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Abstract

Reported news events frequently influence the pricing dynamics of oil-based commodities. We analyze almost 900 oil-related events from 1987 to 2022, categorizing them based on recurring characteristics. We quantify dynamic connectedness among energy commodities and apply a novel bootstrap-after-bootstrap testing procedure to identify 21 statistically significant historical events that triggered abrupt and enduring increases in volatility connectedness. Geopolitical events are more consistently associated with elevated connectedness than economic events, while natural events do not exhibit a similar impact. Events share prevailing characteristics: their negativity, unexpected nature, and the introduction of concerns about oil supply shortages.

JEL-Codes: C320, C580, G150, Q020, Q350.

Keywords: energy commodities, crude oil, volatility connectedness, systemic events, bootstrap-after-bootstrap procedure.

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1 Introduction

The examination of connectedness among financial assets and markets is crucial for comprehending the interdependencies shaping global economic dynamics (Diebold and Yılmaz, 2014).[1] Oil-based energy commodities, integral to the global economy, warrant scrutiny due to their pervasive influence on financial markets, trade, and energy security (Hamilton, 1996; Brown and Yücel, 2002; Nandha and Faff, 2008; Mohaddes and Pesaran, 2017; Gogolin, Kearney, Lucey, Peat and Vigne, 2018). Further, studying connectedness among oil-based energy commodities is vital, with significant implications for policymakers, investors, and risk managers (Gorton and Rouwenhorst, 2006; Malik and Hammoudeh, 2007; Diebold and Yilmaz, 2012; Nazlioglu, Soytas and Gupta, 2015). The degree of connectedness among oil markets is driven by market conditions (Jena, Tiwari, Abakah and Hammoudeh, 2022) and it often reflects specific shocks/events within markets and economies. However, a primary challenge lies in the inherent uncertainty about the timing of shocks, making links between changes in connectedness and specific events subjective and largely untested on statistically significant grounds. Our analysis spanning over four decades quantifies connectedness among key oil-based energy commodities, exploring hundreds of potentially impactful shocks. Utilizing the novel formal testing method of Greenwood-Nimmo, Kočenda and Nguyen (2024), we provide the first statistical evidence revealing the types, numbers, and timing of shocks impacting connectedness among oil-based commodities.

Most assets on the markets are influenced by important events and information from new events is efficiently incorporated into their price (Fama, Fisher, Jensen and Roll, 1969; Malkiel, 2003). Compared to other assets, oil-based energy commodities appear more sensitive to events such as political concerns, supply chain shocks, or natural disasters (Baruník, Kočenda and Vácha, 2015; Karali, Ye and Ramirez, 2019) and commodity market volatility, including energy commodities, co-moves strongly with economic and financial uncertainty (Prokopczuk, Stancu and Symeonidis, 2019). The demand reaction for oil is often disproportionate to actual shocks, and the timing of price change differs due to expectations of future shortages (Kilian, 2009). Volatility increases in one market often lead to similar increases in seemingly unrelated markets or assets, and energy commodities are no exception to such contagion effects.

Detecting precise shock timing is crucial for policymakers, researchers, and investors. It helps establish causal relationships between events and connectedness patterns (Aloui, Aïssa and Nguyen, 2011). If specific events consistently lead to increased connectedness among oil-based commodities, policymakers may design measures to mitigate potential risks. For investors and financial institutions, knowing the timing of shocks is critical for effective risk management (Malkiel, 2003; Elder, Miao and

[1] In economic terms, connectedness denotes the interdependence or interconnectedness between different financial assets or markets. It is a crucial tool for analyzing systemic risk and understanding how shocks or disturbances in one asset or market can propagate and affect others.

Ramchander, 2013). Understanding timing aids in forecasting future connectedness patterns (Baruník and Křehlík, 2018) and helps accurately assess contagion in financial markets (Diebold and Yilmaz, 2012; Greenwood-Nimmo et al., 2024).

The timing of shocks and changes in connectedness is linked to macroeconomic development, indicative of broader economic trends (Nandha and Faff, 2008; Kilian, 2009). This information aids macroeconomic analysis and policymaking, particularly for oil-based commodities with a crucial role in the global economy (Energy Information Administration, 2022). Crude oil, a necessity in the industrial, agricultural, and transportation sectors, is among the most traded items globally. Increased oil price volatility affects investors and entire economies, causing GDP decreases, currency depreciation, inflationary and sovereign risk pressures, and trade disorders (Kilian, 2009; Ding and Vo, 2012; Mohaddes and Pesaran, 2017; Bajaj, Kumar and Singh, 2023; Togonidze and Kočenda, 2022).

For our analysis, we gathered prices of five energy commodities (crude oil, heating oil, gasoline, diesel, and natural gas) from 1987 to 2022. Using daily realized volatility estimates, we computed the rolling spillover index (Diebold and Yilmaz, 2009, 2012). We collected 891 news articles related to oil, categorizing them into geopolitical, economic, and natural events. Employing the novel bootstrap-based test (Greenwood-Nimmo et al., 2024), we statistically assessed the probability of increased spillover index when a specific shock occurs.

Our analysis of volatility spillovers among oil-based commodities and key driving events offers new insights. Quantitatively, we identified over twenty historical events, after which the spillover index spiked, remaining above pre-event levels for at least one trading week. Investors faced higher risk during these periods, with volatile and correlated oil-based commodity price movements. Our analysis serves as a unique reference source for significant events linked to the oil market with a (statistically) proven impact on energy market connectedness.

We detected characteristics prevalent among economically and statistically significant events in qualitative terms. Geopolitical events are more likely to cause a sudden and lasting increase in volatility spillovers than economic events, with most economic events having geopolitical ties. Events after which spillover levels increased shared three common characteristics: negativity, unexpectedness, and association with fear over an oil supply shortage. Our findings align with Greenwood-Nimmo et al. (2024), emphasizing the impact of unexpected adverse events on connectedness. Results also resonate with event-dependence of a system connectedness that includes crude oil and natural gas (Yang, Chen, Liang and Li, 2023); specific events were not statistically tested for, though.

The article is structured as follows: Section 2 reviews previous work on connectedness, emphasizing oil-based commodities. The relationship of crude oil with the global economy and prior studies analyzing the effect of events on oil returns and volatility are presented. Section 3 details the data and procedure leading to realized volatility series for selected commodities and describes the extensive news dataset. Section 4 introduces the connectedness methodology and the novel bootstrap-after-bootstrap test. Section 5 summarizes our findings.

2 Literature review related to oil energy commodities

2.1 Position in Global Economy

Oil is a highly traded commodity that poses volatility risks to investors and industrial producers. The International Energy Agency reported that 67% of crude oil in 2021 was utilized for transportation fuels, with distillate fuels like diesel and heating oil being significant components. Industrial use accounted for 27%, and the remaining 6% served residential, commercial, and electric power needs (Energy Information Administration, 2022). Natural gas, another fossil fuel, is primarily used for electricity generation and heating. These commodities are vital for industrial, transportation, and agricultural sectors, with higher oil prices potentially leading to increased costs, affecting goods, services, and inflation (Sadorsky, 1999). The continuous global demand for crude oil contributes to long-term Consumer Price Index (CPI) increases (Kilian, 2009).

Beyond the industrial impact, oil price volatility affects the global economy through various channels. Rising oil prices elevate production costs, reducing economic output (Sadorsky, 1999; Brown and Yücel, 2002). Temporary price increases prompt increased borrowing by firms and households, causing inflationary pressures (Mohaddes and Pesaran, 2017). Central banks respond by raising interest rates (Gogolin et al., 2018). Moderate oil price volatility leads firms to defer investments due to uncertainty, impacting sectors with increased marginal costs, potentially limiting wage growth and increasing unemployment (Brown and Yücel, 2002; Gogolin et al., 2018). According to Kilian (2009), demand increases and oil-supply disruptions significantly decrease real GDP. Additionally, oil price fluctuations negatively impact stock returns (Sadorsky, 1999). Oil prices can also influence currency depreciation; as oil prices rise, oil importers may deplete US dollar reserves, depreciating their currency (Salisu and Mobolaji, 2013). Conversely, a depreciating dollar may lead oil exporters to raise prices to stabilize export values.

2.2 Volatility spillovers and connectedness studies

Extent of global trading and importance of crude oil has prompted analyses of its volatility spillovers from various perspectives. Zhang and Wang (2014) find bi-directional and asymmetric spillovers between China, the U.S., and the U.K., with an upward trend attributed to China's increasing influence. Liu and Gong (2020) designated Brent and WTI markets as net volatility transmitters and Ouyang, Qin, Cao, Xie, Dai and Wang (2021) expanded their analysis to 31 global crude oil markets. Jena et al. (2022) show that spillovers among major petroleum futures are led by the ICE Brent most of the time.

Given oil's global prominence, its price fluctuations influence global markets and macroeconomic indicators. Beyond oil markets, research explores spillovers between oil and financial markets. For example, Baruník and Kočenda (2019) put forth evidence of time-dependent and directional shock transmissions between the oil and foreign exchange market. Regarding financial impacts, Kang, Hernandez, Sadorsky and McIver (2021) deem crude oil a suitable hedging option for U.S. ETFs, and Baruník and Kočenda (2019) identifies it as a hedge for forex portfolios. In contrast, Diebold, Liu and Yilmaz (2017) ranks crude oil's net connectedness highest among 19 commodities.

Volatility spillovers between oil-based commodities and natural gas are extensively studied. Baruník et al. (2015) notes varying spillover magnitudes before and after the Great Financial Crisis. Technological innovations, particularly shale gas extraction, alter spillover dynamics, with a 15% decrease in the spillover index observed in 2006 (Gong, Liu and Wang, 2021). While natural gas becomes a net volatility transmitter, it remains a preferred hedge due to its inherent volatility – Kočenda and Moravcová (2024) report that natural gas is responsible for 91.03% of its volatility, with other commodities receiving 50% on average. During recessions, natural gas shows the weakest reaction to economic events, with minimal connectedness to other commodities (Diebold et al., 2017). The static spillover index in most studies is around 40%, indicating moderate system connectedness.

The literature recommends using time-varying and asymmetric spillover measures for oil volatility spillovers. Kilian (2009) demonstrates oil price volatility spilling to other markets with different signs and magnitude over time. Asymmetric spillovers affecting the Chinese oil market are emphasized by Zhang and Wang (2014). Xu, Ma, Chen and Zhang (2019) finds time-varying and asymmetric spillovers in the oil, U.S., and Chinese stock markets. Volatility spillovers for petroleum-based commodities are clustered and persistent (Liu and Gong, 2020), suggesting pairing these periods with significant economic events.

2.3 News studies

The impact of news on oil prices and volatility is well-documented in the literature. Kilian (2009) characterizes news-induced oil price changes as a precautionary response to potential future oil supply shortages. In contrast, Kilian and Vega (2011) and Chan and Gray (2017) discover no evidence of oil and gas price reactions to news at daily or monthly horizons. However, Elder et al. (2013) argues that oil prices respond swiftly to economic news. While not exactly a news study, Cunado, Chatziantoniou, Gabauer, de Gracia and Hardik (2023)claim that dynamic total connectedness among precious metals and oil realized volatilities is heterogeneous over time and driven by economic events; specific events were not statistically tested for, though.

Applying a new methodology to map past events to changes in the volatility spillover index, Greenwood-Nimmo et al. (2024) scrutinizes the same data as Diebold and Yilmaz (2009). They find that only 6 out of 19 events analyzed in the original paper exhibit a contemporaneous effect on the spillover index, suggesting that the shock indeed propagates with a lagged effect.

3 Data

3.1 Commodity Price Data

We selected five energy commodities to study oil connectedness: crude oil (oil), heating oil (ho), gasoline (rb), diesel (lgo), and natural gas (ng). These commodities are highly interconnected and one reason is that 60% of global crude oil stock is utilized in the production of heating oil, diesel, and gasoline. Heating oil can also be produced as a side-product when processing crude oil into gasoline. Furthermore, heating oil and natural gas can be regarded as substitutes in many economic processes.[2]

The data were retrieved through Refinitive Eikon Datastream[3]. We used the next month's future contracts from two exchanges: West Texas Intermediate Crude Oil, RBOB gasoline, NY Harbor Ultra Low Sulphur Heating Oil, Henry Hub Natural Gas from New York Mercantile Exchange in the US, and Low Sulphur Diesel from the Intercontinental Exchange in Europe. Eikon Datastream provides daily open, close, high, and low prices for all 5 commodities. Range-based data for gasoline were available on Eikon Datastream only after 2005. Thus, we utilized high-frequency intraday prices from TickData[4], from which we calculate the range-based values for gasoline. Having obtained the set of daily measures, we computed range-based realized volatility (RV) estimates using the method introduced by Garman and Klass (1980), described in Section 4. The data was available from 1 September 1987 to 16 December 2022 for all oil-based commodities. Neither intraday nor daily natural gas prices are available before 3 April 1990 (Natural Gas Intelligence, 2022). Therefore, we conducted two separate analyses for two samples, one for solely petroleum-based commodities without natural gas, and the other with all five commodities starting on 3 April 1990. The importance is being placed on the longer sample with petroleum-based commodities. Significant differences between the results of the samples are noted in Section 5.

[2]Casassus, Liu and Tang (2013) describe the production relationship between crude oil (input) and heating oil (output), and the complementary relationship (in production) between gasoline and heating oil. In addition, heating oil comes as a by-product when crude oil is cracked to produce gasoline, which implies another production relationship between crude oil (input) and gasoline (output). Finally, about 40 and 20 percent of crude oil is refined into gasoline and heating oil, respectively

[3]https://www.refinitiv.com/en/products/datastream-macroeconomic-analysis/

[4]https://www.tickdata.com/product/historical-futures-data/

The price data contained several anomalies. First, there were some occasions when prices were reported on weekends, and these days were removed. Apart from weekends, we removed Christmas and New Year's holidays: 24 December - 26 December, 31 December, and 1 - 2 January. We also removed US Federal holidays, during which the main exchange in our dataset is closed. Further, we identified 486 days where the low (high) price was higher (lower) than the remaining range-based prices for at least one commodity. In these cases, we substituted the low (high) prices with other range-based values.[5] Finally, there were 161 days where at least one commodity had missing data. Since the dates were sparsely distributed, we imputed the values with a 5-day rolling average of RV. Ultimately, we have 8785 days of RV values for petroleum-based commodities and 8141 for natural gas.

Table 1: Summary statistics of returns

Returns	Mean	SD	Median	Min	Max	Skewness	Kurtosis
oil	-0.00010	0.02262	0.00080	-0.47	0.18	-1.94	34.34
ho	-0.00008	0.02451	0.00077	-0.48	0.18	-1.99	28.81
lgo	-0.00006	0.02352	0.00000	-0.54	0.13	-3.42	69.66
rb	-0.00017	0.02635	0.00097	-0.47	0.25	-1.65	27.02
ng	-0.00047	0.03615	0.00000	-0.46	0.32	-0.51	10.81

Notes: The table shows summary statistics of the daily returns for 5 selected commodities: crude oil (oil), heating oil (ho), diesel (lgo), gasoline (rb), and natural gas (ng).

Table 2: Summary statistics or realized volatlities

RV	Observations	Mean	SD	Median	Min	Max
oil	8785	0.00036	0.00087	0.00020	2.477459e-06	0.03871
ho	8785	0.00042	0.00087	0.00024	8.526832e-07	0.04044
lgo	8785	0.00037	0.00150	0.00017	4.370929e-07	0.10330
rb	8785	0.00040	0.00131	0.00019	7.664958e-08	0.05679
ng	8141	0.00090	0.00173	0.00053	3.215678e-06	0.09658

Notes: The table shows summary statistics of the daily estimates of realized volatility for 5 selected commodities: crude oil (oil), heating oil (ho), diesel (lgo), gasoline (rb), and natural gas (ng).

3.2 Oil-related Events Dataset

The dataset consists of 891 events related to oil prices spanning from 1 January 1987 to 30 November 2022. The events were divided into three general categories - economic, geopolitical, and natural events. Any event happening on Saturday or Sunday (holiday) was moved to the upcoming Monday (working day) due to the lack of price data on weekends (holidays), respectively. This strategy allows

[5]Specifically, in line with the literature, the adjustments were made in the following way. First, if the low price was higher than the close (open) price, then the low price was substituted with a close (open) price. Second, if the high price was lower than the close (open) price, then the high price was substituted with a close (open) price.

us to effectively pair an event with the first date during which the market could react to it.

The event data sample was built in the following way. Initially, we curated a list of three sources: prominent news organizations, international organizations, academic journals and books, which were further searched for relevant events. In terms of academic sources, we set up a Google Scholar query to search for articles and books containing relevant information. During the search, we first defined a common part of the query in the following form: ('oil' OR 'petrol' OR 'petroleum' OR 'tanker') AND ('history' OR 'historical' OR 'event' OR 'news' OR 'policy' OR 'headline' OR 'announcement' OR 'chronology' OR 'case study'). This common part of the query was employed for all three event categories. In the second step, we formulated specific queries relevant to each type of event. For geopolitical events, we added to the common part of the query a specific part in the following form: AND ('geopolitical' OR 'geopolitics' OR 'war' OR 'peace' OR 'conflict' OR 'battle' OR 'election' OR 'collapse' OR 'coup' OR 'crisis' OR 'intervention'). Similarly, we searched for economic events by adding: AND ('macroeconomy' OR 'macroeconomic' OR 'economic' OR 'economical' OR 'economics' OR 'OPEC' OR 'sanction' OR 'sanctions' OR 'embargo' OR 'merger' OR 'trade' OR 'market' OR 'reserve' OR 'reserves' OR 'inventory'). Finally, for natural events, we added: AND ('natural' OR 'spill' OR 'leak' OR 'pollution' OR 'flood' OR 'earthquake' OR 'fire' OR 'hurricane' OR 'weather'). These three queries returned approximately 3 870 000, 4 180 000, and 3 560 000 hits, respectively. Nevertheless, the incremental value of including additional studies diminished beyond the first 5 pages on a Google Scholar, which equals 100 results. However, in order not to miss any relevant information, for each of the 3 queries, we analyzed in detail the first 200 results (10 pages on a Google Scholar). In addition, out of 600 academic sources, we selected 45 sources for geopolitical news, 17 for economic news, and 25 for natural-type news, which served as sources of numerous oil-related events.

Further, the international organizations queried for relevant events featured the United Nations, Human Rights Watch, the Federal Trade Commission, OPEC, and NATO. As for the news organizations, we selected Reuters, Bloomberg, NY Times, LA Times, Economic Times, the Washington Post, BBC News, CBS News, CNN, The Wall Street Journal, Yahoo, Cato Institute, The Guardian, and the MarketWatch. When possible, we searched the article database of mentioned news and international organizations by filtering articles containing the words: 'oil', 'petroleum', and 'petrol', with the published date of the articles being restricted to years between 1987 and 2022.

The news events assembled from the above three sources contained some duplication. In addition, articles in academic sources were often event studies, from which we were able to extract more than one news event. Therefore, in the final step the news events were thoroughly cross-checked across the above three sources to prevent their double-counting. Further, to ensure that the events are unique and non-overlapping when two or more events appeared on the same day, the preference was given to an event directly linked to an oil supply and an event that received more extensive coverage quantitatively. After the above steps, the final selection resulted in 891 events.

In total, our news dataset consists of 370 geopolitical, 391 economic, and 130 natural news events. In Table 3, we provide a summary of the events that are divided into the above three main categories and further subdivided into 18 smaller groups characterized by a specific action impacting oil prices.

Table 3: Events dataset summary

Category	Group	Count
geopolitical	political	184
geopolitical	war	66
geopolitical	missile	40
geopolitical	peace	52
geopolitical	threat	23
geopolitical	strike	5
economic	market	147
economic	maintain	65
economic	boost	34
economic	cut	46
economic	merge	13
economic	develop	12
economic	inventory	21
economic	sanctions	35
economic	speculation	18
natural	natural	67
natural	spill	53
natural	pandemic	10

Notes: This table provides a summary of the events dataset. The events were divided into three main categories: economic, geopolitical, and natural, and into 18 smaller groups.

Out of the three categories, geopolitical events (370) include all events of a political nature plus wars. As such the geopolitical events cover the beginning or development of war conflicts, terrorist attacks, missile launches, bombings, governmental elections, civil wars, political statements featured in the news, meetings of political leaders, peace agreements, or strikes.

Further, economic events (391) feature information about global markets, macroeconomic reports, FED reports, OPEC decisions and production changes, the release of information concerning oil reserves and inventory levels, and news of market conditions, including speculations, announcements of bids, or mergers. The economic news events also cover important developments in the oil industry, such as the discovery of oil fields, investments into oil infrastructure such as oil platforms, tankers, or pipelines, the release of oil reserves by the Strategic Petroleum Reserve, and news on embargoes, sanctions, and tariffs.[6]

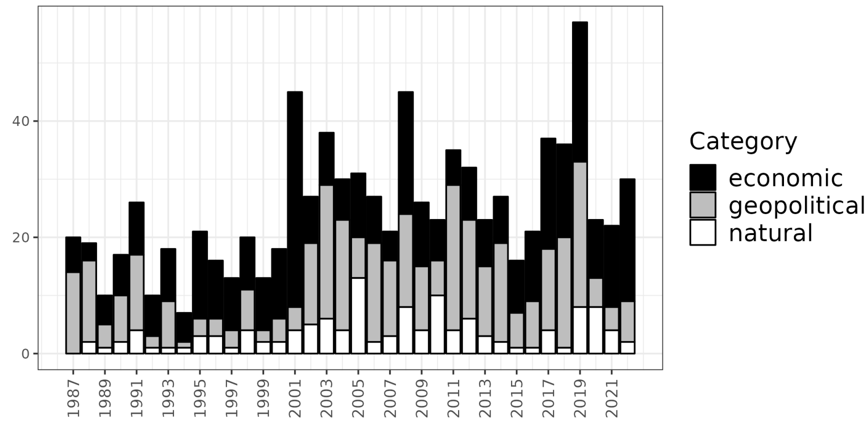
Lastly, natural events (130) mostly refer to natural disasters, accidental (tanker) oil spills, or the

[6] Many of the economic news events indirectly capture sudden changes in actual oil supply/demand shifts.

spread of diseases (pandemic-related news).

In Figure 1, we present the temporal event distribution. A pattern indicates that the sheer volume of news items grew with time as the news coverage improved globally. As expected, most of the events gathered are linked to or originate in oil-exporting countries. However, during our event search, no restriction on the origin of the news was applied.

Figure 1: Event distribution



Notes: The figure shows the count of events grouped into economic, geopolitical, and natural categories per each year of the studied period.

4 Methodology

In our analysis, we employ two methodology frameworks. First, we compute the Spillover index that represents a connectedness measure and enables us to quantify connectedness dynamics. Second, we employ the bootstrap-after-bootstrap procedure to statistically test a link between connectedness and specific shock (event).

4.1 Spillover index - connectedness measure

We compute the rolling spillover index introduced by Diebold and Yilmaz (2009, 2012) that is based on covariance-stationary vector autoregressions (VAR). The spillover index, or connectedness measure, represents the degree of volatility connectedness of the assets put in the network at each point in time. The construction of the spillover index is thoroughly described in the above seminal papers and it is well-known in the field. For that, we formally introduce only the key part of the connectedness measure in the subsequent text, and in Appendix A, we describe the methodology in full.

In order to use the VAR model for the spillover index calculation, we first need to obtain daily volatility estimates of the selected commodities. We use a range-based realized variance measure first introduced by Garman and Klass (1980). For $O_{it}, C_{it}, H_{it}, L_{it}$ being the natural logarithms of daily open, close, high, and close prices for commodity i on day t, the range-based realized variance is computed as:

$$\begin{aligned}\hat{\sigma_{i,t}}^2 &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \\ RealVol_{i,t} &= \sqrt{\hat{\sigma_{i,t}}^2}\end{aligned} \tag{1}$$

The range-based volatility is easy to compute, requires only four inputs per day, and is comparably efficient as high-frequency estimators (Demirer, Diebold, Liu and Yilmaz, 2018). Moreover, this estimate is robust to certain microstructure noise and has been frequently used as a volatility estimate for network connectedness analysis (Diebold and Yilmaz, 2009; Diebold et al., 2017; Demirer et al., 2018; Kočenda and Moravcová, 2019).

Having obtained a vector of daily realized volatility estimates of m variables $\boldsymbol{x_t} = (x_{1t}, x_{2t}, ..., x_{mt})$, we can write VAR of lag p in its reduced matrix form as:

$$\boldsymbol{x}_t = \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \tag{2}$$

where $\boldsymbol{x}_t$ is an $m \times 1$ vector of realized volatilities, $\boldsymbol{A}_j$ is a $m \times m$ matrix of VAR parameters for lag $j = 1, \ldots, p$, $\boldsymbol{u}_t$ is an $m \times 1$ of disturbances, so that $\boldsymbol{u}_t \sim N(0, \boldsymbol{\Sigma})$. The matrix $\boldsymbol{\Sigma}$ is a positive-definitive covariance matrix of size $m \times m$, with unknown distribution. We also explicitly remove the static mean from the equation, as it does not affect variance decomposition.

The vector moving average representation of the VAR model enables us to decompose the variance of the forecast errors from the model into parts using a generalized forecast error variance decomposition (GFEVD). Denoting the $m \times m$ h-step ahead matrix of GFEVD as $\boldsymbol{\theta} = \{\theta_{i \leftarrow j}\}_{i,j}^{h}$. Diebold and Yilmaz (2009) and Diebold and Yılmaz (2014) measure the static total spillover index (S^H) in the following way:

$$\mathcal{S}^H = 100 \times \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{M} \tilde{\theta}_{i \leftarrow j}^{(H)}}{\sum_{i,j=1}^{M} \tilde{\theta}_{i \leftarrow j}^{(H)}} = 100 \times \frac{\boldsymbol{\iota}' \boldsymbol{\theta} \boldsymbol{\iota} - \text{trace}(\boldsymbol{\theta})}{\boldsymbol{\iota}' \boldsymbol{\theta} \boldsymbol{\iota}} \%, \tag{3}$$

where $\boldsymbol{\iota}$ is an $m \times 1$ vector of ones.

The calculation of the rolling spillover index is identical to the static one. Given observations at time $t = 1, ..., T$, we simply choose a rolling window of size w, and compute the forecast error variance matrix $\tilde{\theta}^{(h)}$ using only the last w observations. In the end, we obtain $\tilde{\theta}_t^{(h)}, t = w...T$ matrices, from which we can calculate the rolling total spillover index; choice of the values for the rolling window and forecast horizon is described in detail in the Appendix and robustness checks are presented in Section

5. The dynamic spillover index is crucial for our analysis as it captures the time variation attributable to historical events.[7]

4.2 Bootstrap-after-bootstrap test

The bootstrap-after-bootstrap procedure introduced by Greenwood-Nimmo et al. (2024) enables us to statistically assess the probability that the spillover index increased on several consecutive days after some (endogenously detected) event occurred. Until recently, the changes in connectedness were paired with specific events based on a simple visual inspection. In other words, the timing of an event is matched with a sudden change in the spillover index magnitude without formally testing the link between them (Diebold and Yilmaz, 2009; Baruník, Kočenda and Vácha, 2016; Diebold et al., 2017). Visual inspection is very imperfect as it is often only feasible for long-lasting spillover index changes. However, the events in our dataset can be expected to have abrupt and short-term impacts. Furthermore, the test allows for the assessment of each event individually, which allows for more granular categorization and analysis compared to aggregated risk indices such as the Geopolitical Risk Index (Mei, Ma, Liao and Wang, 2020).

An important feature of the bootstrap-after-bootstrap procedure is that the test does not rely on asymptotic properties. This would pose problems in the estimation of rolling windows since the window is often set to be relatively small. This issue can be treated using residual bootstrapping to construct some empirical interval of the spillover index. Nevertheless, Kilian (1998) shows that the traditional methods of producing confidence intervals for impulse responses have biased results, especially when estimating impulse responses on small samples for long horizons. The reason for the low interval accuracy lies in the bias of the coefficients of the VAR model. Even a small bias in the slope coefficient can result in the confidence band, not including the initial estimate. Thus, we first need to correct the coefficients $\boldsymbol{A}_j$ in Equation 7 for bias, which can be done yet again by bootstrapping. Following Kilian (1998), Greenwood-Nimmo et al. (2024) propose a non-parametric bootstrap-after-bootstrap procedure. For the sake of accuracy and consistency, we use the formal notation as in a seminal work of Greenwood-Nimmo et al. (2024) to describe the bootstrap-after-bootstrap procedure employed in our analysis:

1. Begin with the first rolling sample. Estimate the VAR model and save the resulting parameter matrices $\widehat{\boldsymbol{A}}_j$, residuals $\boldsymbol{u}_t$, and value of the spillover index $\mathcal{S}^H$.

[7] An alternative to the Diebold and Yilmaz (2009) approach is the TVP-VAR based spillover measure by Antonakakis, Chatziantoniou and Gabauer (2020). However, we prefer the original approach as the the bootstrap-based test of Greenwood-Nimmo et al. (2024) that we employ corresponds to the seminal approach of Diebold and Yilmaz (2009) that employs rolling windows. We acknowledge that the TVP-VAR approach removes the need to set a window size and allows the use of the full length of the price data. Both issues do not present a problem as we show in robustness checks.

2. Use the initial parameter space $\widehat{\boldsymbol{A}}_j$ along with $\boldsymbol{u}_t^{(b)}$ residuals obtained either from an assumed multivariate distribution or sampled from residuals of the initial VAR model. Obtain B samples $\boldsymbol{x}_t^{(b)}$ with:

$$\boldsymbol{x}_t^{(b)} = \sum_{j=1}^{p} \widehat{\boldsymbol{A}}_j \boldsymbol{x}_{t-j}^{(b)} + \boldsymbol{u}_t^{(b)}, \tag{4}$$

3. Using the same rolling sample, re-estimate the VAR model B times for each set $\boldsymbol{x}_t^{(b)}$, and B sets of parameters $\widehat{\boldsymbol{A}}_j^{(b)}, j = 1, ..., p$. For each parameter set, calculate the corresponding value of the spillover index $\widehat{\mathcal{S}}^{(b)}$, $b = 1, \ldots, B$.

4. Calculate the bias in given rolling window as $\widehat{\Upsilon} = B^{-1} \sum_{b=1}^{B} \widehat{\mathcal{S}}^{(b)} - \widehat{\mathcal{S}}$.

5. Repeat steps 2 to 4 B times, but subtract the bias $\widehat{\Upsilon}$ from each estimate $\widehat{\mathcal{S}}^{(b)}$. The resulting spillover values represent a bias-corrected distribution for a given rolling window.

6. Repeat steps 1 to 5 for each rolling window, each time saving the final distribution.

Having obtained the empirical spillover distribution for each rolling window, we can proceed with the statistical inference methodology for the effect of events. Suppose some exogenous event happens in the final observation of the rolling sample r_e. Then the probability that the event has increased the spillover index in the following periods $r_e + j$ is evaluated as the probability that the distribution of spillover index $\mathcal{S}_{r_e+j}^{(b)}$ exceeds the mean spillover index from the window preceding the time of event $\overline{\mathcal{S}}_{r_e-1} = B^{-1} \sum_{b=1}^{B}$. This can be formalized as:

$$\Pr\left(\mathcal{S}_{r_e+j} > \overline{\mathcal{S}}_{r_e-1}\right) = B^{-1} \sum_{b=1}^{B} \mathbb{I}\left\{\left(\widehat{\mathcal{S}}_{r_e+j}^{(b)} - \overline{\mathcal{S}}_{r_e-1}\right) > 0\right\}, \tag{5}$$

where $\mathbb{I}\{\cdot\}$ is a Heaviside function equal to 1 if the condition in brackets is met and 0 otherwise. By setting j equal to $1-5$, we can draw statistical inferences of the event $1-5$ days after the event takes place, respectively. A natural limitation for values of j is that some events are densely distributed in time. Therefore, it is not possible to differentiate between the effects of two subsequent events for longer horizons.[8] Finally, simply reversing the equation in the Heaviside function would allow us to identify events resulting in decreased spillovers in the network. Nevertheless, the economic significance of such an analysis is minor, and Greenwood-Nimmo et al. (2024) in their test focus on spillover increases. Hence, we concentrate on events prompting a rise in the overall connectedness.

[8] We can not control for the persistence of events by setting a hard threshold of j. Persistence can be assessed with a novel methodology of Barunik and Vacha (2023) and is intentionally left for further research.

5 Results of the event-driven connectedness and robustness checks

5.1 Dynamics of the total connectedness

The vector autoregressive model's lag order was optimized via AIC, resulting in the selection of lag 1 for the VAR model. In daily time series analysis, a 100-day rolling window (w) is conventionally used for computing the spillover index and horizon (H) for forecast error variance decomposition. To capture event effects, a more volatile rolling spillover index is favored and the motivation for the choice of window length is also linked to the responsiveness of the spillover index. Finally, a 100-day window better captures changes in volatility from the perspective of investors and traders rather than the use of longer windows.[9] The value of the horizon (H) for forecast error variance decomposition was set to 100, which is above 50 trading days as in Bajaj et al. (2023); Kang et al. (2021).[10].

The oil spillover network's overall spillover is 45.23% (Table 4), similar to Baruník et al. (2015)'s 50.6% for crude oil, heating oil, and gasoline. Further evidence shows that each commodity's volatility is influenced chiefly by its own past shocks. Crude oil is a net spillover transmitter, while diesel and gasoline are net receivers, consistent with Baruník et al. (2015) and Gong et al. (2021). Heating oil neither transmits nor receives spillovers. Gasoline and crude oil exhibit the strongest pairwise connectedness, with crude oil responsible for 25.88% of spillovers to gasoline. Gasoline and diesel show the weakest link, with shocks to gasoline explained by diesel shocks at only 8%.

Table 4: Average connectedness for oil-based commodities

	rb	oil	ho	lgo	**FROM**
rb	55.82	25.88	10.23	8.07	11.05
oil	16.69	54.50	18.12	10.69	11.38
ho	11.22	19.94	51.95	16.89	12.01
lgo	10.83	13.65	18.70	56.82	10.79
TO	9.69	14.87	11.76	8.91	45.23

Notes: The table shows the average connectedness of the oil-based commodities network from 1987 to 2022. The commodities included are crude oil (oil), heating oil (ho), diesel (lgo), and gasoline (rb). The 11.38 'FROM' connectedness for crude oil means that 11.38% of spillovers are transmitted FROM other commodities to crude oil. Similarly, 9.69% TO spillovers for gasoline means that, on average, 9.69% spillovers are transmitted from gasoline TO other commodities. To read the pairwise connectedness, we determine FROM which commodity we want to measure the spillovers (columns) and TO which commodity the spillovers should be transmitted (rows). Thus, 25.88% of spillovers TO gasoline are transmitted FROM crude oil.

Figure 2 illustrates the rolling spillover index's fluctuation between 5% and 75%.[11] A pivotal shift

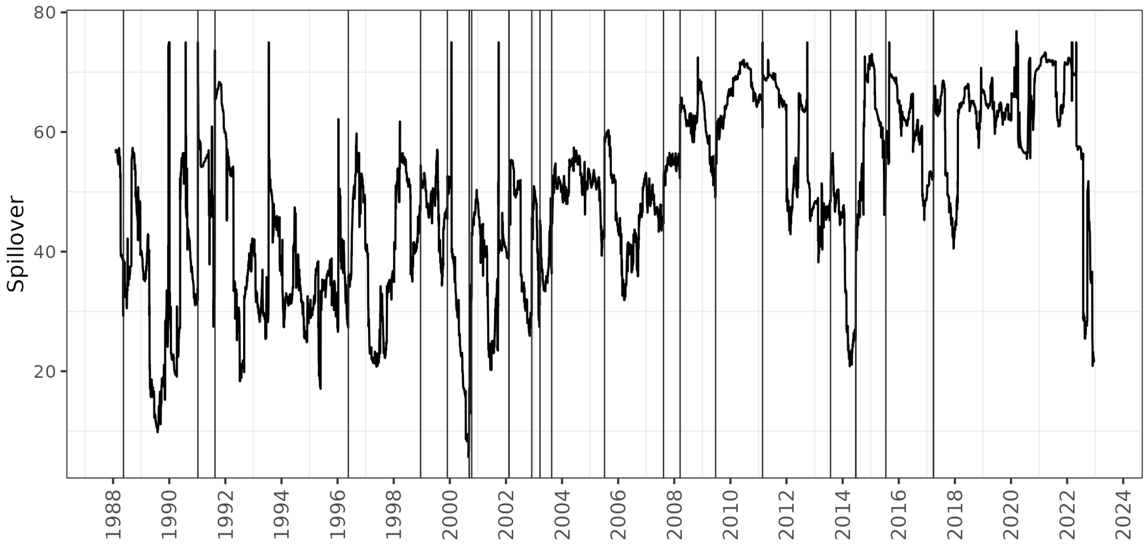
[9] The choice of the rolling window size is made in the spirit of Alter and Beyer (2014) who show that an optimal window size reflects "a trade-off between robustness and reliability of estimated VAR coefficients (the longer the sample the better the quality) on the one hand, and gaining information about a build-up of spillover effects over time (the shorter the sample window the larger the weight on more recent information) on the other hand."

[10] Applications of the Diebold-Yilmaz method to daily data often use horizons of up to about ten days. In our case, we set the horizon to 100 days as a precaution. Since the forecast error variance decomposition of a VAR(1) typically stabilizes rapidly as the horizon increases, our approach serves as a safety measure.

[11] The selection of the window length plays a role in determining the volatility of the rolling spillover index, as it

around 2000 and 2008 mirrors findings in Baruník et al. (2015). Before 2000, lower average spillover levels indicate limited financialization and speculation in energy commodities. After 2008, higher stabilization resulted from increased financialization, global demand, and oil extraction technology. Before 2008, connectedness was more volatile, with the Global Financial Crisis having limited impact.

Figure 2: Connectedness dynamics of oil-based commodities



Notes: This figure shows the evolution of the overall connectedness among oil-based commodities. Spillovers are calculated on the rolling window of 100 days. The vertical lines represent the events that passed the conventional statistical significance threshold.

Between 2010 and 2012, the index averaged around 70%, linking to events during the Arab Spring, especially the Libyan uprising in 2011 and political unrest in Iran in 2012 (Baumeister and Kilian, 2016). After 2012, the U.S. dominance in the shale oil industry, combined with abundant oil supply, lowered the spillover index to 20% in 2014, the first time since 2001. Shale oil likely moderated oil volatility connectedness during 2016-2022 (Naeem, Balli, Shahzad and de Bruin, 2020; Billah, Karim, Naeem and Vigne, 2022).

The China-US trade war in 2018-2019, reducing oil demand in China, led to the spillover index fluctuating around 50% with moderate volatility. OPEC production cuts between 2016 and 2020 increased oil prices. The spillover index peaked in March 2020 due to the COVID-19 pandemic and the Russia-Saudi oil price war. Russia's invasion of Ukraine in February 2022 prolonged extreme spillovers until the end of April. After the EU's ban on most Russian oil and gas exports and Ukraine's resistance success, the spillover index decreased to 20% again.

introduces a trade-off between graph smoothness and the responsiveness of the spillover index. Consequently, our choice of a shorter (100-day) window leads to occasional short-lived spikes, especially during periods of extreme volatility. However, these spikes are an inherent aspect of the methodology and do not undermine the validity of the proposed bootstrap-after-bootstrap methodology. It is important to note that while these spikes typically last for only one day, we require that the increase in the spillover index persists for up to four days after an event. Therefore, even if there is a spike on the day of the event, there must still be a sustained increase compared to the pre-event spillover level.

5.2 Impact of Events

Following Greenwood-Nimmo et al. (2024), we conducted the bootstrap-after-bootstrap test across rolling windows, generating 1000 bootstrap samples for both the bias correction and the final spillover distribution. To consider a change in spillover levels to be statistically significant, we require at least 95% of values in the next day's spillover distribution to be above the mean of yesterday's mean spillover. Under the null hypothesis that the spillover index did not increase in some period after the event, the probability of drawing more than 95% of values higher than the previous mean is less than 5%. This is similar to the conventional significance level of 0.05 in one-sided hypothesis testing. We gathered 891 events, and the test identified 122 dates with statistically significant spillover index increases.

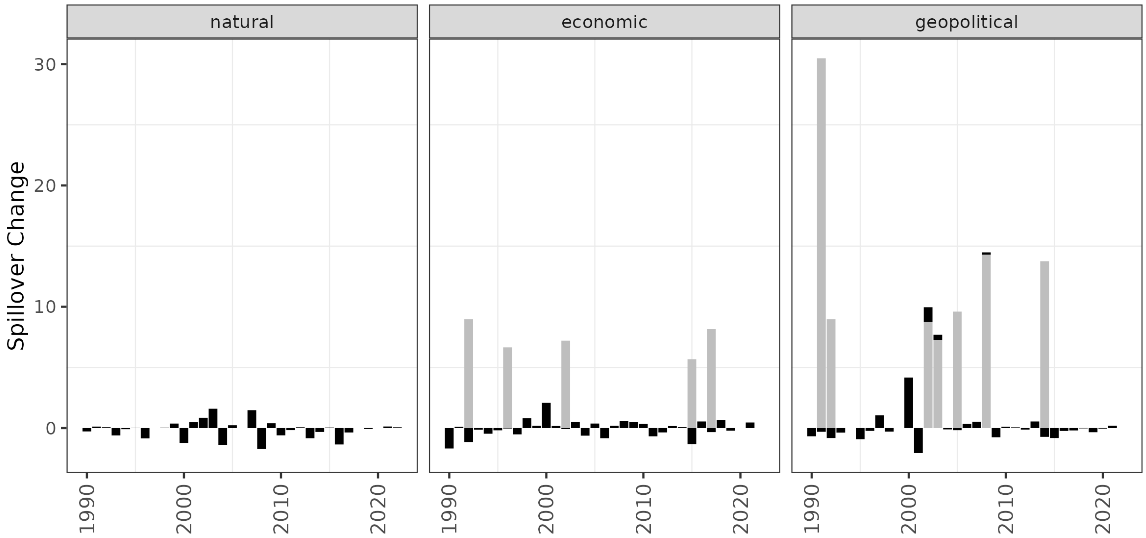
For an event to produce substantial impact, the event has to affect the spillover index continuously for at least 4 days after the day of the event. In the scope of this work, events are labeled as such if they exceed the threshold for $j \in (1, 2, 3, 4)$. In other words, the spillover index needs to be significantly above the pre-event value up to day 5 since the event. We identified 21 impactful events that comply with the above condition, and they are the focus of our analysis (16 geopolitical events, 4 economic events, and 1 natural event). From an investment perspective, when such impactful events materialize, oil-based commodities should be viewed as risky because volatility will be increasingly shared among them.

The event distribution in time is shown in Figure 3, where we plot the total spillover change for three types of events in each year.[12] The grey bars relate to events that passed the statistical significance threshold. The evidence shows that, in general, the mean spillover changes are randomly distributed over time. The plot pattern implies that the spillover increases are not becoming more pronounced with time. Despite the general pattern, the grey bars depicting events that passed the significance threshold of the test indicate that economic events exhibit a relatively stable development associated with a mild spillover increase of around 10%. In contrast, geopolitical events exhibit more varying impacts on the volatility connectedness. A pattern for natural events is less visible due to a common scale used to compare three panels directly.

In the following three sub-sections, we present events that were found to impact connectedness at statistically significant levels. We present those events one by one to (i) illustrate their nature in detail, (ii) provide sufficient background on their potential to impact connectedness, and (iii) draw some generalizations.

[12] Using the bootstrap-after-bootstrap procedure, we first computed the daily average spillover difference. This difference is calculated by subtracting the spillover value before the event from the mean of the total spillover over the five days following the event. In the second step, for each year, we isolated the spillover differences that corresponded to days when events occurred. We then calculated the annual average of these values.

Figure 3: Absolute spillover changes in time



Notes: The figure depicts the average change in spillover effects for three types of events. In the figure, *grey bars* represent the average spillover changes for events that passed the significance threshold, while *black bars* represent the average spillover changes for events that did not pass this threshold.

5.2.1 Geopolitical events

Table 5 highlights the pronounced impact of geopolitical events on the spillover index, surpassing the impact of economic and natural events. Our analysis identified 16 geopolitical events that passed the threshold of exhibiting an impact during four consecutive days after an event occurred.

The first such event in Table 5 occurred on 15 May 1988 and relates to Iraq's bombing of Iran's offshore terminal, damaging the Seawise Giant supertanker and four other large tankers. The event notably heightened connectedness in oil-based commodities (Torbat, 2005a).

The Geneva Peace Conference on 1 September 1991 triggered a substantial spike in connectedness, with the spillover index increasing from 31% to 75% and remaining at around 50% during the following month. The conference, viewed as the last opportunity for peace in the Middle East, failed to negotiate a resolution to the Iraqi invasion of Kuwait (Freedman and Karsh, 1993). Despite subsequent events such as the launch of Operation Desert Storm and the release of 17.3 million barrels of oil from the US Strategic Petroleum Reserve, connectedness remained unaffected. Kilian and Zhou (2020) similarly found that the Strategic Petroleum Reserve release did not prevent a larger increase in oil prices during that period.

After the Soviet army withdrew from Afghanistan, Gorbachev became president and introduced market reforms to modernize the Soviet Union. The Soviet coup d'etat attempt happened on 19 August 1991. The index spiked to levels of 50% and stayed there for more than a year. The Venezuelan coup d'etat, despite being only short-lived (Norden, 1998), triggered another significant spike in connectedness on 27 November 1992. The most likely reason behind the spikes is that both coups were

Table 5: Test results: Geopolitical events

Date	Event Description	Event Count (%) J=0	J=1	J=2	J=3	J=4	Chance of Causality
15.05.1988	Iraq Bombs 5 Huge Tankers at Iran Oil Site	100	100	100	100	100	High
09.01.1991	Geneva Peace Conference	100	100	100	100	100	High
19.08.1991	1991 Soviet coup d'état attempt	100	100	100	100	100	High
27.11.1992	Venezuela: coup against government	58.3	100	99.5	99.1	99.2	High
20.05.1996	Oil-for-Food Programme	100	100	100	100	100	High
12.10.2000	Blast kills sailors on US ship in Yemen	80	97	96.9	96	96.8	Moderate
08.02.2002	Iraq obstructs UN inspectors	47.6	100	99.9	99.8	100	High
03.12.2002	General strike in Venezuela begins	100	100	100	100	100	High
20.03.2003	Start of ground invasion in Iraq by US-led coalition	88.5	99.8	99.8	99.7	99.3	High
19.08.2003	Bomb attack on UN headquarters in Iraq	100	100	100	100	100	Moderate
14.08.2007	Iraq: biggest attack since the beginning of the war	44.8	100	100	100	100	Moderate
23.02.2011	Arab Spring: Half of Libya oil production shut down	75.7	100	99.1	99.6	99.5	Moderate
20.06.2014	Troops Trapped in Iraq's Key Refinery	58.9	100	100	100	100	Moderate
23.06.2014	Iraq confirms oil refinery loss	100	100	100	100	100	Moderate
17.09.2015	Last bid to kill Iran nuclear deal blocked in Senate	99.7	98.7	99.2	98.7	99.6	High
28.03.2017	Donald Trump signs Energy Independence executive order	100	100	100	100	100	High

Notes: The table shows 16 geopolitical events that passed the conventional statistical significance threshold. The 'Event Count' columns show the percentage of the 1000 bootstrapped values higher than the previous mean value. The events exhibit substantial impact as they pass the threshold from 1 to 4 days after the event occurs, which corresponds to one trading week; the effect on the day the event occurred is not included to control for the speed of information flow among news channels. The last column contains credibility assessment results based on the analysis in Section 5.

unexpected and happened in major oil-exporting countries.

On 20 May 1996, the United Nations released a memorandum of understanding regarding the Oil for Food Program with the Government of Iraq. The program initially enabled Iraq to sell crude oil, totaling 1 million US dollars. The proceedings of this sale could only be used to ensure Iraqi citizens' humanitarian needs. However, it was later shown that the program was subject to corruption (United Nations, 1996; Hsieh and Moretti, 2006). The program was set in response to the sanctions placed on Iraq after it invaded Kuwait in August 1990. The spillover index increased from 28% to 35% following the announcement.

On 12 October 2000, oil prices rose sharply following the news of a terrorist attack on an American warship, the USS Cole, in the Yemeni port of Aden. The blast killed several sailors, and the warship was heavily damaged. Crude oil prices rose on the New York Mercantile Exchange (NYMEX) along with Henry Hub natural gas prices. A terrorist attack constitutes an impactful event linked to the increase in connectedness.

On 16 December 1998, Iraq failed to comply with UN inspectors in search of weapons of mass destruction, which broke another resolution declared by the UN (Conversino, 2005). The United States aimed to resume the inspection in 1998. The US was inclined to continue with the inspections after the 9/11 attacks in 2001, as the US expected a connection of Iraq to Al Qaeda.[13] On 8 February 2002, the United Nations failed to make an agreement with the Iraqi officials regarding the return of the inspectors (Squassoni, 2003). This was followed by a mild but permanent increase in the spillover index from 40 to 50%.

As discussed in Section 3, oil prices in 2002 and 2003 were primarily influenced by oil supply disruptions in Venezuela and the Iraq war, both identified by the test. First, the state-owned Venezuelan oil company Petróleos de Venezuela was a key point during the protest. Due to the company shutdown, oil supply and inventories declined, and oil prices increased by 20% in one month (Kilian and Murphy, 2014). The spillover index increased by 15 points when the strike in Venezuela began on 3 December 2002. Second, the invasion of Iraq was based on the results gathered by UN inspectors. Although the inspectors did not find weapons of mass destruction, they provided proof that Iraq continued with its nuclear program. Still, the United States initiated military action against Iraq on 20 March 2002 (Bassil, 2012).

The UN headquarters in Iraq was bombed on 19 August 2003. The head of the UN mission in Iraq was killed during the attack, which likely raised concerns about the future course of the mission. 14 August 2007 brought the most significant attack since the beginning of the war in 2003. There were 580 deaths and 1600 injuries, making it the second deadliest act of terrorism of all time (Bassil, 2012). Once again, the event did not directly influence oil supplies, but it likely caused fear over the development of the war conflict. The connectedness increased significantly by ten basis points.

On 23 February 2011, a major Italian oil company shut down its 150,000 barrels per day production due to the Libyan uprising, causing a 15 percentage points increase in connectedness (Baumeister and Kilian, 2016). This significant shift, combined with concerns about the potential spread to other North African countries, marked the Arab Spring as the first period where the spillover index for oil-based commodities remained around 60% for an extended duration. Subsequent events related to the civil war in Syria and Libya or protests in Egypt in 2011 did not significantly impact connectedness to trigger another shift.

The last significant event in Iraq, which caused an upward shift in the connectedness of oil-based commodities, concerned the Iraqi largest oil refinery in June 2014. On 20 June 2014, Iraqi troops fought with the Islamic State (ISIS) over the control of the vital Baiji oil refinery. The refinery was mainly used to produce fuel for internal consumption. Thus, its control was a critical strategic point in the conflict. The news speculated about Iraqi troops being trapped inside the refinery, which increased the spillover index by 18 points. On Monday, 23 June 2014, Iraqi officials publicly confirmed that the Baiji refinery had been seized by ISIS (CNN, 2014). It is impossible to say which of these events caused

[13] After the attacks on 11 September 2001, major US commodity exchanges were closed for several days, price data were not available, and an increase in the connectedness of oil commodities could not be detected.

the increase in connectedness, but the capture of the Baiji refinery was most certainly influential.

After the Middle Eastern geopolitical tensions finally settled, the spillover index started to be influenced by more political events. One such event is the Iran Nuclear Agreement introduced under the presidency of Barack Obama. On 17 September 2015, the US Senate blocked the legislation meant to disapprove the accord for a third time, which officially secured its subsequent implementation (Zengerle, 2015). Iran agreed to limit its nuclear development and allow external monitoring. In exchange, Iran was able to recover approximately $100 billion worth of assets frozen in banks overseas (Sterio, 2016). The spillover index increased by a modest 5 percentage points on the day of the news.

Another influential policy was the order to undo the measures connected to the Clean Power Plan given by Donald Trump on 28 March 2017. In an attempt to boost the coal industry, Trump loosened the limit on methane and carbon emissions released during coal and gas production (Bomberg, 2017). The connectedness increased from 52% to 64% in a single day. Interestingly, comparable events such as the renegotiation of the Dakota Access Pipeline on 24 January 2017, the withdrawal from the Paris Climate Agreement announced on 1 June 2017, or quitting the Iran Nuclear Agreement on 8 May 2018 did not immediately impact the index.

Almost all of the geopolitical events identified by the test are connected to war conflicts in the Middle East, and Iraq specifically. The events listed are either the first signs of new war conflict, acts of terrorism, or concern with the functioning of important oil facilities. It is important to note that after 2014, tensions in the Middle East are much less frequent. A common trait among the events listed above is that they introduce concerns over the scarcity of oil. Both damaged oil facilities and fear of entering a war with an oil-producing country represent an increased probability to cause supply disruptions, and consequently increase the connectedness of oil-based commodities.

Unsurprisingly, none of the 52 events that fall into the 'peace' group increased the spillover index significantly according to the test results. We observe that the end of war conflicts or peace arrangements is linked with a gradual decrease in connectedness. Similarly, events published in articles without an effectuate topic, such as threats of attacks, deadlines, and warnings, also do not cause an increase in the connectedness of oil commodities. In conclusion, sudden and unexpected war operations or terrorist attacks are the most likely to cause an upward shift in connectedness.

5.2.2 Economic events

Events of an economic nature are much less prevalent in the set of significant events. Among 145 events concerning changes in oil production, the test identified only four statistically significant events that passed the test threshold, exhibiting an impact for four days after an event occurred; results are reported in Table 6. Specifically, it is two decisions to boost production, one to cut it, and a dismal

World Bank report. No decision (event) to maintain production passed the test, and although the decision to maintain oil production is the most frequent, it never raised the spillover index.

Table 6: Test results: Economic events

Date	Event Description	Event Count (%)					Chance of Causality
		J=0	J=1	J=2	J=3	J=4	
27.11.1992	OPEC meeting: production quotas raised	58.3	100	99.5	99.1	99.2	Low
11.02.2002	Russia increases production and oil exports	99.9	99.9	99.7	100	100	High
22.06.2009	World Bank Report	43.2	99.1	96.2	97.7	95.9	Moderate
27.03.2017	OPEC, non-OPEC to look at extending oil-output cut by six months	50.5	100	100	100	100	High

Notes: The table shows 4 economic events that passed the conventional statistical significance threshold. The 'Event Count' columns show the percentage of the 1000 bootstrapped values higher than the previous mean value. The events exhibit substantial impact as they pass the threshold from 1 to 4 days after the event occurs, corresponding to one trading week; the effect on the day the event occurred is not included to control for the speed of information flow among news channels. The last column contains credibility assessment results based on the analysis in Section 5.

The first case of a production boost coinciding with an increase in the spillover index on 27 November 1992, appears to be connected with the OPEC. At the end of its 92nd ordinary meeting (25-27 November 1992), OPEC decided to raise production quotas for its members (Simpson, 2008).

A significant shift in production dynamics occurred with Russia as it announced substantially increasing its oil exports, which conflicted with OPEC's attempts to reduce oil supply worldwide (11 February 2002). This decision to expand exports during a period of extreme oil prices and production cuts, contrasting with OPEC's efforts to maintain high prices, introduced negative and unexpected news, impacting the spillover index (Hill and Fee, 2002). Historically aligned with OPEC until the 2000s, Russia increased exports substantially, reaching 500 million tons in 2009 (Vatansever, 2010).

Apart from production change announcements, a pivotal economic event boosting oil volatility spillovers occurred when the World Bank released its report on 22 June 2009. The report forecasted a 2.9% global output decline, a 10% decrease in world trade, and an almost 50% drop in capital flow to support developing countries in 2009 (World Bank, 2012). There are multiple reasons why this economic outlook could affect the connectedness of oil-based commodities. First, crude oil and its derivatives represent a substantial portion of global output and world trade. Second, as many countries in the Middle East and South Africa are still developing economies, the reduced capital inflow could hinder efficient oil extraction and transportation.

On 27 March 2017, discussions among major OPEC and non-OPEC oil exporters about extending production cuts raised the spillover index from 52% to 64%. Despite the extension being communicated initially in the form of the initial announcement, the uncertainty surrounding the decision differentiated it from other scheduled OPEC meetings. This unexpected news led to a 12.5% increase in crude oil prices in the weeks following the statement (Soldatkin and Gamal, 2017).

Analyzing economically-oriented events reveals notable patterns. Firstly, events related to the discovery of new oil fields, development of oil facilities, or mergers of oil companies do not impact the connectedness of oil-based commodities. The missing link of mergers could be attributed to their small scope or the generally positive market perception of increased and stable oil production resulting from mergers. Secondly, news on the current state of oil stocks or releases from the Strategic Petroleum Reserve never met the bootstrap test threshold. This suggests that reserve releases historically occur in response to other significant events.

Surprisingly, implementing or extending sanctions against specific countries did not induce a reaction in the spillover index. Notably, no sanctions have been imposed on Saudi Arabia, the leading OPEC oil producer and exporter. Sanctions on smaller exporters lack the impact to elevate volatility spillovers among oil-based commodities. The result is in line with Torbat (2005b) who stated that total imports and exports of crude oil remain unchanged with imposed sanctions, as oil, being a necessity good, prompts exporting countries to shift buyers when faced with sanctions.

Surprisingly, none of the events connected to the Russia-Saudi oil price war starting in March 2020 triggered a prompt increase in connectedness. After Saudi Arabia announced the oil price discount and initiated the oil price war on 8 March 2020, the index spiked to its maximum value of 75% several times. Still, it then returned to values between 65 and 70. The event passed the threshold of the test for only two days following the price discount, so the effect could not be perceived as lasting.

5.2.3 Natural events

Considering the natural events overview in Table 7, we see that only 1 out of the 130 events labeled as 'natural' passed the probability threshold. The PTT Global Chemical oil spill occurred on 27 July 2013. The amount of oil spilled was about 50 tonnes or one full tanker. A spill of this magnitude is too negligible to be considered causal compared to OPEC production changes, for example. Thus, we rule the causality of the event out.

The lack of explanatory power of natural events is striking. Understandably, losing a tanker's worth of oil in an accident does not cause massive oil supply disruptions. Even a 3.19 million barrels loss during the Deepwater Horizon oil spill in 2010 represents only about a third of the US daily production in that year (Energy Information Administration, 2022). Even though hurricanes, earthquakes, and extreme temperatures were historically responsible for the shutdowns of oil production facilities, none caused a significant shift in the connectedness. In conclusion, natural disasters in our sample of events do not cause a sudden increase in the connectedness of oil-based commodities, even if they disrupt the oil supply. Most likely, natural disasters seem to be too local and their effect on overall oil supply is too small concerning global oil production.

Table 7: Test results: Natural events

Date	Event Description	Event Count (%)					Chance of Causality
		J=0	J=1	J=2	J=3	J=4	
27.07.2013	PTT Global Chemical Pcl oil pipeline spill	48.7	97.3	99.4	99.1	98.8	Low

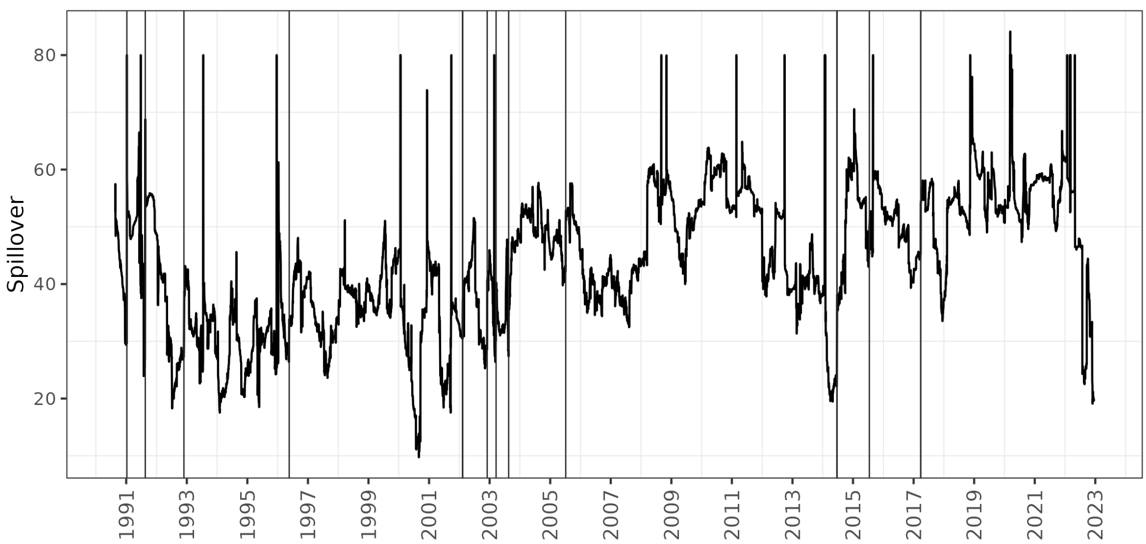
Notes: The table shows 1 natural event that passed the conventional statistical significance threshold. The 'Event Count' columns show the percentage of the 1000 bootstrapped values higher than the previous mean value. The events exhibit substantial impact as they pass the threshold from 1 to 4 days after the event occurs, corresponding to one trading week; the effect on the day the event occurred is not included to control for the speed of information flow among news channels. The last column contains credibility assessment results based on the analysis in Section 5.

5.3 Robustness checks

The results of our study are conditional on the choice of multiple parameters. The selection of assets to include in the network is a parameter as well. We previously stated that the focus of this study was to analyze the connectedness of petroleum-based commodities only, but adding natural gas into the network is worth doing due to its interchangeability with oil-based energy sources (Kočenda and Moravcová, 2024).

Adding natural gas to the network significantly decreases the overall spillover index down to 37.25%. This is because natural gas is the most isolated commodity in the network. Natural gas is responsible for its own volatility from 97.90%. This result is in line with the findings of Kočenda and Moravcová (2024), who also report natural gas to be the best hedge among these commodities. The gasoline-crude oil pair remains the most connected commodity pair.

Figure 4: Connectedness dynamics of energy commodities



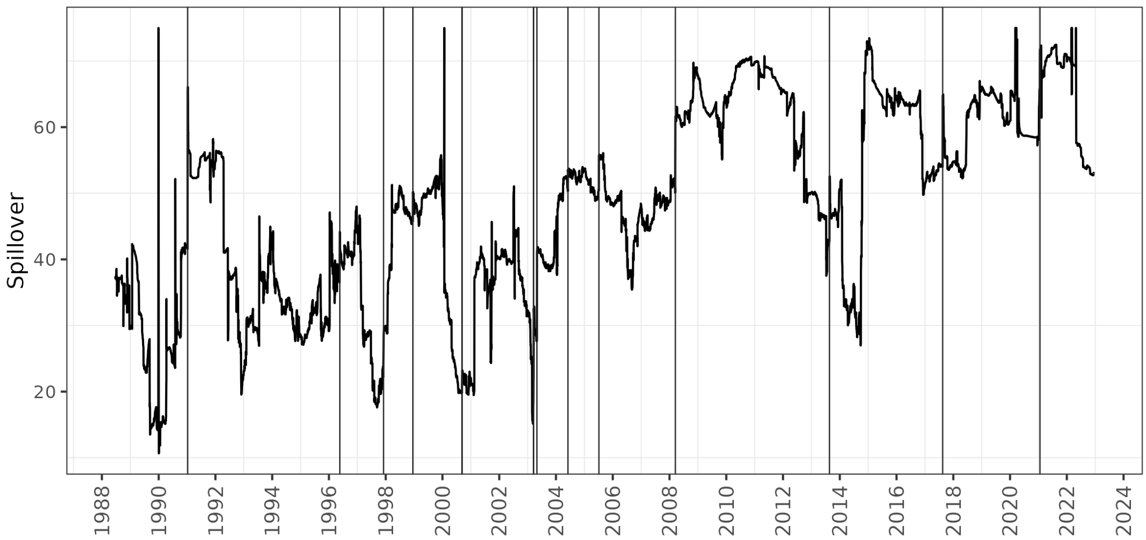
Notes: The figure shows the evolution of the overall connectedness among oil-based commodities and natural gas. Spillovers are calculated on the rolling window of 100 days. The vertical lines represent the events that passed the conventional statistical significance threshold.

The choice of lag order, window length, and horizon is explained at the beginning of this Section. As a robustness check, we experimented with other choices of these parameters. Selecting a higher lag order and longer horizon had almost no impact on the dynamics of the spillover index and the results of the test did not produce any changes for identified events.

The choice of window length produced some differences, though. For daily time series, the literature almost exclusively considers window lengths of 100 and 200 days. Following the literature, we performed the robustness check for a window length of 200. Naturally, a longer window results in more stable VAR coefficients and less volatility in the rolling spillover index.

In terms of the connectedness dynamics, the 200-day rolling window spillover plot in Figure 5 appears to be a smoothed version of the 100-day version presented in Figure 2. Hence, the long-term pattern remains the same. As could be expected, increasing the length of the window to 200 produces a smoother index and reduces the number of identified events from 21 to 10. However, this reduction did not alter the key results since the events with major impacts were identified in connectedness quantified under both rolling windows. The robustness check shows that despite a smaller number of identified events, the varying choice of the lag order, window length, and horizon does not produce materially different results.

Figure 5: Oil commodity connectedness with a 200-day rolling window



Notes: This figure shows the evolution of the overall connectedness among oil-based commodities. Spillovers are calculated on the rolling window of 200 days. The vertical lines represent the events that passed the conventional statistical significance threshold.

6 Conclusion and Policy Implications

We analyzed volatility spillovers between oil-based commodities, endogenously detected events that caused sudden and lasting increases in volatility spillovers, and identified their common characteristics. Using the spillover index methodology proposed by Diebold and Yilmaz (2009, 2012), we observe that the spillover index had much lower values but was more volatile before the year 2008, while it became more stable and higher on average since 2008. Although all the commodities in the network were mostly influenced by their own past shocks, we found that crude oil and heating oil were net volatility transmitters, while gasoline functions as a net volatility receiver, and diesel is neither a net receiver nor a net transmitter. Adding natural gas to the network decreased the overall connectedness since natural gas is dependent on its own volatility shocks from almost 100%.

Based on the novel bootstrap-after-bootstrap testing procedure, we identified 21 statistically significant events after which the spillover index increased. We analyzed the events thoroughly and grouped them into several categories based on their characteristics. The findings suggest that events of a geopolitical nature are notably more likely to cause a shift in the network connectedness of oil-based commodities. Three main characteristics often appeared across all the categories. The selected events were usually unexpected, negative, and associated with a fear of oil supply shortage.

Acts of terrorism or political tensions that caused oil supply disruptions were the most prevalent types of geopolitical events causing the spillover index to increase. On the other hand, positive events such as peace negotiations or signing a peace treaty never caused a rise in volatility connectedness. Among events of an economic nature, we did not identify any effect of mergers and acquisitions of oil companies on the spillover index. Further, trade sanctions imposed on oil-exporting countries never caused a sudden shift in the volatility spillovers among oil commodities as well. Finally, threats and speculations of both geopolitical and economic types were also ineffective.

Out of the 130 events with natural causes, there was no plausible event identified to impact connectedness with a statistical significance. Thus, we believe that natural events are not the primary causes of the shifting volatility connectedness of oil-based commodities. Using these results, investors, hedge funds, and policymakers can easily assess any new oil-related news, and react accordingly to the evidence presented in this analysis.

Our findings contribute to overall knowledge regarding oil volatility connectedness. Investors and policymakers can use these results to identify or be alert to the (classes of) news with potential impact on the oil markets and react accordingly. Furthermore, the events identified by our test can function as a reliable source of reference for future studies aiming to bring more insight into the connectedness of oil-based commodities.

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Appendices

A Measure of connectedness - spillover index

This Appendix provides a full derivation of the spillover index introduced in the work of Diebold and Yilmaz (2009, 2012) that has become a standard measure of connectedness. The volatility spillover index requires some volatility estimate of all the assets in the network. We use a range-based realized variance that was first introduced by Garman and Klass (1980). For $O_{it}, C_{it}, H_{it}, L_{it}$ being the natural logarithms of daily open, close, high, and close prices for commodity i on day t, the range-based realized variance is computed as:

$$\begin{aligned} \hat{\sigma_{i,t}}^2 &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \\ x_{i,t} &= \sqrt{\hat{\sigma_{i,t}}^2} \end{aligned} \tag{6}$$

Having obtained a vector of daily realized volatility estimates of m variables $\boldsymbol{x_t} = (x_{1t}, x_{2t}, ..., x_{mt})$, we can write VAR of lag p in its reduced matrix form as:

$$\boldsymbol{x}_t = \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \tag{7}$$

where $\boldsymbol{x}_t$ is an $m \times 1$ vector of realized volatilities, $\boldsymbol{A}_j$ is a $m \times m$ matrix of VAR parameters for lag $j = 1, \ldots, p$, $\boldsymbol{u}_t$ is an $m \times 1$ of disturbances, so that $\boldsymbol{u}_t \sim N(0, \boldsymbol{\Sigma})$. The matrix $\boldsymbol{\Sigma}$ is a positive-definitive covariance matrix of size $m \times m$, with unknown distribution. We also explicitly remove the static mean from the equation, as it does not affect variance decomposition.

Since this VAR form is simply a finite horizon AR process, we can use the Wold decomposition and convert VAR into a more convenient infinite-order moving average process:

$$\boldsymbol{x}_t = \sum_{\ell=0}^{\infty} \boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell}, \tag{8}$$

where the ℓ-th $m \times m$ VMA parameter matrix is obtained recursively from the parameters of the VAR model as $\boldsymbol{G}_\ell = \boldsymbol{A}_1 \boldsymbol{G}_{\ell-1} + \boldsymbol{G}_2 \boldsymbol{G}_{\ell-2} + \ldots$ for $\ell = 1, 2, \ldots$, with $\boldsymbol{G}_0 = \boldsymbol{I}_m$ and $\boldsymbol{G}_\ell = \boldsymbol{0}_m$ for $\ell < 0$, where $\boldsymbol{I}_m$ represents an $m \times m$ identity matrix, and $\boldsymbol{0}_m$ denotes an $m \times m$ zero matrix. The infinite number of lags in the moving average representation can be sufficiently approximated with coefficients of a finite horizon H

The moving average representation is crucial for calculating the spillover index, as it enables us to decompose the variance of the forecast errors into parts. Nevertheless, the reduced VAR form is not identified, and the errors are just linear combinations of the structural form. Thus, we can not attribute a shock to x_i to innovations in a single variable x_j. It is necessary to deploy some variance decomposition scheme in order to orthogonalize the errors and remove the correlation between them. Diebold and Yilmaz (2009) use the h-steps-ahead orthogonalized forecast error variance decomposition (OVD) for the i-th variable can be obtained the moving average representations as:

$$\theta_{i\leftarrow j}^{(H)} = \frac{\sum_{\ell=0}^{H} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{P} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{H} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i}, \tag{9}$$

where $i, j = 1, \ldots, m$ represent the interaction between variable i and j. Vector $\boldsymbol{e}_i$ is an $m \times 1$ selection vector, such that there are zeros on every position, except for element i, which is equal to 1. $\boldsymbol{P}$ is the $m \times m$ lower-triangular Cholesky factor of the residual covariance matrix $\boldsymbol{\Sigma}$.

The value of $\theta_{i\leftarrow j}^{(h)}$ can be viewed as the h-steps ahead forecast error variance of variable i due to orthogonal shock to variable j. This orthogonalized variance decomposition measure is sensitive to the ordering of the variables in the system. More importantly, it does not enable the measurement of directed volatility spillovers. Therefore, Diebold and Yılmaz (2014) propose a generalized forecast error variance decomposition (GVD), which is order-invariant, and allows the measurement of directed spillovers. Now we are going to derive the generalized version since it is going to be used to compute the spillover index.

Since the errors of Equation 8 are assumed to be serially uncorrelated, and the VAR model is covariance-stationary, the total covariance matrix of Equation 8 of horizon H can be calculated as:

$$\boldsymbol{\Omega}_H = \boldsymbol{E}(\boldsymbol{x}_t \boldsymbol{x}_t') = \boldsymbol{E}(\sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell} * (\boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell})') = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \tag{10}$$

In order to compute the generalized variance decomposition, we must first define the forecasting error conditional on today's innovation in variable j.

$$\boldsymbol{\gamma_t^j} = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell[\boldsymbol{u}_{t-\ell} - E(\boldsymbol{u}_{t-\ell}|\boldsymbol{u}_{j,t-\ell})] \tag{11}$$

Assuming normal distribution of the shocks, we can use the Bayes theorem to rewrite the conditional shock as:

$$\boldsymbol{\gamma_t^j} = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell[\boldsymbol{u}_{t-\ell} - \sigma_{jj}^{-1} \boldsymbol{u}_{j,t-\ell} (\boldsymbol{\Sigma})_{.,j}] \tag{12}$$

where σ_{jj} is the jth diagonal element of the residual covariance matrix $\boldsymbol{\Sigma}$. The covariance matrix conditional on the innovations to variable j is then:

$$\boldsymbol{\Omega}_H^j = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' - \sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{\Sigma}_{.,j} \boldsymbol{\Sigma}_{.,j}{}' \boldsymbol{G}_\ell' \tag{13}$$

The forecast error variance of the i-th component of the VAR system stemming from innovations to variable j is computed as:

$$\boldsymbol{\Delta}_{(i)jH} = (\boldsymbol{\Omega}_H - \boldsymbol{\Omega}_H^j)_{i,i} = \sigma_{jj}^{-1} \sum_{\ell=0}^{H} ((\boldsymbol{G}_\ell \boldsymbol{\Sigma})_{i,j})^2 = \sigma_{jj}^{-1} \sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{e}_j\right)^2 \tag{14}$$

Finally, we can obtain the generalized variance decomposition through scaling Equation 14 by the unconditional forecast error variance of the i-th component:

$$\vartheta_{i \leftarrow j}^{(H)} = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{H} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{H} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i} \tag{15}$$

The notation of Equation 15 is consistent with the OVD specification. In the case of orthogonalized variance, it holds that:

$$\sum_{j=1}^{m} \theta_{i \leftarrow j}^{(h)} = 1, \sum_{i=1}^{m} \sum_{j=1}^{m} \theta_{i \leftarrow j}^{(h)} = m \tag{16}$$

whereas the sum of all proportions of forecast error variance to variable i will generally be greater than 1 because the shocks do not necessarily need to be orthogonal ($\sum_{j=1}^{m} \check{\vartheta}_{i \leftarrow j}^{(h)} > 1$). Thus, Diebold and Yılmaz (2014) apply a row-sum normalization of GVD:

$$\tilde{\vartheta}_{i \leftarrow j}^{(H)} = \vartheta_{i \leftarrow j}^{(H)} \Big/ \sum_{j=1}^{m} \vartheta_{i \leftarrow j}^{(H)}. \tag{17}$$

The matrix of $\tilde{\vartheta}_{i \leftarrow j}^{(h)}, i, j = 1, \ldots, m$ can be viewed as a weighted directed network. For $i \neq j$, the bilateral interactions represent the 'spillovers' - how much of the forecast error variance of a variable i can be attributed to innovations of a variable j.

Denoting the $m \times m$ h-step ahead matrix of the generalized forecast error variances as $\boldsymbol{\vartheta} = \{\vartheta_{i \leftarrow j}\}_{i,j}^{h}$. Diebold and Yilmaz (2009) and Diebold and Yılmaz (2014) measure the total spillover index in the following way:

$$\mathcal{S}^H = 100 \times \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{M} \tilde{\vartheta}_{i \leftarrow j}^{(H)}}{\sum_{i,j=1}^{M} \tilde{\vartheta}_{i \leftarrow j}^{(H)}} = 100 \times \frac{\boldsymbol{\iota}' \boldsymbol{\vartheta} \boldsymbol{\iota} - \mathrm{trace}(\boldsymbol{\vartheta})}{\boldsymbol{\iota}' \boldsymbol{\vartheta} \boldsymbol{\iota}} \%, \tag{18}$$

where $\boldsymbol{\iota}$ is an $m \times 1$ vector of ones.

A static representation of volatility spillovers provides a good overview of network connectedness. It is, however, merely an average throughout the whole studied period. A prolonged period of weak connectedness during a stable economic period followed by a financial crisis would display only a mild average connectedness, while the economic interpretation is entirely different when the two periods are evaluated separately. For petroleum-based commodities in particular, the strength of volatility spillovers varies throughout different historic periods (Kilian, 2009).

Since we aim to analyze the spillover levels before and after a particular event, we must observe temporal changes in the spillover index. The impact of economic events on volatility can not be sufficiently quantified using non-overlapping or arbitrary intervals (Kang and Lee, 2019). Using a rolling spillover measure, we can observe trends and sudden jumps in the spillover index. Trends in volatility spillovers can be attributed to the gradual advancement in technology, progressing globalization, a rise of hedge funds, or the prolonged state of the global economy (Liu and Gong, 2020). Furthermore, we can assess the state of the spillover network each day. Thus, for sudden bursts in volatility spillovers, the daily volatility spillover measure enables us to explore possible causal effects of the events in our dataset.

The calculation of the rolling spillover index is identical to the static one. Given observations at time $t = 1, ..., T$, we choose a rolling window of size w, and compute the forecast error variance matrix $\tilde{\vartheta}^{(h)}$ using only the last w observations. In the end, we obtain $\tilde{\vartheta}_t^{(h)}, t = w...T$ matrices, from which we can calculate a series of spillover index values of size T.