UNRAVELING TIMING UNCERTAINTY OF EVENT-DRIVEN CONNECTEDNESS AMONG OIL-BASED ENERGY COMMODITIES

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Unraveling Timing Uncertainty of Event-driven Connectedness among Oil-Based Energy Commodities

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Abstract:
The pricing dynamics of oil-based commodities are frequently influenced b y r eported events. Our analysis spans almost 900 oil-related events from 1978 to 2022, categorizing them based on recurring characteristics. Employing a novel bootstrap-after-bootstrap testing econometric framework, we quantify dynamic connectedness among energy commodities. Our findings reveal over 20 statistically significant historical events that triggered abrupt and enduring increases in volatility connectedness. Notably, geopolitical events are more consistently associated with elevated connectedness than economic events, while natural events do not exhibit a similar impact. The prevailing characteristics shared by events leading to increased volatility connectedness include their negativity, unexpected nature, and the introduction of concerns about oil supply shortages.

JEL: C32; C58; G15; Q02; Q35
Keywords: energy commodities; crude oil; volatility connectedness; systemic events; bootstrapafter-bootstrap procedure

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1 Introduction

The study of connectedness among financial assets and markets has emerged as a crucial endeavor for understanding the interdependencies that shape global economic dynamics (Diebold and Yılmaz, 2014).[1] Among these assets, oil-based energy commodities stand as a critical component, given the pervasive influence of the oil sector on the global economy, 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). Hence, studying the connectedness among oil-based energy commodities is vital due to its 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 often reflects shocks that materialize within markets and economies, but one of the primary obstacles faced when studying connectedness lies in the inherent uncertainty surrounding the timing of shocks. The precise moment when a shock emerges and its subsequent impact on connectedness remains elusive due to the intricate and dynamic nature of financial markets. So far, links between changes in the connectedness of oil-based commodities and specific events have not been properly tested. In our analysis, we quantify connectedness among the key oil-based energy commodities over more than four decades and explore hundreds of potentially impactful shocks. We employ the novel formal testing method of Greenwood-Nimmo, Kočenda and Nguyen (2023) and provide the first statistical evidence showing the types, numbers, and timing of the shocks that truly impact connectedness among oil-based commodities.

Our motivation for detecting the precise timing of shocks that impact the value of connectedness among oil-based energy commodities is grounded in several essential reasons. Prices of most assets on the markets are closely influenced by important events and information arising from newly appearing events has been empirically shown to be rather quickly and efficiently incorporated into prices (Fama, Fisher, Jensen and Roll, 1969; Malkiel, 2003). Compared to other assets, oil-based energy commodities seem to be more sensitive to events such as political concerns, supply chain shocks, or natural disasters (Baruník, Kočenda and Vácha, 2015; Karali, Ye and Ramirez, 2019). Nevertheless, the demand reaction for oil is often disproportionate to the actual shocks caused by these events, and the timing of the price change differs from the true supply shortage due to the expectations of future shortages (Kilian, 2009). Furthermore, the volatility increase in one market is often followed by a similar volatility increase in seemingly unrelated markets or assets, and energy commodities are no exception to such contagion effects.

Hence, the detection of precise timing for shocks impacting the value of connectedness is essential in

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

a number of areas. First, identifying the timing of shocks helps establish causal relationships between events and connectedness patterns (Aloui, Aïssa and Nguyen, 2011). This knowledge is crucial for policymakers, researchers, and investors to understand the underlying dynamics of the market and take appropriate actions. For example, it has been shown that the connectedness of oil-based commodities was affected by major crisis episodes (Chatziantoniou, Gabauer and de Gracia, 2022). Then, if a specific event, or a class of events, consistently leads to increased connectedness among oil-based commodities, policymakers may design measures to mitigate potential risks arising from such events in the future. Second, since financial markets react quickly to news and events, for investors and financial institutions, knowing the timing of shocks is a critical tool for effective risk management (Malkiel, 2003; Elder, Miao and Ramchander, 2013). Sudden increases in connectedness may signal higher contagion risk, potentially leading to amplified losses during periods of market stress (Diebold and Yilmaz, 2012; Reboredo, 2014; Mohaddes and Pesaran, 2017). Third, understanding the timing of shocks can also help in forecasting future connectedness patterns (Baruník and Křehlík, 2018). If certain events consistently lead to changes in connectedness, predictive models can be developed to estimate connectedness levels in response to similar events in the future. This information can be valuable for long-term investment planning and decision-making. Fourth, the precise timing of shocks is crucial for accurately assessing the extent of contagion in financial markets (Diebold and Yilmaz, 2012; Greenwood-Nimmo et al., 2023). By pinpointing the timing of shocks, researchers can differentiate between spurious correlations and actual contagion effects, leading to more robust and accurate assessments of systemic risk.

In addition to the above motivations, the timing of shocks and changes in connectedness is also linked to macroeconomic development as they can be indicative of broader economic trends (Nandha and Faff, 2008; Kilian, 2009; Husain, Tiwari, Sohag and Shahbaz, 2019). Studying these patterns can offer valuable insights into the health of the global economy, trade relationships, and potential vulnerabilities in different sectors. This information can be used for macroeconomic analysis and policymaking as the analysis of events driving volatility spillovers among oil-based commodities is, in particular, important due to its complexity with respect to the economy. Crude oil and the products refined from it play a crucial role in the global economy as they are a necessity mainly in the industrial, agricultural, and transportation sectors (Energy Information Administration, 2022). Further, due to the disproportionate geological endowments of oil formations, crude oil is one of the most traded items in the world. Thus, increased volatility of oil prices does not only affects investors, but also the economies of entire countries as, among other effects, oil supply disruptions cause a decrease in GDP, currency depreciation, inflationary pressure, and trade disorders (Kilian, 2009; Ding and Vo, 2012; Mohaddes and Pesaran, 2017; Togonidze and Kočenda, 2022).

For all the reasons above, it is essential to understand the causes of volatility spillovers among oil-based commodities. While numerous studies have sought to quantify and analyze the extent of connectedness, a critical challenge lies in establishing the precise timing of shocks that drive these interconnected relationships. In our analysis, we strive to provide a meticulous quantitative remedy.

In our analysis, we gathered prices of five energy commodities: crude oil, heating oil, gasoline, diesel, and natural gas over the span from 1978 to 2022. Using daily realized volatility estimates of the price returns of the commodities, we compute the rolling spillover index introduced by Diebold and Yilmaz (2009, 2012), which represents the degree of volatility connectedness of the network on each day of the studied period. Furthermore, we collected 891 news articles related to oil and categorized them based on a repeating set of characteristics into geopolitical, economic, and natural events. Next, we utilize the novel bootstrap-based test recently introduced by Greenwood-Nimmo et al. (2023), which enables us to statistically assess the probability that the spillover index increased on a given day when a specific shock (event) occurs.

Our analysis of the volatility spillovers among oil-based commodities and key driving events provides several new insights into the topic and contributions to the literature. In quantitative terms, and with statistical confidence, out of about nine hundred events included in our dataset, we identified over twenty historic events, after which the spillover index of oil-based commodities spiked, and remained above the pre-event levels for at least one trading week following the event. After any of these events, it was much riskier for investors and hedge funds to hold their position in any oil commodity. The price movements of all oil-based commodities were too volatile and correlated, so investors are better of by temporarily exiting the oil market. Our coverage of these events and dynamics of the oil-based commodity market is complex and this type of analysis was not performed before on energy commodities. Hence, in addition to the quantitative analysis of showing the link between events and increases in connectedness, our analysis can also serve as a useful reference source of important events linked to the oil and oil market with a subset of events exhibiting a (statistically) proven impact on the energy market's connectedness.

Further, in qualitative terms, we detected several characteristics that were prevalent among the economically and statistically significant events. First, geopolitical events are more likely to cause a sudden and lasting increase in volatility spillovers than economic events. Further, most economic events identified by the test are linked to some geopolitical background. Finally, most of the events after which the spillover levels increased share three common characteristics: they are negative, unexpected, and introduce fear of oil supply shortage. Although our dataset consists of mostly unanticipated events, not a single anticipated event passed the statistical significance threshold, which points to the fact that unexpected outcomes are the main drivers behind increased volatility connectedness.

Our findings are in line with the results of Greenwood-Nimmo et al. (2023) who show that unanticipated and negative events reported in the seminal study of Diebold and Yilmaz (2009) are most likely to cause a sudden increase in the spillover levels of equity markets. Our results show that this relationship holds for oil-based commodities as well.

The rest of the article is structured as follows: Section 2 reviews previous work on connectedness with accent on oil-based commodities. The relationship of crude oil with the global economy, and previous studies analyzing the effect of the events on oil returns and volatility are also presented. Section 3 presents the data and procedure leading to a set of 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 presents the results of the oil-based commodities network connectedness and analyzes events identified by the bootstrap test. Section 6 summarizes our findings.

2 Literature Review

2.1 Position in Global Economy

Oil is one of the most traded commodities in the world, and its price volatility represents a risk to investors, but also to industrial producers. Crude oil categorizes as a fossil fuel, that needs to be refined for further use. The International Energy Agency states that in 2021, 67% of crude oil was used to make transportation fuels: gasoline, distillate fuels, jet fuel, and biofuel (Energy Information Administration, 2022). Distillate fuels comprise diesel, utilized as fuel for construction equipment and heavy vehicles, and heating oil, used in boilers, furnaces, and industrial heating. Furthermore, 27% was used for industrial purposes, and the remaining 6% for residential, commercial, and electric power. Natural gas also classifies as a fossil fuel, but it is used mainly for electricity generation and heating. In summary, oil-based commodities and natural gas are crucial for the industrial, transportation, and agricultural sectors. Higher oil prices can induce a rise in the cost of goods and services, and subsequently higher inflation (Sadorsky, 1999). The steady rise in global aggregate demand for crude oil tends to raise levels of CPI in the long-term (Kilian, 2009).

Apart from the industrial perspective, oil price volatility affects the global economy through a number of other channels. Rising oil prices increase the cost of basic production, which decreases economic output (Sadorsky, 1999; Brown and Yücel, 2002). Under the assumption that the price increase is temporary, firms and households will borrow more, which puts upward pressure on inflation (Mohaddes and Pesaran, 2017). Central banks will then need to increase interest rates in order to handle inflation (Gogolin et al., 2018). During periods of moderate oil price volatility, firms tend to postpone investment decisions due to uncertainty (Henriques and Sadorsky, 2011). For some sectors, the marginal cost increases, which results in lesser wage growth and higher unemployment (Brown and Yücel, 2002; Gogolin et al., 2018). Kilian (2009) argues that increases in demand and oil-supply disruptions significantly decrease real GDP. Furthermore, oil price fluctuations negatively influence stock returns (Sadorsky, 1999). Oil prices can influence currency depreciation as well. When the price of oil increases, oil importers are more likely to deplete the US dollar reserves, which depreciates the currency (Salisu and Mobolaji, 2013). Conversely, if the dollar depreciates, oil exporters might be prone to increasing oil prices in order to stabilize the monetary value of exports.

2.2 Volatility spillovers studies

The volatility of solely petroleum-based commodities was shown to be highly inter-connected, with the strongest dependence between heating oil, gasoline, and crude oil (Baruník and Vácha, 2012). Ji, Zhang and Geng (2018) report that crude oil returns are among the main factors explaining natural gas price volatility. Wang and Guo (2018) suggest that crude oil is a net volatility transmitter, and the Brent Oil index is a volatility receiver. Furthermore, 25% of the volatility in the oil markets is due to spillovers. Similar results hold for oil futures, where approximately 25% of heating oil and gasoline futures volatility is transmitted from crude oil futures (Magkonis and Tsouknidis, 2017). Lastly, futures act as volatility transmitters for spot prices for oil-based commodities (Magkonis and Tsouknidis, 2017).

Crude oil is traded in various markets around the world, which advocates for analyzing volatility spillovers between these markets. Zhang and Wang (2014) argue that volatility spillovers between the oil markets of China, the U.S., and the U.K. are bi-directional and asymmetric. They also report that there is an upward trend in the spillover index throughout the studied period, which is attributed to the increasing influence of the Chinese oil market. Chang, McAleer and Tansuchat (2010) used an asymmetric GARCH model to study volatility spillovers between four major crude oil markets, namely West Texas Intermediate (USA), Brent (North Sea), Dubai/Oman (Middle East), and Tapis (Asia-Pacific). The results show that Brent and WTI markets are net volatility transmitters. Similar results were obtained by Liu and Gong (2020), where WTI produces the most net volatility (18,59 %) to the remaining three markets, and Brent seconds its position. A likely explanation behind these results is that WTI and Brent are viewed as global benchmarks for oil prices. Ouyang, Qin, Cao, Xie, Dai and Wang (2021) expand former studies by calculating the volatility spillovers of 31 global crude oil markets, finding significant spillovers for both returns and volatility.

Since oil is the most traded commodity in the world, its price fluctuation clearly influences global markets and macroeconomic indicators. While previously mentioned studies considered volatility spillovers solely within the oil market, there is a growing body of literature that explores spillovers between oil and financial markets as well. For example, Kang, Hernandez, Sadorsky and McIver (2021) find that crude oil is the best hedging option for the U.S. ETFs and Baruník and Kočenda (2019) show that crude oil functions as a hedge for the forex portfolio. The findings differ in the case of a commodity portfolio as Diebold, Liu and Yilmaz (2017) conclude that crude oil has the highest net connectedness out of 19 commodities, followed by heating oil, soybeans, and zinc.

Volatility spillovers between oil-based commodities and natural gas are already covered in the literature by several studies. Baruník et al. (2015) were the first to analyze spillovers between crude oil, heating oil, and gasoline. Their findings suggest that the magnitude of spillovers was stronger before the Great Financial Crisis (45,5%), rather than after it (58,3 %), emphasizing the often-mentioned switch in the oil market's fundamentals after the crisis. Similar results were found by (Kočenda and Moravcová, 2023). All three commodities alter between receiving and transmitting spillovers throughout the studied period. Crude oil was often found as the main volatility transmitter, although the findings are not homogeneous (Mensi, Rehman and Vo, 2021; Gong, Liu and Wang, 2021). On the other hand, Kočenda and Moravcová (2023) argue that spillovers from crude oil are not as large as could be expected, which is in line with the findings of (Baruník, Kočenda and Vácha, 2016).

The literature argues that technological innovations in oil and gas extraction, which enabled effective drilling of shale gas and tight oil sources, changed the way spillovers propagate through the system. Gong et al. (2021) observe a 15% decrease in the spillover index as a result of the shale gas revolution in 2006. Lovcha and Perez-Laborda (2020) mention that natural gas has become a net volatility transmitter as a result of the shale gas revolution. Nevertheless, natural gas was generally reported to be the best hedge, as it is mainly influenced by its own idiosyncratic volatility (Mensi et al., 2021). Kočenda and Moravcová (2023) conclude that natural gas is responsible for 91,03% of its volatility, while the rest of the commodities receive on average 50% of volatility from the system. Diebold et al. (2017) also state that during periods of recession, natural gas has the weakest reaction to economic events out of all energy commodities studied. Moreover, it has the smallest connectedness to and from other commodities. In most of the studies mentioned, the static spillover index is approximately 40%, which shows moderate connectedness of the system.

The literature advocates for using time-varying and asymmetric spillover measures in case of oil volatility spillovers. Kilian (2009) shows that oil price volatility spills to other markets with different sign and magnitude, depending on time. Zhang and Wang (2014) argue that oil price volatility spillovers affecting the Chinese oil market are asymmetric. The results hold for world oil indexes as well (Baruník et al., 2015). Xu, Ma, Chen and Zhang (2019) studied volatility spillovers between oil, U.S., and Chinese stock market, and reported that spillovers are time-varying and asymmetric, which highlights the effect that various events can have on the spillover index. Furthermore, volatility spillovers for petroleum-based commodities are clustered and persistent (Liu and Gong, 2020). Thus, it makes sense to pair periods of clustered volatility spillovers on significant economic periods, such as the Great Financial Crisis, the COVID-19 pandemic, or the war in Ukraine.

2.3 News studies

The possibility that news can affect oil prices and volatility has already been documented in the literature. Kilian (2009) defines news-induced oil price change as a precautionary reaction to a possible shortage of future oil supply. Kilian and Vega (2011) and Chan and Gray (2017) find no evidence of oil and gas price reaction to news at daily or even monthly horizons. Contrarily, Elder et al. (2013) state that oil price responds rapidly to economic news.Greenwood-Nimmo et al. (2023) applied their new methodology for mapping past events to changes in the volatility spillover index on the same data as in Diebold and Yilmaz (2009) and found 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],

[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/

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 September 1, 1978 to December 16, 2022 for all oil-based commodities. Neither intraday nor daily natural gas prices are available before April 3, 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 April 3rd, 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.

The price data contained several anomalies. First, there were some occasions of prices being reported on weekends and these days were removed. Apart from weekends, we removed Christmas and New Year's holidays: December 24 - December 26, December 31, and January 1 - 2. We also removed US Federal holidays, during which the main exchange in our dataset is closed. Afterward, 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 substitute the low (high) with another range-based value.

In the end, 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. In the end, we had 8785 days of RV values for petroleum-based commodities and 8141 values 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	0	0.03871
ho	8785	0.00042	0.00087	0.00024	0	0.04044
lgo	8785	0.00037	0.00150	0.00017	0	0.10330
rb	8785	0.00040	0.00131	0.00019	0	0.05679
ng	8141	0.00090	0.00173	0.00053	0	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 January 1, 1987, to November 30, 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 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 the academic sources, we set up a Google Scholar query to search 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 conducted a search 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 results became consistently irrelevant after the first 200 results. Hence, for each of the 3 queries, we analyzed in detail the first 200 results. In addition, out of 600 academic sources, we selected 45 for geopolitical, 17 for economic, and 25 for natural news events, which served as sources of numerous oil-related events.

Further, the international organizations that were queried for relevant events featured the United Nations, the 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 and the final selection resulted in 891 events.

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.[5]

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 spread of diseases (pandemic-related news).

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. Further, the temporal event distribution in Figure 1 indicates that the sheer volume of news items grew with time as the news coverage improved globally. As can be 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. In order to better understand the dynamics and connections of individual events in our dataset, we provide a detailed review of the oil market and its role in modern history in Appendix B, summarizing the historical development of the global oil market.

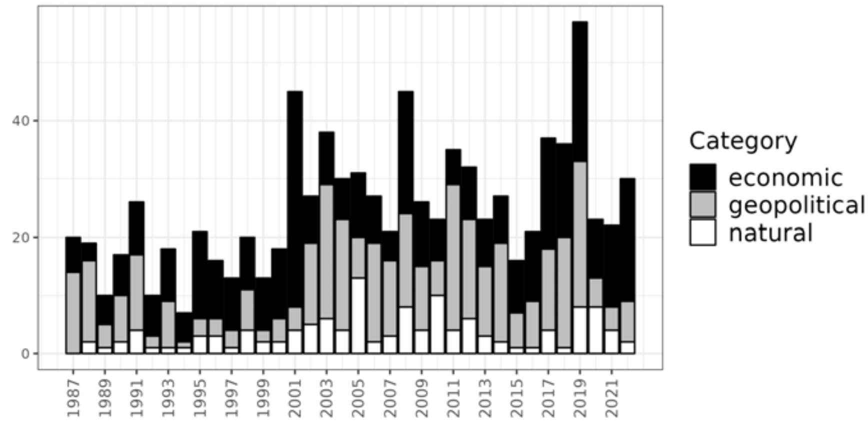
4 Methodology

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 test to statistically test a link between connectedness and specific shock (event).

[5]We acknowledge that historical evidence of wars resulting from low or high energy prices (or their volatilities) might be at odds with the assumption that oil-related prices are endogenous while events are exogenous. From our standpoint, this is not an issue as the oil-induced war conflicts were already preceded by high oil price volatility, so the test will rightfully not identify the events as causal.

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

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.

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.

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; Wang and Guo, 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 Section 5. The spillover index computed on rolling windows is crucial for our analysis as it captures the time variation attributable to historical events.[7]

4.2 Bootstrap-after-bootstrap test

The bootstrap-based test introduced by Greenwood-Nimmo et al. (2023) 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 et al., 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 methodology is that the test does not rely on asymptotic properties. This would pose problems in the case of the rolling windows estimation since the window is often set 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, which is especially true 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

[7]An alternative to the Diebold and Yilmaz (2009) approach is the TVP-VAR based spillover measure by Antonakakis and Gabauer (2017). 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. However, the bootstrap-based test of Greenwood-Nimmo et al. (2023) that we employ corresponds to the seminal approach of Diebold and Yilmaz (2009) that employs rolling windows.

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. (2023) 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. (2023) to describe the bootstrap test methodology 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 $\mathcal{S}^H$.

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 step 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 methodology of statistical inference 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 inference 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. (2023) in their test focus on spillover increases. Hence, we concentrate on events prompting a rise in the overall connectedness.

5 Results of the event-driven connectedness and robustness checks

5.1 Dynamics of the total connectedness

We optimized the lag order of the vector autoregressive model according to the AIC. Since the AIC values were very similar for all lag orders, we parsimoniously decided to choose lag 1 for the VAR model. When dealing with daily time series, it is conventional to use a 100- or 200-day rolling window (w) to compute the spillover index. Similar logic is applied for the horizon (H) on which the forecast error variance decomposition is calculated. Since our task is to capture the effect of events, it is favorable to have a more volatile rolling spillover index. Therefore, we chose a value of 100 for both the rolling window and the horizon.

The overall spillover for the oil spillover network is 45.23%. Comparable results were obtained by Baruník et al. (2015), who arrived at an overall spillover index of 50.6% for a network made of crude oil, heating oil, and gasoline. The idiosyncratic volatility spillover is the strongest for all commodities, implying that the volatility of each commodity is mostly influenced by its own past shocks. Crude oil appears to be a net spillover transmitter, while diesel and gasoline are mostly net receivers. The result is in line with Baruník et al. (2015) and Gong et al. (2021) who find that crude oil transmits most of the spillovers. Heating oil is neither a transmitter nor a receiver. The strongest pairwise connectedness can be found between gasoline and crude oil. Crude oil is responsible for 25.88% of spillovers to gasoline. The weakest link is between gasoline and diesel, where shocks to gasoline are explainable by shocks to diesel from only 8%.

Figure 3 shows that the rolling spillover index ranges from 5% to 75% throughout the studied period. Similarly to Baruník et al. (2015), we observe a fundamental change around the years 2000 and 2008. The average spillover level was lower before the year 2000, likely because the energy commodities were not yet financialized enough, they were not part of broader indices, and they were not traded by speculators. On the other hand, the geopolitical tensions in the Middle East along with the fear of sanctions caused sudden spikes in the index. After the invasion of Kuwait and the Persian Gulf War in the 1990s, oil prices stabilized, which lowered the average spillover index back to levels around 35%. Repeating war conflicts and sanctions led to the depletion of oil inventories in the US

[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.

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: This table shows the average connectedness of the oil-based commodities network from 1979 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 all other commodities on average 9.69% spillovers are transmitted from gasoline TO other commodities. In order 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.

from 1995 to 1996, which also affected the production of gasoline (Baruník et al., 2015). During this period, the spillover index rose from 30% to 50%, before returning to low levels in February 1997.

Later in 1997, the spillover index increased again from 20 to 50%, which is likely attributable to the Asian financial crisis followed by regional crises in Russia and South America (Kilian, 2014). The steadily increasing demand for oil combined with some major oil production disruptions in Venezuela and Iraq kept the spillover index volatile until 2003. After 2003, we see an indisputable rise in overall connectedness but also a decrease in the volatility of the index. The findings are consistent with those of Baruník et al. (2015). As argued in Section 3, the stabilization of the index at higher levels is likely due to the progressive financialization of petroleum commodities, further increase of global aggregate demand, and technological development in oil extraction methods. Hence, the connectedness was much more volatile before 2008 but the Global Financial Crisis itself did not significantly influence the connectedness. Although the demand for oil commodities decreased substantially, and oil price plummeted from $134 in June 2008 to $39 in February 2009, the spillover index only decreased from 60% to 50%.

The index resided around 70% in the years 2010-2012, which is likely linked to the events that occurred during the Arab Spring, mainly the Libyan uprising in 2011, and political unrest in Iran during 2012 (Baumeister and Kilian, 2016). After 2012, OPEC managed to hold a dominant position in the shale oil industry by over-producing crude oil. Given the abundance of oil on the market, the spillover index decreased to 20% at one point in 2014, for the first time since 2001. Most likely, shale oil has played a moderating role in the development of the oil volatility connectedness during the years 2016 and 2022 (Naeem, Balli, Shahzad and de Bruin, 2020; Billah, Karim, Naeem and Vigne, 2022).

The China-US trade war led in years 2018 and 2019 decreased the demand for oil in China - the biggest oil consumer in the world. This caused the spillover index to fluctuate around 50% with moderate volatility. Multiple production cuts by OPEC between 2016 and 2020 also pushed oil prices higher during this period. The spillover index peaked in March 2020 due to the COVID-19 pandemic and the Russia-Saudi oil price war. In February 2022, Russia invaded Ukraine, which prolonged the period of extreme spillovers until the end of April 2022. After the European Union leaders decided to ban most Russian oil and gas export, and Ukraine has shown the first signs of successful resistance, the spillover index decreased to 20% again.

5.2 Impact of Events

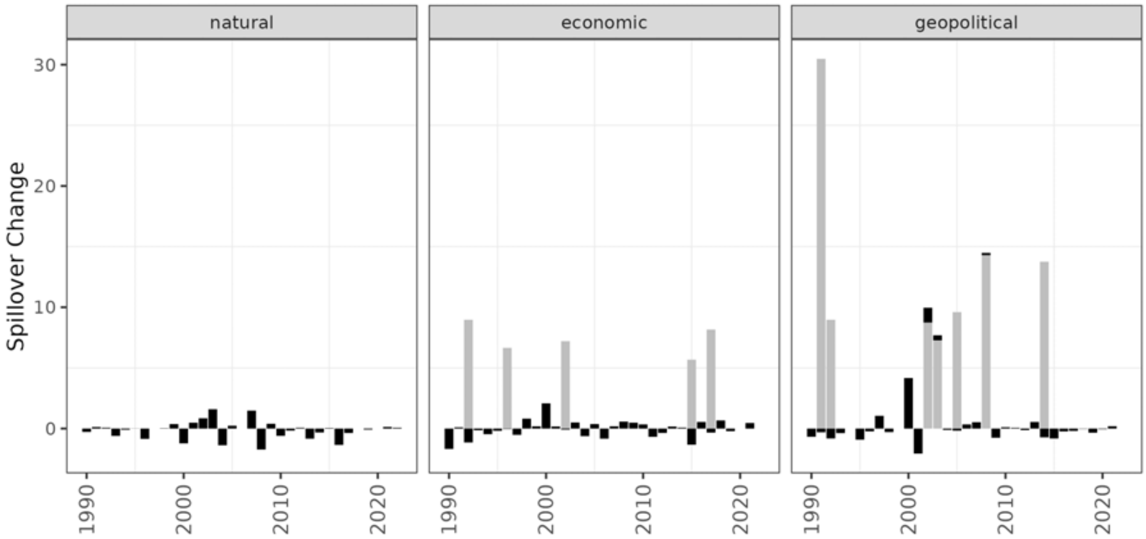
We ran the bootstrap-after-bootstrap test to obtain the spillover distributions for each of the rolling windows. The number of bootstrap samples to generate was set to 1000 for both the bias correction and for generating the final spillover distribution. During the computation of the bootstrap samples in step 2 of the bootstrap test, we sampled the disturbances from a normal multivariate distribution with a mean equal to 0 and standard errors equal to the deviation of the respective asset. Since we iteratively generate one hundred auto-correlated observations, the disturbance inflates the variance of the results substantially. The spillover resulting from this iterative approach is almost always lower than the initial spillover estimate $\widehat{S}$. Nevertheless, the difference between the bias-corrected mean of spillovers and the initial spillover has a normal distribution with a mean close to zero and a standard deviation of 0.15. Thus, the correction is never too extreme.

In order 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 mimics the conventional significance level equal to 0.05 in a one-sided hypothesis testing. Since we gathered 891 events with mostly distinct dates, and the test identified 122 dates, we can expect some events to have a similar date as one of the test dates even though it is not responsible for the increase. This spurious correlation is the reason why we can not draw causal inferences in all cases.

We require the events to influence 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. When an event of this description appears, oil-based commodities should be viewed as a risky investment as volatility will be increasingly shared between them. Only 7 out of the 29 events did not have an effect lasting for 4 days after the event, which leaves us with 22 events on which we focus in our analysis. The event distribution in time is shown in Figure 3.

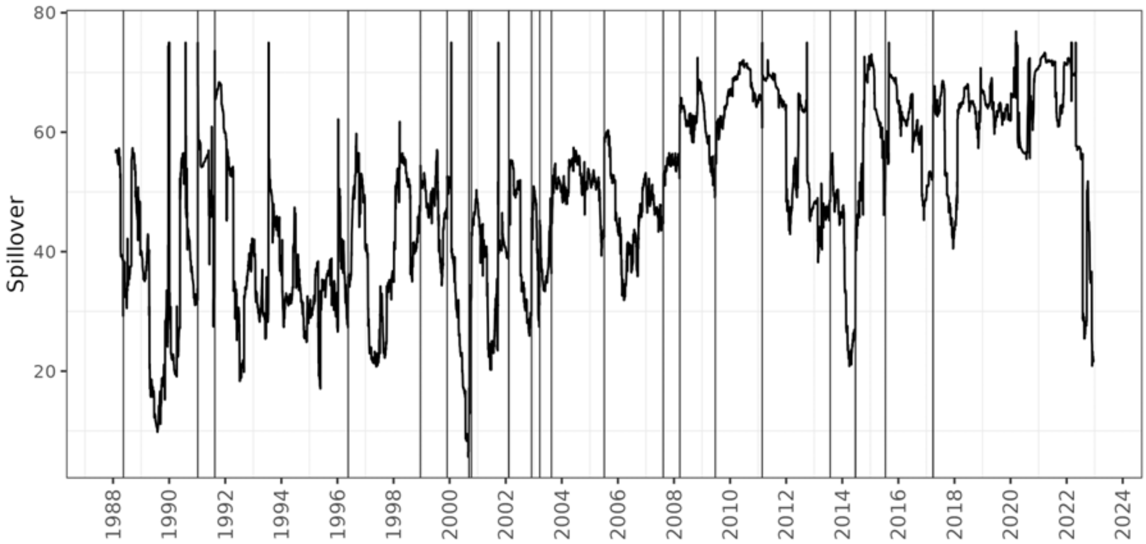
Further, in Figure 2 we show that, in general, the mean spillover changes are randomly distributed over time. The plot pattern implies that the spillover increases are not becoming more pronounced with time. Despite the general pattern, the grey bars depicting events that did pass the significance threshold of the test indicate that economic events exhibit a rather stable development associated with mild spillover increase of around 10%, while geopolitical events exhibit more varying impacts on the volatility connectedness.

Figure 2: Absolute spillover changes in time



Notes: This figure shows the mean change in spillover of all events. For each event, the mean change is calculated as the difference between the means spillover in the 5 days following the event, and the spillover value prior to the event. These mean changes are then average over all years. The grey bars are means of events that passed the significance threshold, while the black bars are means of the other events.

Figure 3: 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.

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 in order to (i) illustrate their nature in detail, (ii) to provide sufficient background on their potential to impact connectedness, and (iii) to draw some generalizations.

5.2.1 Geopolitical events

Table 5: Test results: Geopolitical events

Date	Event Description	Window	Event Count (%) J=0	J=1	J=2	J=3	J=4	Threshold passed	Chance of Causality
15.05.1988	Soviet Union begins removal of its troops from Afghanistan	100	100	100	100	100	100	Yes	Low
15.05.1988	Iraq Bombs 5 Huge Tankers at Iran Oil Site	100	100	100	100	100	100	Yes	High
09.01.1991	Geneva Peace Conference	100	100	100	100	100	100	Yes	High
		200	100	100	100	100	100	Yes	
19.08.1991	1991 Soviet coup d'etat attempt	100	100	100	100	100	100	Yes	High
		200	38,8	34,6	38	38,4	35,7	No	
27.11.1992	Venezuela: coup against government	100	58.3	100	99.5	99.1	99.2	Yes	High
		200	2,2	3	3,1	2,5	2,8	No	
20.05.1996	Oil-for-Food Programme	100	100	100	100	100	100	Yes	High
		200	100	99,8	100	100	100	Yes	
12.10.2000	Blast kills sailors on US ship in Yemen	100	80	97	96,9	96	96,8	Yes	Moderate
		200	55,5	56,9	52	47,7	48,3	No	
08.02.2002	Iraq obstructs UN inspectors	100	47,6	100	99,9	99,8	100	Yes	High
		200	51,1	44,2	44,6	45,2	41,5	No	
03.12.2002	General strike in Venezuela begins	100	100	100	100	100	100	Yes	High
		200	47,7	43,9	46,5	43,1	45,5	No	
01.05.2003	US claims victory in Iraq	100	52,4	51,5	49	47,7	42,1	No	Low
		200	53,3	100	100	100	100	Yes	
17.03.2003	British Cabinet Minister resigns over plans for the war with Iraq	100	26,3	82,2	68,9	94,7	100	No	Low
		200	99,3	100	100	100	100	Yes	
17.03.2003	US: Bush gives Saddam Hussein and his sons 48 hours to leave Iraq	100	26,3	82,2	68,9	94,7	100	No	High
		200	99,3	100	100	100	100	Yes	
20.03.2003	Start of ground invasion in Iraq by US-led coalition	100	88,5	99,8	99,8	99,7	99,3	Yes	High
		200	100	100	100	100	100	Yes	
19.08.2003	Bomb attack on UN headquarters in Iraq	100	100	100	100	100	100	Yes	Moderate
		200	44	43,2	48,1	54,1	52	No	
14.08.2007	Iraq: biggest attack since the beginning of the war	100	44,8	100	100	100	100	Yes	Moderate
		200	42,5	41,4	46,2	48,6	46,8	No	
23.02.2011	Arab Spring: Half of Libya oil production shut down	100	75,7	100	99,1	99,6	99,5	Yes	Moderate
		200	18	65,3	54,9	55,4	58,6	No	
21.08.2013	Syrian Opposition Claims 1300 Killed in Chemical Attack	100	57	64,1	58,8	66,1	34,6	No	Moderate
		200	55,8	100	100	100	100	Yes	
20.06.2014	Troops Trapped in Iraq's Key Refinery	100	58,9	100	100	100	100	Yes	Moderate
		200	58	32,9	26,1	99,1	98,6	No	
23.06.2014	Iraq confirms oil refinery loss	100	100	100	100	100	100	Yes	Moderate
		200	25,8	18,7	96,3	96,5	96,6	No	
17.07.2015	Last bid to kill Iran nuclear deal blocked in Senate	100	99,7	98,7	99,2	98,7	99,6	Yes	High
		200	51,2	45,5	48,7	49,1	50,5	No	
28.03.2017	Donald Trump signs Energy Independence executive order	100	100	100	100	100	100	Yes	High
		200	43,3	46,5	46,3	51,7	48,7	No	
20.01.2021	Biden set to rejoin Paris climate accord	100	52,1	53,5	53	56,8	63,4	No	High
		200	99	99,6	99,8	100	99,8	Yes	

Notes: This table features all geopolitical events that passed the conventional statistical significance threshold. Each event shows evaluation for a window length of 100 and 200 days. The 'Event Count' columns show the percentage of the 1000 bootstrapped values that were higher than the previous mean value. To deem the effect continuously influential, we require the event to pass the threshold for 1 to 4 days after the event occurs, which corresponds to one trading week. We do not include the effect on the day that the event occurred to control the speed of information flow among news channels. The last column contains our results credibility assessment based on the analysis in Section 5.

As apparent from Table 5, geopolitical events were notably more influential on the spillover index in comparison with the economic and natural event categories. Although the ratio of geopolitical and economic events was balanced, we identified 17 geopolitical and only 4 economic events. Two of the significant events appeared in the news on May 15, 1988. First, the Soviet Union publicly announced the removal of its troops from Afghanistan. Although this act likely boosted the expectations for Soviet development, the decision to withdraw was already brought to the public by February 1988, so this event was likely not influential on the spillover index. However, on the same day, Iraq bombed Iran's offshore terminal and damaged the Seawise Giant supertanker, which is the world's largest ship ever built (Torbat, 2005a). Four other large tankers were damaged as well. The fear of losing that much transporting capacity likely triggered an increase of connectedness in oil-based commodities.

The Geneva Peace Conference that took place on December 1, 1991 triggered a significant spike in connectedness. The spillover index increased from 31% to 75% and remained around 50% for the subsequent month. On that day the representatives of Iraq and the US failed to negotiate a peaceful solution for the Iraqi invasion of Kuwait. The conference was viewed as the last chance to secure peace in the Middle East (Freedman and Karsh, 1993). The Geneva Peace Conference is a good example of an event with an unanticipated outcome and effective market reaction. A week after the conference, Operation Desert Storm was launched, and the US immediately released 17.3 million barrels of oil from the Strategic Petroleum Reserve. Nevertheless, these events did not affect the connectedness. Kilian and Zhou (2020) reach a similar conclusion regarding the release from the Strategic Petroleum Reserve, stating that there is no clear evidence of the oil reserves having prevented a larger increase in the oil price during that period.

After the Soviet army withdrew from Afghanistan, Gorbachev became president and introduced market reforms meant to modernize the Soviet Union. The Soviet coup d'etat attempt happened on August 19, 1991. The index spiked to levels of 50% and stayed there for more than a year. The Venezuelan coup d'etat triggered another significant spike in connectedness on November 27, 1992. Both coups were unexpected and happened in major oil-exporting countries, which is likely the reason behind the spike.

On May 20, 1996, the United Nations released a memorandum of understanding with the Government of Iraq regarding the Oil for Food Program. The program initially enabled Iraq to sell crude oil worth 1 million US dollars. The proceedings of this sale could only be used for ensuring the humanitarian needs of Iraqi citizens, although 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 and increased steadily through the rest of the year 1996.

On December 16, 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 1988. 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. On February 8, 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 of the spillover index from 40 to 50%.

As argued in Section 3, oil prices in the years 2002 and 2003 were mostly driven by oil supply disruptions in Venezuela and the war against Iraq. Both these events were identified by the test. First, the state-owned Venezuelan oil company Petróleos de Venezuela was a key point during the protest. The company was shut down for more than a month due to general protests across the country. Consequently, 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 December 4, 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. Despite that there was not enough evidence to gain approval from Russia and China, the United States initiated military action against Iraq on 20 March 2002 (Bassil, 2012). Since the invasion was anticipated days before, its effect on the market and connectedness was mild and short-lasting.

The UN headquarters in Iraq was bombed on August 19, 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. In any case, given that the index stabilized at levels between 50 to 60% for several years after the attack, it is not feasible to attribute all the behavior to just this event. August 14, 2007, brought the biggest 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 does not directly influence oil supplies, but it likely caused fear over the development of the war conflict. The connectedness increased significantly by 10 basis points.

The attacks of September 11, 2001, did not trigger a direct and permanent increase in the connectedness of oil commodities. As major US commodity exchanges were closed for several days after the attacks, the index decreased in value for the subsequent week due to the substitution of the missing data as described in Section 3.

On February 23, 2011, a large Italian oil company operating in North Africa was forced to shut down its 150,000 barrels per day production due to the Libyan uprising (Baumeister and Kilian, 2016). A shift in production of that magnitude combined with the fear that the protests would quickly spread to other countries in North Africa increased the connectedness by 15 percentage points up to 75%. The Arab Spring was the first period during which the spillover index for oil-based commodities stayed around 60% for a prolonged period of time. None of the remaining events connected to the civil war in Syria, Libya, or the protests in Egypt, affected the connectedness enough to cause another shift in

2011.

The last important 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 June 20, Iraqi troops fought with 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 key 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, June 23, 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 the increase in connectedness, but the capture of the Baiji refinery as a whole was most certainly influential.

After the Middle Eastern geopolitical tensions finally settled, the spillover index started to be influenced by events more political in nature. One such event is the Iran Nuclear Agreement introduced under the presidency of Barack Obama. On May 17, 2015, the US Senate blocked the legislation meant to disapprove the accord for a third time, which officially secured its subsequent implementation (Zengerle, 2015). Even though the Nuclear Plan was publicly debated since 2013, only this decisive event had an effect on the connectedness. 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). Moreover, various economic sanctions would be lifted, which include the sale of Iran's crude oil. The spillover index increased by a modest 5 percentage points on the day of the news.

Another important policy with regards to oil volatility spillovers was Obama's Clean Power Plan. It was not the implementation that caused volatility spillovers, but rather the order to undo the measures connected to the Clean Power Plan given by Donald Trump on March 28, 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 January 24, 2017, the withdrawal from Paris Climate Agreement announced on June 1, 2017, or quitting the Iran Nuclear Agreement on May 8, 2018, did not have any immediate impact on 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 are linked with a gradual decrease of 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

Table 6: Test results: Economic events

Date	Event Description	Window	Event Count (%) J=0	J=1	J=2	J=3	J=4	Threshold passed	Chance of Causality
27.11.1992	OPEC meeting: increase in production quota	100	58,3	100	99,5	99,1	99,2	Yes	Low
		200	2,2	3	3,1	2,5	2,8	No	
11.02.2002	Russia increases production and oil exports	100	99,9	99,9	99,7	100	100	Yes	High
		200	41	42,8	42,9	39	39,4	No	
03.06.2004	OPEC agrees to raise output	100	92,1	92,4	83,9	82,3	76,4	No	Moderate
		200	100	99,8	100	100	99,5	Yes	
22.06.2009	World Bank Report	100	43,2	99,1	96,2	97,7	95,9	Yes	Moderate
		200	46,4	54,5	58,3	56,5	53	No	
27.03.2017	OPEC, non-OPEC to look at extending oil-output cut by six months	100	50,5	100	100	100	100	Yes	High
		200	44,8	42,4	45,2	45	51	No	

Notes: This table features all economic events that passed the conventional statistical significance threshold. Each event shows evaluation for a window length of 100 and 200 days. The 'Event Count' columns show the percentage of the 1000 bootstrapped values that were higher than the previous mean value. In order to deem the effect continuously influential, we require the event to pass the threshold for 1 to 4 days after the event occurs, which corresponds to one trading week. We do not include the effect on the day that the event occurred to control the speed of information flow among news channels. The last column contains our results credibility assessment based on the analysis in Section 5.

Events of an economic nature are much less prevalent in the set of significant events. Official decisions to boost, maintain, or cut oil production had an insufficient amount of hits to draw conclusions about the difference in the effect of these decisions. Among the 145 events concerning changes in oil production, only three passed the test threshold. Specifically, it is two decisions to boost production and one decision to cut it. 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.

The first production boost that coincides with a spillover index increase occurred on November 27, 1992. However, since the boost was not accompanied by any unexpected circumstances, the previously mentioned coup in Venezuela that broke out on the same day is more likely to be causal on this day. The next production boost did not come from OPEC, but from Russia. Until 2001, Russia acted mostly in accord with OPEC decisions and cut their petroleum exports along with OPEC. A change came during the 2000s when Russia increased their exports from 300 million tons (in 2000) to 500 million tons in 2009 (Vatansever, 2010). While OPEC cut production in an attempt to keep petroleum prices high, Russia expanded into Europe (Hill and Fee, 2002). By 2002, Russia exported over 7 million barrels daily. In an environment of extreme oil prices and production cuts, the decision to boost exports could have been influential on the spillover index. Again, Russia's decision to boost production while the rest of the oil producers attempted to decrease their production presented itself as negative and unexpected news that introduced uncertainty. On March 26, 2017, major OPEC and non-OPEC oil exporters debated an extension of production cuts from December 10, 2016. While the initial cut had almost no effect on the spillover index, the possibility of an extension for an additional 6 months raised the index from 52% to 64% despite the possibility of the extension being communicated only in the form of the initial announcement. The cut was slightly above average compared to other historical production changes. Thus, the differentiating factor against other scheduled OPEC meetings seems to be the uncertainty. While it was expected that the cut would be extended in an earlier draft of the statement, the final version pushed the decision to April (Soldatkin and Gamal, 2017). The crude oil price increased by 12.5% in the weeks following the statement.

Apart from the production change announcements, there was only one other economic event that significantly increased oil volatility spillovers. The World Bank released an analysis of global trade and the economic outlook of developing countries on June 22, 2009. According to the report, the global output was supposed to fall by 2.9% and the world trade by 10%. The capital flow needed to support developing countries was expected to drop by nearly 50% in 2009 (World Bank, 2012). The stock market reacted negatively to the news, with commodity prices to follow. There are multiple reasons why this economic outlook could affect the connectedness of oil-based commodities. First, crude oil and its products constitute a non-negligible part of global output and world trade. Second, a majority of countries in the Middle East and South Africa are still developing economies. Thus, the decrease in capital inflow to these countries could worsen the condition for efficient oil extraction and transportation. The spillover index reached a local minimum of 49% during that day and kept increasing until the end of the year 2012.

By analyzing the list of events that are more economic in nature, there are a few observations that we can draw. First, events involving the discovery of new oil fields, development of oil facilities, or mergers of oil companies do not affect the connectedness of oil-based commodities. There are two possible explanations for the unrelatedness of mergers: (i) events connected to mergers and developments are too local in scale to cause a shift in the oil spillover index, (ii) mergers and acquisitions of oil companies are essentially good news for the oil market, as investors can expect increased and stable production of oil-based commodities. Second, news reporting on the current state of oil stock, or the release of reserves from the Strategic Petroleum Reserve, never passed the threshold of the bootstrap test. One possible explanation is that releases from the Strategic Petroleum Reserve historically happened in reaction to some other significant event. Lastly, the most surprising finding is that the implementation or extension of sanctions against specific countries never caused a reaction in the spillover index. As was the case with releases from the Strategic Petroleum Reserve, sanctions typically follow after a war conflict, which is more likely to be a source of increased connectedness. More importantly, no sanctions have ever been implemented against Saudi Arabia, which is the main producer and exporter of oil among OPEC members. Sanctions imposed on smaller exporters are not substantial enough to cause an increase in volatility spillovers among oil-based commodities. The ineffectiveness of trade sanctions was further analyzed by Torbat (2005b) who concludes that total imports and exports of crude oil do not change when sanctions are imposed. As oil is a necessity good, exporting countries will simply change buyers when presented with sanctions. On the other hand, financial sanctions are much more effective in comparison to trade sanctions.

It is especially surprising that neither of the events connected to the Russia-Saudi oil price war starting in March 2020 triggered a prompt increase in the connectedness. After Saudi Arabia announced the oil price discount and initiated the oil price war on March 8, 2020, the index spiked to its maximum value of 75% several times but 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 for the main window length of 100 days. The PTT Global Chemical oil spill occurred on July 27, 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 when compared to the production changes of OPEC, 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 is approximately just a third of the US daily production in the year 2010 (Energy Information Administration, 2022). Even though hurricanes, earthquakes, and extreme temperatures were historically responsible for the shutdowns of oil production facilities, none of them 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, as they are too local and their effect on overall oil supply is too small with respect to global oil production.

Table 7: Test results: Natural events

Date	Event Description	Window	Event Count (%) J=0	J=1	J=2	J=3	J=4	Threshold passed	Chance of Causality
27.07.2013	PTT Global Chemical Pcl oil pipeline spill	100	48,7	97,3	99,4	99,1	98,8	Yes	Low
		200	66,3	67,1	72,2	74,9	78,2	No	
17.08.2017	Hurricane Harvey	100	37,7	38,7	36,9	36,9	38,6	No	Low
		200	100	100	100	100	100	Yes	

Notes: This table features all natural events that passed the conventional statistical significance threshold. Each event shows evaluation for a window length of 100 and 200 days. The 'Event Count' columns show the percentage of the 1000 bootstrapped values that were higher than the previous mean value. In order to deem the effect continuously influential, we require the event to pass the threshold for 1 to 4 days after the event occurs, which corresponds to one trading week. We do not include the effect on the day that the event occurred to control for the speed of information flow among news channels. The last column contains our results credibility assessment 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, 2023).

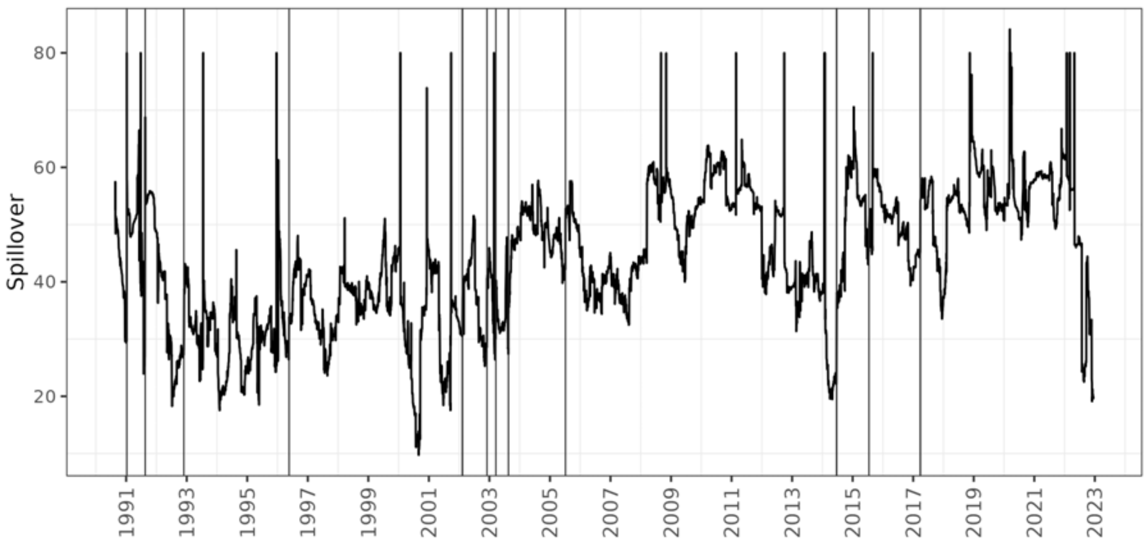
Adding natural gas to the network significantly decreases the overall spillover index down to 37.25%. This is due to the fact that natural gas is the most isolated commodity in the network. Natural gas is responsible for its own volatility from 97.90%. This result is in line with the findings of Mensi et al. (2021) and Kočenda and Moravcová (2023), who also report natural gas to be the best hedge among these commodities. Gasoline-crude oil pair remains to be the most connected pair.

The rolling spillover index retains its dynamic pattern after adding natural gas to the network. However, natural gas reduces the volatility of connectedness and pushes its average to lower level. On the other hand, more brief spikes appear, which are usually tied to sudden correlated moves in all the assets. March 2020 represents perhaps the only period of the energy commodities spillover index (see Figure 4) being higher than the oil spillover index (see Figure 3). Due to the reduced volatility, there were no new events identified by the test that were not previously included in the oil-only set of events.

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 text did not produce any changes with respect to 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. In accordance with 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.

Figure 4: Connectedness dynamics of energy commodities



Notes: This 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.

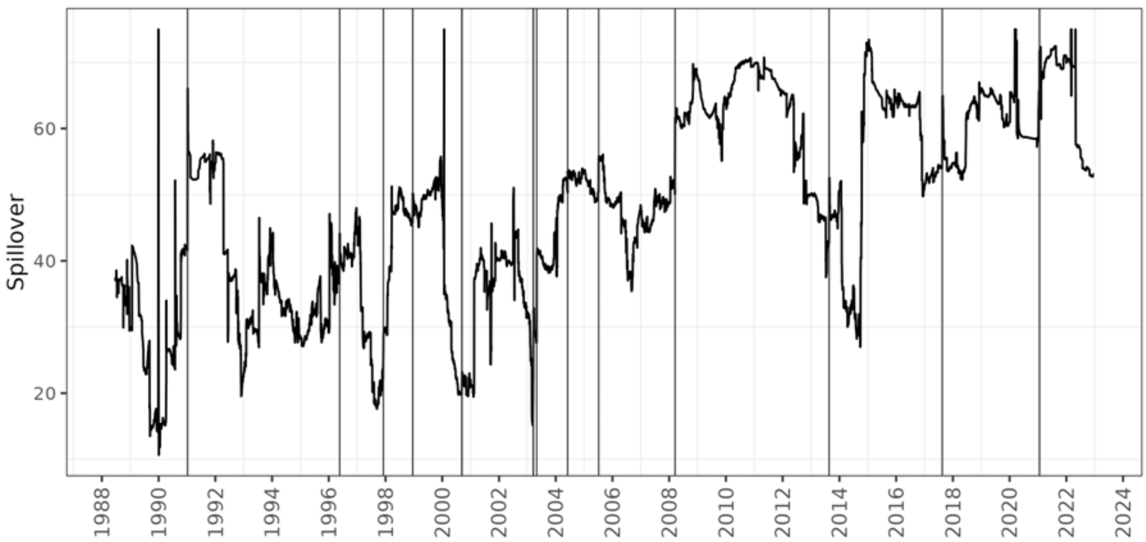
In terms of the connectedness dynamics, the 200-day rolling window spillover plot in Figure 5 appears to be a smoothed version of the 100-day version. Hence, the long-term development stays the same. As could be expected, increasing the length of the window to 200 produces a smoother index and reduces the number of identified events from 22 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.

6 Conclusion

The objective of this study was to analyze volatility spillovers between oil-based commodities, detect events that caused sudden and lasting increases in volatility spillovers of the commodities, and identify 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 22 statistically sig-

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.

nificant 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.

References

Aguilera, Roberto F and Marian Radetzki, "The synchronized and exceptional price performance of oil and gold: explanations and prospects," *Resources Policy*, 2017, *54*, 81–87.

Almutairi, Hossa, Axel Pierru, and James L Smith, "The value of OPEC's spare capacity to the oil market and global economy," *OPEC Energy Review*, 2021, *45* (1), 29–43.

Aloui, Riadh, Mohamed Safouane Ben Aïssa, and Duc Khuong Nguyen, "Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?," *Journal of Banking & Finance*, 2011, *35* (1), 130–141.

Ansari, Esmail, Robert Kaufmann et al., "The effect of oil and gas price and price volatility on rig activity in tight formations and OPEC strategy," *Nature Energy*, 2019, *4* (4), 321–328.

Antonakakis, Nikolaos and David Gabauer, "Refined measures of dynamic connectedness based on TVP-VAR," 2017.

Baruník, Jozef and Evžen Kočenda, "Total, asymmetric and frequency connectedness between oil and forex markets," *The Energy Journal*, 2019, *40* (Special Issue).

_ and Lukáš Vácha, "Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis," *Energy Economics*, 2012, *34* (1), 241–247.

Barunik, Jozef and Lukas Vacha, "The Dynamic Persistence of Economic Shocks," *arXiv preprint arXiv:2306.01511*, 2023.

Baruník, Jozef and Tomáš Křehlík, "Measuring the frequency dynamics of financial connectedness and systemic risk," *Journal of Financial Econometrics*, 2018, *16* (2), 271–296.

_ , Evžen Kočenda, and Lukáš Vácha, "Volatility spillovers across petroleum markets," *The Energy Journal*, 2015, *36* (3).

_ , _ , and _ , "Asymmetric connectedness on the US stock market: Bad and good volatility spillovers," *Journal of Financial Markets*, 2016, *27*, 55–78.

Bassil, Youssef, "The 2003 Iraq war: operations, causes, and consequences," *Journal of Humanities and Social Science*, 2012, *4* (5), 29–47.

Baumeister, Christiane and Lutz Kilian, "Forty years of oil price fluctuations: Why the price of oil may still surprise us," *Journal of Economic Perspectives*, 2016, *30* (1), 139–60.

Billah, Mabruk, Sitara Karim, Muhammad Abubakr Naeem, and Samuel A. Vigne, "Return and volatility spillovers between energy and BRIC markets: Evidence from quantile connectedness," *Research in International Business and Finance*, 2022, *62*, 101680.

Bomberg, Elizabeth, "Environmental politics in the Trump era: an early assessment," *Environmental Politics*, 2017, *26* (5), 956–963.

Brown, Stephen PA and Mine K Yücel, "Energy prices and aggregate economic activity: an interpretative survey," *The Quarterly Review of Economics and Finance*, 2002, *42* (2), 193–208.

Bubák, Vít, Evžen Kočenda, and Filip Žikeš, "Volatility transmission in emerging European foreign exchange markets," *Journal of Banking & Finance*, 2011, *35* (11), 2829–2841.

Casassus, Jaime, Peng Liu, and Ke Tang, "Economic linkages, relative scarcity, and commodity futures returns," *The Review of Financial Studies*, 2013, *26* (5), 1324–1362.

Chan, Kam Fong and Philip Gray, "Do Scheduled Macroeconomic Announcements Influence Energy Price Jumps?," *Journal of Futures Markets*, 2017, *37* (1), 71–89.

Chang, Chia-Lin, Michael McAleer, and Roengchai Tansuchat, "Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets," *Energy Economics*, 11 2010, *32* (6), 1445–1455.

Chatziantoniou, Ioannis, David Gabauer, and Fernando Perez de Gracia, "Tail risk connectedness in the refined petroleum market: A first look at the impact of the COVID-19 pandemic," *Energy Economics*, 2022, *111*, 106051.

CNN, "Kerry assures Iraqis of U.S. support if they unite against militants," Jun 2014. In: CNN [online] `http://edition.cnn.com/2014/06/23/world/meast/iraq-crisis/`, Accessed: 2023-02-22.

Conversino, Mark J, "Operation Desert Fox: effectiveness with unintended effects," *Air & Space Power Journal*, 2005.

Demirer, Mert, Francis X. Diebold, Laura Liu, and Kamil Yilmaz, "Estimating global bank network connectedness," *Journal of Applied Econometrics*, 2018, *33* (1), 1–15.

Diebold, Francis X and Kamil Yilmaz, "Measuring financial asset return and volatility spillovers, with application to global equity markets," *The Economic Journal*, 2009, *119* (534), 158–171.

_ and _ , "Better to give than to receive: Predictive directional measurement of volatility spillovers," *International Journal of forecasting*, 2012, *28* (1), 57–66.

— **and Kamil Yılmaz**, “On the network topology of variance decompositions: Measuring the connectedness of financial firms,” *Journal of econometrics*, 2014, *182* (1), 119–134.

— **, Laura Liu, and Kamil Yilmaz**, “Commodity Connectedness,” Working Paper 23685, National Bureau of Economic Research 8 2017.

Ding, Liang and Minh Vo, “Exchange rates and oil prices: A multivariate stochastic volatility analysis,” *The Quarterly Review of Economics and Finance*, 2012, *52* (1), 15–37.

Elder, John, Hong Miao, and Sanjay Ramchander, “Jumps in oil prices: the role of economic news,” *The Energy Journal*, 2013, *34* (3).

Energy Information Administration, “Oil and petroleum products explained,” 2022. In: Energy Information Administration [online] `https://www.eia.gov/energyexplained/oil-and-petroleum-products/`, Accessed: 2023-09-28.

Fajgelbaum, Pablo D and Amit K Khandelwal, “The economic impacts of the US–China trade war,” *Annual Review of Economics*, 2022, *14*, 205–228.

Fama, Eugene F, Lawrence Fisher, Michael C Jensen, and Richard Roll, “The adjustment of stock prices to new information,” *International economic review*, 1969, *10* (1), 1–21.

Fattouh, Bassam, *An anatomy of the crude oil pricing system*, Oxford institute for energy studies, 2011.

Freedman, Lawrence and Efraim Karsh, *The Gulf conflict, 1990-1991: Diplomacy and war in the new world order*, Princeton University Press, 1993.

Garman, Mark B and Michael J Klass, “On the estimation of security price volatilities from historical data,” *Journal of business*, 1980, pp. 67–78.

Gogolin, Fabian, Fearghal Kearney, Brian M Lucey, Maurice Peat, and Samuel A Vigne, “Uncovering long term relationships between oil prices and the economy: a time-varying cointegration analysis,” *Energy Economics*, 2018, *76*, 584–593.

Gong, Xu, Yun Liu, and Xiong Wang, “Dynamic volatility spillovers across oil and natural gas futures markets based on a time-varying spillover method,” *International Review of Financial Analysis*, 2021, *76*, 101790.

Gorton, Gary and K Geert Rouwenhorst, “Facts and fantasies about commodity futures,” *Financial Analysts Journal*, 2006, *62* (2), 47–68.

Greenwood-Nimmo, Matthew, Evžen Kočenda, and Viet Hoang Nguyen, "Does the Spillover Index Respond to Adverse Shocks? A Bootstrap-Based Probabilistic Analysis," CESifo Working Paper Series 10668, CESifo 2023.

Hamilton, James D, "This is what happened to the oil price-macroeconomy relationship," *Journal of monetary economics*, 1996, *38* (2), 215–220.

_ , "Understanding crude oil prices," *The energy journal*, 2009, *30* (2).

_ , *Historical oil shocks*, Routledge, 2013.

Henriques, Irene and Perry Sadorsky, "The effect of oil price volatility on strategic investment," *Energy Economics*, 2011, *33* (1), 79–87.

Hill, Fiona and Florence Fee, "Fueling the future: the prospects for Russian oil and gas," *Demokratizatsiya*, 2002, *10* (4), 462–487.

Hsieh, Chang-Tai and Enrico Moretti, "Did Iraq Cheat the United Nations? Underpricing, Bribes, and the Oil for Food Program*," *The Quarterly Journal of Economics*, 11 2006, *121* (4), 1211–1248.

Husain, Shaiara, Aviral Kumar Tiwari, Kazi Sohag, and Muhammad Shahbaz, "Connectedness among crude oil prices, stock index and metal prices: An application of network approach in the USA," *Resources Policy*, 2019, *62*, 57–65.

Ji, Qiang, Hai-Ying Zhang, and Jiang-Bo Geng, "What drives natural gas prices in the United States?–A directed acyclic graph approach," *Energy Economics*, 2018, *69*, 79–88.

Kang, Sang Hoon and Jang Woo Lee, "The network connectedness of volatility spillovers across global futures markets," *Physica A: Statistical Mechanics and its Applications*, 2019, *526*, 120756.

Kang, Sanghoon, Jose Arreola Hernandez, Perry Sadorsky, and Ronald McIver, "Frequency spillovers, connectedness, and the hedging effectiveness of oil and gold for US sector ETFs," *Energy Economics*, 2021, *99*, 105278.

Karali, Berna and Octavio A Ramirez, "Macro determinants of volatility and volatility spillover in energy markets," *Energy Economics*, 2014, *46*, 413–421.

_ , Shiyu Ye, and Octavio A Ramirez, "Event study of the crude oil futures market: A mixed event response model," *American Journal of Agricultural Economics*, 2019, *101* (3), 960–985.

Karsh, Efraim, "The Iran-Iraq War, 1980-1988," *Air & Space Power Journal*, 2003, *17* (4), 111–113.

Kilian, Lutz, "Small-sample confidence intervals for impulse response functions," *Review of economics and statistics*, 1998, *80* (2), 218–230.

_ , "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market," *American Economic Review*, 2009, *99* (3), 1053–69.

_ , "Oil price shocks: Causes and consequences," *Annu. Rev. Resour. Econ.*, 2014, *6* (1), 133–154.

_ **and Clara Vega**, "Do energy prices respond to US macroeconomic news? A test of the hypothesis of predetermined energy prices," *Review of Economics and Statistics*, 2011, *93* (2), 660–671.

_ **and Daniel P Murphy**, "The role of inventories and speculative trading in the global market for crude oil," *Journal of Applied econometrics*, 2014, *29* (3), 454–478.

_ **and Xiaoqing Zhou**, "Does drawing down the US Strategic Petroleum Reserve help stabilize oil prices?," *Journal of Applied Econometrics*, 2020, *35* (6), 673–691.

Kočenda, Evžen and Michala Moravcová, "Exchange rate comovements, hedging and volatility spillovers on new EU forex markets," *Journal of International Financial Markets, Institutions and Money*, 2019, *58*, 42–64.

_ **and** _ , "Frequency Volatility Connectedness and Portfolio Hedging of US Energy Commodities," 2023. Available at SSRN. `https://ssrn.com/abstract=4190873`.

Liu, Tangyong and Xu Gong, "Analyzing time-varying volatility spillovers between the crude oil markets using a new method," *Energy Economics*, 2020, *87*, 104711.

Lovcha, Yuliya and Alejandro Perez-Laborda, "Dynamic frequency connectedness between oil and natural gas volatilities," *Economic Modelling*, 2020, *84*, 181–189.

Ma, Richie Ruchuan, Tao Xiong, and Yukun Bao, "The Russia-Saudi Arabia oil price war during the COVID-19 pandemic," *Energy economics*, 2021, *102*, 105517.

Magkonis, Georgios and Dimitris A Tsouknidis, "Dynamic spillover effects across petroleum spot and futures volatilities, trading volume and open interest," *International Review of Financial Analysis*, 2017, *52*, 104–118.

Malik, Farooq and Shawkat Hammoudeh, "Shock and volatility transmission in the oil, US and Gulf equity markets," *International Review of Economics & Finance*, 2007, *16* (3), 357–368.

Malkiel, Burton G, "The efficient market hypothesis and its critics," *Journal of economic perspectives*, 2003, *17* (1), 59–82.

Mei, Dexiang, Feng Ma, Yin Liao, and Lu Wang, “Geopolitical risk uncertainty and oil future volatility: Evidence from MIDAS models,” *Energy Economics*, 2020, *86*, 104624.

Mensi, Walid, Mobeen Ur Rehman, and Xuan Vinh Vo, “Dynamic frequency relationships and volatility spillovers in natural gas, crude oil, gas oil, gasoline, and heating oil markets: Implications for portfolio management,” *Resources Policy*, 2021, *73*, 102172.

Mohaddes, Kamiar and M Hashem Pesaran, “Oil prices and the global economy: Is it different this time around?,” *Energy Economics*, 2017, *65*, 315–325.

Naeem, Muhammad Abubakr, Faruk Balli, Syed Jawad Hussain Shahzad, and Anne de Bruin, “Energy commodity uncertainties and the systematic risk of US industries,” *Energy Economics*, 2020, *85*, 104589.

Nandha, Mohan and Robert Faff, “Does oil move equity prices? A global view,” *Energy economics*, 2008, *30* (3), 986–997.

Natural Gas Intelligence, “Ngi Methodologies & User Guides,” 2022. In: Natural Gas Intelligence [online] `https://www.naturalgasintel.com/methodologies/`, Accessed: 2023-02-020.

Nazlioglu, Saban, Ugur Soytas, and Rangan Gupta, “Oil prices and financial stress: A volatility spillover analysis,” *Energy policy*, 2015, *82*, 278–288.

Ouyang, Zhi-Yi, Zheng Qin, Hong Cao, Tian-Yu Xie, Xing-Yu Dai, and Qun-Wei Wang, “A spillover network analysis of the global crude oil market: Evidence from the post-financial crisis era,” *Petroleum Science*, 2021, *18* (4), 1256–1269.

Reboredo, Juan C., “Volatility spillovers between the oil market and the European Union carbon emission market,” *Economic Modelling*, 2014, *36*, 229–234.

Sadorsky, Perry, “Oil price shocks and stock market activity,” *Energy economics*, 1999, *21* (5), 449–469.

Salisu, Afees A and Hakeem Mobolaji, “Modeling returns and volatility transmission between oil price and US–Nigeria exchange rate,” *Energy Economics*, 2013, *39*, 169–176.

Soldatkin, Vladimir and Rania El Gamal, “OPEC, non-OPEC to look at extending oil-output cut by six months,” 3 2017. In: Reuters [online] `https://www.reuters.com/article/us-oil-opec-idUSKBN16X07V`, Accessed: 2023-02-05.

Squassoni, Sharon A, “Iraq: UN Inspections for Weapons of Mass Destruction,” 2003. Library of Congress Washington DC Congressional research service.

Sterio, Milena, "President Obama's Legacy: The Iran Nuclear Agreement," *Case W. Res. J. Int'l L.*, 2016, *48*, 69.

Sun, Meihong, Huasheng Song, and Chao Zhang, "The effects of 2022 Russian invasion of Ukraine on global stock markets: An event study approach," 2022. Available at SSRN. `https://ssrn.com/abstract=4051987`.

Tang, Ke and Wei Xiong, "Index investment and the financialization of commodities," *Financial Analysts Journal*, 2012, *68* (6), 54–74.

Togonidze, Sophio and Evžen Kočenda, "Macroeconomic responses of emerging market economies to oil price shocks: An analysis by region and resource profile," *Economic Systems*, 2022, *46* (3), 100988.

Torbat, Akbar E., "Impacts of the US Trade and Financial Sanctions on Iran," *The World Economy*, 2005, *28* (3), 407–434.

_ , "Impacts of the US Trade and Financial Sanctions on Iran," *The World Economy*, 2005, *28* (3), 407–434.

United Nations, "Memorandum of understanding between the Secretariat of the United Nations and the Government of Iraq on the implementation of Security Council resolution 986," 1996. In: United Nations Resolutions [online] `https://documents-dds-ny.un.org/doc/UNDOC/GEN/N96/127/71/PDF/N9612771.pdf?OpenElement`, Accessed: 2023-01-18.

Vatansever, Adnan, "Russia's Oil Exports: Economic Rationale Versus Strategic Gains," 2010.

Wang, Qiang, Xi Chen, Awadhesh N Jha, and Howard Rogers, "Natural gas from shale formation–the evolution, evidences and challenges of shale gas revolution in United States," *Renewable and Sustainable Energy Reviews*, 2014, *30*, 1–28.

Wang, Yudong and Zhuangyue Guo, "The dynamic spillover between carbon and energy markets: New evidence," *Energy*, 2018, *149*, 24–33.

World Bank, "The financial crisis: Charting a Global Recovery," 12 2012. In: World Bank Group [online] `https://www.worldbank.org/en/news/feature/2009/06/22/the-financial-crisis-charting-a-global-recovery`, Accessed: 2023-02-05.

Xu, Weiju, Feng Ma, Wang Chen, and Bing Zhang, "Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States," *Energy Economics*, 2019, *80*, 310–320.

Zengerle, Patricia, "Last bid to kill Iran nuclear deal blocked in Senate," 9 2015. In: Reuters [online] `https://www.reuters.com/article/us-iran-nuclear-congress-idUSKCN0RF2VX20150917`, Accessed: 2023-02-05.

Zhang, Bing and Peijie Wang, "Return and volatility spillovers between china and world oil markets," *Economic Modelling*, 2014, *42*, 413–420.

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 orthogonalised 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:

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

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:

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

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 our goal is to analyze the spillover levels before and after a certain event, it is necessary to observe temporal changes of 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). By 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 are able to 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 possibly 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 simply 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.

B Brief history of the oil market

We devote this section to summarizing the historical development of the global oil market. To understand the dynamics and connections of individual events in our dataset, it is necessary to acquire an overall picture of the oil market and its role in modern history. It can be argued that oil price volatility is also influenced by major historical events seemingly unrelated to oil as such. Nevertheless, using the U.S. macroeconomic news, Kilian and Vega (2011) showed that news that is not directly related to energy commodities explains only 0.69 and 1,6% of monthly oil and gas price variation. Thus, we only account for events clearly related to oil in our events dataset, as well as the following overview. For a more comprehensive summary, we refer to the work of Hamilton (2009, 2013); Kilian (2009, 2014).

The 1960s and 1970s brought a series of conflicts in the Middle East, which was the main factor behind oil price changes for the following decades. The price of oil increased in October 1973 due to the Arab-Israeli War. The global output decreased by 7.5 % in November 1973 (Hamilton, 2013). Due to the embargo on oil exports imposed by the Arab States combined with the depletion of US oil fields during this period, the United States experienced a critical shortage of gasoline from 1974 to 1980, which led to long lines at gas stations, rationing of gasoline, massive inflationary pressure, and industrial disruptions. Oil production dropped by another 7% in 1978 due to the Iranian Revolution (Hamilton, 2013). The price of oil more than doubled during this period, leading to a substantial decline in petroleum consumption in the early 1980s.

The Iraq-Iran war was waged in the period from 1980 to 1988. Both countries targeted oil facilities, tankers, and merchant ships to reduce oil exports of the opposing party, which further increased the volatility of oil prices (Karsh, 2003). The war resulted in combined financial losses of over $1 trillion, and a loss in global oil production of 6% (Hamilton, 2013).

In 1988, oil prices began to be mostly market-driven. One significant factor was the collapse of OPEC in 1985, which weakened the cartel's ability to control prices and led to increased competition among oil-producing countries. Additionally, there were more suppliers outside of OPEC, as the nationalization of the oil industry in many countries had led to the emergence of new players in the market. The oil market had also become more complex and interlinked, with a wider range of products and an increased ability to trade oil on global markets. These factors contributed to a shift towards a more market-driven pricing system for oil (Fattouh, 2011).

In 1990, Iraq started yet another war by invading Kuwait. Kuwait ramped up its oil production levels, which kept revenues down for Iraq and further weakened its economic prospects. Kuwait was supported by a military coalition led by the United States, the United Kingdom, France, Saudi Arabia, and Egypt. The price of crude oil doubled in a short time span. The cumulative global production loss due to the conflict was estimated at 9% (Hamilton, 2013). Oil prices started to be more influenced by macroeconomic indicators during this time (Gogolin et al., 2018)

In the mid-1990s, many emerging economies started to develop rapidly, especially in Asia. The so-called Asian Tigers were a group of newly industrialized economies that emerged in the 1980s and 1990s. These countries, which include South Korea, Taiwan, Hong Kong, and Singapore, were responsible for much of the rise in global oil consumption during this time. Although they used only 17% of the world's oil production, they were responsible for 69% of the increase in consumption during this time (Hamilton, 2013). The rapid growth was followed by the Asian financial crisis of 1997, which led to a decrease in demand for oil (Hamilton, 2013). In response to the crisis, OPEC shifted its policy in order to raise the price of crude oil, which had fallen to $10 per barrel by late 1998.

The increased demand in Asian states, tensions in the Middle East, a general strike in Venezuela, and a weak US dollar caused a second energy crisis, which lasted from 2003 to 2008. Despite the repeated attack on Iraq by the United States, and missiles launched by Iraq on Kuwait, the key factor for the steady price increase until 2005 was the growth in demand (Kilian, 2009; Hamilton, 2013; Karali and Ramirez, 2014).

The 2000s brought significant technological advancement in terms of oil and gas extraction. It became possible to extract gas and oil from shale deposits found in close proximity to lakes and rivers using a combination of horizontal drilling and fracking (hydraulic fracturing) (Wang, Chen, Jha and Rogers, 2014). Furthermore, there has been ongoing financialization of commodities since the early 2000s (Tang and Xiong, 2012). Oil became tradable through spot transactions, futures, and forward contracts, which opened a possibility to invest in oil for speculative purposes (Hamilton, 2009). In conclusion, the financialization of commodities has influenced the volatility spillovers across oil-based commodities in a way that oil prices became more sensitive to seemingly unrelated macroeconomic news, and their volatility started to be more connected to overall market volatility (Gogolin et al., 2018; Wang and Guo, 2018).

The Great Financial Crisis induced a sharp drop in energy commodities from the peak of $140 to $40 due to lowered demand. Volatility spillovers between financial assets and commodities spiked significantly (Bubák, Kočenda and Žikeš, 2011; Zhang and Wang, 2014; Xu et al., 2019; Kang and Lee, 2019). The strong linkage between the global economy and oil prices started to weaken after the Global Financial Crisis (Baruník et al., 2015).

The effective extraction of shale oil developed only after 2011, and it increased the US production of crude oil by 3.6 million barrels per day (Ansari, Kaufmann et al., 2019). The influence of OPEC weakened as the private shale oil companies did not regulate their production depending on global needs and the spare capacity of OPEC became less effective (Almutairi, Pierru and Smith, 2021).

OPEC attempted to squeeze shale oil producers out of the market by lowering oil prices, which was partially successful until 2014. As a result of the rapid innovation and increased productivity of oil rigs, OPEC was no longer able to control the market (Diebold et al., 2017; Ansari et al., 2019; Almutairi et al., 2021). During the 2010s, the production share of OPEC fell to approximately a third of global oil output, while the United States increased its oil output by 78% from 2008 to 2016 (Aguilera and Radetzki, 2017).

After 2016, oil prices increased steadily due to demand increases, and production constraints from OPEC, but mainly the US-China Trade War. During this period, both countries imposed tariffs on imports. The U.S. targeted approximately \$350 billion of Chinese imports (Fajgelbaum and Khandelwal, 2022). China also raised the tariffs on crude oil, which induced global demand adjustments and oil price increase.

In March 2020, OPEC decided on a production cut. Russia did not respect the decision, and increased production and exports, to which Saudi Arabia reacted in a similar manner. Russia - Saudi Arabia oil price war coincides with the COVID-19 pandemic, which introduced quarantine measures and reduced the need to commute. Due to these reasons, global consumption of gasoline dropped by 46.40% in March, and the price per barrel fell from \$50 to \$30 (Ma, Xiong and Bao, 2021). There was a massive increase in spare capacity, which caused the price of crude oil to fall to minus \$37 on April 20, 2020. The negative price of crude oil reflects the fact that it was too costly for firms to store the surplus of supply, but investors were willing to pay for not having the oil physically delivered (Ma et al., 2021; Kočenda and Moravcová, 2023).

On February 24, 2022, Russia invaded Ukraine and started yet another volatile period for the oil markets. The Brent Crude oil price spiked to \$105 and gas prices rose by 40-50% on that day (Sun, Song and Zhang, 2022). Nonetheless, Europe managed to cut most of the Russian oil imports by the end of 2022. The price of oil and gas started to decline in the second half of 2022 due to the release of US reserves and the OPEC production increase.

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