pandemic. During crises WTI acts as a net transmitter to both natural gas and coal, while coal is a net transmitter to natural gas.

Several important conclusions can be drawn from the literature. There is evidence of integration within and across the three primary energy commodities although there is less support for the pairwise relationship between coal and natural gas. Most spillover studies either exclude coal (e.g., Ma et al., 2021; Lin & Su, 2021) or include other financial markets (Zolfaghari et al., 2020; Asadi et al., 2022; Zhang et al., 2023) making it difficult to reliably assess direct connectedness among the three primary fossil fuels. Moreover, these cross-commodity studies rely on a single pricing benchmark for each energy market. This approach may overlook important dynamics, as the chosen benchmark for that market may be segmented from other benchmarks for that same commodity, especially in markets like natural gas. Importantly, the 2021-2023 GEC disrupted traditional energy markets. Countries desperate to access energy such as natural gas and coal to make up for lost supply from Russia or due to domestic climatic conditions sought energy imports from other sources. For European countries this included coal from China, natural gas from the U.S., Qatar and Algeria, and oil from the U.S. and Angola. These shifting supply patterns may have impacted connectedness both within and across fossil fuel energy price benchmarks. Although Szafranek et al. (2023) confirm that dynamics among natural gas benchmarks in Europe changed after Russia's invasion of Ukraine (the decoupling of the U.K. gas price but greater dependence between continental European benchmarks), no study has focused on the energy commodity market connectedness during the GEC. The energy crisis is unique given its origins in the energy market and supply shortfalls and, as such, findings may vary compared to prior crises such as the COVID-19 pandemic which was characterised by a reduction in energy demand. We study energy market connectedness using multiple pricing benchmarks for oil, natural gas and coal to evaluate how connectedness evolved both within and across energy commodities during the GEC. We also compare these relationships to those witnessed during another distinct crisis period – the COVID-19 pandemic – which heavily impacted the energy sector due to the demand shock (Chen, Wang and Zhu, 2022; Papież et al., 2022) and prior to the crisis.

3. Data and Methodology

3.1. Data

Our study employs data daily data from 1 October 2017 to 15 August 2023 for 15 energy price benchmarks. Oil price movements are measured using WTI (U.S.), Brent (Europe), DME Oman, Canada and Urals (Russia) crude price series. For coal, Newcastle (Australian), Richards Bay (South Africa), Amsterdam-Rotterdam-Antwerp (ARA) (Europe) and Qinhuangdao (China) prices are used. For natural gas, we use Henry Hub (U.S.), NBP (U.K.), Dutch TTF (Europe), AECO (Canada), Wallumbilla (Australia) and Japan/Korea Marker (JKM) (Asia) prices. Returns are calculated as logarithmic differences in daily energy prices. To account for outliers, the highest and lowest 1% of observations are trimmed. Table 1 reports descriptive statistics for the return series. The Phillips-Perron and Augmented Dickey Fuller tests are applied to each series, confirming stationarity.

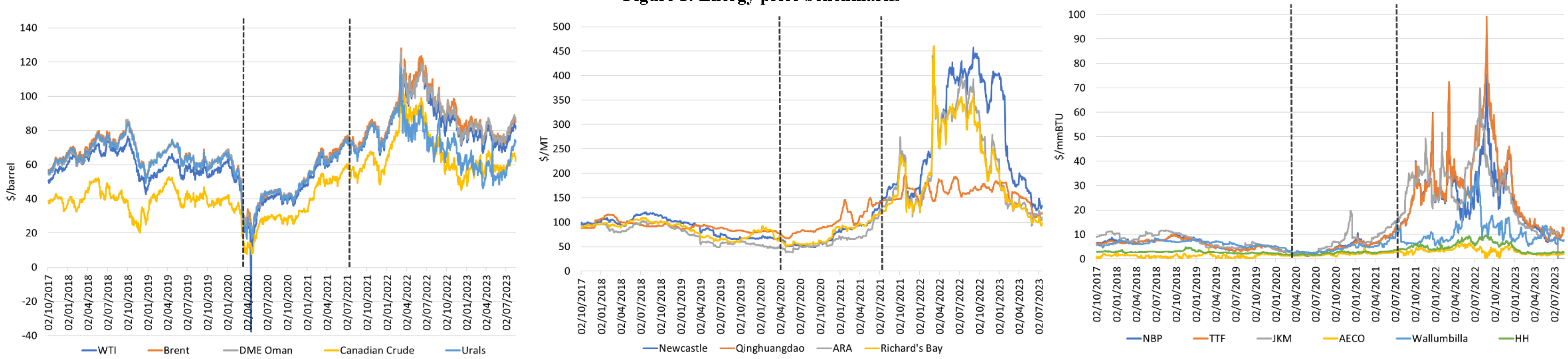
Table 1: Descriptive statistics for international energy price benchmarks

	Mean	Median	Max.	Min.	Std. dev.	Skew.	Kurt.	SW
Panel A: Oil								
Brent	0.001	0.002	0.069	-0.069	0.020	-0.385	3.952	0.982***
Canada	0.000	0.000	0.133	-0.121	0.032	-0.309	4.447	0.976***
Urals	0.001	0.002	0.087	-0.099	0.026	-0.409	4.757	0.970***
WTI	0.001	0.002	0.074	-0.080	0.022	-0.378	4.172	0.981***
DME Oman	0.000	0.001	0.073	-0.078	0.021	-0.446	4.409	0.975***
Panel B: Coal								
Qinhuangdao	6.39E-05	0.000	0.030	-0.027	0.009	0.176	5.234	0.886***
ARA	0.001	0.000	0.090	-0.092	0.018	0.370	8.817	0.873***
Newcastle	0.001	0.000	0.085	-0.061	0.014	0.466	8.262	0.905***
Richards Bay	0.000	0.000	0.089	-0.078	0.018	0.272	8.388	0.878***
Panel C: Natural gas								
TTF	0.001	0.000	0.184	-0.124	0.044	0.526	5.002	0.963***
NBP	0.002	0.000	0.229	-0.150	0.052	0.552	5.327	0.957***
Henry Hub	0.001	0.000	0.106	-0.110	0.035	-0.050	3.666	0.988***
Wallumbilla	0.001	0.000	0.223	-0.188	0.038	0.525	11.471	0.751***
JKM	0.001	0.000	0.175	-0.133	0.030	0.846	10.696	0.808***
AECO	0.022	0.000	1.930	-0.680	0.247	3.065	20.921	0.673***

Notes: This table reports the descriptive statistics for each of the energy price benchmarks. Returns are calculated as logarithmic differences in daily energy prices. SW is the Shapiro-Wilk normality test statistic. *** indicates statistical significance at 1%.

The full sample period is divided into three sub-periods. The pre-crisis period is defined as 1 October 2017 to 31 December 2019. This is the followed by the COVID-19 crisis period, spanning 1 January 2020 to 31 May 2021. Thereafter, the GEC period is designated from 1 June 2021 to 15 August 2023. While global energy markets began rebounding in the first half of 2021 following the peak of the COVID-19 crisis in 2020, price increases were initially gradual. However, from August/September 2021, there was a substantial surge in energy prices, particularly noteworthy for natural gas and coal. This surge informs our approximate start of the GEC, consistent with the approach of using milestone events – significant financial or economic events – to identify the start of a distinct period (Kenourgios & Dimitriou, 2015). The energy price surge followed a European wind drought in the summer of 2021, resulting in an increase in the demand for coal and natural gas, driving up prices and preceded events that contributed to rising energy prices, such as the build up to Russia's invasion of Ukraine (Fleming, 2021; Logan, 2022). The energy price benchmarks with designated sub-periods are plotted in levels in Figure 1.

Figure 1: Energy price benchmarks



Panel A: Oil **Panel B: Coal** **Panel C: Natural gas**

Notes: This figure plots oil, coal and natural gas price benchmarks in levels over the period 1 October 2017 to 15 August 2023. The vertical dashed lines delineate the pre-crisis period (1 October 2017 to 31 December 2019), the COVID-19 crisis (1 January 2020 to 31 May 2021) and the GEC (1 June 2021 to 15 August 2023).

3.2. Methodology

A prominent method for assessing market connectedness is that of Diebold and Yılmaz (2012; 2014). This approach relies on rolling windows to estimate a vector autoregression (VAR) and measures dynamic connectedness, referred to as the DY connectedness index.[2] However, this method is subject to several limitations, namely the loss of observations because of the rolling window, the selection of an arbitrary window length and sensitivity to outliers (Korobiliz & Yilmaz, 2018).

We employ the time-varying parameter VAR (TVP-VAR) with heteroscedastic variance-covariances, introduced by Koop and Korobilis (2014) and refined by Antonakakis et al. (2020) and Chatziantoniou and Gabauer (2021) to model connectedness between commodity price benchmarks. The TVP-VAR represents an advancement over the conventional rolling-window VAR as it is resistant to outliers and preserves parameter estimates without employing a rolling-window approach.[3] The TVP-VAR(p) model is formulated as follows:

$$x_t = \sum_{i=1}^{p} B_i x_{t-i} + u_t \text{ with } u_t \sim N(0;S) \tag{1}$$

where x_t, x_{t-1} are $k \times 1$ dimensional vectors of endogenous variables, u_t is an $k \times 1$ dimensional vector of independently and identically distributed disturbances; B and S are $k \times k$ dimensional time-varying parameter and variance–covariance matrices, respectively and k is the number of time-series observations (Chatziantoniou & Gabauer, 2021).

After estimating the time-varying parameters, the TVP-VAR is transformed to a time-varying parameter vector moving average model (TVP-VMA) through the application of the Wold representation theorem:

$$x_t = \sum_{p=0}^{\infty} A_{pt} u_{t-p} \text{ where } A_p = B_1 A_{p-1} + \cdots + B_{p-1} A_1 + B_p A_0 \tag{2}$$

where $A_p = 0$ for $p < 0$ and A_0 is $k \times k$ identity matrix.

The time-varying coefficients and time-varying variance-covariance matrices are then used to construct the generalised impulse response functions (GIRF) and generalised forecast error variance decompositions (GFEVD) (Koop et al., 1996; Pesaran & Shin, 1998) from which the dynamic connectedness framework of Diebold and Yilmaz (2012; 2014) is developed. The scaled GFEVD, denoted $\tilde{\psi}_{i\leftarrow j}^{g}(H)$, is defined as follows:

$$\psi_{i\leftarrow j}^{g}(H) = \frac{\sum_{h=0}^{H-1} (e_i{}' A_h S e_j)^2}{(e_j' S e_j) \sum_{h=0}^{H-1} (e_i' A_h S A_h' e_i)}, \tag{3}$$

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[2] The Diebold and Yilmaz approach has been widely adopted in research examining issues such as inter-commodity market dependence and stock market connectedness (such as Alter & Beyer, 2014; Tiwari et al., 2020; Zhang et al., 2020).

[3] This extension has also been used in several studies, such as Bouri, Lucey et al. (2021) and Antonakakis et al. (2018) who examine commodity futures connectedness and spillovers of uncertainty across developed economies respectively.

$$\tilde{\psi}^g_{i\leftarrow j}(H) = \frac{\psi^g_{i\leftarrow j}(H)}{\sum_{j=1}^{k}\psi^g_{i\leftarrow j}(H)} \tag{4}$$

where $\sum_{j=1}^{k}\tilde{\psi}^g_{i\leftarrow j}(H) = 1$, $\sum_{i,j=1}^{k}\tilde{\psi}^g_{i\leftarrow j}(H) = k$, where H represents the forecast horizon, e_i is the selection vector with one as the i^{th} element and zero otherwise and $'$ denotes the operation of transposition. $\tilde{\psi}^g_{i\leftarrow j}(H)$ normalises the unscaled $\psi^g_{i\leftarrow j}(H)$ so that each row sums to unity. Following Chatziantoniou and Gabauer (2021), we employ a 10-step forecast horizon. $\tilde{\psi}^g_{i\leftarrow j}(H)$ is the *pairwise directional connectedness* from variable j to variable i i.e., the influence of j on i in terms of its forecast error variance share. As a result, the *net pairwise directional connectedness* ($NPDC$) index is defined as the difference between two directional connectedness measures as follows:

$$NPDC_{i\leftarrow j}(H) = \tilde{\psi}^g_{j\leftarrow i}(H) - \tilde{\psi}^g_{i\leftarrow j}(H) \tag{5}$$

If $NPDC_{i\leftarrow j}(H) > 0$ variable i is driving variable j; whereas if $NPDC_{i\leftarrow j}(H) < 0$ variable i is driven by variable j.

We then assess the aggregated impact of a shock in variable i on all other variables j, defined as the *total directional connectedness TO others,* C_{TO_i}:

$$C_{TO_i} = \sum_{j=1,i\neq j}^{k}\tilde{\psi}^g_{j\leftarrow i}(H) \tag{6}$$

The *total directional connectedness FROM others*, C_{FROM_i}, quantifies the aggregated influence of all other variables on variable *i* and is defined as:

$$C_{FROM_i} = \sum_{j=1,i\neq j}^{k}\tilde{\psi}^g_{i\leftarrow j}(H) \tag{7}$$

From the above, we then compute the *net total directional connectedness* for variable *i*, denoted C_{NET_i}, which is the difference between the impact of variable *i* on all other variables (total directional connectedness to others) and the impact of all other variables on i (the total directional connectedness from others), which is interpreted as the influence of variable *i* on the system. It is calculated as:

$$C_{NET_i} = C_{TO_i} - C_{FROM_i} \tag{8}$$

where C_{NET_i} indicates whether variable i is a net transmitter or net receiver of shocks. If $C_{NET_i} > 0$ $\left(C_{NET_i} < 0\right)$ variable i is a net transmitter (receiver) of shocks.

The *total connectedness index* (TCI) measures systemwide connectedness as follows:.

$$TCI = \sum_{i,j=1,i\neq j}^{k}\tilde{\psi}^g_{i\leftarrow j}(H)/k \tag{9}$$

A relatively high (low) TCI implies that a shock in one variable has on average a high (low) impact on the whole network.

To quantify the extent of spillovers within energy markets, irrespective of their geographical location, we aggregate the GFEVD across d groups:

$$C^{a}_{m\leftarrow n} = \sum_{i\in k_m}\sum_{j\in k_n}\tilde{\psi}^{g}_{j\leftarrow i}(H) \tag{9}$$

where $C^{a}_{m\leftarrow n}$ is the aggregated impact group n has on group m, where k_m and k_n represent two disjoint index sets. Group-specific spillovers are calculated in a similar way as for single variables:

$$C^{a}_{TO_m} = \sum_{n=1,n\neq m}^{d} C^{a}_{n\leftarrow m} \tag{10}$$

$$C^{a}_{FROM_m} = \sum_{n=1,n\neq m}^{d} C^{a}_{m\leftarrow n} \tag{11}$$

$$C^{a}_{NET_m} = C^{a}_{TO\_m} - C^{a}_{FROM_m} \tag{12}$$

$$C^{a}_{TOTAL} = \sum_{n,m=1,n\neq m}^{d} C^{a}_{m\leftarrow n}/d \tag{13}$$

where $C^{a}_{TO_m}$ reflects total group-specific connectedness to others, $C^{a}_{FROM_m}$ is the total group-specific connectedness from others, $C^{a}_{NET_m}$ is net total group specific connectedness and C^{a}_{TOTAL} is the total group-specific connectedness index.

The connectedness approach allows for the selection of a prior, which refers to the pre-specified beliefs or assumptions about the parameters of the model before observing the actual data. For daily data, the TVP-VAR often relies on the Bayesian Information Criterion (BIC) with κ_1 ranging from 0.97 to 0.99 and κ_2 ranging from 0.96 to 0.99 (Chatziantoniou & Gabauer, 2021). κ_1 controls the overall shrinkage strength for coefficients on own lags and κ_2 controls the shrinkage strength for lags of other variables. However, Chan et al. (2020) indicate that the choice of prior can influence the results and inferences drawn from the TVP-VAR. We apply the Minnesota prior with parameters κ_1 and κ_2 and gamma which is an extended version of the standard Minnesota prior used in Bayesian econometrics, particularly in TVP-VAR models. Our choice is motivated by Chan (2021), who introduces priors combining the best features of adaptive hierarchical priors and Minnesota priors. This approach particularly highlights the Minnesota-type prior with a normal gamma distribution. In this prior, the precision of the coefficients (the inverse of their variance) follows a gamma distribution, controlling shrinkage strength. The parameter, κ_1, determines the speed of parameter change over time, with higher values indicating slower changes and lower values allowing quicker adaptation to new information. The parameter, κ_2, influences sensitivity to past information, with larger values meaning the prior is more influenced by past parameter values resulting in smoother parameter trajectories. This approach provides greater flexibility in modelling time-varying parameters as it follows from the underlying assumption of model parameters evolving by following a random walk, a characteristic that can avert issues related to 'exploding' coefficients and numerical instability (Korobiliz & Yilmaz, 2018; Chatziantoniou & Gabauer, 2021; Chan, 2021). Furthermore, Korobiliz and Yilmaz (2018) demonstrate that the TVP-VAR with the

Minnesota prior outperforms indices estimated using the rolling-window VAR in forecasting future extreme events. This is because the TVP-VAR model's connectedness index does not suffer from excessive persistence but exhibits more pronounced jumps during major crises, thereby better capturing the heightened tension in financial markets.

In this study, we employ TVP-VAR with Minnesota prior with gamma and use the net connectedness (C_{NET}) to explore the relationships and spillovers in the oil, coal and natural gas markets. For robustness checks, we apply the traditional VAR model with a rolling window, the quantile VAR model for three different quantile values (0.25, 0.5, 0.75) and TVP-VAR model in frequency domain to investigate the connectedness in the short run.

4. Results

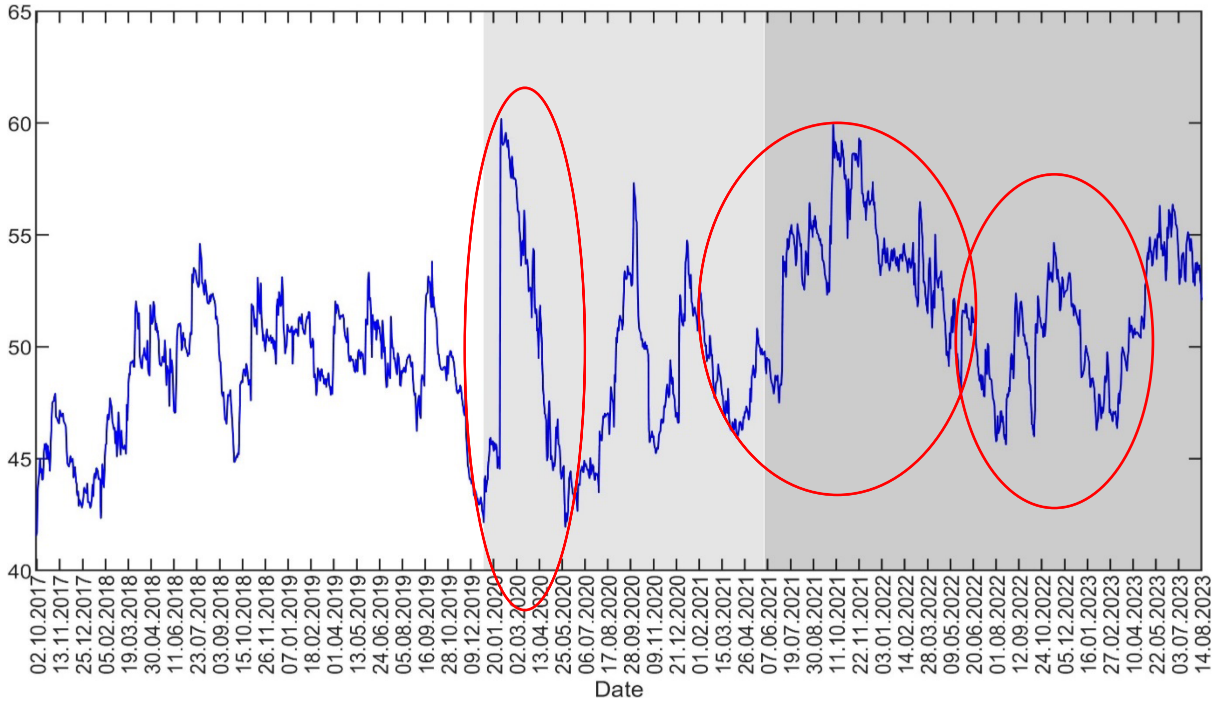
4.1. Dynamic total connectedness

The time-varying TCI for oil, coal and natural gas price benchmarks is plotted in Figure 2. Energy market connectedness spiked in late July 2018. This happened when Iran threatened to block the Strait of Hormuz in response to U.S. oil sanctions, prompting a swift counter-warning from the U.S. military (Dehghan, 2018). A significant jump in connectedness occurred on 3 February 2020, peaking the following day (TCI of 60.18) and remaining elevated until mid-March 2020. This spike in connectedness coincides with several early and substantial developments in the spread of COVID-19. Wuhan (where the outbreak occurred) imposed a lockdown on 23 January, followed by similar restrictions in Wenzhou (a city in another part of China) on 2 February 2020. The World Health Organisation [WHO] (2020) declared COVID-19 a Public Health Emergency of International Concern on 30 January 2020, with cases reported in 19 countries. Italy declared a state of emergency on 31 January 2020 (Regan et al., 2020). Russia, Japan, Italy, the U.S. and Australia implemented bans on all foreign visitors who had recently travelled to China in early February (McDonnell, 2020). Energy prices were impacted by these events, with oil prices decreasing from the start of 2020 due to reduced travel and the implementation of lockdowns (see Panel A of Figure 1). However, the dramatic fall in the oil price in March and April was spurred by the Saudi Arabia-Russia price war in response to the demand shock (Iyke, 2020). Natural gas prices followed a similar downward trend during January and February 2020 with a steeper decline after WHO declared COVID-19 a pandemic on 11 March. The coal price decline occurred later (April-June 2020) (see Panel B of Figure 1). Accordingly, the spike in energy market connectedness was not synchronous with the dramatic oil (and to a lesser extent natural gas and coal) price declines in March-April 2020. Lin and Su (2021) also observe a rise in energy market connectedness prior to the rapid fall in energy prices which they argue demonstrates that energy demand and prices may not be the primary determinant of connectedness. Szczygielski et al. (2023) note that increased COVID-19 uncertainty impacted energy commodities from late January.

Return connectedness spiked again in late September/ early October 2020 (peaking on 5 October with a TCI of 57.32). This coincides with the rapid spread of COVID-19 in India, a resurgence of cases in France and the U.K., and the reimplementation of stricter lockdown measures in several countries (IEA, 2020a; Amamou & Bargaoui, 2022). These developments decreased energy demand leading to lower oil and natural gas prices in September and October 2020. The IEA (2020a) emphasised the persistence of COVID-19 uncertainty at this time as cases soared. The TCI peaked again on 11 January 2021 at 54.75 and remained elevated to early March 2021, corresponding with record daily COVID-19 infections and deaths in the U.K. (due to the Alpha variant) (Duong, 2021). This peak also aligned with a significant increase in Asian natural gas (JKM) prices (see Panel C of Figure 1). Dubreuil and Molnar (2021) note that unexpectedly cold weather in December 2020 led to a surge in demand while supply was limited due to plant outages in parts of Asia and Australia, causing Asian buyers to seek more remote suppliers such as the U.S. and Europe, increasing prices in these markets.

The spikes in return connectedness during the COVID-19 pandemic were relatively short-lived, with subsequent spikes less pronounced than the first. This suggests that market participants adapted quickly to COVID-19 developments affecting energy markets. Wang et al. (2022) attribute the easing of energy market turmoil to the Federal Reserve's quantitative easing policy which began in March 2020.

Figure 2: Dynamic total connectedness



***Notes**:* This figure plots the TCI for the period 1 October 2017 to 15 August 2023. The three sub-periods are denoted: pre-crisis (1 October 2017 to 31 December 2019) in white, COVID-19 crisis (1 January 2020 to 31 May 2021) in light grey and GEC (1 June 2021 to 15 August 2023) in dark grey.

Energy return connectedness jumped on 6 July, spiked again on 24 August (TCI of 56.43) and remained elevated until mid-September 2021. This period coincides with volatility in energy markets. Energy prices rose due to increased demand as countries recovered from COVID-19 lockdowns. Oil reached six-year highs on 6 July as OPEC+ members (Saudi Arabia and the United Arab Emirates) disagreed about production increases, but then fell when an agreement was reached on 19 July. WTI and Brent crude prices experienced their largest week of losses (9% and 8%, respectively) in over nine months in mid-August before climbing more than 5% on 23 August 2021. Kumar (2021) attributes the losses to concerns about the economic recovery due to the spread of the Delta variant and new COVID-19 restrictions in New Zealand and Japan. However, Asu (2021) suggests that sentiment also influenced oil prices as fundamentals had not substantially deteriorated. Asu (2021) attributes the rapid recovery in oil prices on 23 August to bullish risk appetite following news of zero new COVID-19 cases in China.

Energy return connectedness jumped on 5 October, peaked on 6 October (TCI of 59.95) which persisted until late November 2021. On 5 October, U.K., European and Asian natural gas prices soared to record levels, while U.S. gas prices hit highs last seen in 2008. Stevens (2021) attributes the price surge to a 'perfect storm' – heightened energy demand due to the rapid economic rebound post-COVID-19, a cold winter in 2021 depleting supplies, slow supplier response to increase production, low renewable energy supply due to still and dry conditions and Russia's reduced natural gas supply to Europe. On the same day, WTI and Brent crude prices hit levels last seen in 2014 and 2018, respectively, due to OPEC+ deciding to maintain its agreed production rise without further increases (Williams, 2021). Coal prices also hit record highs due to increased demand and supply challenges (rain and logistics) in Australia, China and Indonesia (Stringer, 2021). Disavino (2021) highlights that uncertainty in energy markets also spiked at this time, with the Henry Hub implied volatility index reaching a record high due to fears of insufficient gas supplies for winter in Europe. OVX also jumped more than 25% on 2 October. Nagel and Temaj (2021) confirm high integration of natural gas and coal markets in late 2021 as shortages in one region led to higher prices globally and increased pressure on substitute energy commodities.

The TCI showed a brief spike from 14 to 17 March 2022 (peak of 56.47 on 15 March). On 24 February, Russia invaded Ukraine, which threatened Russia's supply of natural gas to Europe and raised concerns about lost Russian oil and coal supplies to the world market.[4] This event sharply increased energy prices, with oil, natural gas and coal all reaching peaks a few days thereafter (4, 7 and 7 March, respectively). On March 14, Germany confirmed a reduction in Russian crude and oil imports (Eckert, 2022). The peak in connectedness on 15 March coincided with intensified attacks on Ukraine by Russian forces and the imposition of sanctions on the U.S. president and other top officials by Russia. These largely

[4] At the time of the invasion, Russia was a major energy exporter, accounting for approximately 17% of the world's natural gas supply (mostly to the European Union), 11% of global oil production and 5.5% of global coal production (Brown et al., 2023).

retaliatory sanctions[5], which underscored growing tensions between Russia and the U.S., heightened uncertainty and affected energy markets.

Another spike in the TCI occurred in late August, peaking on 7 September and persisting until the end of September 2022. On 5 September, U.K and European natural gas prices rose by an unprecedented 30% and 23%, respectively. Twidale and Buli (2022) attribute this to Russia's decision to indefinitely shut Nord Stream 1, a major supply pipeline to Europe, due to a leak, sparking concerns about winter gas shortages. Coal prices also reached new highs on 5 September in anticipation of increased demand given natural gas shortfalls. The suspected sabotage of Nord Stream 1 and 2 pipelines on 26 September kept prices and uncertainty in the energy market elevated (Wulandari, 2023). Oil prices similarly rose on 5 September reflecting OPEC+'s decision to marginally reduce output in response to declining oil prices amid ongoing concerns about economic growth due to China's continued COVID-19 lockdowns (Somasekhar, 2022).

From November 2022 to early March 2023, the TCI declined, coinciding with a period of greater stability in energy markets. According to Tertre (2023), decisive policies implemented by the European Union helped alleviate concerns over energy shortages. These measures included increasing gas storage, reducing demand, diversifying gas supplies and accelerating renewable energy adoption. Additionally, Europe experienced a mild winter further reducing energy demand. These factors collectively supported lower energy prices during this period. Concurrently, coal prices declined due to increased exports from South Africa and Colombia, coupled with lower demand from China (Agnolucci et al., 2023). Weaker Chinese demand contributed to falling oil prices. From early March until August 2023, the TCI gradually increased, peaking at 56.36 on 22 June. During this period, recession fears abounded. Emran (2023) noted that energy markets could face a significant demand shock if a recession materialises.

The analysis of the TCI indicates that energy markets became more connected during the COVID-19 crisis, although these periods were short-lived. Initially, there was asynchrony between energy prices and connectedness, but alignment increased as the pandemic continued. Throughout the energy crisis, greater synchronicity was observed between energy prices and energy commodity return connectedness, with prolonged periods of elevated connectedness as prices remained high. However, uncertainty persisted during periods when the TCI was higher.

4.2. Static and dynamic net commodity connectedness

We examine the net connectedness for each commodity. The aggregated results in Table 3 show that oil is a net transmitter of spillovers to coal and natural gas throughout the sample period. This aligns with previous findings by Bachmeier and Griffin (2006), Brown and Yücel (2008) and Zolfaghari et al.

[5] The U.S. and several other countries imposed sanctions on Russian banks, the country's leaders and its oil in the weeks immediately following the invasion.

(2020). Several factors may explain oil's leading role. First, and crucially, oil prices are often seen as a barometer of economic activity (Lescaroux & Mignon, 2008; Troster et al., 2018). When economic activity increases (decreases), oil prices rise (fall) due to changing demand. Market participants incorporate news (such as weekly oil inventories and manufacturing data) which provides a signal about future economic output (Elder et al., 2013; Loughran et al., 2019). This information is then transmitted through to natural gas and coal prices due to their roles in electricity production and industrial processes and because price discovery in energy markets is concentrated in oil (Mohammadi, 2011). Second, investor sentiment influences oil prices, potentially spilling over to natural gas and coal prices (Qadan & Nama, 2018; Zhao et al., 2023). Third, according to Jin et al. (2023) geopolitical risks reflected in oil prices contribute to contagion across energy markets. Lastly, Hasanli (2024) argues that the pricing of some long-term natural gas contracts still rely on oil prices, which contributes to spillovers.

Table 3: Aggregated net connectedness

	Oil	Coal	Natural Gas
Pre-crisis	8.44	-9.21	0.77
COVID-19 crisis	5.49	-10.07	4.58
GEC	8.67	-10.09	1.42

Notes: This table reports the aggregated results of the net connectedness for oil, natural gas and coal across the pre-crisis (October 2017 – December 2019), COVID-19 crisis (January 2020 – May 2021) and GEC (June 2021 – August 2023) periods.

Figure 3 presents the dynamic net connectedness for each commodity, highlighting how net connectedness varied in response to specific events. Before the COVID-19 crisis, oil's transmission of spillovers to natural gas and oil spiked in February, April and August 2018, followed by a sustained rise from late 2018, peaking in February 2019. These movements coincide with major news affecting the oil market, including U.S. sanctions on Venezuela's state-owned oil company, the reimposition of sanctions on Iranian oil exports[6] and supply cuts in Canada (IEA, 2019; Quint, 2019). Oil prices rose in the first half of 2018 in response to these policy changes, reaching a high in October 2018. However, prices fell significantly thereafter (see Panel A of Figure 1) due to high U.S. oil inventories because of the country's trade dispute with China, the waiving of sanctions on some countries importing Iranian oil and increased supply by OPEC (Rapier, 2018). Quint (2019) confirms that this period of oil price collapse was associated with high levels of uncertainty (as reflected by OVX), which spilled over to other energy markets.

During the COVID-19 crisis, oil's role as a transmitter of spillovers declined from 8.44% in the pre-crisis period to 5.49% (Table 3). This suggests that the unprecedented energy demand shock caused by lockdowns and travel bans altered the transmission of information from oil to natural gas and coal, with less price discovery occurring in the oil market and less sentiment transmitted from oil prices (De Blasis

[6] The U.S. withdrew from the 2015 Iran nuclear agreement.

& Petroni, 2021). In March 2020, when COVID-19 was declared a pandemic, spillovers from oil to natural gas and coal initially spiked before declining sharply until the end of May 2020 (Figure 3). Another spike occurred in September 2020, coinciding with a resurgence of cases and stricter lockdown measures (see Section 4.1), followed by a sustained downfall in connectedness, with oil briefly becoming a net receiver of shocks in February 2021. These spikes in connectedness during the crisis align with jumps in uncertainty caused by the pandemic rather than prices or economic fundamentals (Altig et al., 2020).

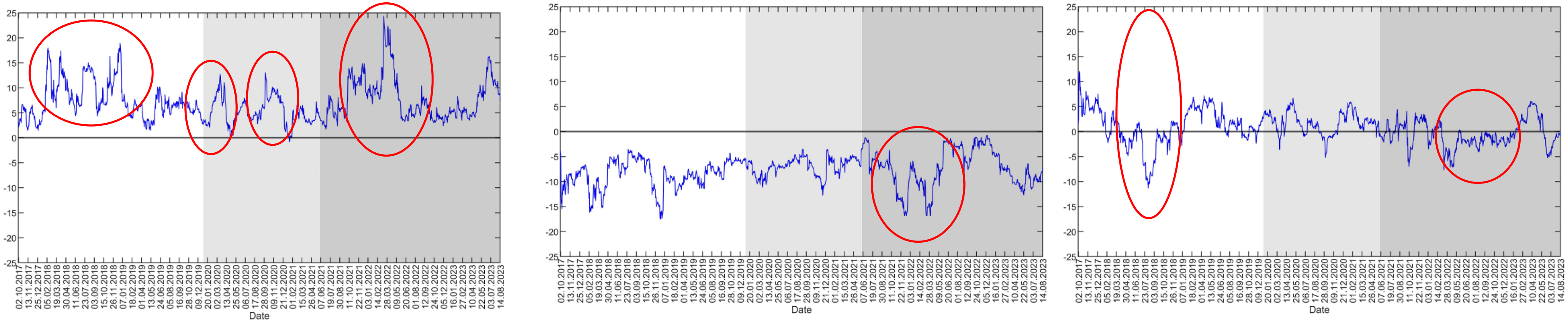
During the GEC, oil's overall transmission role increased to 8.67%, comparable to pre-crisis levels, reinforcing its leading role in price discovery as economic information is first incorporated into oil prices before spilling over to natural gas and coal prices, despite the other two energy sources being at the forefront of the crisis (Szczygielski et al., 2024a). Oil's net connectedness jumped in October 2021, when natural gas and coal prices reached record levels and oil prices hit highs not seen in several years (Figure 3). Another spike occurred in February 2022, corresponding with Russia's invasion of Ukraine and peaks in the TCI (see Section 4.1). However, oil's transmission of return spillovers to coal and natural gas declined thereafter. These heightened spillovers from the oil market were temporary and linked to specific events with high uncertainty (Disavino, 2021).

Coal remained a net receiver of spillovers from oil and natural gas, with little variation in net connectedness before or during the two crises (-9.21%, -10.07% and -10.09%, respectively – Table 3). Wang et al. (2022) note that the gradual replacement of coal with clean energy sources insulated coal prices from demand shocks. According to Birol (2023), market participants viewed coal prices reaching record highs during the GEC as a temporary aberration (Panel B Figure 1). Varadhan et al. (2022) confirm that the coal market is influenced more by policy, limiting notable variation in spillovers from other energy sources. Coal prices became more sensitive to spillovers from other energy markets when natural gas and coal prices soared in October 2021 and during Russia's invasion of Ukraine in February 2022 (Figure 3). However, coal prices received fewer spillovers from May to December 2022, despite reaching successive highs, consistent with increased demand for coal to offset lost natural gas and renewable energy supplies (Saul, 2022; Wehrmann, 2023).

Natural gas is a net transmitter of return spillovers, increasing during the COVID-19 crisis but decreasing during the GEC (0.77% to 4.58% to 1.42% - Table 3). However, the periods of natural gas transmitting spillovers were relatively short, interspersed with periods where natural gas was a net recipient of spillovers (Figure 3). Natural gas experienced a notable increase in receipt of spillovers in 2018-2019, attributable to both oil market developments (described above) and an abundance of natural gas supplies, especially from the U.S. and Russia. However, a subsequent surge in demand from China, the U.S. and Europe prevented prices from falling (U.S. Bureau of Labor Statistics, 2019). As demand and supply forces rebalanced, natural gas reverted to its role as a net transmitter of spillovers. Natural gas became an increasingly important transmitter of spillovers during the COVID-19 crisis. This reflects the reduced role of oil and the substitutability and aligned production processes of oil and natural gas. The natural gas market experienced severe oversupplies, pushing prices to historic lows, while the industry cut spending and postponed or cancelled investment decisions (IEA, 2020b; IEF, 2020). The IEA (2020b) notes that these decisions will impact oil and coal demand in the post-pandemic recovery, aligning with the increased spillovers observed. During the GEC, as oil's connectedness spiked, natural gas became a net recipient of spillovers in October 2021 and February 2022. It remained a net recipient of spillovers through to February 2023, despite rapid price surges (see Panel C of Figure 1). Therefore, price rises were not the sole drivers of spillovers. The increase in net spillovers from natural gas to oil and coal from early 2023 onwards coincides with greater stability in energy markets due to policies limiting the effects of high energy prices on consumers and sourcing supplies from alternative locations to avoid gas shortages (see Section 4.1). Consequently, with greater market stability, connectedness patterns reverted to oil leading but natural gas also transmitting some spillovers.

Our analysis reveals that oil consistently transmits spillovers to coal and natural gas, driven by its role as an economic indicator, investor sentiment and geopolitical risks. During the COVID-19 crisis, oil's spillovers decreased due to reduced demand, while natural gas emerged as a stronger transmitter. However, in the GEC, oil's spillover role rebounded, underscoring its continued significance in price discovery and reflecting global uncertainty, while natural gas fell back to pre-pandemic levels. Coal remained a net receiver with minimal change.

Figure 3: Dynamic net connectedness for oil, natural gas and coal markets



Panel A: Oil **Panel B: Coal** **Panel C: Natural gas**

***Notes**:* This figure plots the net connectedness for each energy group for the period 1 October 2017 to 15 August 2023. The three sub-periods are denoted: pre-crisis (1 October 2017 to 31 December 2019) in white, COVID-19 crisis (1 January 2020 to 31 May 2021) in light grey and GEC (1 June 2021 to 15 August 2023) in dark grey. Positive (negative) values of net spillovers indicate that the energy group is a net transmitter (receiver) of spillovers.

4.3. Pairwise energy price benchmark connectedness

Table 4 shows that oil benchmarks are net return transmitters to other energy prices in the pre-crisis period, except for Canada, with Brent (14.68%), WTI (11.78%) and Urals (10.47%) the largest net transmitters. This aligns with Brent's role as a benchmark for approximately 78% of globally traded physical crude oil, WTI's use by U.S. market participants and Urals' providing a reference point for Russian oil (Wittner, 2020). Chatziantoniou et al. (2023) also identify European and U.S. oil prices as the main transmitters of spillovers among oil price benchmarks. Canadian oil being a net recipient of spillovers is consistent with most of the country's oil being exported to the U.S., with WTI primarily used as the benchmark for U.S. and Canadian physical oil trading. The return spillovers from the oil price benchmarks declined during the pandemic, except for a brief spike at the onset of the crisis (see Panels A – E of Figure 4). The jump in connectedness was particularly severe for Urals. In response to Russia and Saudi Arabia's disagreement over oil production cuts due to the COVID-19 demand shock, Saudi Arabia flooded the market with oil, causing a dramatic fall in oil prices. This contributed to an increase in spillovers from Urals to other energy commodities whereas DME Oman became a net receiver at this time (Panel C). This suggests that this event pushed price discovery away from DME Oman. However, it returned to being a net transmitter from July 2020 onwards as relations normalised within OPEC+ (Bildirici et al., 2020). These dramatic events contributed to DME Oman being a net receiver (-1.39%) during the pandemic.

The transmission roles of Brent and WTI increased during the GEC to above pre-crisis levels, especially WTI (14.28%). WTI's increased role reflects the rising contribution of U.S. oil globally since the shale revolution resulting in a surge in oil production and exports to Europe and Asia, and the dominance of WTI contracts in futures trading (Caporin et al., 2019; Johnson, 2023). The importance of Urals declined during the GEC, becoming the weakest transmitter (1.22%). This aligns with the ban on Russian oil imports by the U.S., Canada and EU and the price cap imposed by the G7 countries, Australia and EU during 2022, limiting the price discovery contribution of this benchmark (Villafranca Serrano, 2022; Wiseman et al., 2023). Canadian oil becomes a net transmitter during the GEC, consistent with the country's increased exports to Europe as countries sought to replace Russian oil (Archer, 2022).

Individual coal price benchmarks are net receivers of return spillovers from other energy sources in the pre-crisis period (except for Richards Bay). Qinhuangdao (-11.25%) and Newcastle (-10.92%) are the largest net recipients. Li et al. (2019) and Zhu et al. (2022) argue that China's large reliance on energy makes the country's coal price susceptible to international coal prices and global energy market developments. Li and Broadstock (2021) confirm that China's coal prices are heavily influenced by oil prices. Beirne et al. (2013) and Kilian and Hicks (2013) demonstrate that expectations of economic growth in China, the world's second largest economy, influence oil prices. These growth expectations may spill over to Australian coal, which is driven by demand from China (Guttman et al., 2019). ARA serves as a key hub for coal distribution across Europe. While European coal demand has been declining due to the energy transition, remaining demand is predictable and stable, making it less susceptible to external market shocks (-3.19%) (European Commission, 2024). Richards Bay coal is neither a net transmitter/ recipient (0.04%). It is exported to a wide range of countries in Asia, Europe and the Americas, with this diversification diluting the impact of any single market on its price (Elliot, 2022). However, during the pandemic, ARA (-4.03%) and Richards Bay (-5.76%) became larger recipients of spillovers, in line with the significant global energy demand shock due to lockdowns and travel bans. ARA's transmission of spillovers to other energy price benchmarks spiked at the onset of the COVID-19 crisis, while most other coal benchmarks saw an increase in receipt of spillovers (Figure 4). This suggests that price discovery was occurring in ARA, driven by its central role in global coal trade and its close link to natural gas prices due to their competition in European power generation and location (Nick and Thoenes, 2014; Euracoal, 2022). During the GEC, Qinhuangdao, Newcastle and Richards Bay coal revert to approximate pre-crisis levels (and transmitter/ recipient positions), while ARA becomes neutral in net connectedness. Figure 4 (Panel G) shows ARA is a large net transmitter of spillovers, with a spike in late February/ early March 2022 at the time of Russia's invasion of Ukraine. Spillovers dropped from late March to early May 2022 before rising again. This rise reflects increased coal demand in Europe as Europe sought to replace lost Russian energy supplies.

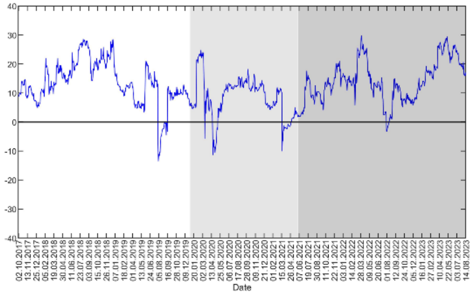
TTF and NBP are net transmitters while the remaining four natural gas benchmarks are net recipients of return spillovers in the pre-crisis period. TTF is the largest transmitter (5.73%), with Wallumbilla (-10.9%) the largest recipient. From August to October 2018, both TTF and NBF became net recipients of spillovers from energy benchmarks (Panels J and K, Figure 4). This shift coincides with the European Commission's pledge to significantly increase LNG imports from the U.S., aimed at averting a trade war with the U.S. and diversifying Europe's natural gas supplies (DiChristopher, 2018). The spike in spillovers in late 2018 across most natural gas benchmarks coincides with sharp rises in natural gas prices due to low storage, high demand and supply constraints (Woroniuk, 2018; U.S. Bureau of Labor Statistics, 2019).

During the COVID-19 crisis, spillovers from TTF and NBP increased while Henry Hub and Wallumbilla received less spillovers. As key natural gas benchmarks, TTF and NBP became more central to price discovery in the energy sector as the pandemic disrupted energy markets (see Section 4.2). During the GEC, natural gas benchmark spillovers mostly returned to pre-crisis levels except for Henry Hub and JKM, both becoming larger net recipients of return spillovers from energy markets. The Russia-Ukraine conflict severely disrupted global energy markets, with Europe's reliance on Russian gas leading to an urgent search for alternative sources. As European countries turned to markets such as the U.S, Qatar and Nigeria for natural gas, the demand effect spread across global energy markets. Countries in Asia, such as Pakistan and Bangladesh, experienced shortages as LNG suppliers prioritised high-paying markets, particularly in Europe (Sullivan, 2022). This heightened the sensitivity of Henry

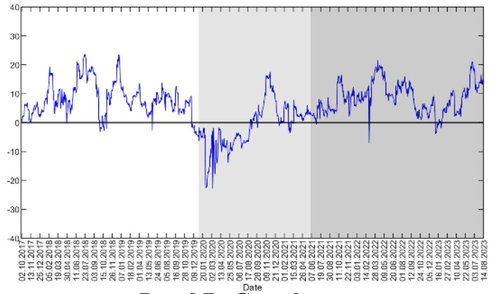
Hub (a major U.S. gas pricing point) and JKM (the key benchmark for pricing in the Pacific Basin) to shocks from other energy benchmarks (European Council and Council of the European Union, 2023; Timera Energy, 2024). Savcenko (2023) confirms that Europe's competition with Asia for LNG intensified the connectedness of energy markets.

Our analysis indicates that Brent, WTI and Urals consistently transmit return spillovers to other energy prices across periods, with WTI's influence rising and Urals sharply declining during the GEC. TTF and NBP increased their spillover transmission during the COVID-19 crisis but not during the GEC, although JKM and Henry Hub became more sensitive to energy market dynamics during the energy crisis. Among coal benchmarks, Qinhuangdao and Newcastle are most affected by other energy sources whereas ARA and Richards Bay show greater resilience, although they were significantly impacted by other energy sources during the pandemic.

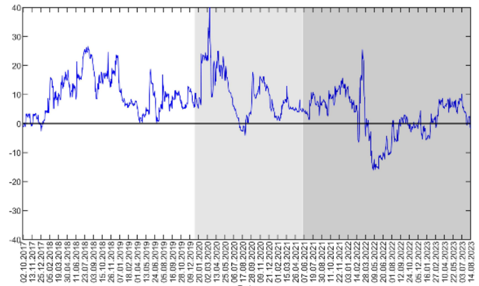
Figure 4: Dynamic net connectedness among energy price benchmarks



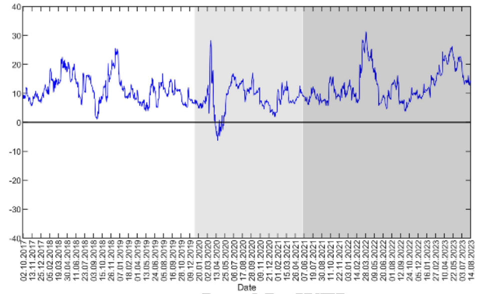
Panel A: Brent



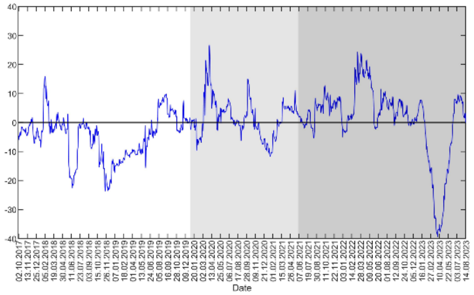
Panel B: Canada



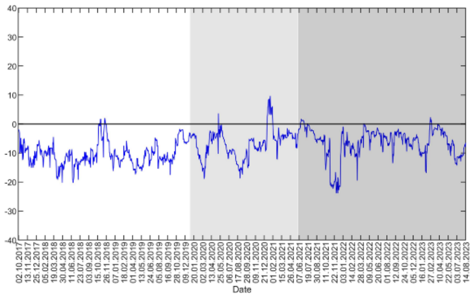
Panel C: Urals



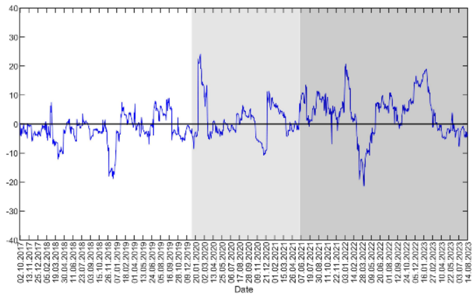
Panel D: WTI



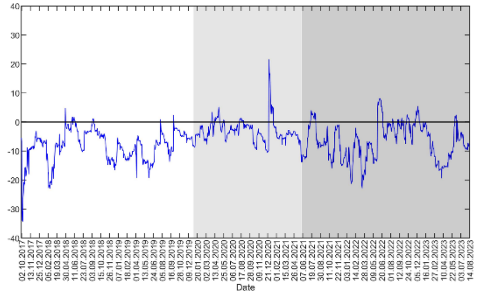
Panel E: DME Oman



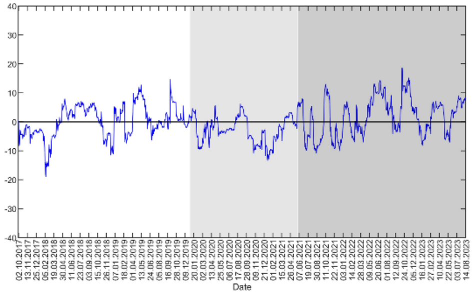
Panel F: Quinhuangdao



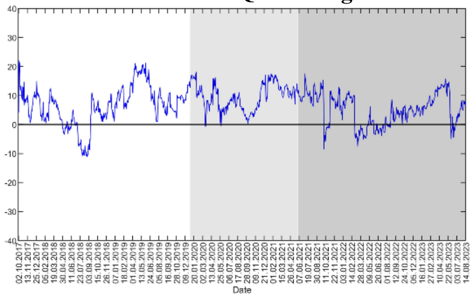
Panel G: ARA



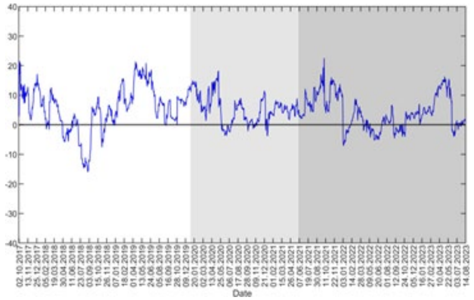
Panel H: Newcastle



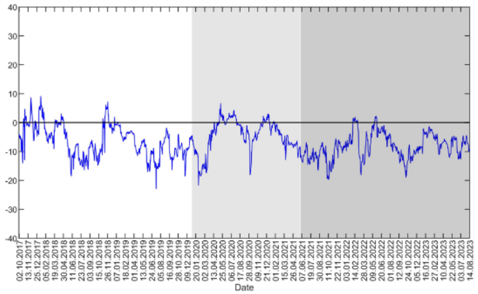
Panel I: Richards Bay



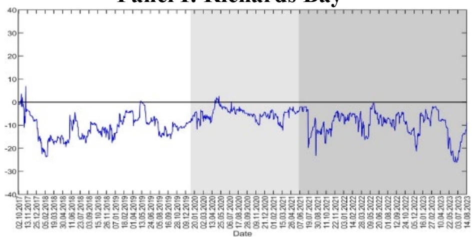
Panel J: TTF



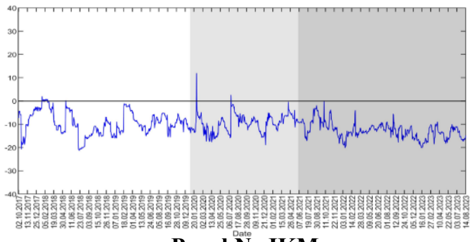
Panel K: NBP



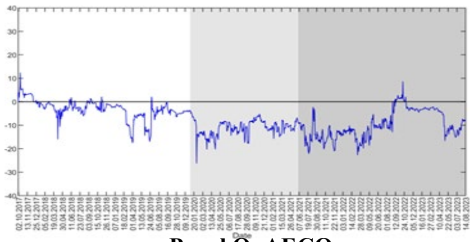
Panel L: Henry Hub



Panel M: Wallumbilla



Panel N: JKM



Panel O: AECO

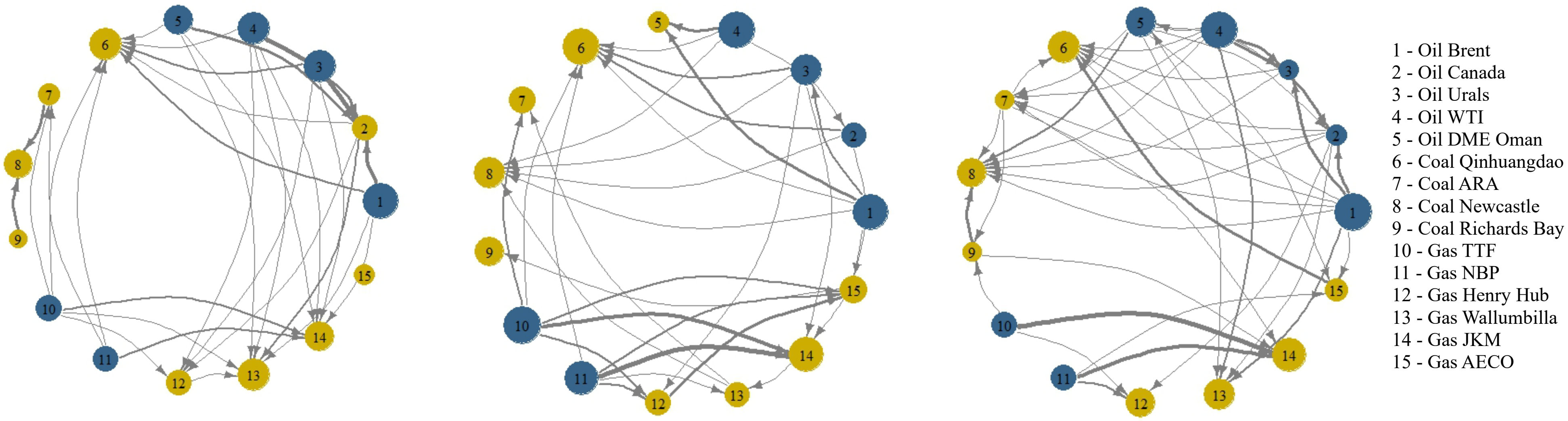
Notes: This figure displays the dynamic net connectedness index for oil, coal and natural gas price benchmarks for the period 1 October 2017 to 15 August 2023. The three sub-periods are denoted: pre-crisis (1 October 2017 to 31 December 2019) in white, COVID-19 crisis (1 January 2020 to 31 May 2021) in light grey and GEC (1 June 2021 to 15 August 2023) in dark grey. Positive (negative) values of net spillovers indicate that the energy group is a net transmitter (receiver) of spillovers.

Table 4: Net connectedness among energy price benchmarks

	Panel A: Oil					Panel B: Coal				Panel C: Natural Gas						Panel D: TCI
Benchmark	**Brent**	**Canada**	**Urals**	**WTI**	**DME Oman**	**Qinhua-ngdao**	**ARA**	**Newcastle**	**Richards Bay**	**TTF**	**NBP**	**Henry Hub**	**Wallum-billa**	**JKM**	**AECO**	
Pre-crisis	14.69	-4.73	10.47	11.78	9.51	-11.25	-3.19	-8.05	0.04	5.73	5.10	-6.94	-10.90	-9.17	-3.09	49.24
COVID-19 crisis	9.45	3.33	6.84	9.63	-1.39	-9.54	-4.03	-6.59	-5.76	10.31	8.40	-3.66	-3.44	-8.68	-4.85	49.24
GEC	15.29	2.05	1.22	14.28	9.46	-10.92	-0.09	-8.59	-0.29	5.70	5.28	-8.31	-9.85	-12.26	-2.96	52.52

Notes: This table presents the net connectedness for each energy benchmark for the three sub-periods: pre-crisis (1 October 2017 to 31 December 2019) in white, COVID-19 crisis (1 January 2020 to 31 May 2021) in light grey and GEC (1 June 2021 to 15 August 2023) in dark grey. Positive (negative) values of net spillovers indicate that the energy benchmark is a net transmitter (receiver) of spillovers.

Figure 5: Network diagrams showing pairwise spillovers



Panel A: Pre-crisis **Panel B: COVID-19 crisis** **Panel C: GEC**

Notes: This figure reports the net pairwise directional connectedness in three sub-periods: the pre-crisis period (panel A), COVID-19 crisis (panel B) and GEC (panel C). Blue (yellow) nodes indicate that a variable is a net transmitter (receiver) of shocks. The size of the nodes indicate the magnitude of the net transmitted (received) spillovers. The width of the arrow lines indicates the strength of the pairwise spillovers.

While Figure 4 and Table 4 offer insights into net pairwise connectedness, they do not identify the specific source or recipients of a price benchmark's spillovers. To address this, we consider the network diagrams in Figure 5. In the pre-crisis period, intra-oil market integration is relatively limited, except for strong spillovers to Canadian oil. Its net recipient status (Table 4) thus stems from spillovers from oil benchmarks due to Canadian oil predominantly being exported to the U.S., where WTI serves as the primary benchmark (Wittner, 2020). During the COVID-19 crisis, intra-market spillovers shift. Spillovers from Urals and WTI to Canadian oil disappear, although Brent transmits strong spillovers to Urals and Oman and WTI influences Oman. Oman's net recipient status during this period (Table 4) reflets these intra-market spillovers, arising from the Saudi Arabia-Russia oil price war. Intra oil market spillovers intensify during the GEC, with Brent, WTI and Urals transmitting spillovers to Canadian oil and Brent and WTI continuing to transmit spillovers to Urals and Oman. This confirms the rising influence of WTI is primarily to other oil benchmarks. We observe less integration between oil price benchmarks than in previous studies, such as Ji and Fan (2016) and Chatziantoniou et al. (2023), suggesting that when considering other energy sources, oil price connectedness is weaker.

The coal market exhibits lower intra-market integration than oil or natural gas in the pre-crisis period. Qinhuangdao is segmented from all coal price benchmarks, while ARA and Richards Bay influence Newcastle coal. This contrasts with Batten et al. (2019), who found substantial spillovers across coal benchmarks. This difference may stem from changing market dynamics or the inclusion of other energy sources in our analysis. The segmentation of coal prices could be due to the high transportation costs and regional differences in industrial activity and energy needs. For example, Asian markets have high coal demand due to their reliance on coal-fired power plants, while Europe and the U.S. have been shifting toward cleaner energy sources (Agnolucci & Temaj, 2024). These regional differences lead to distinct pricing patterns and reduce market connectedness. While Batten et al. (2019) found Newcastle led intra-coal market spillovers, our study identifies Newcastle coal as a net recipient of spillovers from other coal benchmarks. Factors such as flood-induced supply disruptions in Australia, China's informal ban on Australian coal imports and China's increased access to cheaper, lower-quality coal from Indonesia and other markets, may have reduced the leading role for Australian coal (Cunningham et al., 2019; Meredith, 2021; Russell, 2023). We also find no support for Li et al.'s (2019) finding that Chinese coal prices transmit spillovers to the Australian coal market, which reflects China's reduced reliance on Australian coal. Coal price benchmarks decoupled during the COVID-19 crisis likely arising from curtailed coal demand and disrupted coal supply (Gilbert & Bazilian, 2020; Wang et al., 2022). Freight rates also soared during the pandemic which, according to Papież and Śmiech (2015), lowers coal market integration. However, during the GEC, ARA and Richards Bay again transmitted spillovers to Newcastle, and Richards Bay became more integrated, transmitting spillovers to Newcastle and receiving them from ARA. ARA's role as a prominent transmitter reflects increased demand in Europe due to natural gas shortages in the region, while countries being forced to source coal from other markets such as Colombia, South African and India, contributing to the increased connectedness of Richards Bay (see also Figure 4 and Table 4) (Meredith, 2021; Nagel & Temaj, 2022; Saul, 2022).

Intra-natural gas market spillovers in the pre-crisis period are substantial, except for AECO, which is segmented (Figure 5). TTF and NBP transmit strong spillovers to JKM, with TTF also influencing Henry Hub and Wallumbilla. According to Bennet (2019), TTF's leading role is consistent with its position as Europe's primary natural gas trading hub, characterised by excellent infrastructure and high liquidity, which has made it the global benchmark and balancing market for natural gas prices, surpassing NBP (Bennet, 2019). This evidence of strong global intra-market integration is consistent with the findings of Chiappini et al. (2019), Nakajima and Toyoshima (2019) and Kim et al. (2020). During COVID-19, connectedness increased, with AECO becoming more integrated and receiving spillovers from TTF, NBP and Wallumbilla. Wallumbilla also became more connected, receiving spillovers from NBP and JKM. TTF and NBP's influence on JKM and Henry Hub intensified during this period. This heightened integration contrasts with findings from Chen, Wang and Zhu (2022) and Papież et al. (2022), who noted a decline in integration due to the pandemic's demand shock, possibly due to differences in our sample's inclusion of other energy sources. We attribute the increased integration due to the continued usage of natural gas for power generation resulting in prices moving together more closely due to common global (rather than country-specific) trends. Intra-market integration shifted during the GEC, with some relationships weakening and others strengthening. Wallumbilla became segmented and AECO remained linked only with NBP whereas TTF and NBP transmitted stronger spillovers to Henry Hub and JKM. Wallumbilla's segmentation may be due to the Australian government's imposition of a price cap on natural gas (MacDonald-Smith, 2022). Non-market forces, such as government interference, impede market integration (He & Westerhoff, 2005).[7] The GEC led to natural gas shortages in Europe and the U.K., prompting these regions to import LNG from other markets (such as the U.S.), which centred global natural gas trade in Europe, enhancing TTF and NBP's role in natural gas price discovery (Emiliozzi et al., 2024).

Turning to intermarket spillovers, in the pre-crisis period, Brent and Urals are significant transmitters to Qinhuangdao coal. Oil prices, reflecting economic growth prospects in China and the U.S. (the two largest economies), influence coal prices because China's heavy reliance on coal for power generation links coal consumption to economic growth (Chen, Liu et al., 2022; Khan, 2024). Urals, WTI and Oman are weak transmitters to Henry Hub, Wallumbilla and JKM natural gas prices. The relationship between WTI and Henry Hub aligns with expectations, as natural gas is often a byproduct of oil production in parts of the U.S., and, according to Hasanli (2024), crude oil prices continue to influence the pricing of

[7] Goodell et al. (2024) demonstrate that the announcement of the price cap imposed on TTF by the EU had no discernible impact on prices or volatility. Moreover, it likely had no effect on price discovery because the price did not exceed the cap after its introduction and therefore the price cap was never triggered. This differs from Australia, where the price cap was seen to force contract prices downwards (Australia Competition and Consumer Commission, 2023).

long-term natural gas contracts. While spillovers from natural gas to coal are limited, TTF and NBP transmit spillovers to Qinhuangdao and ARA. In both Europe and China, natural gas and coal compete as energy sources; higher natural gas prices can prompt switching to coal, consistent with spillovers (Alvarez & Molnar, 2021).

During the pandemic, all oil benchmarks (except Oman) transmitted spillovers to Newcastle and spillovers to Qinhuangdao continued. China's ban on Australian coal, following Australia's call for an investigation into the virus's origins, led to Australia exporting to other markets like India and Indonesia (Peng, 2023). This diversification increased susceptibility to global economic conditions, reflected in oil prices. Spillovers from oil to natural gas decreased; for instance, WTI ceased to transmit to Henry Hub, Wallumbilla or JKM. Conversely, natural gas and coal prices became more integrated; TTF's spillovers to Qinhuangdao and ARA intensified, NBP continued to influence Qinhuangdao, Wallumbilla affected both ARA and Newcastle, while AECO impacted Richards Bay.

During the GEC, Henry Hub, Wallumbilla and JKM received significant spillovers from all oil benchmarks except Urals, with these relationships stronger than in the pre-crisis period (Figure 5). Oil benchmarks also transmitted spillovers to Newcastle and Qinhuangdao and, to a lesser extent, ARA. Although the GEC primarily impacted natural gas and coal prices, price discovery continued in oil price benchmarks, spilling over more to other energy sources than before. Surprisingly, natural gas and coal price benchmarks became more segmented during the crisis, with TTF and NBP no longer influencing Qinhuangdao and ARA. However, Richards Bay became more connected, receiving spillovers from TTF and transmitting them to JKM. Nagel and Temaj (2021) confirm that some natural gas and coal markets have become increasingly integrated as a shortage of coal in one region not only results in higher prices of coal in other regions but also exerts upward pressure on substitutes. TTF remained the leading natural gas benchmark, but its influence shifted to South African coal markets rather than those in China and Europe, reflecting changes in coal supply sources.

Overall, the network diagrams suggest relatively low intra-market integration in oil and coal but higher integration among natural gas. During COVID-19, natural gas market integration increased, especially with TTF, NBP, JKM, Henry Hub and Wallumbilla, while coal became segmented and oil market connectedness weakened (especially Canada). In contrast, the GEC saw intensified spillovers within oil and coal markets but a decline in natural gas integration. Inter-energy market spillovers shifted, with oil benchmarks (except Urals) transmitting to Qinhuangdao and Newcastle during the pandemic but ceasing during the GEC. WTI no longer transmitted spillovers to several natural gas benchmarks during the COVID-19 crisis but strengthened during the GEC.

4.4. Robustness checks

4.5.1. Alternative model specifications

To validate the findings derived using the TVP-VAR model (with decay factors $\kappa_1 = 0.99$ and $\kappa_2 = 0.97$; a 1-day lag, a 10-day forecast horizon and using a Minnesota prior), we compare our results against those obtained using alternative TVP-VAR specifications. First, we extend the forecast horizon to 20 days (see column 2 in Tables A1, A2 and A3 in the appendix). Second, we consider alterative lag specifications from 1 to 5 days (see columns 3 to 5 in Tables A1, A2 and A3). The choice of lag is motivated by significant (at 5%) partial autocorrelation functions (PACF) at lag one within the whole data range, though exceptions exist in different sub-periods. For instance, during the GEC, half of the energy benchmarks show significant PACFs at lag two. Third, we consider different decay factor values, with the results presented in columns 6 and 7 in Tables A1, A2 and A3. The alternative specifications produce consistent results. The greatest divergences from the base model (column 1 in Tables A1, A2 and A3) occur when the lag parameter exceeds 2, as such values are inconsistent with the PACF for most benchmarks. For example, Canadian oil during the pre-crisis period is a net recipient of spillovers (-4.73%) when estimated with the base TVP-VAR model but becomes a net transmitter (2.73%) when a lag of 5 is used (see Table A1).

Next, we estimated connectedness using the constant coefficients VAR model of Diebold and Yılmaz (2009) across the three periods, applying rolling windows of 100, 60 and 30 days (see columns 8-10 in Tables A1, A2 and A3). Using different window sizes allows us to obtain dynamic connectedness metrics. However, a window size that is too narrow can drastically influence results, as confirmed by Lin and Su (2021) and Zhang et al. (2020). Additionally, a traditional VAR model is sensitive to outliers, unlike the TVP-VAR model (Chatziantoniou & Gabauer, 2021). Therefore, we expect significant divergences between the base model and the outcomes obtained with the VAR specification. For instance, in Table 2A, DME Oman oil is a net recipient of spillovers (-1.39%) during COVID-19 but is a net transmitter (8.38% and 10.84%) when the VAR model with a rolling window of 30 or 60 days is applied.

We also considered a Quantile-VAR model (QVAR), which uses quantile regression for estimating each equation (Gabauer et al., 2021). This approach allows us to explore connectedness across various quantiles ($Q = 0.05$, $Q = 0.5$, $Q = 0.95$, see columns 11-13 in Tables A1, A2 and A3 in the Appendix). Estimates for the lower quantile ($Q = 0.05$) and the upper quantile ($Q = 0.95$) show the tail connectedness measures of the conditional distribution, reflecting the impact of extreme negative/positive shocks on the connectedness. For large data samples, the 50% quantile ($Q = 0.5$) should provide the average connectedness magnitude (Bouri, Saeed et al., 2021; Chatziantoniou et al., 2021); however, for small sample this is not the case (as in our study). In our base model, Qinhuangdao coal is a net recipient (-10.92%); for the QVAR model at $Q = 0.5$, it is a net transmitter (4.02%). Such divergence can result from the narrow window size applied (with a rolling window of 100) and of a short data set. Chatziantoniou et al. (2021) and Bouri, Saeed et al. (2021) use a 200-day rolling window which we cannot apply due to the short data samples in the investigated sub-periods.

Additionally, the quantile model provides unique insights. For example, Wallumbilla natural gas is a weak net receiver of spillovers during the COVID-19 crisis (-3.44%). However, it becomes a larger receiver of spillovers (-21.07%) during extreme negative shocks and a large net transmitter (17.45%) during extreme positive shocks (17.45%). This is surprising since natural gas markets are typically led by TTF or NBP (European) or Henry Hub (U.S.) prices. This may be due to the Australian government's plan for a gas-fired post-pandemic recovery, which aims to create abundant and affordable gas supplies by unlocking supply chains and improving pipeline and transportation efficiency (Taylor, 2021). This plan also impacts Korea, Japan and China, major importers of Australian natural gas, contributing to the observed spillovers. The quantile analysis also reveals notable trends regarding the GEC. During this period, all oil benchmarks are net transmitters of spillovers according to the base model. However, when extreme positive shocks occur, all oil benchmarks except Brent, become net receivers. This does not occur during the COVID-19 crisis. This attests to the nature of the GEC whereby, when large upward movements in energy prices occurred, this mostly originated in natural gas and coal markets, which then spilled over to oil benchmarks. Brent was not immune as it does exhibit a lower net transmitter role in the upper quantile. While the role of oil benchmarks in transmitting spillovers declined during extreme positive shocks during the GEC, the role of natural gas benchmarks increased. NBP, AECO, JKM and Wallumbilla, for example, all transmit spillovers in the positive tail whereas they are net recipients in the base model. In contrast, Henry Hub changes from a net recipient to a net transmitter in the negative tail.

Finally, we also utilise a frequency-based TVP-VAR model, following the methodology outlined by Chatziantoniou et al. (2023), which provides granular information by differentiating between short- and long-run connectedness. Specifically, we focus on estimating connectedness measures over investment horizons of 1 to 5 days (the short run). The choice of this range is based on the lag parameters from the PACF. The short-run connectedness dynamics shed additional light on market integration. According to Chatziantoniou et al. (2023), if benchmarks respond similarly in the short run (having similar directions and magnitudes), connectedness is stronger, indicating market integration. Comparing the findings of the frequency-based TVP-VAR model (column 14 in Tables A1, A2 and A3) with the base model, we observe that connectedness magnitudes are very close and net transmitter/recipient status remains the same across all benchmarks and periods.

Overall, the results from the robustness tests confirm the validity of the results obtained via the TVP-VAR model. Deviations observed are in line with expectations regarding the limitations of the use of other models.

4.5.2. Mutual information

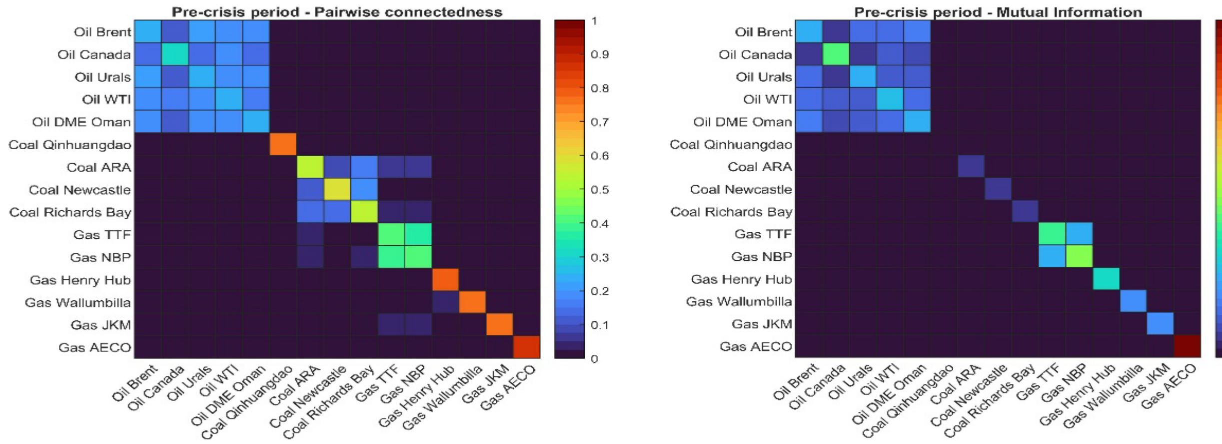
To validate the share of information between each variable X and Y, representing energy benchmarks, obtained by the TVP-VAR base model, we applied the mutual information method. Mutual information, denoted $I(X, Y)$ is a measure of dependency (linear and nonlinear) between two variables X and Y. Since $I(X, Y)$ captures nonlinear relationships, it is a broader measure than linear correlation. $I(X, Y)$ quantifies the amount of information (in bits) the variable X has about the variable Y. It is related to Shannon Entropy (Shannon, 1948), which is the measure of uncertainty about the variable's outcomes, in the following way:

$$I(X, Y) = H(X) - H(X|Y) \tag{14}$$

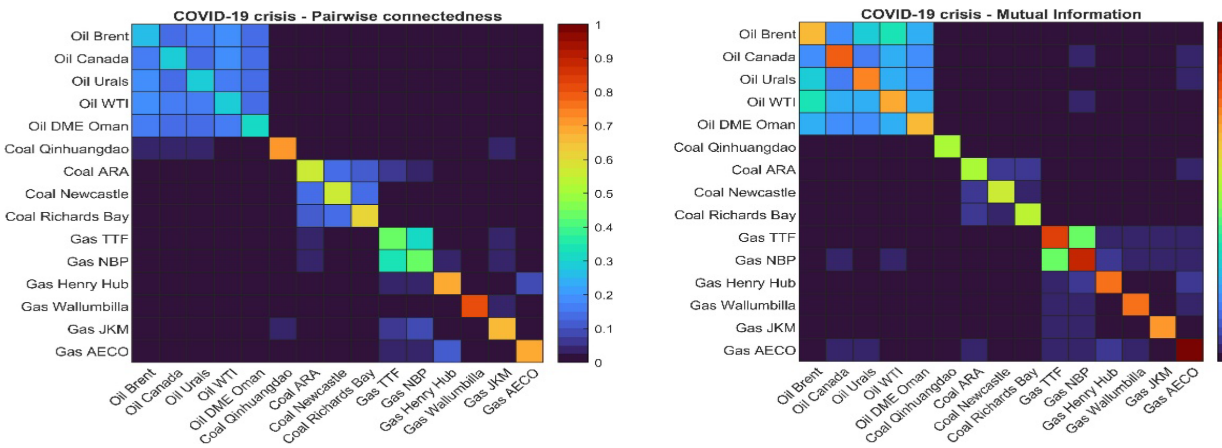
where $H(X) = -\sum_{x \in X} p(x) \, log \, p(x)$ is the Shannon entropy; $H(X|Y) = H(X, Y) - H(Y)$ is a conditional entropy and $H(X, Y) = -\sum_{x \in X, y \in Y} p(x, y) \, log \, p(x, y)$ is a joint entropy. $p(x)$ and $p(y)$ are marginal probabilities of X and Y, respectively and $p(x, y)$ represents their joint probability. $I(X, Y)$ takes on values between zero and one. The higher the mutual information, the stronger the dependency between X and Y. This means that knowing X significantly reduces the uncertainty about Y (and vice versa). Weak dependence indicates that knowing X provides little or no information about Y (and vice versa). If $I(X, Y) = 0$, X and Y are independent.

The results from the mutual information analysis, shown in Figure A1 as heatmaps, confirm the results from the TVP-VAR heatmaps in Figure 6. The correlation coefficients of the results are 0.7016, 0.9124 and 0.9121 for the pre-crisis, COVID-19 crisis and GEC periods respectively and are significant at 1%. This validates the use of the TVP-VAR base model for this analysis.

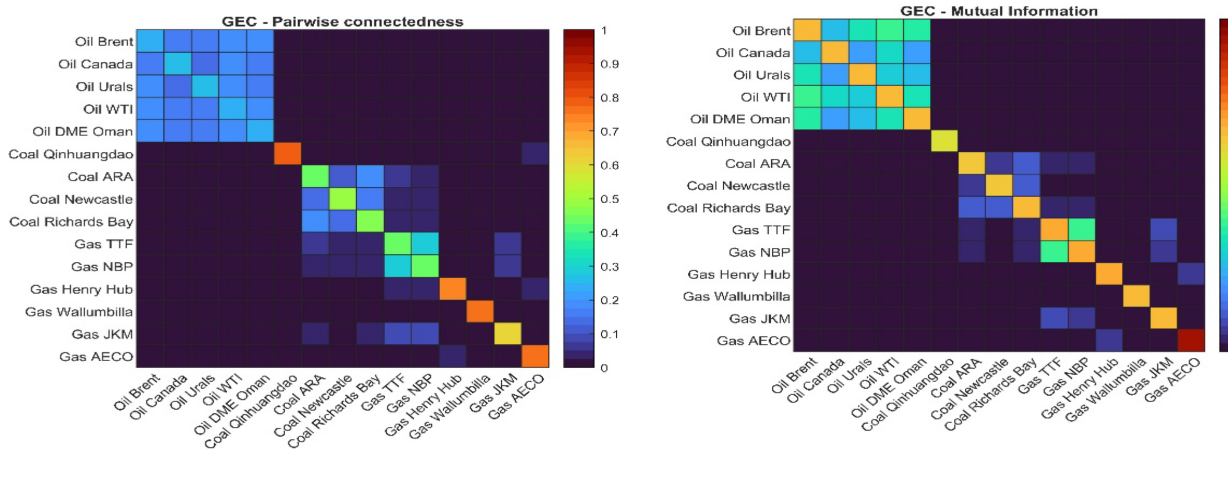
Figure 6. Heatmaps showing pairwise connectedness and mutual information content



Panel A: Pre-crisis



Panel B: COVID-19 crisis



Panel C: GEC

Notes: This figure reports the results of the pairwise connectedness and mutual information content obtained by the use of the TVP-VAR base model and mutual information method in three sub-periods: pre-crisis period (panel A), COVID-19 crisis (panel B) and GEC (panel C). The results of the TVP-VAR base model have been rescaled to values in the interval [0,1].

5. Conclusion and Implications

We undertake a thorough investigation of the connectedness of oil, natural gas and coal price benchmarks, the three main energy sources, over three distinct periods – a pre-crisis period, the COVID-19 crisis where energy demand experienced a substantial shock, and the GEC where energy supply was substantially impacted. This allows us to investigate the return spillovers across benchmarks, identifying transmitters and recipients and how these roles varied over the crisis periods.

The TCI analysis reveals that energy market connectedness is driven by major events/ news. During the COVID-19 crisis, spikes in connectedness were substantial but brief and, in the early stages, did not align with energy price changes. During the energy crisis, this synchronicity increased, with sustained high connectedness as prices and uncertainty stayed elevated. The net connectedness analysis shows that oil consistently leads in transmitting spillovers to coal and natural gas, influenced by its status as an economic indicator, investor sentiment and geopolitical events. During the COVID-19 crisis, oil's influence diminished due to lower demand, while natural gas played a more significant role. However, during the GEC, oil's influence resurged while natural gas's impact receded to pre-pandemic levels. Coal remained largely a net recipient of spillovers with little change across the crisis periods. At an individual benchmark level, Brent, WTI, and Urals consistently transmit return spillovers to other energy prices, with WTI's influence increasing and Urals declining during the GEC. TTF and NBP heightened their spillover transmission during COVID-19 but not the GEC, while JKM and Henry Hub became more sensitive to energy market dynamics during the GEC. Qinhuangdao and Newcastle coal are most affected by other energy sources, while ARA and Richards Bay show greater resilience except during COVID-19. The network diagrams indicate low intra-market integration in oil and coal but higher integration among natural gas. During COVID-19, natural gas market integration increased, especially with TTF and NBP, while coal became segmented and oil market connectedness weakened. In contrast, the GEC saw intensified spillovers within oil and coal markets but a decline in natural gas integration. Inter-energy market spillovers shifted, with oil benchmarks transmitting to coal during the pandemic but weakening during the GEC, while natural gas benchmarks like TTF and NBP reduced their influence on coal.

Our results have important implications for market participants. First, the analysis highlights the importance of understanding how energy market connectedness responds to major events. During crises like COVID-19 or the GEC, market participants should be prepared for spikes in connectedness that may not always align with immediate price changes. Participants may need to adjust their hedging strategies more dynamically during such periods, especially in response to sudden shifts in market connectedness and the leading role of specific energy sources like oil or natural gas. The role of oil as a consistent transmitter of spillovers, especially during geopolitical events and crises, suggests that oil prices will likely continue to be a significant driver of energy market dynamics. However, the varying influence of natural gas and coal across different crises also indicates that relying solely on oil-related assets might expose investors to greater risk. Investors should consider diversifying their energy portfolios to include a mix of oil, natural gas and coal, with careful attention to the timing and nature of crises. Monitoring benchmark-specific dynamics, such as the growing influence of WTI and the varying sensitivity of natural gas benchmarks, can help in making more informed investment decisions.

The sustained high connectedness during the energy crisis and the shifts in spillover dynamics among benchmarks like TTF, NBP, and Henry Hub during the GEC have implications for policymakers and regulators. These shifts reflect the broader economic and geopolitical influences on energy markets. Policymakers should consider these findings when designing interventions or regulations aimed at stabilising energy markets. Recognising which energy sources are most vulnerable to spillovers can help in crafting targeted policies that mitigate systemic risks.

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Appendix:

Table A1 : Robustness checks in the pre-crisis period

Benchmark	TVP-VAR (0.99,0.97) L = 1,H=10 (1)	TVP-VAR (0.99,0.97) L=1,H=20 (2)	TVP-VAR (0.99,0.97) L=2,H=10 (3)	TVP-VAR (0.99,0.97) L=3,H=10 (4)	TVP-VAR (0.99,0.97) L=5,H=10 (5)	TVP-VAR (0.99,0.96) L=1,H=10 (6)	TVP-VAR (0.99,0.98) L=1,H=10 (7)	VAR L=1,H=10 RW=100 (8)	VAR L=1,H=10 RW=60 (9)	VAR L=1,H=10 RW=30 (10)	QVAR,Q=0.05 L=1,H=10 RW=100 (11)	QVAR,Q=0.5 L=1,H=10 RW=100 (12)	QVAR,Q=0.95 L=1,H=10 RW=100 (13)	TVP-VAR (0.99,0.97) L=1,H=10, Freq=1-5 (14)
Panel A: Oil														
Brent	14.69	13.79	16.44	16.93	19.63	14.42	13.11	16.31	19.06	19.96	11.71	12.77	-3.89	13.79
Canada	-4.73	-5.44	-3.23	-2.32	2.73	-4.13	-6.87	-2.89	2.88	10.1	0.02	-7.58	-6.47	-5.44
Urals	10.47	10.78	13.05	13.76	15.65	11.23	10.14	14.11	16.79	16.25	16.30	10.75	0.80	10.78
WTI	11.78	11.3	12.67	13.75	17.21	11.88	10.57	12.26	14.49	16.24	19.92	9.07	1.03	11.3
DME Oman	9.51	8.88	11.45	12.17	13.96	9.66	7.97	10.18	12.32	13.97	12.03	7.34	3.55	8.88
Panel B: Coal														
Qinhuangdao	-11.25	-11.2	-16.13	-18.29	-22.8	-12.3	-9.71	-11.65	-15.91	-15.86	0.42	-6.12	-3.91	-11.2
ARA	-3.19	-3.23	-4.41	-5.73	-8.53	-3.19	-3.29	-2.94	-3.4	-1.63	-11.74	-2.44	-2.08	-3.23
Newcastle	-8.05	-8.32	-12.3	-13.17	-15.51	-8.41	-8.49	-8.49	-9.83	-8.42	-11.16	-6.75	-0.45	-8.32
Richards Bay	0.04	-0.06	-0.86	-2.04	-3.26	-0.38	0.11	2.66	-0.11	-4.53	-11.84	2.06	-0.48	-0.06
Panel C: Natural Gas														
TTF	5.73	6.18	8.45	10.13	10.08	6.73	5.49	5.07	8.36	4.36	-2.22	-0.1	2.02	6.18
NBP	5.1	5.63	8.45	10	9.72	6	5.22	4.1	7.97	3.78	6.55	0.02	21.60	5.63
Henry Hub	-6.94	-5.8	-10.76	-11.53	-13.66	-6.36	-4.98	-8.72	-11.07	-13.03	-6.31	-13.01	0.55	-5.8
Wallumbilla	-10.9	-10.97	-12.52	-14.72	-16.07	-11.68	-9.87	-11.91	-17.4	-12.85	-15.15	-3.53	-9.23	-10.97
JKM	-9.17	-9.08	-9	-11.76	-16.22	-9.91	-8.07	-8.16	-10.73	-16.42	-7.44	-0.16	-11.82	-9.08
AECO	-3.09	-2.47	-1.33	2.83	7.05	-3.55	-1.34	-9.94	-13.41	-11.9	-1.08	-2.32	2.02	-2.47

Notes: This table reports the net total directional connectedness for each energy price benchmark during the pre-crisis period (October 2017 – December 2019). The results presented in columns (1)-(7) are alternative specifications of the TVP-VAR, (8)-(10) from a VAR, (11)-(13) from the QVAR and (14)) from the frequency TVP-VAR.

Table A2 : Robustness checks during the COVID-19 crisis

Benchmark	TVP-VAR (0.99,0.97) L=1,H=10 (1)	TVP-VAR (0.99,0.97) L=1,H=20 (2)	TVP-VAR (0.99,0.97) L=2,H=10 (3)	TVP-VAR (0.99,0.97) L=3,H=10 (4)	TVP-VAR (0.99,0.97) L=5,H=10 (5)	TVP-VAR (0.99,0.96) L=1,H=10 (6)	TVP-VAR (0.99,0.98) L=1,H=10 (7)	VAR L=1,H=10 RW=100 (8)	VAR L=1,H=10 RW=60 (9)	VAR L=1,H=10 RW=30 (10)	QVAR,Q=0.05 L=1,H=10 RW=100 (11)	QVAR,Q=0.5 L=1,H=10 RW=100 (12)	QVAR,Q=0.95 L=1,H=10 RW=100 (13)	TVP-VAR (0.99,0.97) L=1,H=10, Freq=1-5 (14)
Panel A: Oil														
Brent	9.45	9.45	9.72	10.91	14.05	10.05	8.9	8.7	11.6	12.53	6.27	6.31	2.22	9.45
Canada	3.33	3.33	4.84	5.86	8.05	3.83	3.09	3.15	5.77	7.39	6.74	0.45	-1.99	3.33
Urals	6.84	6.84	6.33	7.05	11.42	7.79	5.73	7.12	10.6	14.18	11.92	5.2	3.18	6.84
WTI	9.63	9.63	11.03	12.68	14.82	10.12	9.04	11.79	13.13	10.04	14.72	7.8	8.58	9.63
DME Oman	-1.39	-1.39	-1.63	-0.44	-0.06	-0.51	-2.34	6.27	8.38	10.84	7.97	5.68	8.99	-1.39
Panel B: Coal														
Qinhuangdao	-9.54	-9.54	-12.78	-14.22	-20.89	-9.86	-9.04	-7.24	-7.49	-3.34	-7.79	-3.66	-4.15	-9.54
ARA	-4.03	-4.03	-4.75	-7.12	-7.09	-3.71	-4.82	-4.64	-4.21	-3.94	-5.29	-0.79	-10.92	-4.03
Newcastle	-6.59	-6.59	-10.17	-12.7	-15.77	-6.65	-6.81	-5.15	-6.54	-5.16	-0.74	-2.9	-5.78	-6.59
Richards Bay	-5.76	-5.76	-7.72	-10.79	-17.74	-5.9	-5.68	-4.89	-9.71	-8.95	-5.86	-0.24	-2.97	-5.76
Panel C: Natural Gas														
TTF	10.31	10.31	13.24	14.65	19.97	10.13	10.29	8.39	7.92	2.98	-0.55	3.78	2.89	10.31
NBP	8.4	8.4	13.22	15.86	19.39	8.04	9	8.45	9.3	2.12	-2.47	0.78	4.68	8.4
Henry Hub	-3.66	-3.66	-3.49	-3.89	-6.46	-4.15	-3.08	-6.54	-8.86	-4.53	4.64	-12.87	-5.91	-3.66
Wallumbilla	-3.44	-3.44	-4.54	-6.8	-12.18	-4.28	-2.6	-11.11	-14.18	-14.91	-21.07	1.73	17.45	-3.44
JKM	-8.68	-8.68	-8.95	-8.58	-7.69	-9.16	-7.8	-7.19	-6.97	-13.21	-2.76	-2.06	-8.32	-8.68
AECO	-4.85	-4.85	-4.35	-2.46	0.16	-5.73	-3.88	-7.12	-8.73	-6.04	-5.72	-9.23	-7.96	-4.85

***Notes*:** This table reports the net total directional connectedness for each energy price benchmark during the COVID-19 crisis period (January 2020 – May 2021). The results presented in columns (1)-(7) are alternative specifications of the TVP-VAR, (8)-(10) from a VAR, (11)-(13) from the QVAR and (14)) from the frequency TVP-VAR.

Table A3 : Robustness checks during the GEC

Benchmark	TVP-VAR (0.99,0.97) L=1,H=10 (1)	TVP-VAR (0.99,0.97) L=1,H=20 (2)	TVP-VAR (0.99,0.97) L=2,H=10 (3)	TVP-VAR (0.99,0.97) L=3,H=10 (4)	TVP-VAR (0.99,0.97) L=5,H=10 (5)	TVP-VAR (0.99,0.96) L=1,H=10 (6)	TVP-VAR (0.99,0.98) L=1,H=10 (7)	VAR L=1,H=10 RW=100 (8)	VAR L=1,H=10 RW=60 (9)	VAR L=1,H=10 RW=30 (10)	QVAR,Q=0.05 L=1,H=10 RW=100 (11)	QVAR,Q=0.5 L=1,H=10 RW=100 (12)	QVAR,Q=0.95 L=1,H=10 RW=100 (13)	TVP-VAR (0.99,0.97) L=1,H=10, Freq=1-5 (14)
Panel A: Oil														
Brent	15.29	15.29	16.13	16.68	16.7	16.27	13.99	16.72	19.18	17.3	6.14	13.24	2.30	15.29
Canada	2.05	2.05	2.35	2.7	3.27	3.23	1	1.4	4.07	8.17	7.50	-4.28	-7.88	2.05
Urals	1.22	1.22	1.96	3.39	3.56	2.41	-0.34	3.71	9.47	10.67	5.94	1.03	-4.93	1.22
WTI	14.28	14.27	13.99	14.51	15.03	15.06	13.14	16.37	19.71	15.5	6.81	14.87	-6.40	14.28
DME Oman	9.46	9.46	9.94	10.55	11.34	10.51	8.14	10.32	14.96	15.65	10.54	7.82	-9.35	9.46
Panel B: Coal														
Qinhuangdao	-10.92	-10.92	-13.97	-15.16	-20.69	-11.69	-9.93	-7.44	-10.17	-4.12	-1.31	4.02	-6.81	-10.92
ARA	-0.09	-0.09	0.66	-1.28	-1.62	-0.84	0.38	1.81	-0.22	-6.92	9.86	2.35	-2.32	-0.09
Newcastle	-8.59	-8.59	-10.84	-12.02	-11.75	-8.71	-8.65	-6.88	-4.52	-1.18	-6.29	-5.61	4.45	-8.59
Richards Bay	-0.29	-0.29	-0.98	-2.13	-4.56	-0.33	0	1.91	0.81	-2.02	-10.25	3.48	0.91	-0.29
Panel C: Natural Gas														
TTF	5.7	5.7	6.77	7.06	8.14	5.39	6.11	5.1	4.21	-1.25	-8.69	-0.35	4.03	5.7
NBP	5.28	5.28	6.51	8.34	10.67	5.25	5.35	4.16	2.52	-4	-4.33	-0.78	14.68	5.28
Henry Hub	-8.31	-8.31	-9.02	-11.17	-11.3	-9.07	-7.6	-8.52	-11.98	-14.84	4.69	-17.35	-6.08	-8.31
Wallumbilla	-9.85	-9.85	-10.14	-9.48	-9.28	-10.44	-8.93	-14.5	-18.84	-16.97	6.49	-1.35	2.29	-9.85
JKM	-12.26	-12.26	-11.85	-11.79	-11.43	-12.75	-11.63	-10	-12.36	-4.33	-12.16	-6.31	3.91	-12.26
AECO	-2.96	-2.96	-1.52	-0.2	1.94	-4.28	-1.02	-14.18	-16.84	-11.67	-14.92	-10.76	11.21	-2.96

***Notes*:** This table reports the net total directional connectedness for each energy price benchmark during the GEC (June 2021 – August 2023). The results presented in columns (1)-(7) are alternative specifications of the TVP-VAR, (8)-(10) from a VAR, (11)-(13) from the QVAR and (14)) from the frequency TVP-VAR.