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The impact of oil-related events on volatility spillovers across oil-based commodities

Master's thesis

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Declaration of Authorship

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Abstract

Although oil-based commodities play a crucial role in the world from an industrial perspective, their prices are often heavily influenced by the occurrence of various events covered in the news. These events often trigger a sudden increase in volatility, that spills across all oil-based commodities. As a result, it becomes riskier to invest in this group of commodities. Furthermore, the increase in oil price volatility introduces friction in oil trade due to pricing uncertainty. In this thesis, we processed over 900 events related to oil from 1978 to 2022 and grouped them based on a set of repeating characteristics. Utilizing a novel bootstrap-after-bootstrap econometric framework developed by Greenwood-Nimmo *et al.* (2021), we identified over 20 historical events that triggered a sudden and persistent rise in volatility connectedness. We discover that geopolitical events are twice as likely to cause an increase in volatility spillovers than economic events. We did not find evidence for natural events influencing oil volatility spillover levels. Furthermore, a majority of the events after which the spillover levels increased share three common characteristics: they are negative, unexpected, and introduce fear of oil supply shortage. Investors and policymakers can use our findings to assess the potential effect of newly appearing news articles on the volatility of oil-based commodities. Our paper can also serve as a reference source of important events with proven impact on the energy markets.

JEL Classification	N20, N22, N24, N25, N26, N27, G14
Keywords	volatility spillovers, oil commodities, event study
Title	The impact of oil-related events on volatility spillovers across oil-based commodities

Abstrakt

Přestože komodity na bázi ropy hrají ve světě klíčovou roli z hlediska průmyslu, jejich ceny jsou často silně ovlivňovány výskytem různých událostí pokrytých ve zprávách. Tyto události často vyvolávají náhlý nárůst volatility, který se přelévá do všech ropných komodit. V důsledku toho se investice do této skupiny komodit stává rizikovější. Zvýšení volatility cen ropy navíc komplikuje obchodování s ropou v důsledku nejistoty cen. V této práci jsme zpracovali více než 900 událostí souvisejících s ropou od roku 1978 do roku 2022 a seskupili je na základě opakujících se charakteristik. S využitím nové ekonometrické metodologie na bázi bootstrapu od Greenwood-Nimmo *et al.* (2021) jsme identifikovali více než 20 historických událostí, které vyvolaly náhlý a trvalý nárůst přelivů volatility. Zjistili jsme, že geopolitické události jsou dvakrát pravděpodobnější příčinou nárůstu přelivů volatility než ekonomické události. Nenašli jsme důkazy o vlivu přírodních událostí na úroveň přelévání volatility ropných komodit. Většina identifikovaných událostí má tři společné charakteristiky: jsou negativní, neočekávané a vyvolávají obavy z nedostatku ropy. Investoři mohou naše výsledky využít k posouzení potenciálního vlivu nově se objevujících zpráv na volatilitu ropných komodit. Náš článek může také sloužit jako referenční zdroj důležitých událostí s prokázaným dopadem na energetické trhy.

Klasifikace JEL	N20, N22, N24, N25, N26, N27, G14
Klíčová slova	přelivy volatility, ropné komodity, event study
Název práce	The impact of oil-related events on volatility spillovers across oil-based commodities

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Acronyms

WTI West Texas Intermediate

OPEC Organization of the Petroleum Exporting Countries

HAR heterogeneous autoregressive

RV realized volatility

VMA vector moving average

GARCH generalized autoregressive conditional heteroskedasticity

AIC akaike information criterion

UN United Nations

VAR vector autoregressive

Chapter 1

Introduction

The price of most assets on the markets is closely influenced by the current development globally important events. It has been proven empirically that the market usually prices in information arising from newly appearing events rather quickly and efficiently (Fama *et al.* 1969; Malkiel 2003). Compared to other assets, oil commodities are more sensitive to macroeconomic events such as supply chain shocks, political concerns, or natural disasters (Baruník *et al.* 2015; Karali *et al.* 2019). Nevertheless, the demand reaction for oil is often disproportionate to the actual shock 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. Thus, two important questions arise: How can we assess, whether a sudden change in volatility spillover levels is associated with a particular event? And what are the characteristics of the events that influence volatility spillovers?

Asset volatility reflects the arrival of new information into the market, and volatility spillovers depict the information flow between markets (Reboredo 2014). Spillovers can be attributed to supply and demand imbalances, transaction costs, or information asymmetries (Kilian 2009; Magkonis & Tsouknidis 2017). These causes reveal arbitrage opportunities for informed traders, who can take advantage of these opportunities with cross-market transactions until the arbitrage disappears (Roll & Ross 1980). Conversely, uninformed investors are likely to follow the herd with their investments because they expect a major change in economic fundamentals (Bohl *et al.* 2017; Liu & Gong 2020).

Volatility can be viewed as a proxy for risk. Thus, proper identification and measurement of volatility spillovers can be a valuable input for portfolio diversification strategies for investors and financial institutions. It helps investors with risk management and portfolio diversification by identifying hedging opportunities (Baruník *et al.* 2017). The stability of financial systems can be easily disrupted by idiosyncratic shocks to one asset. Thus, causes of volatility spillovers between markets are also important for policymakers, as they can identify early warning signs of an upcoming crisis (Diebold & Yilmaz 2012).

The topic of volatility spillovers among oil-based commodities in particular is as important as it is complex. Crude oil and the products refined from it play a crucial role in the global economy as they are a necessity in the industrial, agricultural, and transportation sectors. Due to the disproportionate geological endowments of oil formations, it is one of the most traded items in the world. Thus, increased volatility of oil prices does not only affect investors but also the economies of entire countries. Oil supply disruptions cause a decrease in GDP, currency depreciation, and inflationary pressure (Kilian 2009; Ding & Vo 2012; Mohaddes & Pesaran 2017). For all these reasons, it is necessary to understand the causes of volatility spillovers among oil-based commodities.

In this thesis, we gathered prices of 5 energy-based commodities: crude oil, heating oil, gasoline, diesel, and natural gas between the years 1978 and 2022. Using daily realized volatility estimates of these commodities, we compute the rolling spillover index introduced by Diebold & Yilmaz (2009); Diebold & Yılmaz (2014), which represents the degree of volatility connectedness of the network on each day of the studied period. Furthermore, we collected 900 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 bootstrap-based test introduced by Greenwood-Nimmo *et al.* (2021), which enables us to statistically assess the probability that the spillover index persistently increased on any given day.

This analysis provides two key insights into the topic of volatility spillovers among oil-based commodities. Out of the 900 events included in our dataset, we identified over 20 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. Therefore, our paper can also serve as a reference source of important events with proven impact on the energy markets.

We detected several characteristics that were prevalent among the significant events. Firstly geopolitical events are twice as much likely to cause a sudden and persistent increase in volatility spillovers than economic events. Furthermore, most economic events identified by the test are based on some geopolitical reasoning. A majority of the events were unexpected, negative, and caused a decrease in oil exports. These findings are in line with results of (Greenwood-Nimmo *et al.* 2021) who show that unanticipated and negative events are most likely to cause a sudden increase in the spillover levels reported in the seminal study of Diebold & Yilmaz (2009).

We further divided the three main categories into 18 distinct groups based on the features of the event in question. Using this division we were able to further generalize our results into more useful suggestions. Our analysis confirms some predictable outcomes such as acts of terrorism being highly influential on the spillover index, while acts of peace and other good news never increase the connectedness of oil-based commodities. Another impactful conclusion obtained by our analysis concerns decisions on production changes. We arrive at results that are contrary to the rational notion that production cuts are more likely to increase volatility spillovers among oil-based commodities.

The thesis is structured as follows: Chapter 2 describes previous work done in the field of volatility spillovers both in general and of oil-based commodities specifically. The relationship of crude oil with the global economy, and previous studies analyzing the effect of the news on oil returns and volatility are also presented. Chapter 3 outlines the data cleaning procedure leading to a set of realized volatility for selected commodities and describes the news dataset. Chapter 4 introduces the relevant methodology of volatility spillovers and the novel bootstrap-after-bootstrap test. Chapter 5 presents the results of the oil-based commodities network connectedness and analyzes events identified by the bootstrap test. Chapter 6 summarizes our findings.

Chapter 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 industrial, transportation, and agricultural sectors. Higher oil prices can induce a rise in the cost of goods and services, and subsequently higher inflation (Nandha & Faff 2008). 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 (Brown & Yücel 2002). Under the assumption that the price increase is temporary, firms and households will borrow more, which puts upward pressure on inflation (Mohaddes & Pesaran 2017). Central banks will then need to increase interest rates in order to handle inflation (Gogolin *et al.* 2018). During periods of high oil price volatility, firms tend to postpone investment decisions due to uncertainty. For some sectors, the marginal cost increases, which results in lesser wage growth and higher unemployment (Brown & Yücel 2002; Gogolin *et al.* 2018). Kilian (2009) argues that increases in demand and oil-supply disruptions significantly decrease real GDP. 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 & 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.

Significant oil price changes are typically indicators of a shift in a global economic environment (Kilian 2009; Husain *et al.* 2019). In general, oil price volatility is associated with negative stock market returns (Reboredo 2014; Mohaddes & Pesaran 2017). Higher oil prices usually foreshadow periods of lower economic growth (Nandha & Faff 2008), although this relationship has been unstable since the early 2000s (Mohaddes & Pesaran 2017). During the Great Financial Crisis and the Covid Crisis, there was a positive correlation between oil and equity markets. The period from 2014 to 2016 was specific in the sense that the oil price decrease was not accompanied by a global economic shock. Thus, the equity markets remained stable. According to Mohaddes & Pesaran (2017), the discrepancy was caused by equity markets ignoring economic fundamentals. The negative relationship holds in the case of oil markets and real dividends, which is considered a better proxy for economic activity by the authors. In conclusion, there is a definite link between oil and the global economy, although the sign of this link is not always stable.

2.2 Volatility spillovers studies

The volatility spillover measure has been used to study most markets, from commodities to cryptocurrency. Apart from the traditional markets, the methodology is well applicable to macroeconomic variables. Authors of the spillover index used it to measure the connectedness of 6 developed countries' industrial production (Diebold & Yilmaz 2013). The findings show that countries with trade deficits, such as the U.S. and Japan in the 2000s, tend to be net transmitters of volatility. Greenwood-Nimmo *et al.* (2015) also apply the methodology to study the links of the global economy, but expand the list of countries, and use more macroeconomic variables such as real exchange rate, imports, and exports, equity prices, GDP, or oil price. The results suggest that the more developed world economies are net volatility transmitters. Crude oil was also identified as a net transmitter. Foglia *et al.* (2022) identify high interconnectedness of the Eurozone banking sector, with spillover peaks detected during crises, including the recent Covid-19 era.

Cross-market volatility spillovers are a useful topic of interest in the literature as well. A study of forex and oil market interaction shows that crude oil reduces volatility spillover of the overall network (Baruník & Kočenda 2019). Similarly, adding commodity futures to a portfolio of index futures provides diversification benefits due to reduced volatility spillovers (Kang & Lee 2019). In a study of spillovers between metal commodities and cryptocurrency, Bitcoin was found to be a net volatility receiver, while also being a heavy transmitter of positive spillovers (Mensi *et al.* 2019). The connectedness was not strong, implying that Bitcoin is a good hedge for the metal commodity market. Not all studies determine a safe asset with little volatility transmission withing their studied network. For example, a study of South African financial markets identified commodities and equity markets as volatility transmitters, while bond and currency markets are volatility receivers (Duncan & Kabundi 2013).

2.3 Oil spillover 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 & Vácha 2012). Ji *et al.* (2018) report that crude oil returns are among the main factors explaining natural gas price volatility. Wang & Guo (2018) suggest that crude oil is a net volatility transmitter, and the Brent Oil index is a volatility receiver. Moreover, the authors conclude that 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 & Tsouknidis 2017). Lastly, futures act as volatility transmitters for spot prices for oil-based commodities (Magkonis & Tsouknidis 2017).

Crude oil is traded in various markets around the world, which advocates for analyzing volatility spillovers between these markets. Zhang & Wang (2014) argue that volatility spillovers between the oil markets of China, the U.S., and the U.K. are bi-directional and asymmetric. The authors 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 *et al.* (2010) used an asymmetric generalized autoregressive conditional heteroskedasticity (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 West Texas Intermediate (WTI) markets are net volatility transmitters. Similar results were obtained by Liu & 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 *et al.* (2021) expand former studies by calculating the volatility spillovers of 31 global crude oil markets. The authors find significant spillovers for both returns and volatility. Using the spillover frequency decomposition by Baruník & Křehlík (2018), it was shown that spillover returns propagate mainly in a short-term horizon, meaning that price discrepancies between regional oil markets are removed within a week. On the other hand, long-term horizons dominate in the context of volatility spillovers, which is likely due to economic cycles and oil supply-demand fundamentals. The source of medium-term volatility spillovers was the Middle East, while Asia-Pacific markets were responsible for the long-term volatility spillovers. By using the frequency decomposition, and including more regional markets, the authors obtained results different from the previously mentioned studies.

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 other markets as well. Gold and silver serve as volatility transmitters mainly during financial crises (Kang *et al.* 2017). In a study of volatility spillovers between U.S. stocks, crude oil, and metal commodities, Husain *et al.* (2019) show that crude oil is a net volatility receiver. The results are driven by platinum, implying that crude oil is otherwise a good hedging option for U.S. stocks and other metal commodities. Similar results were obtained by Baruník & Kočenda (2019) in a study of volatility spillovers between the forex market and crude oil. By adding crude oil, the volatility connectedness of the network decreased, suggesting that crude oil functions as a hedge for the forex market. The findings differ in the case of a commodity portfolio. Diebold *et al.* (2017) concludes that crude oil has the highest net connectedness out of 19 commodities in its analysis, followed by heating oil, soybeans, and zinc.

Due to environmental concerns and the fear of oil sources depletion, there has been a shift toward more environmentally friendly energy sources. These more ecological alternatives serve as substitutes for oil fuels, so we can expect volatility spillovers across related assets. Contrary to these expectations, Umar *et al.* (2022) finds strong volatility connectedness among natural gas, fuel oil, and crude oil markets, but reports very little volatility spillovers for clean energy stock prices. Similar results were obtained by Ferrer *et al.* (2021), adding that most of the volatility connectedness propagates itself in a short-term time frame, implying that crude oil and clean energy stocks are driven by their own fundamentals in the long term. These findings imply that the profitability of clean energy stocks is independent of the crude oil market's development, but also that the crude oil market is still resilient to events associated with clean energy. Lastly, crude oil's volatility is not connected to the price volatility of EU emission allowances (Reboredo 2014), although there are significant volatility spillovers from natural gas prices to the carbon emission market (Wang & Guo 2018). During periods of high oil price volatility, prices of agricultural commodities such as corn, soybean, or wheat, tend to receive this volatility, possibly through the link of using biofuel as a substitute for oil (Yip *et al.* 2020). Diebold *et al.* (2017) argues that soybeans have high net connectedness in a system of commodities, and their connectedness is comparable to crude oil, precisely due to their use in biofuel production.

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. The 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 & 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 *et al.* 2021; Gong *et al.* 2021). On the other hand, Kočenda & 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 *et al.* 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 of the spillover index as a result of the shale gas revolution in

2006. Lovcha & Perez-Laborda (2020) mentioned 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 & 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 news 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 & 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 *et al.* (2019) studied volatility spillovers between oil, U.S., and Chinese stock market. The authors report 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 & 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 pandemic, or the war in Ukraine.

2.4 News studies

The possibility that news can affect oil prices and volatility has already been documented in the literature. Several studies researched the link between the volume of searched articles about oil on Google Scholar (GSV) and oil price volatility. For example, Campos *et al.* (2017) show that the search volume for oil-related articles increases the predictive power in a heterogeneous autoregressive (HAR) model of oil price volatility. Similarly, Gong & Lin (2018) use the oil volatility index (OVX), which is a measure of investor fear gauge in the crude oil market, and find that adding OVX to HAR models significantly improves out-of-sample forecasts of oil volatility. Mei *et al.* (2020) used the Geopolitical Risk index (GPR), which is influenced mainly by wars, terrorism, and tensions among states, and measured its effect the volatility of oil futures. Similarly to Campos *et al.* (2017), the authors state that the GPR index can help in volatility prediction.

Although the aforementioned studies present good proxies, the design of these studies does not differentiate between new and old oil-related articles. Furthermore, the effect of volatility spillovers between oil-based commodities is not accounted for. As far as we are aware, there is only one study that connects oil volatility spillovers to the flow of news about oil-based commodities. The results suggest that as the rate of news about crude oil rises, volatility spillovers from equity to oil markets decrease (Aromi & Clements 2019). Thus, oil price volatility is more idiosyncratic in nature when oil-related news is announced, implying that news articles have some effect on oil price volatility.

Previous studies use methods to aggregate the volume of news in order to measure oil price dependency, which does not allow us to measure the effect of separate articles. Some studies have already proposed methodologies that enable effect evaluation for individual events. Unfortunately, there is little consensus regarding the results, or even what should the assumptions be. Kilian (2009) defines news-induced oil price change as a precautionary reaction to a possible shortage of future oil supply. Kilian & Vega (2011) 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. The authors used high-frequency data to model shocks as statistically significant jumps in the realized bi-power variation. Chan & Gray (2017) applied a similar methodology for evaluating the effect of scheduled macroeconomic news on price jumps of energy commodities. The results are contrary to Elder *et al.* (2013), but in line with Kilian & Vega (2011): there is little evidence of a linkage between news and price jumps. Greenwood-Nimmo *et al.* (2021) applied their new methodology for mapping past events to changes in the volatility spillover index. The authors used similar data to Diebold & 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.

Another important topic, that is often a source of controversy in the literature regarding oil-price shocks, is the categorization of oil shocks. There is an important distinction to be made between demand and supply shocks to the oil market. A supply shock is defined as a reduced availability of a basic input to production (Brown & Yücel 2002). Literature that differentiates between these types of events is not unanimous on which type influences the oil market more. Kilian (2009) was the first to thoroughly analyze the types of oil price shocks. The author used four predictors: oil supply shocks due to exogenous political events in Organization of the Petroleum Exporting Countries (OPEC) countries, real economic activity, the percentage change in crude oil production, and the real price of oil, to model oil price shocks. Kilian (2009) decomposed errors of a reduced vector autoregressive (VAR) model into supply-side shocks driven by geopolitical events in the OPEC countries, supply-side shocks caused by disruptions in production, aggregate demand shocks due to long-term development in the world economy, and precautionary demand shocks that materialize as a result of altered expectations for future oil supply levels. The results indicate that precautionary demand shocks and shocks to aggregate demand are much more important than physical oil supply disruptions. These findings went against the typical view, that oil price shocks are mainly caused by disruptions to the oil supply due to political unrest in the Middle East. Furthermore, precautionary demand shocks tend to affect the price instantly, while aggregate demand shocks propagate over a long horizon. Kilian & Murphy (2014) add a change in global crude oil inventories as a proxy for speculative demand into the specification, but group all supply-side shocks into one variable. The inclusion of inventory levels modestly raises the importance of supply shocks, which is especially apparent for the Persian Gulf War in 1990, or the Venezuelan Crisis in combination with the Iraq War in 2002/2003. One would expect inventory levels to decrease in case of a supply shock. While supply shocks decrease inventories, the speculative demand shocks offset the decrease. This justifies supply shocks as an explanation for the real oil price increase during these events. Kilian & Murphy (2014) also reevaluated and put forward the importance of aggregate demand shocks as the main mover of oil prices. The methodology of quantifying oil shocks brings valuable insights into which events should we expect to have a significant effect on oil price volatility.

Logically, precautionary and speculative demand shocks can be identified more often than pure shocks to supply. Typical examples of supply shocks are the decisions of OPEC, as they have a direct and rapid effect on oil supply. Still, an immediate market reaction to an OPEC decision is due to precautionary demand. Similarly to the aforementioned conclusions, Xu *et al.* (2019) argue that demand-related shocks are much greater than OPEC-induced shocks to oil supply. OPEC meetings are planned, and they can affect oil prices before the meeting takes place. Schmidbauer & Rösch (2012) identify a positive preannouncement effect on oil price volatility, which is the most pronounced for decisions to cut oil supply. The authors also state that the decisions to cut or maintain oil supply have a negative impact on the conditional volatility of oil prices. Mensi *et al.* (2014a) confirm this result, but add that cut or maintain decisions have a gradual long-term impact on volatility. Elder *et al.* (2013) on the other hand do not observe oil price shocks caused by economic news to be very persistent. By dividing OPEC decisions into periods of conflict and non-conflict regimes, it appears that the reaction is efficient and not persistent only for non-conflict regimes. During periods of conflict, the reaction is delayed (Guidi *et al.* 2006). The decisions of OPEC also directly affect the volatility of natural gas. Karali & Ramirez (2014) conclude that the decision to cut production significantly increases the conditional volatility of natural gas.

Despite the inconsistencies in methodology, most studies find a significant effect of oil-related news on oil prices and oil price volatility, which underpins the benefit of studying volatility spillovers connected to news (Schmidbauer & Rösch 2012; Elder *et al.* 2013; Mensi *et al.* 2014a).

Chapter 3

Data

3.1 Prices Data

We selected 5 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 by nature. One reason is that 60% of global crude oil stock is utilized in the production of heating oil, diesel, and gasoline (Kočenda & Moravcová 2023). Heating oil can also be produced as a side-product when processing crude oil into gasoline. Furthermore, heating oil and natural gas are substitutes in many situations.

The data were retrieved through Refinitive Eikon Datastream[1]. 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. Having obtained the set of daily measures, we computed range-based realized volatility estimates using the method introduced by Garman & Klass (1980), described in Chapter 4. The data was available from September 1st 1978 to December 16 2022 for crude oil, heating oil, and diesel. Gasoline was only available since 2005. Therefore, we substituted the missing data with high-frequency realized volatility estimates computed using 5-minute gasoline prices from TickData[2].

Kilian & Vega (2011) state that daily prices are enough for event-based volatility analysis since any reaction will be reflected in the daily returns, and

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

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

consequently in the realized volatility. Thus, the precise timing of the event is not needed. Furthermore, the timing of events is not important for our purposes, as we concern ourselves with the moment the general public is notified, which is subject to uncontrollable factors.

Neither intraday nor daily natural gas prices are available before April 3rd, 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 5 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 Chapter 5.

3.1.1 Data Cleaning

Data obtained both from Eikon and TickData contained several anomalies. Firstly, there were some occasions of prices being reported on weekends. These days were removed. Apart from weekends, we removed Christmas days: December 24 to December 26, and New Year's days: December 31st, January 1st, and January 2nd. 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.

Since commodities on the NY Mercantile Exchange trade for 5 hours and 30 minutes, we should have 66 5-minute ticks from TickData for each day. Unfortunately, the data began to be this consistent only after 2006. The median number of ticks per day in our data is 60. For 4 days, there was only one value reported, which prevents us to calculate returns, and consequently realized volatility. We omit these days. Since we observe that the range-based realized volatility (RV) copies high-frequency RV well enough, we impute missing values of gasoline range-based RV with the high-frequency RV even after the year 2005. As a result, more than half of the values for gasoline come from the high-frequency RV.

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 3.1: 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
ng	-0.00047	0.03615	0.00000	-0.46	0.32	-0.51	10.81
rb	-0.00036	0.02832	0.00104	-0.47	0.25	-1.96	31.93

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 3.2: 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	0.00048	0.00132	0.00028	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 Brief history of the oil market

We devote this section to summarizing the historical development of 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 throughout history. We prioritized oil-related news in our search. Using the U.S. macroeconomic news, Kilian & Vega (2011) showed that news not directly related to energy commodities explain only 0.69 and 1,6% of monthly oil and gas price variation.

After World War II, the economic growth in newly industrialized countries led to a significant increase in demand for oil (Hamilton 2013). The oil market became increasingly important, and the price of oil became a major factor in the global economy. To confront this increase in demand, the Organization of the Petroleum Exporting Countries (OPEC) was founded in 1960. In 1973, OPEC countries had the ability to influence the supply and price of oil as they accounted for about half of the global oil supply. The United States ceased to be the main exporter of oil, and the center of oil production transitioned from the Gulf of Mexico to the Persian Gulf (Kilian 2014). Then came 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, also known as the Yom Kippur War. The war was triggered by the tensions between Israel and its neighbors, and the increasing influence of the Soviet Union in the region. Several Arab countries, including Saudi Arabia, imposed an embargo on oil exports to the United States and other countries supporting Israel, which affected the oil market significantly. Baumeister & Kilian (2016) argue that the price shock was primarily driven by an increase in demand, rather than a supply reduction. The global output decreased by 7.5 % in November 1973 (Hamilton 2013). 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. The price of oil more than doubled during this period, leading to a substantial decline in petroleum consumption in the early 1980s.

Oil production dropped drastically in 1978 due to the Iranian Revolution. The revolution resulted in an establishment of the Islamic republic, the nationalization of Iran's oil industry, and the disruption of oil exports. The world production of oil dropped by 7% (Hamilton 2013). The revolution had also impacted oil prices due to fears of oil fields being attacked, which induced precautionary demand Hamilton (2013). The production increased a year after, but only to half of pre-revolution levels. Kilian (2009) concludes that the rise in oil prices during the years 1975 to 1978 is best explainable by positive shocks to oil supply, rather than demand shocks. On the other hand, the period from 1978 to 1980 is characterized by a negative shock to other oil supplies, but also large oil-market-specific demand shocks, partially offsetting the effect of the disruption in exports.

In addition to the Iranian Revolution, the former Soviet Union invaded Afghanistan in 1979 as part of a broader effort by the Soviet Union to support the communist government of Afghanistan, which was facing a rebellion by anti-government forces. After the drastic rise in oil prices in 1979, the wealth of the Soviet Union increased enormously since it provided approximately 18% of the global production. Brown (2013) argues that the invasion was partially oil-fueled, as the Soviets had an interest in Afghan gas and oil resources in the Persian Gulf. The invasion was met with widespread international condemnation, mainly from the United States, which supported local Afghan rebels. The Soviet invasion of Afghanistan was one of the key events of the Cold War and contributed to the deteriorating relationship between the Soviet Union and the United States.

The Iraq-Iran war was led in a similar period, from 1980 to 1988. Thanks to the oil boom in 1979, Iraq was in a similar situation to the Soviets, which might have triggered the invasion. Iraq's primary rationale for the attack against Iran was to prevent the spread of Iran's Islamic Revolution to Iraq and to prevent Iran from exploiting sectarian tensions in Iraq (Karsh 2003). Iraq also wished to replace Iran as the power player in the Persian Gulf. The proceedings from oil exports powered the war. Thus, both countries targeted oil facilities to reduce oil exports of the opposing party (Karsh 2003).

In 1984, Iraq began the "tanker war", in which both countries attacked oil tankers and merchant ships in an effort to deprive the opponent of trade options. Iran responded by attacking tankers carrying Iraqi oil from Kuwait and any tanker of the Persian Gulf states supporting Iraq. The number of attacks on ships reached a peak of over 30 per month at one point (Kilian 2009). The attacks on ships of noncombatant nations in the Persian Gulf led to cargo being escorted by the US and Soviet navies (Karsh 2003). The war resulted in the deaths of around 500,000 people, combined financial losses of over $1 trillion, and a loss in oil production of 6% (Hamilton 2013).

The price change from 1980 to 1985 is mainly explainable by a large negative aggregate demand shock (Kilian 2009). Supply shock was not causal here, because any attempt by OPEC to cut production was nullified by a production boost in some other country. OPEC opted for a supply reduction to fight the decline in prices due to over-production and lowered demand. Saudi Arabia shut down 3/4 of its production, but other OPEC members did not act in accordance with the decision. In 1985, OPEC collapsed, and Saudi Arabia resumed its earlier production. Consequently, the price per barrel collapsed from $27/barrel in 1985 to $12/barrel at one point in 1986 (Hamilton 2013). The real price of oil was mainly driven by a positive supply shock (Kilian & Murphy 2014). The drop in speculative demand also played a role in the decrease in real oil prices.

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. One of the main reasons was that Iraq was heavily indebted to Kuwait, having borrowed more than $14 billion from the country to finance its military efforts during the Iran-Iraq War. Kuwait, however, was not willing to forgive the debt and instead demanded repayment, which put further strain on Iraq's already weakened economy (Encyclopedia Britannica 2014). In addition, Kuwait ramped up its oil production levels, which kept revenues down for Iraq and further weakened its economic prospects. Iraq interpreted Kuwait's refusal to decrease oil production as an act of aggression towards the Iraqi economy, leading to hostilities and later to invasion of Kuwait. Kuwait was supported by a coalition of the United States, the United Kingdom, France, Saudi Arabia, and Egypt. They sought to remove the Iraqi forces from Kuwait and restore its sovereignty. The conflict was fought in two key phases: Operation Desert Shield, which involved a military buildup from August 1990 to January 1991, and Operation Desert Storm, which began with an aerial bombing campaign against Iraq on January 17, 1991 (Wright *et al.* 1995). The coalition forces were successful in liberating Kuwait, and the conflict came to an end on February 28, 1991. 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). The price change was mainly driven by a speculative demand shock during this period (Kilian & Murphy 2014), although oil prices started to be more influenced by macroeconomic indicators during this time (Gogolin *et al.* 2018)

In 1995, the United States imposed comprehensive sanctions on Iranian crude oil. Although the embargo temporarily caused some losses for Iran in terms of oil transport, the country was able to find new buyers quickly. In the long run, the oil import embargo was ineffective due to the competition from other oil exporters and did not significantly affect either Iran's oil exports or US oil imports (Torbat 2005a).

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). Should the rate of consumption growth persist, China would have surpassed the USA in oil consumption by the year 2022.

The rapid growth was followed by the Asian financial crisis of 1997, which started in Thailand with the collapse of the Thai baht after the local government was forced to float the baht due to a lack of foreign currency. The economic downturn of the Asian tigers 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 organization sought to restore higher oil prices and protect the interests of its member countries (Karali & Ramirez 2014). Kilian (2009) confirms that the price change was entirely due to a negative oil market-specific demand shock. Precautionary demand did not play a role, as the price of oil was too low.

The increased demand in Asian states, tensions in the Middle East, a general strike in Venezuela, and 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 & Ramirez 2014). The reason behind the lack of supply shock is that production shortfalls in Venezuela and Iraq were offset by production in other countries. Oil consumption grew by 3% per year in 2004 and 2005. The production growth stopped after 2005 due to oil field depletion in the North Sea, Mexico, and Indonesia, which pushed oil prices even higher. Saudi Arabia saw the biggest decline in output, as their daily production fell by 850000 barrels from 2005 to 2007 (Hamilton 2013). The price of a barrel fluctuated under $25 before the energy crisis and rose over $140 in July 2008.

The 2000s brought significant technological advancement in terms of oil and gas extraction. Shakya *et al.* (2022) argue that the investment was motivated by the steep rise in oil and gas prices due to the energy crisis. 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 *et al.* 2014). The United States was motivated to expand on gas extraction technology as they lacked conventional fossil fuel sources. The North American shale gas revolution took off in 2006 and accounted for nearly 40% natural gas production in the United States by 2012, which is a 12-fold increase since 2000 (Wang *et al.* 2014). Although the US gas production increased rapidly in 2007 and the market was oversupplied, gas prices increased until late 2008. This can be attributed to the financialization of commodities, and the high connectedness of gas prices to crude oil prices (Wiggins & Etienne 2017).

There has been ongoing financialization of commodities since the early 2000s (Tang & Xiong 2012). Oil became tradable through spot transactions, futures, and forward contracts, which opens a possibility to invest in oil for speculative purposes (Hamilton 2009). The prices of petroleum-based commodities are now more integrated into the global flow of the economy. Moreover, due to globalization and advancements in information technology, the transaction transmission for various financial assets is effortless and rapid, which pushes the integration of commodities into global financial markets (Tang & Xiong 2012). In conclusion, oil prices are now more sensitive to seemingly unrelated macroeconomic news, and their volatility is more connected to overall market volatility (Gogolin *et al.* 2018; Wang & 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 *et al.* 2011; Zhang & Wang 2014; Xu *et al.* 2019; Kang & Lee 2019). During this period, the connectedness between different types of markets became more pronounced. Metal commodities such as gold and silver acted as net sources of volatility spillovers to oil-based commodities (Kang *et al.* 2017). The price started to recover a year after, when it became clear that the crisis will come to end (Baumeister & Kilian 2016). 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 extraction developed only after 2011, and it increased the US production of crude oil by 3.6 million barrels per day (Ansari *et al.* 2019). The price of crude oil declined from $100 to $50 in 2014. Baumeister & Kilian (2016) state that $16 of that decline can be directly attributed to the positive supply shock from shale oil exploration. Due to the revolution, the influence of OPEC weakened as the private shale oil companies did not regulate their production depending on the global needs, and the spare capacity of OPEC became less effective (Almutairi *et al.* 2021). The shale oil revolution is largely responsible for the divergence of the two major crude oil benchmark prices - WTI and Brent (Kilian 2016).

The rest of the price decline can be explained by the effort of OPEC to control the market. 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 & Radetzki 2017). In 2017, shale oil already made up 50% of the US oil production. 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 & 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 in society. 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 *et al.* 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 & 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 *et al.* 2022). In 2021, Russia was the world's largest natural gas exporter, and the second largest crude oil exporter (Statista 2022). Further, Russia relied on the stability of its position as a crucial source of oil and gas for Europe. 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.

3.3 Events Dataset

The dataset consists of 900 events related to oil prices spanning from January 1, 1987, to November 30, 2022. The events were divided into three general types - economic, geopolitical, and natural. Economic events cover OPEC decisions, news about oil reserves and inventory levels, news of market conditions including speculations, mergers and developments in the oil industry, and sanctions. Geopolitical news articles include all events of political nature and wars. Lastly, natural news articles mostly refer to natural disasters, tanker spills, or the spread of some disease. In total, we processed 395 economic, 130 natural, and 375 geopolitical articles. Observing the temporal event distribution in **??**, we can see an increase in the event count as time progresses due to better news coverage.

The events can be further divided into 18 distinct groups based on the recurrence of specific characteristics. Following the group summary in Table 3.3, we will briefly describe each of the 18 groups, starting with those that fall under the 'geopolitical' category. The first major group features purely political events. Some typical news articles labeled as political events in our dataset are governmental elections, civil wars, political statements featured in the news, or meetings of political leaders. Altogether, there are 183 such events in our dataset.

News about the beginning or development of some war conflict is also put into one group. This group features major events such as the day of the Iraq invasion of Kuwait and the subsequent US intervention in January 1991, the war declaration by Osama bin Laden against the United States in August 1998, or the first day of the Russian invasion of Ukraine in February 2022. Any terrorist attacks, missile launches, or bombings were grouped into a separate group 'missile'. Together, these two groups encompass 70 and 41 events, respectively.

News announcing a peace agreement, treaty, ceasefire, or end of a war conflict, is marked as 'peace'. Such events are typically positive in nature, which enables us to validate and draw inference about the effect difference between good and bad news. Some examples of such events are the end of the Iran-Iraq war in April 1988, the end of the Gulf War in February 1992, and the end of the Russia-Saudi Arabia oil war in April 2020. We gathered 52 events classifiable into the 'peace' group.

The protests against the government or strikes of oil workers are separated into their own group 'strike'. News articles that are not effective, such as the threats of cutting ties, imposed deadlines, threats of attacks, and general warnings, are separated from the rest of the geopolitical event groups into their own group 'threat'. We identified 24 articles that can be grouped under 'threat'.

We move onto the event groups that fall into the economic category. News articles that are tied to the the global markets, but are not necessarily connected to a political party, were labeled as 'market'. Macroeconomic news releases, monetary policies or Federal Reserve Board reports fall into this group. News related to financial crises or recessions is also included. Furthermore, countries frequently create organizations and agreements with the purpose to trade goods more effectively, such as the Arab Cooperation Council or NAFTA. News about these organizations is also comprised in the 'market' group. Lastly, any humanitarian initiative, such as the Paris Agreement, the Clean Air initiative, or the Oil for Food program, is represented in the 'market' group as well. This group contains 151 news. Some examples of events belonging to this group are the beginning of the Asian financial crisis in 1997, the stock market crash in 2008, and the beginning of the Russia-Saudi oil war in March 2020.

The next important economic group of events comprises all the decisions related to crude oil production. A majority of such news is directly connected to OPEC, and has some economic reasoning behind it. Still, there are decisions not related to OPEC, which usually occur as a result of some geopolitical conflict. One such example would be the Russia-Saudi oil price war. According to OPEC, the organization's mission is to stabilize oil markets and provide a regular supply of petroleum to consumers. The usual methods to achieve oil price stability are to cut, maintain, or boost oil supply. The organization meets several times per year, which gives us enough data to draw conclusions on the effect of OPEC meetings on volatility spillovers. There have been 145 OPEC meetings that resulted in either of these decisions since 1987. Specifically, there were 45, 65, and 35 decisions to cut, maintain, and boost production, respectively. No obvious pattern seems to exist in the decisions across the years, apart from the streak of the decisions to maintain production from March 2009 to June 2016. If the meeting resulted in a decision to cut or boost production, we encode the event as having a direct effect on the supply of crude oil. After the decision is announced to the public, oil price volatility usually spikes significantly, which has been documented by a few studies already (Schmidbauer & Rösch 2012; Mensi *et al.* 2014a). Lastly, OPEC meetings represent a rare group of news that is scheduled. In a study of forex markets, Mensi *et al.* (2014b) argue that scheduled announcements have no impact on price volatility, as opposed to a significant impact of unscheduled news. Similar logic could hold for oil markets as well.

We continue with 3 relatively sparsely represented groups of economic events. Firstly, announcements of bids or mergers of oil companies are labeled as 'merge'. If there is news involving the discovery of oil fields or investments into oil infrastructure such as oil platforms, tankers, or pipelines, we label these events as 'develop'. Lastly, news related to the current state of oil storage or the release of oil reserves by the Strategic Petroleum Reserve is grouped into the 'inventory' group. There are 46 events belonging to these 3 groups. Major events included in this group are the release of oil from the Strategic Petroleum Reserve during Operation Desert Storm in 1991, and during the worst period of Hurricane Katrina in May 2005.

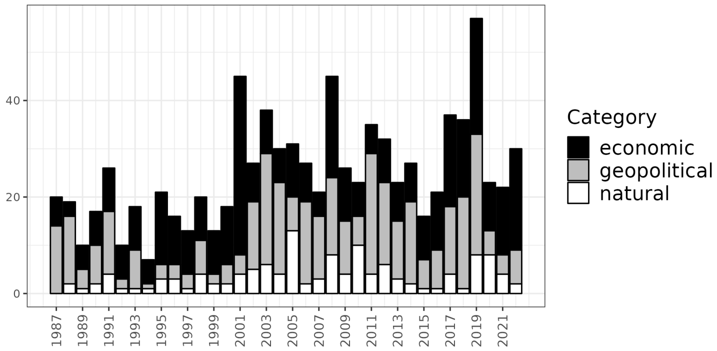
The next group contains news about embargoes, sanctions, and tariffs imposed between the countries. There are 35 news articles of this type. An important condition for this group is that the sanction has to be valid and effective.

Any articles involving threats of sanctions or speculation about the economic development have their own group 'speculation'. News of market expectations, doubts, intentions, or signals without a resolute action promised, also falls here. We identified 18 events of this type.

Natural events such as earthquakes, tornadoes, volcanic eruptions, storms, heat waves, and cold waves, are grouped into the 'natural' group. Further, we identified 53 articles informing about oil terminal leaks, pipeline leaks, tanker explosions, or oil rig crashes. These events are marked as 'spill', and all of them intrinsically affect the oil supply. These events do not necessarily have to be caused by nature although it is the most prevalent cause. The final group of natural events, called 'pandemic', captures all news revolving around the recent COVID-19 outbreak with a possible connection to the oil market. We only collected 10 events related to the pandemic. As an example, it is January 31, 2020, when WHO issued Global Health Emergency, and also March 11, 2020, which is the date on which WHO declared COVID-19 a pandemic.

Since we can not compute spillover values for weekends, any event happening on Saturday or Sunday was moved to the upcoming Monday. In doing so, we pair the event with the first date during which the market can react to it.

Figure 3.1: 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 3.3: News dataset summary

Category	Group	Count
geopolitical	political	183
geopolitical	war	70
geopolitical	missile	41
geopolitical	peace	52
geopolitical	threat	24
geopolitical	strike	5
economic	market	151
economic	maintain	65
economic	boost	35
economic	cut	45
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 summary of the news dataset. The events were divided into three main categories: economic, geopolitical, and natural, and into 18 smaller groups.

Chapter 4

Methodology

Our analysis employs two methodological frameworks. Firstly, we will compute the rolling spillover index introduced in the work of Diebold & Yilmaz (2009); Diebold & Yılmaz (2014), which represents the degree of volatility connectedness of the assets put in the network at each point of time. Next, we utilize the bootstrap-based test introduced by Greenwood-Nimmo *et al.* (2021), which enables us to statistically assess the chance that the spillover index persistently increased after some event occurred.

4.1 Volatility estimation

In order to compute the volatility spillover index created by Diebold & Yilmaz (2009), it is necessary to estimate daily volatility. We combine the results of two estimators: high-frequency realized variance and range-based realized variance.

4.1.1 Range-based volatility estimate

The range-based realized variance was first introduced by Garman & Klass (1980). It is a great improvement over the most basic volatility estimator using only two closing prices P: $\hat{\sigma}^2 = (P_t - P_{t-1})^2$.

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:

$$\begin{aligned}\hat{\sigma_{i,t}}^2 &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \\ RealVol_{i,t} &= \sqrt{\hat{\sigma_{i,t}}^2}\end{aligned} \tag{4.1}$$

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

4.1.2 High-frequency volatility estimate

Realized variance (RV) by Andersen & Bollerslev (1998) provides an improved method to estimate volatility. The measure is defined as the sum of squared intra-day returns, based on the frequency of underlying data:

$$\begin{aligned}RV_{i,t} &= \sum_{j=1}^{m} r^2_{i,t-1+jn} \\ RealVol_{i,t} &= \sqrt{RV_{i,t}}\end{aligned} \tag{4.2}$$

Assuming that the underlying asset's price follows a jump diffusion model introduced by Andersen *et al.* (2003):

$$\begin{aligned}y_t &= p_t + \epsilon_t \\ \epsilon_t &\sim N(0, \sigma^2) \\ dp_t &= \mu_t dt + \sigma_t dW_t + c_t dJ_t\end{aligned} \tag{4.3}$$

The quadratic variation (QV) of this process can be decomposed into integrated variance and the variation of jumps:

$$QV_t = \int_0^t \sigma_s^2 ds + \sum_{s=1}^{t} J_s^2 \tag{4.4}$$

As data frequency gets smaller, and the number of intra-day returns larger, it can be shown that the realized volatility measure is an unbiased and consistent estimator of integrated variance (Andersen *et al.* 2003). Therefore, it appears to be an optimal input for the volatility index calculation (Bubák *et al.* 2011). Baruník *et al.* (2015) argue that spillovers from high-frequency data show a larger magnitude as opposed to using daily data.

Barndorff-Nielsen *et al.* (2008) proposes, that RV can be decomposed into realized semivariances (RS) by computing realized volatility from positive and negative intra-day returns separately:

$$\begin{aligned} RS^{-}_{i,t} &= \sum_{j=1}^{m} r^2_{i,t-1+jn} 1_{\{r_{i,t-1+jn}<0\}} \\ RS^{+}_{i,t} &= \sum_{j=1}^{m} r^2_{i,t-1+jn} 1_{\{r_{i,t-1+jn}>0\}} \end{aligned} \tag{4.5}$$

The sum of positive and negative realized semivariances converges to the integrated variance under previously described assumptions (Barndorff-Nielsen *et al.* 2008).

4.2 Static Spillover index

This spillover index measure introduced by Diebold & Yilmaz (2009) is based on covariance-stationary vector autoregressions (AR). For a vector 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:

$$\boldsymbol{x}_t = \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{x}_{t-j} + \boldsymbol{u}_t, \tag{4.6}$$

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:

$$\boldsymbol{x}_t = \sum_{\ell=0}^{\infty} \boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell}, \tag{4.7}$$

where the ℓ-th $m \times m$ vector moving average (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 & 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:

$$\theta_{i \leftarrow j}^{(H)} = \frac{\sum_{\ell=0}^{H} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{P} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{H} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i}, \tag{4.8}$$

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 & 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 4.7 are assumed to be serially uncorrelated, and the VAR model is covariance-stationary, the total covariance matrix of Equation 4.7 of horizon H can be calculated as:

$$\boldsymbol{\Omega}_H = \boldsymbol{E}(\boldsymbol{x}_t \boldsymbol{x}_t') = \boldsymbol{E}(\sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell} * (\boldsymbol{G}_\ell \boldsymbol{u}_{t-\ell})') = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \tag{4.9}$$

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

$$\boldsymbol{\gamma}_t^j = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell [\boldsymbol{u}_{t-\ell} - E(\boldsymbol{u}_{t-\ell} | \boldsymbol{u}_{j,t-\ell})] \tag{4.10}$$

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

$$\boldsymbol{\gamma_t^j} = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell[\boldsymbol{u}_{t-\ell} - \sigma_{jj}^{-1}\boldsymbol{u}_{j,t-\ell}(\boldsymbol{\Sigma})_{.,j}] \tag{4.11}$$

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:

$$\boldsymbol{\Omega}_H^j = \sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' - \sum_{\ell=0}^{H} \boldsymbol{G}_\ell \boldsymbol{\Sigma}_{.,j} \boldsymbol{\Sigma}_{.,j}{}' \boldsymbol{G}_\ell' \tag{4.12}$$

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

$$\boldsymbol{\Delta}_{(i)jH} = (\boldsymbol{\Omega}_H - \boldsymbol{\Omega}_H^j)_{i,i} = \sigma_{jj}^{-1} \sum_{\ell=0}^{H} ((\boldsymbol{G}_\ell \boldsymbol{\Sigma})_{i,j})^2 = \sigma_{jj}^{-1} \sum_{\ell=0}^{h} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{e}_j\right)^2 \tag{4.13}$$

Finally, we can obtain the generalized variance decomposition through scaling Equation 4.13 by the unconditional forecast error variance of the i-th component:

$$\check{\vartheta}_{i\leftarrow j}^{(H)} = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{H} \left(\boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{e}_j\right)^2}{\sum_{\ell=0}^{H} \boldsymbol{e}_i' \boldsymbol{G}_\ell \boldsymbol{\Sigma} \boldsymbol{G}_\ell' \boldsymbol{e}_i} \tag{4.14}$$

The notation of Equation 4.14 is consistent with the OVD specification. In the case of orthogonalized variance, it holds that:

$$\sum_{j=1}^{m} \theta_{i\leftarrow j}^{(h)} = 1, \sum_{i=1}^{m} \sum_{j=1}^{m} \theta_{i\leftarrow j}^{(h)} = m \tag{4.15}$$

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 & Yılmaz (2014) apply a row-sum normalization of GVD:

$$\tilde{\theta}_{i\leftarrow j}^{(H)} = \check{\theta}_{i\leftarrow j}^{(H)} \Big/ \sum_{j=1}^{m} \check{\theta}_{i\leftarrow j}^{(H)}. \tag{4.16}$$

The matrix of $\tilde{\theta}_{i\leftarrow j}^{(h)}, i, j = 1, \ldots, m$ 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.

4.2.1 Total Spillover

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

$$\mathcal{S}^H = 100 \times \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{M} \tilde{\theta}_{i \leftarrow j}^{(H)}}{\sum_{i,j=1}^{M} \tilde{\theta}_{i \leftarrow j}^{(H)}} = 100 \times \frac{\boldsymbol{\iota}' \boldsymbol{\theta} \boldsymbol{\iota} - \mathrm{trace}(\boldsymbol{\theta})}{\boldsymbol{\iota}' \boldsymbol{\theta} \boldsymbol{\iota}} \%, \tag{4.17}$$

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

4.2.2 Directional Spillover

Although total spillovers provide a useful measurement of the overall connectedness in the system, the main advantage of the spillover framework is the potential to uncover the shock transmission mechanism from or to a specific asset. Diebold & Yilmaz (2012) define two variations of the spillover index. 'From' spillovers are defined as a mean of spillovers received by commodity i from other commodities:

$$\mathcal{S}_{i \leftarrow \bullet}^H = 100 \times \frac{1}{M} \sum_{\substack{i=1 \\ i \neq j}}^{M} \tilde{\theta}_{i \leftarrow j}^{(H)} \tag{4.18}$$

Whereas 'to' spillovers represent the mean spillover value transmitted by commodity i to all other commodities:

$$\mathcal{S}_{i \rightarrow \bullet}^H = 100 \times \frac{1}{M} \sum_{\substack{j=1 \\ i \neq j}}^{M} \tilde{\theta}_{j \leftarrow i}^{(H)} \tag{4.19}$$

Finally, the net directional volatility spillover for commodity i is the difference between how much spillovers does a commodity receive, and how much it transmits:

$$\mathcal{S}_i^H = \mathcal{S}_{i \leftarrow \bullet}^H - \mathcal{S}_{i \rightarrow \bullet}^H \tag{4.20}$$

4.3 Dynamic Spillover index

A static representation of volatility spillovers provides a good overview of the network connectedness. It is, however, merely an average throughout the whole studied period. A prolonged period of weak connectedness during 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 & 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, rise of hedge funds, or prolonged state of global economy (Liu & Gong 2020). Furthermore, we are able to asses the state of spillover network on each day. Thus, for sudden bursts in volatility spillovers, daily volatility spillover measure enables us to explore possibly causal effects of the events in our dataset.

The calculation of 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 total and directed spillover indices,

4.4 Frequency decomposition

We can expect the events in our dataset to have a different impact for investors depending on the time horizon of their investments. Different horizons represent varying perception of economic stability for investors (Baruník & Kočenda 2019). Short-term investment horizons are likely associated with trading strategies involving technical analysis, while long-term investment is primarily focused on fundamentals (Kočenda & Moravcová 2023). Thus, negative news can nudge short-term investors to buy the underlying asset due to market overreaction, while long-term investors might be prompt to selling under the belief that news will negatively impact the price gradually. In context of oil volatility spillovers, while some negative geopolitical event involving crude oil could create arbitrage opportunities on the energy market, and consequently cause short-term volatility spillovers to other oil-related commodities. On the other hand, long-term investors might anticipate the effect of such event to temporarily affect the volatility of crude oil only, while other commodities would remain stable due to the solid state of current oil inventory levels.

Baruník & Křehlík (2018) propose a methodology to measure the impact of shocks at various frequencies. The methodology builds upon spectral representations of time series. Using the inverse Fourier transform, we can express any time series as a sum of sines and cosines at any frequency ω. We can write the Fourier transform of $\boldsymbol{G}_\ell$ as: $\boldsymbol{G}(e^{-i\omega}) = \sum_\ell e^{-i\omega\ell}\boldsymbol{G}_\ell$. Furthermore, the total variance-covariance matrix of the VMA VAR representation can be expressed through a Fourier transform, which is called the spectral density:

$$\boldsymbol{S}_x(\omega) = \sum_{\ell=-\infty}^{\infty} \boldsymbol{E}(\boldsymbol{x}_t\boldsymbol{x}'_{t-\ell})e^{-i\omega\ell} = \boldsymbol{G}(e^{-i\omega})\Sigma\boldsymbol{G}(e^{+i\omega}) \tag{4.21}$$

where we again make use of the fact, that the errors in the VMA definition are uncorrelated, and the cross-spectral densities are equal to 0. The spectrum in Equation 4.21 describes the distribution of $\boldsymbol{x}_t$ over all the frequency components ω. Using this, Baruník & Křehlík (2018) define the generalized causation spectrum over frequency ω as:

$$\boldsymbol{f}(\omega)_{j\leftarrow k} = \frac{\sigma_{kk}^{-1}\left|\boldsymbol{e}_j\boldsymbol{G}(e^{-i\omega})\Sigma\boldsymbol{e}_k\right|^2}{\boldsymbol{e}_j\boldsymbol{G}(e^{-i\omega})\Sigma\boldsymbol{G}(e^{+i\omega})\boldsymbol{e}_j} \tag{4.22}$$

Similarly to Equation 4.14, $\boldsymbol{f}(\omega)^{(H)}_{j\leftarrow k}$ represents the portion of the density spectrum for variable j stemming from shocks to variable k at a given frequency ω. In order to compare the variance share of a given frequency proportional to all frequencies, it is necessary to weight $\boldsymbol{f}(\omega)^{(H)}_{j\leftarrow k}$ with the frequency share of the total variance for variable j, which is defined as:

$$\boldsymbol{\Gamma}_j(\omega) = \frac{\boldsymbol{e}_j\boldsymbol{G}(e^{-i\omega})\Sigma\boldsymbol{G}(e^{+i\omega})\boldsymbol{e}_j}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\boldsymbol{e}_j\boldsymbol{G}(e^{-i\lambda})\Sigma\boldsymbol{G}(e^{+i\lambda})\boldsymbol{e}_j)d\lambda} \tag{4.23}$$

Finally, under the assumption that $\tilde{\theta}^{(H)}_{i\leftarrow j}$ can be viewed as the weighted average of $\boldsymbol{f}(\omega)_{j\leftarrow k}$ as $H \to \infty$, we can reconstruct the normalized GVD using the inverse Fourier transform of the variance decomposition:

$$\tilde{\theta}_{j\leftarrow k} = \frac{1}{2\pi}\int_{-\pi}^{\pi} \boldsymbol{e}_j \boldsymbol{\Gamma}_j(\omega)(\boldsymbol{f}(\omega)_{j\leftarrow k})\boldsymbol{e}_k d\omega \tag{4.24}$$

Since our analysis is concerned with observing the variance decomposition over short-, medium-, and long-term frequency ranges, rather than a single frequency, it makes sense to split Equation 4.24 into frequency bands. Baruník & Křehlík (2018) define the share of variance on a given frequency band $d = (a, b)$ as:

$$(\tilde{\theta}_d)_{j\leftarrow k} = \frac{1}{2\pi}\int_{d} \boldsymbol{e}_j \boldsymbol{\Gamma}_j(\omega)(\boldsymbol{f}(\omega)_{j\leftarrow k})\boldsymbol{e}_k d\omega \tag{4.25}$$

It must hold, that the intervals d_s are disjoint, and their union returns the full range: $(-\pi, \pi)$. It is necessary to apply a row-sum normalization, similarly to Equation 4.16. Contrary to the previous normalization, here we scale the generalized variance decomposition at given frequency d by rows of Equation 4.24, so that $\sum_k \sum_d (\tilde{\theta}_d)_{j\leftarrow k} = 1$.

4.4.1 Parameter estimation

As was the case with the classical connectedness estimation, frequency decomposition relies on an infinite process. Thus, it also needs to be approximated with a finite horizon H. In frequency decomposition, the finite horizon is only applied for parameter approximation, as it does not play a role in the computation of the power spectrum (Baruník & Křehlík 2018).

The cross-spectral density on a given frequency interval $d = (a, b) : a, b \in (-\pi, \pi)$ is approximated as:

$$\begin{aligned} &\int_d \boldsymbol{G}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{G}(e^{+i\omega})d\omega \approx \sum_{w} \widehat{\boldsymbol{G}}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{G}'}(\omega), \\ &\widehat{\boldsymbol{G}}(\omega) = \sum_{\ell=0}^{H-1} \widehat{\boldsymbol{G}}_{\ell} e^{-2i\pi\omega/H} \end{aligned} \tag{4.26}$$

for $w \in \{\lfloor \frac{aH}{2\pi}, ..., \frac{bH}{2\pi} \rfloor\}$. The estimate of $\boldsymbol{\Sigma}$ is corrected for a loss of degrees of freedom depending on the number of parameters in the VAR specification. By summing the coefficients $\widehat{\boldsymbol{G}}_{\ell}(\omega)$ for all the frequencies ω, we obtain an estimate of the impulse response function on a given frequency band d. This relationship allows us to plug in previously formulated estimates to compute the estimates of the generalized causation spectrum and the corresponding weighting function:

$$\widehat{\boldsymbol{f}}(\omega)_{j\leftarrow k} = \frac{\widehat{\sigma}_{kk}^{-1}\left|\boldsymbol{e}_j\widehat{\boldsymbol{G}}(\omega)\widehat{\boldsymbol{\Sigma}}\boldsymbol{e}_k\right|^2}{\boldsymbol{e}_j\widehat{\boldsymbol{G}}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{G}}(\omega)\boldsymbol{e}_j} \tag{4.27}$$

$$\widehat{\boldsymbol{\Gamma}}_j(\omega) = \frac{\boldsymbol{e}_j\widehat{\boldsymbol{G}}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{G}}(\omega)\boldsymbol{e}_j}{\sum_\omega \boldsymbol{e}_j\widehat{\boldsymbol{G}}(\omega)\widehat{\boldsymbol{\Sigma}}\widehat{\boldsymbol{G}}(\omega)\boldsymbol{e}_j} \tag{4.28}$$

Finally, the estimated share of variance on a given frequency band can be derived by summing the weighted values of generalized causation spectrum for each frequency:

$$(\widehat{\theta}_d)_{j\leftarrow k} = \sum_\omega \boldsymbol{e}_j\widehat{\boldsymbol{\Gamma}}_j(\omega)(\widehat{\boldsymbol{f}}(\omega)_{j\leftarrow k})\boldsymbol{e}_k \tag{4.29}$$

Using $\widehat{\theta}_{j\leftarrow k}$,and its frequency band decomposition: $(\widehat{\theta}_d)_{j\leftarrow k}$, we can define the total and directed spillover indices across varying horizons. The connectedness within a given frequency band ω is defined as:

$$\mathcal{S}_d = 100 \times \frac{\sum_{\substack{j,k=1\\ j\neq k}}^M (\widehat{\theta}_d)_{j\leftarrow k}}{\sum_{i,j=1}^M \widehat{(\theta)}_{d_{j\leftarrow k}}}, \tag{4.30}$$

while the frequency connectedness of the network is defined as the share of the overall connectedness for a given frequency band d:

$$\mathcal{S} = 100 \times \frac{\sum_{\substack{j,k=1\\ j\neq k}}^M (\widehat{\theta}_d)_{j\leftarrow k}}{\sum_{i,j=1}^M \widehat{\theta}_{j\leftarrow k}} = \mathcal{S}_d * \frac{\sum_{\substack{j,k=1\\ j\neq k}}^M (\widehat{\theta}_d)_{j\leftarrow k}}{\sum_{i,j=1}^M \widehat{\theta}_{j\leftarrow k}}. \tag{4.31}$$

'From' and 'to' frequency spillovers can be defined in a similar fashion.

Summing the values of frequency connectedness for all frequency bands returns the total connectedness, or the total spillover index defined by Diebold & Yilmaz (2009). It is important to note that frequency connectedness is not equal to within connectedness. Frequency connectedness is the connectedness within a specific frequency band, weighted by the power spectrum share of that given frequency band. The main implication of this definition is that high connectedness within a specific frequency band does not necessarily translate to high-frequency connectedness. If the within connectedness is high on a given frequency band, but that frequency band accounts for only a small percentage of the overall spectral density, the total connectedness will not be as influenced by high within connectedness of this frequency band.

4.5 GARCH Comparison

In the past, variations of the multivariate GARCH model have been used to study volatility spillovers, even though there are several limitations to the GARCH family. The variance-covariance matrix from GARCH does not provide information about the direction of spillovers (Kang *et al.* 2017). Moreover, the significance of GARCH parameters can not measure the extent, or even the direction of volatility spillovers (Xu *et al.* 2019). Lastly, as the number of variables in the system gets larger, they can not quantify the spillovers in sufficient detail. In conclusion, GARCH models are more suited to explore volatility correlations between pair-wise markets, while the spillover index can capture directional and time-varying dependencies between multiple assets or markets.

4.6 Bootstrap-after-bootstrap test

As mentioned previously, the spillover index computed on rolling windows is crucial for our analysis as it captures the time-variation attributable to historical events. Until recently, this analysis relied on a simple visual inspection, where the time of an event is matched with a sudden change in the spillover index magnitude (Diebold & Yilmaz 2009; Baruník *et al.* 2016; Diebold *et al.* 2017). Visual inspection is often only feasible for long-lasting spillover index changes. Nonetheless, we expect many events in our dataset to have an abrupt and short-term effect. Therefore, Greenwood-Nimmo *et al.* (2021) develop a methodological framework allowing to draw inference about these events with statistical power. The authors test the methodology on events used by the authors of the spillover index (Diebold & Yilmaz 2009). The test identified a 90% probability of a volatility spillover index increasing within one month after the event for 15 out of 19 events analyzed by Diebold & Yilmaz (2009). The findings are in line with the original results, implying that the spillover index is indeed a sound method to study the connectedness of various time series. Consequently, we can expect the index to provide valuable insights into which events coincide with a shift in network connectedness between petroleum-based commodities.

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 the coefficients $\boldsymbol{A}_j$ in Equation 4.6 for bias, which can be done yet again by bootstrapping. Following Kilian (1998), Greenwood-Nimmo *et al.* (2021) propose a non-parametric bootstrap-after-bootstrap procedure. For the sake of accuracy and consistency with the notation in a seminal work, we use the formal notation of Greenwood-Nimmo *et al.* (2021) in the subsequent account of 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:

$$\boldsymbol{x}_t^{(b)} = \sum_{j=1}^{p} \widehat{\boldsymbol{A}}_j \boldsymbol{x}_{t-j}^{(b)} + \boldsymbol{u}_t^{(b)}, \tag{4.32}$$

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 $\widehat{\boldsymbol{A}}_j, j = 1, ..., p$. 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 $\mathcal{S}^{(b)}_{r_e+j}$ 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:

$$\Pr\left(\mathcal{S}_{r_e+j} > \overline{\mathcal{S}}_{r_e-1}\right) = B^{-1}\sum_{b=1}^{B}\mathbb{I}\left\{\left(\widehat{\mathcal{S}}^{(b)}_{r_e+j} - \overline{\mathcal{S}}_{r_e-1}\right) > 0\right\}, \tag{4.33}$$

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 effect of two subsequent events for longer horizons.

Chapter 5

Results and robustness checks

We optimized the lag order of the vector autoregressive model according to the akaike information criterion (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.

5.1 Spillovers

5.1.1 Static Spillover

The overall spillover for the oil spillover network is 45.67%. 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. Baruník *et al.* (2015) and Gong *et al.* (2021) find that crude oil transmits most of the spillovers as well. Heating oil is neither transmitter nor a receiver. The strongest pairwise connectedness can be found between gasoline and crude oil. Crude oil is responsible for 26.42% 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%.

Table 5.1: Average connectedness for oil-based commodities

	oil	ho	lgo	rb	**FROM**
oil	53.83	17.95	10.58	17.65	11.54
ho	19.90	51.76	16.83	11.51	12.06
lgo	13.67	18.73	56.82	10.78	10.79
rb	26.42	10.68	8.00	54.91	11.27
TO	15.00	11.84	8.85	9.98	45.67

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 11.54 'FROM' connectedness for crude oil means that 11.54% of spillovers are transmitted FROM other commodities to crude oil. Similarly, 9.98% TO spillovers for gasoline means that all other commodities on average 9.98% 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 should the spillovers be transmitted (rows). Thus, 26.42% of spillovers TO gasoline are transmitted FROM crude oil.

5.1.2 Rolling Spillover

Figure 5.3 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 connectedness was much more volatile pre-2008. Since energy commodities were not yet financialized well, and they were not part of broader indices, they were not traded by speculators. Thus, the average spillover level was lower before the year 2000. 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 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 Chapter 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. 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 attributable to the tight oil exploration. The next plausible explanation lies within the events that occurred during the Arab Spring, mainly the Libyan uprising in 2011, and political unrest in Iran during 2012 (Baumeister & 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.

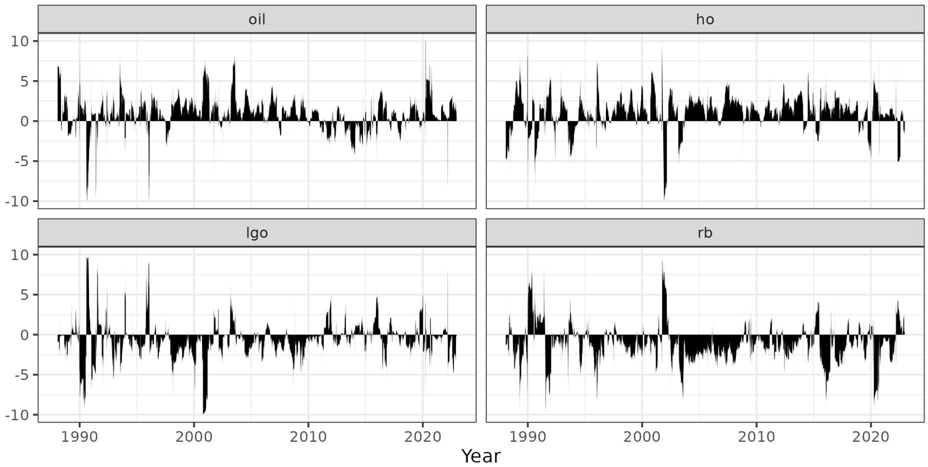
The China-US trade war led in years 2018 and 2019 decreased the demand for oil in China - the biggest oil consumer in the world. This caused the spillover index to fluctuate around 50% with moderate volatility. Multiple production cuts by OPEC between 2016 and 2020 also pushed oil prices higher during 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.

5.1.3 Net Spillovers

All commodities were both net receivers and net transmitters at some point during the studied period. Nevertheless, we can observe that crude oil and heating oil were net transmitters for the majority of the time, while gasoline functions as a net receiver. This result is contrary to that of Baruník *et al.* (2015), who found heating oil to be a net spillover receiver for both high-frequency and range-based estimation of realized volatility. Similarly to our findings, Baruník *et al.* (2015); Gong *et al.* (2021); Mensi *et al.* (2021) also identify crude oil to be the main source of volatility spillovers. Kočenda & Moravcová (2023) find heating oil to be the main net volatility transmitter as well. Still, most of the studies mentioned state that the spillovers from crude oil are not overwhelming, which is also in line with our findings. The mean spillover value of crude oil is only 3.5%. Diesel switches between the two states too often to be labeled as a net receiver or transmitter.

Although crude oil is a net transmitter, the status is not as apparent after the year 2011, which is likely due to the abundance of crude oil on the market resulting from the shale oil revolution. In the year 2020, crude oil briefly resumed its status as a net transmitter with the Russia-Saudi oil price war. Regarding gasoline, there were only two periods during which it was a net transmitter: during the shortage of gasoline in the US in the years 1990 and 1991, and the energy crisis of 2001, also accompanied by a shortage of gasoline. Both diesel and heating oil served as prominent net receivers of shocks during the energy crisis of 2001. On the other hand, the reduced need for commuting combined with the Russia-Saudi oil price war made gasoline a net receiver during the start of the COVID-19 pandemic.

Figure 5.1: Net Spillovers



Notes: This figure shows the net evolution of the net spillovers for the network of oil-based commodities: crude oil (oil), heating oil (ho), diesel (lgo), and gasoline (rb). Positive net spillovers means that given commodity spills more volatility than it receives in a specific window.

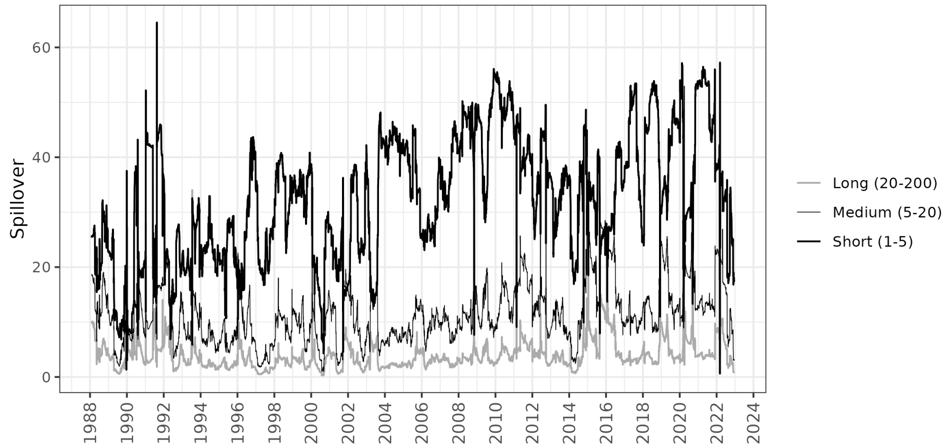
5.1.4 Frequency decomposition

Regarding the spectral decomposition of the spillover index, we decided to use the conventional bands corresponding to a short-term horizon of 1 trading week, a medium-term horizon of 1 trading month, and a long-term horizon of 1 year. Although the within connectedness for the short-term frequency band is only 40.92%, and both the medium and long-term horizon show within connectedness of approximately 50%, the share of the whole power spectrum is the highest for the highest frequency band (the shortest horizon). In other words, shocks to the system are most pronounced within a few trading days. This finding is contrary to Lovcha & Perez-Laborda (2020); Kočenda & Moravcová (2023), who conclude that short-term horizon rarely dominates in networks of energy commodities. The results are not directly comparable. Lovcha & Perez-Laborda (2020) use the range-based estimator as well but study only the connectedness between crude oil and natural gas. Furthermore, the authors only decompose the spillover index into two frequency bands corresponding to horizons of 1 trading week, and longer than 1 trading week. Kočenda & Moravcová (2023) work with the same set of commodities as used in this study, but use a weekly rolling realized volatility estimation. This method makes the spillover index more smooth, and likely results in more power share being attributed to longer horizons. Although the overall power share among the three frequencies is different, there are similar patterns to those of Kočenda & Moravcová (2023) in most periods.

Commodities show uniformly distributed FROM and TO spillovers in the short-term horizon. As for longer horizons, crude oil is clearly the dominant volatility transmitter. While gasoline receives the least spillovers in the network for the short-term horizon, it receives the most for the medium and long-term horizons.

Observing the frequency decomposition plot in Figure 5.2, we can see a rising divergence between the short and longer horizons. This finding underlines an increasing effect of speculators entering the commodity market since they are more likely to trade energy commodities in a short-term horizon. In the 1990s, the gap between short and long-term horizons was not that striking as geopolitical tensions likely caused investors in the oil market to be more forward-looking. After that, there were several occasions, where the frequency band corresponding to the short-term horizon fell in its share of power. The first period is again the US Energy Crisis of 2001, where the medium-term horizon reached a similar share of the power spectrum as the short-term horizon. Evidently, the lack of gasoline during this time pushed speculative trading back, as the US government made effort to supply fuel to places where it was most needed. Another period, where longer horizons increased in power, was the years 2015 and 2016. Again, this occurrence hints at the increasing demand for oil production combined with OPEC production cuts. Consequently, oil commodities were likely traded to cover production needs. Finally, the start of COVID-19 together with the Russia-Saudi oil price war exhibits a similar pattern. In conclusion, the shock to the system is mostly transmitted in 5 trading days throughout most of the studied period, while longer horizons gain importance in periods of distress and actual lack of oil reserves.

Figure 5.2: Frequency decomposition



Notes: This figure shows the frequency decomposition of the rolling spillover measure. The bold black line corresponds to the short-term horizon of 1-5 days. The black thin line represents shock reactions to the system in a medium-term horizon of 5-20 trading days. Lastly, the gray bold line pictures the connectedness created at low frequencies that correspon to the long-term horizon of 20 to 300 days.

5.2 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 are iteratively generating 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.

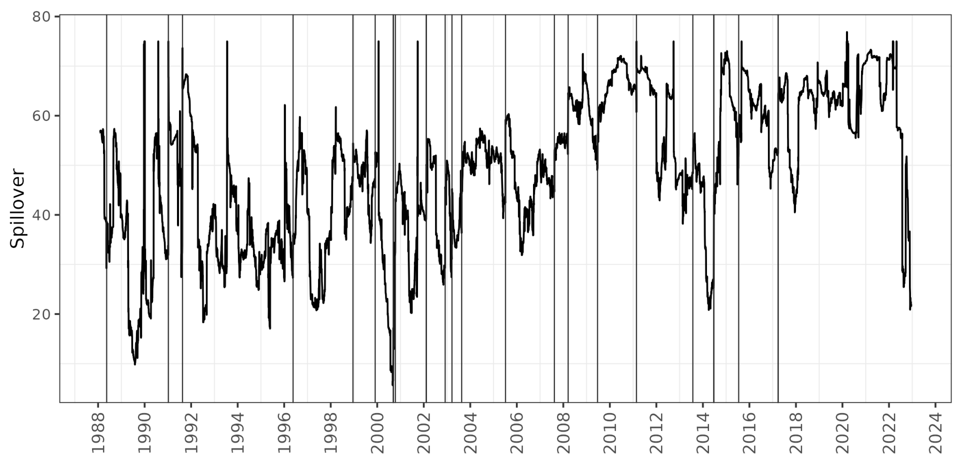
When evaluating the probability of spillover increase after an event according to Equation 4.33, we evaluated the effect primarily for $j = 1$. In other words, we observe, how the spillover index changed a day after the event was first published in the news. Doing so, we can be sure that the event was covered by major news channels. In order to consider a change in spillover levels statistically significant, we require at least 95% of values in the next day 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 900 news with mostly distinct dates, and the test identified 125 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 inference in all cases.

5.2.1 Results

The test returns 125 days above the set probability threshold. Nevertheless, if the event triggered a market reaction a day after the event, both the day of the event and the day after will likely be above the threshold. In fact, 35 out of the 125 days identified come right after the date of the test. This is not a consequential observation, as we are fine with the event being identified on any of the two days. From 900 events described in our dataset, only 31 were featured in those days. We also require the events to influence the spillover index persistently. We deem an event persistently influential if it exceeds 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 5 out of the 31 events were not persistent, which leaves us with 26 events. The event distribution in time is shown in Figure 5.3.

Although the ratio of geopolitical and economic news was balanced, we identified 17 geopolitical and only 8 economic news. Thus, geopolitical news has a higher probability of triggering a persistent increase in volatility connectedness, than economic news. While political and market news had the highest representation among the categories, only 4 to 5 events were identified by the test, which translates to approximately 2-3% of events in these groups. In addition, most of the significant economic events have a geopolitical origin, which further strengthens the notion that geopolitical events are responsible for sudden shifts in the oil commodities network. For example, it could be argued that the Oil for Food program was put into effect for humanitarian purposes, while the Iran Nuclear Agreement was purely economic. Nevertheless, both policies canceled previously imposed sanctions on oil-exporting countries and were put into effect by some political decision. Thus, the line between economic and geopolitical labels is thin.

Figure 5.3: Overall Spillover



Notes: This figure shows the evolution of the overall spillover calculated on the rolling window of 100 days. The vertical lines represent the events that passed the significance threshold.

Geopolitical events

As apparent from Table 5.2, geopolitical events were more influential on the spillover index in comparison with the economic and natural event categories. Two of the significant events appeared in the news on May 15, 1988. Firstly, 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. On the same day however, Iraq bombarded 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 Seawise Gaint was not reconstructed until 1991. The fear of losing that much transporting capacity likely triggered an increase in oil-based commodities. Neither of the subsequent events: the end of the Cold War and the peace talks between the US and Iraq, triggered a significant increase in connectedness.

Table 5.2: 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	98,9	100	99,6	99,4	99,4	Yes	Low
15.05.1988	Iraq Bombs 5 Huge Tankers at Iran Oil Site	100	98,9	100	99,6	99,4	99,4	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	36,1	37,2	36,8	36,9	38,6	No	
16.12.1998	Operation Desert Fox	100	63,4	96,9	97,8	95,9	95,5	Yes	High
		200	58,9	100	100	100	100	Yes	
08.09.2000	UK farmers and truckers threaten more blockades	100	41,1	100	100	100	99,8	Yes	Low
		200	63,9	99,5	99,6	99,4	99	Yes	
12.10.2000	Blast kills sailors on US ship in Yemen	100	98,7	100	100	100	100	Yes	Moderate
		200	75,9	87,5	81,2	76,6	80,2	No	
08.02.2002	Iraq obstructs UN inspectors	100	50	100	100	100	100	Yes	High
		200	51,1	42,7	40,1	36,7	31,2	No	
03.12.2002	General strike in Venezuela begins	100	100	100	100	100	100	Yes	High
		200	48,7	54,3	54,9	59,2	63	No	
17.03.2003	British Cabinet Minister resigns over plans for the war with Iraq	100	35,6	86	68,9	97,1	100	No	Low
		200	90,5	100	100	100	100	Yes	
17.03.2003	US: Bush gives Saddam Hussein and his sons 48 hours to leave Iraq	100	35,6	86	68,9	97,1	100	No	High
		200	90,5	100	100	100	100	Yes	
20.03.2003	Start of ground invasion in Iraq by US-led coalition	100	90,9	100	99,2	100	99,6	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	49,6	50	45,6	37,8	33,5	No	
07.07.2005	Terrorist attacks in London	100	100	100	100	100	100	Yes	High
		200	100	100	100	100	100	Yes	
14.08.2007	Iraq: biggest attack since the beginning of the war	100	40,7	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	81	100	99,9	99,7	99,3	Yes	Moderate
		200	20,6	66,2	57	58,6	56,5	No	
21.08.2013	Syrian Opposition Claims 1300 Killed in Chemical Attack	100	54,3	59,4	48,8	60,9	26,4	No	Moderate
		200	51,5	100	100	100	100	Yes	
20.06.2014	Troops Trapped in Iraq's Key Refinery	100	61,6	100	100	100	100	Yes	Moderate
		200	57,5	36,2	28,8	98,2	98,5	No	
23.06.2014	Iraq confirms oil refinery loss	100	100	100	100	100	100	Yes	Moderate
		200	26,8	20,1	95,4	95,3	97,6	No	

Notes: This table features all geopolitical events that passed the 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 persistent, 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 Chapter 5.

The Geneva Peace Conference that took place on December 1st, 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 & 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 started, 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 & Zhou (2020) reach a similar conclusion regarding the SPR release. According to the authors, there is no clear evidence of the oil reserves preventing 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 that happened on August 19, 1991, was unanticipated as well and triggered a reaction of the spillover index almost identical to that of the Geneva Peace Conference. This coup foreshadowed the economic collapse during the 1990s. Oil production decreased from 550 million tons in the year 1990 to 300 million tons in 1994 (Vatansever 2010). The index spiked to levels of 50% and stayed there for more than a year. Two months after the coup, the Soviets suspended the export of all petroleum products, though this had minimal effect on the connectedness.

In the years 1991 to 1996, the index was mostly below 40%, and no event in our dataset triggered a significant rise in connectedness. On December 16, 1998, Iraq failed to comply with United Nations (UN) inspectors in search of weapons of mass destruction, which broke another resolution declared by the UN (Conversino 2005). In response, the United States launched a four-day bombing of selected Iraqi sites, known as Operation Desert Fox. The operation received mixed reactions from some other big nations, such as the Russian Federation. According to the general in charge of the operation, the bombing was perfectly executed and achieved total surprise (Conversino 2005). This again supports the claim that unexpected events are much more likely to trigger a change in volatility connectedness.

Obstructing UN inspectors in Iraq holds a lot of information regarding oil prices as a similar pattern occurred a few years later. The United States aimed to resume the inspection in 1988. The US was inclined to continue with the inspections after the attacks on September 11, 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 Chapter 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. 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 over the country. Consequently, oil supply and inventories declined, and oil prices increased by 20% in one month (Kilian & Murphy 2014). The spillover index increased by 15 points when the strike in Venezuela began on December 4, 2002. 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 pictures of proof that Iraq continued with its nuclear program. While this was not enough evidence for the approval of Russia and China, the United States initiated military action regardless on 20 March 2002 (Bassil 2012). Since there was a lot of anticipation days before the invasion, the effect it had on the spillover market was mild and short-lasting.

The UN headquarters in Iraq have been 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 attack 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 Chapter 3. After September 18, 2001, the spillover index increased, while oil-based commodities decreased in price. In the context of the events mentioned, the retaliatory US invasion of Afghanistan on October 7 did not affect the spillover index, despite its historical importance. Following the incident, there was a massive surge in similar acts of terrorism in the western world. According to Hoffman (2009), 78% of terrorist incidents between the years 1968 and 2004 happened after the 9/11 incident. On July 7, 2005, the terrorist attacks in London triggered yet another spike in connectedness. Although the attack was initially perceived as unorganized and small in scope, further investigation revealed a deeper link to Al Qaeda commanders (Hoffman 2009). The attacks in London are the only event without a clear connection to the state of oil production or export. Thus, the rise in connectedness was possibly triggered by other markets. The effect it had on the spillover index is indisputable. The index jumped from 42% to 59% in just one day.

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 & Kilian 2016). A shift in production of that magnitude combined with the fear that the protests will 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. As a result, the civil war in Egypt and Syria did not affect the connectedness enough to cause another shift.

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.

Finally, there are two dates with oil-related news that triggered a significant increase in the spillover index, both tied to the Shell company. Firstly, UK farmers and truckers cut off the distribution of oil from a Shell refinery in the UK, which caused substantial supply disruptions of fuel over Northern England on September 8, 2000 (The Guardian 2000). Still, this event is too local to be labeled as causal for the increase in the spillover index. Despite the extreme prices that triggered the protests, the index was at its all-time minimum before the protests and increased from 6% to 17% in a few days. The other event was on March 17, 2008, when hundreds of villagers protested against the return of Shell trying to resume its oil production in Nigeria (BBC 2008). In 2008, the area was still full of oil pipelines 15 since Shell ceased its operations there. Interestingly, the CEO of Shell made a statement to Reuters on the day of the protests saying that the high oil prices have no justification given that there is no bottleneck in oil supply (Lawler 2008).

Almost all of the geopolitical events identified by the test are connected to war conflicts in the Middle East, and Iraq specifically. There are only two events that can not be labeled as attacks perpetuated by terrorist groups from the Middle East, or events that took place directly in the Middle East. The return of Soviet troops from Afghanistan on May 15, 1988, can be ruled out with the bombing of tankers happening on the same day. The geopolitical events listed above are either the first signs of new war conflict, acts of terrorism or concern 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 have a chance to cause supply disruptions, and consequently increase the connectedness of oil-based commodities.

Unsurprisingly, none of the 52 news articles that fall into the 'peace' group increased spillover index significantly according to the test results. We observe that the end of war conflicts or peace arrangements gradually decreases the connectedness. Similarly, 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. Only 3% and 4.29% of articles that belong to the 'political' and 'war' categories, respectively, have passed the threshold of the test. On the other hand, nearly 10% of news flagged as 'missile' reached the threshold. In conclusion, sudden and unexpected war operations or terrorist attacks are the most likely to cause an upward shift in the connectedness.

Economic events

Although the count of economic events in Table 5.3 is lower, we see that the only causal events after year 2014 were of economic nature. The first economic event that triggered a persistent increase in the spillover index is tied to Iraq, similarly to the majority of the geopolitical events. 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 & 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.

The first significant event of a strictly market nature was the divestiture of Exxon/Mobil. The Federal Trade Commission stated on November 11, 1999, that Exxon and Mobil are too large and their merger would disturb competition in the gasoline market. By resolution of the Federal Trade Commission, the two companies were required to sell 2431 US gas stations, refineries, terminals, and pipelines, in order to protect customers from predatory pricing (Federal Trade Commission 2013). The news raised the spillover index only by 4%, although the increase was persistent. The announcement of the merger itself on December 1, 1998, did not trigger a reaction. There was only one other acquisition with some effect on the spillover index. On September 26, 2001, the energy supplier Reliant Resources announced an acquisition of Orion Power Holdings. The spillover index spiked from 54% to 75% following the announcement but decreased to lower levels than prior to the announcement just a day after. The two companies are too local in scale to consider the effect on the spillover index causal with certainty.

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 news articles that reported on a change in oil production, only three passed the test threshold. Specifically, it is two decisions to boost production, one decision to cut, and no decision to maintain. Although the decision to maintain oil production is the most frequent, it never raised the spillover index. On September 11, 2000, the first significant production boost by OPEC members was announced. The increase was set to 800,000 barrels per day. It is surprising that this boost specifically increased the spillover index, as 800 thousand barrels is not too drastic given that OPEC increased its production by 3.7 million barrels in total throughout the year 2000 (Kohl 2002). It

Table 5.3: 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
20.05.1996	Oil-for-Food Programme	100	100	100	100	100	100	Yes	High
		200	100	99,4	100	100	99,9	Yes	
04.12.1997	Iraq will not allow oil flow during the 3rd 6-month phase of Oil for food program	100	46,9	86,8	87,4	92,5	94,4	No	High
		200	76	99,9	100	100	100	Yes	
30.11.1999	Exxon/Mobil FTC Divestiture	100	62,5	100	100	100	100	Yes	Moderate
		200	42,5	71,3	93,8	95,4	96	No	
11.09.2000	OPEC announces 800,000 bpd increase	100	98,7	100	100	100	100	Yes	High
		200	96,9	98,6	96,5	96,6	95,2	Yes	
11.02.2002	Russia increases production and oil exports	100	99,9	100	100	100	100	Yes	High
		200	39,5	37	32,4	28,8	27,4	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	
17.03.2008	Nigeria's Ogoni accuse Shell of staging a return	100	99,8	100	99,7	99,9	99,8	Yes	Low
		200	100	100	100	100	100	Yes	
22.06.2009	World Bank Report	100	43,2	99,1	96,2	97,7	95,9	Yes	Moderate
		200	46,7	50,6	48,3	53,2	49,4	No	
17.07.2015	Last bid to kill Iran nuclear deal blocked in Senate	100	99	98,3	98	98,7	98,6	Yes	High
		200	47,2	51,9	49,7	53,2	51,5	No	
27.03.2017	OPEC, non-OPEC to look at extending oil-output cut by six months	100	51,9	100	100	100	100	Yes	High
		200	50,8	55,1	54,7	50,4	58,1	No	
28.03.2017	Donald Trump signs Energy Independence executive order	100	51,7	50,7	47,2	54,7	54,8	No	High
		200	100	100	100	100	100	Yes	
20.01.2021	Biden set to rejoin Paris climate accord	100	48,4	54,1	49,6	55,4	61,1	No	High
		200	99,3	99,7	99,8	99,6	100	Yes	

Notes: This table features all economic events that passed the 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 persistent, 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 Chapter 5.

was likely the concerns over the spare capacity of OPEC members that pushed the index higher. Due to the lack of oil stock, the real increase was estimated at around 300,000 barrels (Kohl 2002). Thus, even though the decision to boost production would normally lower oil prices and stabilize markets, it only brought more uncertainty about the future oil stock. This explanation can be backed by the findings of Almutairi *et al.* (2021), who state that the spare capacity of OPEC serves as a significant means of mitigating supply and demand shocks.

On September 22, President Bush announced a 30 million barrels release from the Strategic Petroleum Reserve, which did not trigger a reaction in the spillover index. In both of these cases, the price reaction was mild and temporary, hinting at the insufficiency of the decisions. OPEC and Venezuela continued with their attempts to stabilize oil prices and boost production, but their policies were ineffective due to the low stock of heating oil combined with an upcoming winter in the US (Kohl 2002). During September and October, the spillover index shows an extreme increase from 6% to levels above 40%.

The next production boost did not come from OPEC, but from Russia specifically. Until 2001, Russia acted mostly in accord with OPEC decisions. By 2001, they cut their petroleum exports along with OPEC. That was only a small step in the context of the 2000s, during which Russia increased their exports from 300 million tons in the year 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 & 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 in the initial announcement. The cut was slightly above average compared to other historical production changes. Thus, the differentiating factor against other scheduled OPEC meetings was 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 & Gamal 2017). The crude oil price increased by 12.5% in the weeks following the statement.

OPEC decisions are not the only economic events that influence the connectedness of oil commodities. 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. Firstly, crude oil and its products constitute a non-negligible part of global output and world trade. Secondly, a majority of countries in the Middle East and South Africa are still labeled as developing. Thus, the decrease in capital inflow to these countries could worsen the condition for efficient oil extraction and transportation. The spillover index reach a local minimum of 49% during that day and kept increasing until the end of the year 2012.

The next event that significantly influenced the spillover index 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 Iran Nuclear Agreement is sometimes considered the greatest foreign policy achievement during Obama's presidency. The spillover index increased by a modest 5 percentage points on the day of the news.

Another important policy implemented was part of Obama's Clean Power Plan. It was not the implementation, but rather the order to undo these measures 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 news such as the renegotiation of the Dakota Access Pipeline on January 24, 2017, the withdrawal from Paris Climate Agreement announced on June 1st, 2017, or quitting the Iran Nuclear Agreement on May 8, 2018, did not have any immediate impact on the index.

By analyzing the list of news that are more economic in nature, there are a few observations that we can draw. Firstly news 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. The only event connected to a merger that impacted the index was the divestiture resulting from the Exxon and Mobil merger, although the reaction was mild. There are two possible explanations for the unrelatedness of mergers. First, news of mergers and developments are too local in scale to cause a shift in the oil spillover index. Second, 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. News reporting on the current state of oil stock, or the release of reserves from the SPR, also 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. The most surprising finding is that implementation or extension of sanctions against specific countries never caused a reaction in the spillover index.

As was the case with releases from the SPR, 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 volatility spillovers among oil-based commodities. The ineffectiveness of trade sanctions was further analyzed by Torbat (2005b). The author concludes that total imports and exports of crude oil do not change when sanctions are imposed. Exporting countries are quickly able to find new buyers for their oil reserves. 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% value several times but then returned to values between 65 and 70. The event passed the threshold of the test for two days following the price discount, which is not enough to consider the event persistently influential. It is possible that the news focusing on the oil price war or the COVID-19 pandemic was not identified by the test simply due to the limitations of the spillover index. Similar reasoning can be applied to the Suez Canal obstruction starting on March 23, 2021, or the event following the Russian invasion of Ukraine after February 24, 2022.

Although the events in this section that passed the significance threshold are labeled as economic, the source for most of them can be generalized as geopolitical. For example, it has been shown that the reasoning behind OPEC production changes is too complex to be modeled with any behavioral model (Kaufmann *et al.* 2008). Pierru *et al.* (2018); Almutairi *et al.* (2021) conclude that oil price stability is indeed the main driver of OPEC production adjustments, while making opportunistic sales and stabilizing own revenues from oil exports are secondary. Still, assuming that the production changes are imposed exclusively to control oil prices and production would not be correct, as geological endowments and political situations are also important determinants of OPEC decisions. The implementation of the Iran Nuclear Agreement and the cancellation of the Clean Power Plan are also economic events based on political decisions.

Natural events

Considering the natural events overview in Table 5.4, 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 approximated at around 50 tonnes or one full tanker. A spill of this magnitude is too negligible compared to, for example, the production changes of OPEC to be considered causal. 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 the 3.19 million barrels lost during the Deepwater Horizon spill is approximately just a third of US daily production in the year 2010 (Energy Information Administration 2022). Even though hurricanes, earthquakes, and extreme temperatures were historically responsible for shutdowns of oil production, none of them caused a significant shift in the connectedness. In conclusion, news of natural disasters does not cause a sudden increase in the connectedness of oil-based commodities even if they disrupt the oil supply.

Table 5.4: 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	52	97,6	99,3	99,6	99,2	Yes	Low
		200	70,8	67,1	76,3	79,4	79,6	No	
17.08.2017	Hurricane Harvey	100	37,7	38,8	38,9	34,1	36,8	No	Low
		200	100	100	100	100	100	Yes	

Notes: This table features all natural events that passed the 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 persistent, 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 Chapter 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 & Moravcová 2023).

Adding natural gas to the network significantly decreases the overall spillover index down to 37.60%. 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 97.88%. This result is in line with the findings of Mensi *et al.* (2021); Kočenda & 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 evolution even after adding natural gas to the network. Natural gas merely reduced the volatility and pushes the average lower. On the other hand, more brief spikes appear, which are usually tied to sudden correlated moves in all the assets. March 2020 is perhaps the longest consecutive period of the energy commodities spillover index being higher than the oil spillover index. 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.

As mentioned at the beginning of the chapter, the choice of lag order, window length, and horizon are set in such a way that the spillover index is more volatile. We experimented with other choices of these parameters for the sake of consistency. Selecting higher lag order and longer horizon had almost no impact on the spillover index. On the other hand, the choice of window length matters substantially. A longer window results in more stable VAR coefficients and less volatility in the rolling spillover index. The literature almost exclusively considers window lengths of 100 and 200 days for daily time series. Moreover, calculating the bootstrap samples for the test is computationally demanding. Thus, we only performed the robustness check for a window length of 200.

Thee 200-day rolling window spillover plot in Figure 5.4 appears to be a smoothed version of the 100-day version. Thus, the long-term development stays the same. As could be expected, increasing the length of the window to 200 reduced the number of events identified from 26 to 17. Approximately half of the 17 events are also present in the results of the 100-day rolling window, while the other half has similar characteristics to those identified in the 100-day rolling window. We will briefly discuss the events that were not included in the main results. Firstly, the extension of the Oil for Food program announced on December 4, 1997, triggered a statistically significant spike in connectedness followed by a steady increase in the connectedness in the following years. The extension once again ignited the controversy surrounding the program (Hsieh & Moretti 2006).

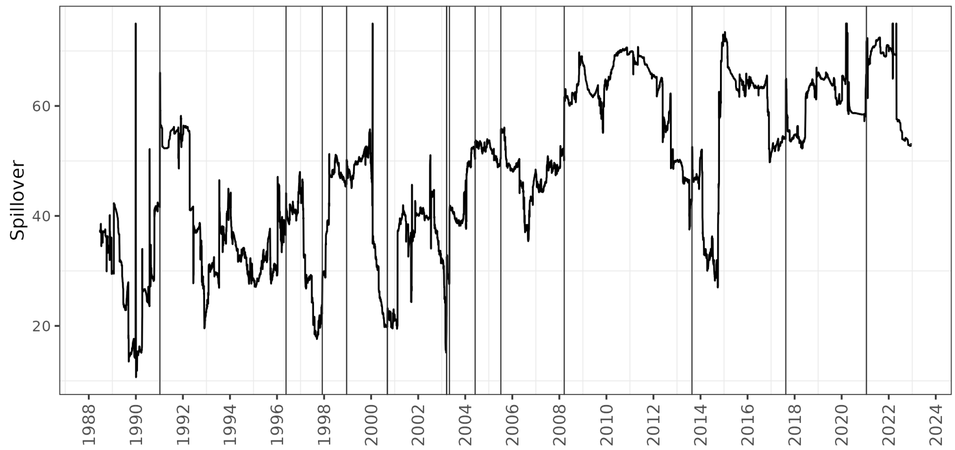
The first notable discrepancy between the two versions appears on May 1st, 2003. On that day, George Bush made his 'Mission Accomplished' speech regarding the victory in Iraq. The spillover index was not affected on that day for the 100-day window version, while it e a sudden and persistent increase in the 200-day version. Although the war conflict continued even after the speech, the event is inherently positive, so the reasoning behind its effect on the spillover index is not clear.

During the Syrian Civil War in the years 2012 and 2013, there was another event that caused a short-lived spike in the 200-day rolling window spillover index. On August 20, 2013, there was a massive chemical attack that killed over 1300 people, making it the deadliest incident of the war. United nations along with the United States representatives were shocked by the escalation, and immediately took action by sending in UN chemical weapon investigators (The Guardian 2013). The event is closely similar to the bombing in Iraq on August 14, 2007, in the sense that there is no direct connection to the oil supply, but the gravity of the events raised concerns over future development.

The last noteworthy event identified by the 200-day rolling window is the announcement that the United States is going to rejoin Paris Climate Accord. The White House announced the news on January 20, 2021, under the presidency of Joe Biden. The decision featured curbing methane emissions of oil companies and the revocation of the Keystone XL oil pipeline permit was also a part of the announcement. Thus, it was perceived negatively by the oil market and caused fears over the stability of oil production.

To summarize, the 200-day rolling window identified the same events as the 100-day rolling window. Events that were not previously identified had characteristics in line with those presented in the main part of our results. Thus, we conclude that the choice of window length has some impact on the results, but the general event characteristics stay the same.

Figure 5.4: Overall Spillover



Notes: This figure shows the evolution of the overall spillover calculated on the rolling window of 200 days. The vertical lines represent the events that passed the significance threshold.

Chapter 6

Conclusion

The objective of this study was to analyze volatility spillovers between oil-based commodities, detect events that caused sudden and persistent increases in volatility spillovers of the commodities, and identify their common characteristics. Using the spillover index methodology proposed by Diebold & Yilmaz (2009), 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. The volatility before the year 2008 was mainly caused by war conflicts and political tensions in the Middle East. The increase in overall connectedness can be attributed to the financialization of commodities and tight oil exploration in the United States that oversupplied the oil market, as argued by Baruník *et al.* (2015). After April 2022, the spillover index sharply decreased and reached values last observed in 2014, which were caused by the abundance of oil on the market. The decrease around April 2022 was caused by the stabilization of market conditions after the war in Ukraine. Further contributing factors were likely of macroeconomic nature, mainly recession fears and interest rate hikes in the United States and European Union.

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 for the majority of the studied period. Hence, shocks to these commodities are responsible for the increased volatility of other oil-based commodities. Gasoline functions as a net volatility receiver and diesel is neither a net receiver nor a net transmitter. Adding natural gas to the network only decreased the overall connectedness, since natural gas is dependent on its own volatility shocks from almost 100%. The findings are consistent with that of Kočenda & Moravcová (2023).

We calculated the spectral decomposition of the spillover index as proposed by Baruník & Křehlík (2018). The shocks to the system propagate themselves mainly in a short-term horizon of 5 trading days. The short-term horizon grows in importance after 2008, which further confirms the notion that financialization is responsible for the increasing connectedness. We identified several periods during which the connectedness in the short-term horizon fell in power, all of which correspond to periods of low oil stock and uncertainty. Two recent examples include the start of the COVID-19 crisis around March 2020 and the Russian invasion of Ukraine in February 2022.

We identified 26 statistically significant events after which the spillover index persistently increased. We analyzed the events thoroughly and grouped them into several categories based on their characteristics. The findings suggest that events of geopolitical nature are twice as likely to cause a shift in the network connectedness of oil-based commodities. Furthermore, most economic news that passed the significance threshold has some geopolitical reasoning behind them. There was no natural event identified as significant.

There were three main characteristics that often appeared across all the categories. The selected events were usually unexpected, negative, and associated with a decrease in oil exports. The first two characteristics were also found by Greenwood-Nimmo *et al.* (2021) in their event replication of Diebold & Yilmaz (2009).

Acts of terrorism or political tensions that oil supply disruptions were the most prevalent type of geopolitical events causing the spillover index to persistently 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 economic nature, we did not identify any effect of mergers and acquisitions of oil companies on the spillover index. Trade sanctions imposed on oil exporting countries never caused a sudden shift in the volatility spillovers among oil commodities as well. As oil is a necessity good, exporting countries will simply change buyers when presented with sanctions (Torbat 2005b). Threats and speculations of both geopolitical and economic type were also ineffective.

Furthermore, our study sheds some light on the effect of OPEC production changes on volatility spillovers. As OPEC decisions are announced in regular meetings, they should not bring too much surprise to the market. It has also been shown that the decisions sometimes leak prior to the announcement (Schmidbauer & Rösch 2012). A logical assumption would be that the decisions to cut production cause an increase in volatility spillovers, while decisions to boost or maintain production do not have an effect. Out of the 140 announced production changes of both OPEC and non-OPEC members, we do not find completely concordant results. While there was no decision to maintain with an effect on the spillover index, there were two decisions to boost production identified as opposed to only one decision to cut. Both boost decisions were announced in situations when they only brought more uncertainty to the market, and are described thoroughly in Chapter 5. Therefore, announcing production boosts in periods of uncertainty can raise concerns over the spare capacity of exporting countries. This finding is in line with that of Almutairi *et al.* (2021), who conclude that the spare capacity of OPEC has significant influence over oil price volatility.

Out of the 130 events with natural causes in our dataset, there was no plausible event identified as significant. 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 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. Still, there are some potential caveats to our thesis. Firstly, it was necessary to combine varying data sources due to the lack of data quality available to use. Furthermore, we chose the ranged-based realized volatility estimator as our primary method for computing the volatility of selected commodity prices. It has been shown that this method is almost as efficient as the high-frequency estimator, but the difference between using the range-based estimator to calculate volatility spillovers as opposed to the high-frequency estimator has not been thoroughly analyzed.

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