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Abstract

We analyze (frequency) connectedness and portfolio hedging among U.S. energy commodities from 1997 to 2023. We show that the total connectedness increased over time, likely due to the increasing financialization of energy commodities. It fluctuates with respect to (i) different investment horizons and (ii) different periods of distress. The early stage of the Russia-Ukraine war is associated with the highest systemic risk, followed by the Covid-19 pandemic and global financial crisis (GFC). In the frequency domain, the results imply that investors perceive the greatest risk at longer investment horizons, particularly during the three major distress periods. We also show that despite it is difficult and more costly to diversify an energy portfolio during distress periods, adding natural gas seems to bring non-marginal diversification benefits.

JEL-Codes: C580, F650, G150, Q340, Q410.

Keywords: connectedness, volatility spillovers, frequency decomposition, portfolio weights and hedge ratios, energy commodities, distress.

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1. INTRODUCTION AND MOTIVATION

Understanding the intricate web of global economic dynamics hinges on grasping the interconnectedness of financial assets and markets (Diebold and Yilmaz, 2015). Among these assets, oil-based energy commodities assume critical significance due to their universal impact on the economies, financial markets, and trade (Elsayed et al., 2020). This significance is further underscored by the fact that geopolitical tensions, periods of economic turmoil, and abrupt shifts in supply and demand are primary drivers behind the oscillations in energy commodity prices (Bouoiyour et al., 2019; Smales, 2021; Gong and Xu, 2022). These fluctuations not only reverberate within the energy sector but also permeate through other asset classes, creating a ripple effect that resonates in financial markets (Gomez-Gonzalez et al., 2022). The interconnectedness, quantifiable in terms of its extent, is closely intertwined with risk assessment and investment strategies and impacts a score of stakeholders. Consequently, it serves as a crucial metric that informs prudent decision-making and risk management practices.[1] Surprisingly, the financial effects of volatility spillovers (connectedness) across energy commodities in the U.S. market, along with their dynamics and impact on portfolio structures, have not been sufficiently analyzed. For that, we present a comprehensive analysis of volatility spillovers among five key energy commodities (oil, diesel fuel, heating oil, gasoline, and natural gas) in the U.S. financial market over a 27-year period (1997-2023). Our contribution is threefold: (i) to the best of our knowledge, we provide the first detailed analysis of frequency connectedness among U.S. energy commodities at investment horizons of different lengths, (ii) we cover all recent stressful periods, and (iii) we quantify the portfolio composition weights and hedging costs under different degrees of distress.

Motivation for the above broad topic of our research comes from several grounds. Fluctuations in international energy prices may lead to serious macroeconomic turbulence, particularly for energy-dependent countries, as most production and consumption activities require energy as an essential input (Chontanawat et al., 2008; Soytas and Sari, 2003). Energy prices are also a driver of inflation due to the share of energy in consumption expenditures and the degree of pass-through of oil price developments to consumer energy prices in each country (Dagoumas et al., 2020). Further, the volatility of energy commodities may greatly impact their role in traditional portfolio diversification, asset allocation, and downside risk reduction since commodity markets have become an important asset class in global financial markets with

[1] Volatility connectedness quantifies the dynamic and directional characterization of volatility spillovers among assets or across markets (Diebold and Yilmaz, 2015). In the text, we use the terms connectedness and spillovers interchangeably, as both have been used in the literature to describe the same phenomenon.

increased spillover transmission to the rest of the financial system (Mensi et al., 2021; Gomez-Gonzalez et al., 2022). Finally, the financialization of commodities led them to become part of the indices and structured financial products commonly used by average investors, as well as large institutional investors such as hedge funds, pension funds, or mutual funds (Adams and Glück, 2015; Babalos and Balcilar, 2017). Moreover, Adams et al. (2020) uncover that the financialization of the commodity market has altered the behavior of commodity prices in the way that financial variables have become the main driving factor of price returns. Finally, Iqbal (2023) show that the financialization of commodities exhibits a significant effect on commodity price booms and busts. For all the above reasons, studying connectedness among oil-based commodities is crucial, given the significant role that oil plays in the global economy and its impact on various industries and financial markets. Hence, the results of our analysis also provide policy implications for various stakeholders such as investors, policymakers, and major central banks.

The academic importance of studying connectedness among energy commodity price returns is grounded in the economic and financial nature of the links among commodities. There are two theoretical approaches that inspire the links leading to connectedness. From an economic point, the existence of the production and substitution relationships among energy commodities produces an impact on their prices. First, crude oil and natural gas can be regarded as imperfect substitutes in the industrial and energy sectors. In terms of price development and its volatility, the substitutional relationship can also be applied to other energy commodities. Second, energy commodities also exhibit a production relationship since one commodity is produced from another, and the link transfers to their prices. Specific examples are shown by Casassus et al. (2013), who describe how the petroleum refining process transforms crude oil (input) into heating oil, gasoline, and diesel fuel (outputs). In addition, a complementary relationship (in production) exists between gasoline and heating oil since heating oil can also be produced as a by-product (output) of the “cracking” process of crude oil (input) into gasoline (output). From a financial perspective, further theoretical support originates in the theory that connects hedging and speculation in commodity futures (Leland, 1960). Such a concept is quite relevant in our case because the increased financialization of crude oil, as the world's most widely traded commodity since 2000 (Cevik et al., 2020), has prompted the demand for oil-derivate instruments - futures and options - as hedge assets against the extreme volatility of stock prices (Büyükşahin and Robe, 2014). The theoretically grounded economic and financial links among the energy commodities constitute a solid basis for the strong links among their prices and their interconnectedness, which is expected to materialize due to the commodities’ ongoing and strong financialization. Consequently, analyzing connectedness among energy commodities has practical implications. Market participants such as airlines and oil producers prefer oil-based futures and options to hedge against swings in the price of oil itself. Speculators profiting from price swings use the same securities but for a different reason. Such hedging instruments are important to many oil producers and consumers because oil prices can be extremely volatile.

Large investment flows into commodity markets can be attributed to price distortions and increased volatility. Since volatility represents a proxy to measure risk, substantial changes in volatility and spillovers across assets in financial markets have an impact on risk-averse investors. Hence, understanding volatility spillover dynamics has crucial implications for portfolio construction, diversification, hedging, asset pricing models, and forecasting (Gorton and Rouwenhorst, 2005; Chuliá et al., 2019). Research on volatility propagation has increased after Diebold and Yilmaz (2009, 2012, 2014) introduced a new approach to analyzing spillovers based on network analysis. Baruník and Křehlík (2018) further extended this technique to empirically examine volatility spillovers at various time-frequencies that proxy for different investment horizons. However, the research on frequency connectedness, specifically among energy commodities, is limited and not adequately explored. One strand of the literature analyzes the volatility spillovers in the energy market between different trading centers (Lin and Tamvakis, 2001; Hammoudeh et al., 2003; Chang et al., 2010). A second and recent strand of the literature explores frequency volatility connectedness between energy commodities and other asset classes (Baruník and Kočenda, 2019; Guhathakurta et al., 2020; Zhang and Yan, 2020; Li et al., 2021; Adeleke and Awodumi, 2022; Jiang and Chen, 2022). The third strand of the literature examines the mutual connectedness among different energy assets, mostly oil-based ones, and constitutes the closest set of the literature related to our energy commodity sample. Baruník et al. (2015) apply the DY index methodology to analyze asymmetries in volatility spillovers of petroleum commodities (crude oil, gasoline, and heating oil) and reveal that volatility spillovers rise after 2001, while the asymmetries in spillovers decline after the GFC. The oil-gas relationship is further examined by Ji et al. (2018). They combine the connectedness network framework of Diebold and Yilmaz (2012) with the ensemble empirical mode decomposition method to examine the oil-gas relationship. Their results suggest that WTI and its refinery products tend to act as net information transmitters, while the United States and United Kingdom natural gas markets act as net receivers. Chuliá et al. (2019) also analyze the oil-gas relationship and conclude that natural gas may replace crude oil as the global benchmark price for energy commodities. Lovcha and Perez-Laborda

(2020) study the frequency volatility connectedness between the U.S. oil and natural gas markets from 1994 to 2018. Their results reveal that connectedness typically forms at low frequencies, with volatility shocks across markets having long-lasting effects. Polat (2020) and Lin and Su (2021) demonstrate varying connectedness in energy commodities linked to the Covid-19 period but cover only the early stage of the pandemic. Wei et al. (2022) bring evidence of the information connectedness of international crude oil futures.

While the above studies provide valuable contributions, we identify the following research gaps. The above studies jointly (i) do not sufficiently cover both recent periods of distress (the Covid-19 pandemic and the Russia–Ukraine war); this is understandable given their publication time frame, (ii) do not account for the financialization of the energy commodities by analyzing their portfolio structure, and (iii) do not adopt frequency connectedness approach to assess risk and investment horizons. In this context, the dynamics of volatility spillovers across energy commodities in the U.S. and their impact on portfolio structures have not been sufficiently analyzed. We *simultaneously* cover these three key features and differentiate our contribution to the literature from earlier ones. Our motivation for assessing and quantifying volatility connectedness among energy commodities and their portfolio composition is driven by the research gap and the fact that we want to bring an analysis determining the most appropriate methodologies and tools for managing energy commodities' extreme price risk.

We analyze the core research objectives by conducting a comprehensive assessment of system-wide connectedness as follows: (i) we examine five key energy commodities (oil, diesel fuel, heating oil, gasoline, and natural gas), (ii) we cover periods before and after the Global Financial Crisis (GFC) (1997-2008, 2009-2014), the period of low oil prices (2014-2017), and the period of rising interest rates in the U.S. (2017-2019). Within these research periods, we also examine the specific impacts of a particular crisis: the global financial crisis itself (2007-2009) and the Covid-19 pandemic (2020-2021).[2] Yarovaya et al. (2022) discuss the unique characteristics of the Covid-19 crisis and demonstrate how the impacts of the pandemic differ from previous crises with an accent on its financial contagion effects. In addition to the GFC and the Covid-19 crisis, we also cover the first year of the Russia–Ukraine war, which can be regarded as a severe exogenous shock to the energy market. The conflict between Russia and

[2] Jebabli et al. (2022) argue that the two crises show similarities in some features, such as uncertainty, economic recession, and monetary and fiscal authorities' reactions, but they also demonstrate differences. While the global financial crisis affects mainly the demand side, the Covid-19 pandemic impacted chiefly the supply side (Papanikolaou and Schmidt, 2022).

Ukraine presents a distinctive challenge to international financial markets due to Russia's significant influence in energy markets and its status as a major global economy, (iii) we apply the frequency decomposition spillover index as that proxy for different investment horizons introduced by Baruník and Křehlík (2018). The motivation for quantifying frequency connectedness among assets in the financial market stems from the fact that market participants do have distinct investment horizons, varying preferences at different time frequencies, and transmissions of shocks through market transactions may vary based on the time scale (Reboredo and Rivera-Castro, 2014), (iv) we quantify the portfolio composition weights and hedging costs under different degrees of distress. To the best of our knowledge, a complex analysis of the energy market exploring time frequency linkages during recent events plus portfolio structure is missing in the literature.

In terms of the key findings, we document an upward trend in the volatility spillover index over the examined period, indicating that the financialization of the energy commodity market creates a more connected system where shocks are transmitted extensively. The long-term component of connectedness dominates the market during all examined sub-periods. In contrast, the medium-term connectedness exhibits the highest values in post-GFC and period of rising U.S. interest rates. The short-term component of connectedness displays the lowest values during all examined sub-periods. This analysis reveals that spillovers among energy assets are characterized by longer persistence, which could have major implications for the decision-making process of policymakers and regulators, particularly reliant on exporting and importing commodities that are vulnerable to price shocks. With respect to optimal portfolio strategy and risk management, our outcomes reveal that including natural gas in the energy portfolio has substantial diversification benefits, leading to reduced portfolio weights and hedging costs. All the above results demonstrate that studying connectedness among oil-based commodities is crucial, given the significant role that oil plays in the global economy and its impact on various industries and financial markets. The intensifying connectedness within the energy market is a subject of interest for both energy economists and actively involved businesses. Hence, our results provide policy implications for various stakeholders such as investors, policymakers, and major central banks.

The remainder of the paper is structured as follows. In Section 2, we present the literature review. Section 3 displays the data and variables. Section 4 describes the methodological approach based on volatility spillovers. We report our results in Section 5. The last section concludes.

2. LITERATURE REVIEW

The prices of energy assets exhibit substantial volatility, which can be attributed to various factors such as geopolitical tensions, economic conditions, and environmental factors. The varying market conditions make it imperative for economists, policymakers, businesses, and investors to define and apply the most relevant methods and tools to manage energy price risk effectively. The research on *frequency connectedness*, specifically among energy commodities, is limited and not adequately explored. Our study is mainly related to two strands of literature.

The first one explores frequency volatility connectedness between energy commodities and a wide range of other asset classes, including agricultural commodities (Kang et al., 2019; Dahl et al., 2020; Tiwari et al., 2020), metals (Tiwari et al., 2020; Yousaf, 2021; Ding et al., 2023), stocks (Costola and Lorusso, 2022; Dai et al., 2022; Mensi et al., 2022b), foreign exchange (Baruník and Kočenda, 2019), gold (Younis et al., 2023;), bonds (Yousaf et al., 2023), and non-energy commodities (Chen et al., 2022).

The second strand of the literature examines the mutual connectedness on the financial market during various turbulent periods, such as the Global financial crisis (GFC), the European Debt Crisis, the oil crisis, the China Stock Market Crash, the Brexit referendum, the Covid-19 pandemic, and the Russia-Ukraine war. The examination of distress periods has become an area of research interest due to their potential to introduce substantial risks to financial markets. Understanding how markets function during crises is paramount for risk assessment and management. Mensi et al. (2022a) and Younis et al. (2023) empirically document a heightened system-wide interconnectedness and contagion effect during periods marked by elevated geopolitical risk. This strand of literature dedicated to the analysis of volatility transmission mechanisms during turmoil periods has experienced expansion in the aftermath of the past two major crises, namely the COVID-19 pandemic and the Russia-Ukraine war. The measurement of financial market connectedness and cross-market information spillovers from the *time-varying frequency* volatility perspective has been facilitated by Baruník and Křehlík (2018) and Antonakakis et al. (2020) models. Huang et al. (2023) demonstrate that volatility spillovers between financial markets and energy commodities during the Covid-19 pandemic are mainly driven by long-term components. Athari and Hung (2022) reveal that Covid-19 pandemic intensified interdependences between stocks, bonds, commodities, and cryptocurrencies across all time scales and frequency bands. The increased volatility linkages and coherence during Covid-19 pandemic are further documented between cryptocurrencies (Goodell and Goutte, 2021), stocks (Rehman et al., 2021), bonds (Hanif et al., 2023), and commodities (Ma et al., 2021).

The Russia-Ukraine conflict stands as the most significant European war since World War II, exerting a severe influence on global financial markets (Umar et al., 2022a). This event offers a unique chance to enhance the current body of research on how geopolitical risk influences financial markets. volatility linkages. Umar et al. (2022b) suggest that the dynamic volatility transmission pattern among Russia, European financial markets, and the global commodity markets is altered by geopolitical risks stemming from the Russian-Ukrainian conflict. Wu et al. (2023) document the significant surge in all volatility frequency components of examined stocks at the onset of the Russia-Ukraine conflict.

Grounded in the above review, we identified the research gap and analyzed it by (i) covering the last distress periods from 2007 to 2023 (the GFC, the Covid-19 pandemic, and the Russia-Ukraine war) to understand shock propagation mechanism in turbulent periods, (ii) analyzing frequency volatility propagation on among the key energy (chiefly petroleum-based) commodities, (iii) analyzing the financialization of energy commodities by assessing their portfolio structure as investors are interested in energy commodities to generate returns and mitigate risks (Lin and Li, 2015; Lin and Su, 2021). In accordance with the research topic and the literature gap, we formulate the following testable hypotheses:

Hypothesis 1: Mutual volatility linkages in the energy market do not strengthen during the distress periods of the GFC, the COVID-19 pandemic, and the Russia-Ukraine war.

Hypothesis 2: The long-term connectedness does not dominate during the distress periods of the GFC, the COVID-19 pandemic, and the Russia-Ukraine war.

Hypothesis 3: Adding natural gas to the portfolios of oil-based commodities does not bring diversification benefits.

Hypothesis 4: Turbulent periods of the GFC, the COVID-19 pandemic, and the Russia-Ukraine war do not increase portfolio hedging costs.

In sum, we bring a unique aspect to the literature by examining the frequency connectedness and portfolio hedging among U.S. energy commodities. We concentrate on the specific set of energy commodities linked together via production/supply processes, plus we determine the most appropriate methodologies and tools for managing energy commodities' extreme price portfolio risk. Our results provide qualified support for the notion that the spillover index responds to exogenous events such as the global financial crisis, low oil prices, rising U.S. interest rates, the Covid-19 pandemic, and the Russia–Ukraine war. To the best of our knowledge, a complex analysis of the energy market exploring time frequency linkages during recent events plus portfolio structure has been missing in the literature.

3. METHODOLOGY

We assess volatility spillovers by employing the Diebold and Yilmaz (2009, 2012, 2014) spillover index methodology and the frequency decomposition advancement of Baruník and Křehlík (2018) to analyze the effect of connectedness at various frequencies that proxy for investment horizons of different lengths.

3.1 Diebold Yilmaz spillover index – total and directional spillovers

We model the *N*-dimensional vector of weekly realized volatilities $RV_t = (RV_{1t}, \dots, RV_{Nt})'$ by a weekly stationary VAR(*p*) process. $RV_t = \sum_{l=1}^{p} \phi_1 RV_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim N(0, \Sigma_\epsilon)$ is a vector of *iid* disturbances and ϕ_1 denotes *p* coefficient matrices. For the invertible VAR process, the moving average is computed as follows:

$$RV_t = \sum_{l=0}^{\infty} \psi_1 \varepsilon_{t-1}. \quad (1)$$

The definition of the moving average representation describes the dynamics of the VAR system as it allows isolating forecast errors used to calculate the connectedness of the system. Diebold and Yilmaz (2012) use the generalized VAR framework developed by Pesaran and Shin (1998), in which variance decompositions are invariant in terms of variable ordering. In this case, the H-step-ahead forecast (*H = 1,2, ...*) of error variance and the corresponding forecast error vector are computed as follows:

$$\theta_{jk}^{H} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H=-1} \left(e_j' \psi_h \Sigma_\epsilon e_k\right)^2}{\sum_{h=0}^{H-1} e_j' \psi_h \Sigma_\epsilon \psi_h' e_k}, \quad j,k = 1, \dots, N, \quad (2)$$

where ψ_h are moving average coefficients from the forecast time *t*, Σ_ϵ is the variance matrix for the error vector ε_t, σ_{kk} is the *k*th diagonal element of Σ_ϵ, and e_j and e_k are the selection vectors, with a value of one for the *j*th or *k*th element and zero otherwise. In the generalized VAR framework, shocks to each variable are not orthogonalized; therefore, the sum of each row of the variance decomposition matrix is not unity $\left(\sum_{k=1}^{N} \theta_{jk}^{H} \neq 1\right)$. In this case, each element of the decomposition matrix is normalized by dividing it by the row sum

$$\widetilde{\theta_{jk}^{H}} = \frac{\theta_{jk}^{H}}{\sum_{k=1}^{N} \theta_{jk}^{H}}, \quad (3)$$

where, by construction, $\sum_{k=1}^{N} \widetilde{\theta_{jk}^{H}} = 1$ and $\sum_{j,k=1}^{N} \widetilde{\theta_{jk}^{H}} = N$.

Using normalized elements of the decomposition matrix of equation (3), the total volatility spillover index is constructed as:

$$S^H = \frac{\sum_{\substack{j,k=1 \\ j\neq k}}^{N} \widetilde{\theta_{jk}^H}}{\sum_{j,k=1}^{N} \theta_{jk}^H} * 100 = \frac{\sum_{\substack{j,k=1 \\ j\neq k}}^{N} \widetilde{\theta_{jk}^H}}{N} * 100. \quad (4)$$

To capture the spillover dynamics, we follow Liu et al. (2020) and use a 100-day rolling window running from point $t - 99$ to point t. Further, we assume a forecast horizon H = 100 as in Wang et al. (2022), which is consistent with the setting in Baruník and Křehlík (2018), and a VAR lag length of 1 based on the information criteria results.[3]

To examine spillover effects *from-* and *to-* a specific commodity, we use directional volatility spillovers. Spillovers received by commodity *j* from all other commodities *k* (*from*-spillovers) are defined as follows:

$$S_{N,j\leftarrow\circ}^H = \frac{1}{N}\sum_{\substack{k=1 \\ j\neq k}}^{N} \tilde{\theta}_{jk}^H * 100. \quad (5a)$$

The *N* in the subscript denotes the use of the *N* – dimensional VAR. In a similar fashion, directional volatility spillovers transmitted by commodity *j* to all other commodities *k* (*to*-spillovers) are defined as:

$$S_{N,j\rightarrow\circ}^H = \frac{1}{N}\sum_{\substack{k=1 \\ j\neq k}}^{N} \tilde{\theta}_{jkkj}^H * 100. \quad (5b)$$

Finally, the net directional volatility spillover is defined as a difference between two directional spillovers in (5a) and (5b):

$$S_{N,j}^H = S_{N,j\leftarrow\circ}^H - S_{N,j\rightarrow\circ}^H. \quad (6)$$

3.2 Frequency decomposition across investment horizons

The Diebold-Yilmaz spillover index described above measures both system-wide connectedness and directional spillovers (*from-* and *to-*). We continue with an introduction of time-frequency decompositions of the spillover index proposed by Baruník and Křehlík (2018) to compute the frequency decomposition of *to-* and *from-* volatility spillovers capturing short-, medium- and long-term dynamics. In our case, we employ the following intervals: short-term (1 - 5 days), medium-term (5 - 20 days), and long-term (20 - 200 days). These intervals reflect a business week, a business month, and a business year, respectively, and represent investment horizons of corresponding length (Baruník and Kočenda, 2019; Brož and Kočenda, 2022).

[3] As a robustness check, we have experimented with different rolling windows and forecasting horizons with no material changes in the results. For these reasons, we prefer to use a standard Diebold-Yilmaz technique while we acknowledge the merit of the recent advancement in a form of the Time-Varying Parameters Vector Autoregression (TVP-VAR) based on the Diebold-Yilmaz technique introduced by Antonakakis et al. (2020) that avoids rolling window setting. The technique was recently adopted by Balcilar et al. (2021).

Baruník and Křehlík (2018) use a spectral representation of variance decompositions based on frequency responses to shocks (instead of impulse responses to shocks) for measuring the frequency dynamics of connectedness in the financial market. They introduce as a starting point a frequency response function: $\left(e^{-i\omega}\right) = \sum_h e^{-i\omega h}\, \psi_h$. The frequency response function can be calculated as a Fourier transform of coefficients ψ_h with $i = \sqrt{-1}$. The spectral density of the annualized daily percentage volatility RV_t described in equations 12 and 13 at frequency ω can be quantified as a Fourier transform of the *MA(∞)* filtered series:

$$S_{RV}(\omega) = \sum_{h=-\infty}^{\infty} E(RV_t\, RV'_{t-h})e^{-i\omega h} = \Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}), \quad (7)$$

where $S_{RV}(\omega)$ is the power spectrum specifying how the variance of RV_t is distributed over frequency components ω. Baruník and Křehlík (2018) describe the frequency domain counterparts of variance decomposition by the application of the spectral representation for covariance, i.e., $\Sigma_\omega\, \hat{\psi}(\omega)\, \hat{\Sigma}\, \hat{\psi}'(\omega)$ for $\omega \in \left\{\left|\frac{aH}{2\pi}\right|, \dots, \left|\frac{bH}{2\pi}\right|\right\}$, where $\hat{\psi}(\omega) = \sum_{h=0}^{H-1} \hat{\psi}_h\, e^{-2i\pi\omega/H}$ and $\hat{\Sigma} = \hat{\epsilon}'\hat{\epsilon}\,/(T-z)$, where *z* depends on the VAR specification and is a correction for a loss of degrees of freedom.

The decomposition of the impulse response function at the given frequency band can be calculated as $\hat{\psi}(d) = \Sigma_\omega\, \hat{\psi}(\omega)$. The generalized variance decomposition at a specific frequency band is computed as:

$$\hat{\theta}_{j,k}(d) = \sum_\omega \hat{\Gamma}_j\ (\omega) \frac{\sigma_{kk}^{-1}\left(e_j'\hat{\psi}(\omega)\hat{\Sigma}e_k\right)^2}{e_j'\hat{\psi}(\omega)\hat{\Sigma}\,\hat{\psi}'(\omega)e_j}, \quad (8)$$

where $\hat{\Gamma}_j\,(\omega) = \frac{e_j'\hat{\psi}(\omega)\hat{\Sigma}\,\hat{\psi}'(\omega)e_j}{e_j'\Omega e_j}$ is an estimation of the weighting function, where $\Omega = \Sigma_\omega\, \hat{\psi}(\omega)\, \hat{\Sigma}\, \hat{\psi}'(\omega)$. The connectedness measure at a specific frequency band can by computed by substituting the $\hat{\theta}_{j,k}(d)$ estimate into the measures described above. For computation, we apply a vector auto-regression model with one lag based on an information criterion to measure the dynamics in the window. Following Baruník and Křehlík (2018), the rolling-sample window is set at 100 days, and the predictive horizon for the variance decomposition is set at 100 days.[4]

Similar approaches were recently adopted in the literature to analyze time-varying exchange rate co-movements and volatility spillovers in the forex market (Kočenda and Moravcová, 2019), the systemic risk in the U.S. banking industry (Brož and Kočenda, 2022), volatility spillovers across precious and industrial metal markets (Liu et al., 2020), and the

[4] As a robustness check, we have experimented with different lag lengths, and we also tested a VAR-LASSO model specification, with no material changes in the results.

time-frequency dynamics of volatility spillovers among major stock indices during the Covid-19 pandemic (Wang et al., 2022).

3.3 Portfolio weights and hedge ratios

Markowitz (1991), in his optimal portfolio theory, defines the optimal portfolio, which maximizes the expected return considering a certain level of market risk. Following this idea, we estimate the ADCC model to compute hedge ratios and portfolio weights for energy commodities in an optimal portfolio. We also account for different examined periods that reflect distress in the market.

First, we calculate appropriate GARCH models for each commodity in a specific time period. In the next step, we use time-varying conditional correlations obtained from the second stage of the ADCC model estimation to calculate the optimal diversification of the energy commodity portfolio. Kroner and Sultan (1993) employ conditional variance and covariance to calculate hedge ratios. Kroner and Ng (1998) then use conditional variance and covariance to design optimal portfolio weights. Based on the above approaches, the hedge ratio is calculated as:

$$\beta_{j,k,t} = h_{j,k,t}/h_{k,k,t} \, , \tag{9}$$

where $h_{j,k,t}$ is the conditional covariance between the exchange rates of commodities j and k and $h_{k,k,t}$ is the conditional variance of commodity k at time t. This formula implies that a long position in one commodity (e.g., j) can be hedged by a short position in another commodity (e.g., k).

In a portfolio of two energy commodities, optimal portfolio weights between commodity j and k at time t are calculated based on the following formula:

$$w_{j,k,t} = \frac{h_{kk,t} - h_{j,k,t}}{h_{jj,t} - 2h_{jk,t} + h_{kk,,t}} \, . \tag{10}$$

In (10), $w_{jk,t}$ is the weight of commodity j and $(1 - w_{jk,t})$ is the weight of commodity k. Weights implying the portfolio composition follow the conditions shown below:

$$w_{jk,t} = \begin{cases} 0, & if\ w_{jk,t} < 0 \\ w_{jk,t}, & if\ 0 \leq w_{jk,t} \leq 1 \\ 1, & if\ w_{jk,t} > 1 \end{cases} \, . \tag{11}$$

A similar approach was recently adopted in the empirical financial literature analyzing Central European currencies (Kočenda and Moravcová, 2019) or examining the co-movements between the World Stock Index and the World Energy Index (Elsayed et al., 2020).

4. DATA

We analyze total volatility spillovers, directional volatility spillovers, and frequency volatility spillovers among five energy assets over the period from January 8, 1997 to February 6, 2023, which constitutes a sample of 6742 observations; the sample period begins with a major oil price downturn that occurred from 1997 to 1999 and ends with the first year of the Russia-Ukraine war.[5] For our analysis, we use daily spot prices available from the U.S. Energy Information and Administration (EIA) website.[6] In terms of oil, we follow the standard in the literature and report West Texas Intermediate (WTI-Cushing) oil. As for gasoline, we report prices for New York Harbor Regular Gasoline, which exhibits lower volatility compared to gasoline prices in California.[7] The rest of the energy assets are reported as: Ultra-Low Sulfur No. 2 Diesel Fuel (Diesel), New York Harbor Heating Oil (Heating Oil), and Natural Gas Spot Prices Henry Hub (Natural Gas). Crude oil prices are denoted in U.S. Dollars per Barrel, while the remaining energy products are expressed in U.S. Dollars per Gallon.[8]

From our data, we calculate a weekly realized volatility (RV_t) over a rolling window to measure market volatility in the same way as Dai et al. (2020), Liu and Gong (2020), and Tang et al. (2021).[9] The realized volatility is defined as:

$$RV_t = \sum_{i=1}^{K} r_{it}^2 , \tag{12}$$

where r_{it} is the daily return on day i during week t. K represents the number of business days during the week (normally, $K = 5$). The daily return r_{it} is computed as a logarithmic return by using the standard formula $r_{it} = (\ln p_{it} - \ln p_{it-1})$, where p_{it} is the spot price of a commodity on day i in week t, and p_{it-1} is the commodity spot price one day before. As suggested by Diebold and Yilmaz (2012), we estimate the corresponding annualized daily percent standard deviation (volatility) as:

$$\hat{\sigma}_t = \ln(100.\sqrt{52 \, .RV_t}). \tag{13}$$

[5] The dataset is cleaned from trades completed on Saturdays and Sundays, December 24 to 26, and December 31 to January 2, due to low activity on these days, which may lead to estimation bias (see Baruník and Křehlík, 2018). The crude oil price fell to negative territory on April 20, 2020, precluding the computation of logarithmic returns. We substitute the price with the average value of the previous and following days.

[6] Data were downloaded from https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm.

[7] California gasoline prices are generally higher and more variable than prices in other U.S. states because relatively few supply sources offer California's unique blend of gasoline outside of the state. California refineries need to run at near full capacity to meet the state's gasoline demand. If more than one of its refineries experiences operating problems at the same time, California's gasoline prices can increase substantially.

[8] https://www.eia.gov/dnav/pet/PET_PRI_SPT_S1_D.htm

[9] Volatility quantification in terms of realized variance was presented by Andersen et al. (2001) and Barndorff-Nielsen (2002) and applied in Diebold and Yilmaz (2014). We acknowledge that the realized volatility is often computed using the 5-min intraday data. However, the U.S. Energy Information and Administration does not report the data at such frequency, plus our intention is to calculate weekly realized volatility as in Dai et al. (2020), Liu and Gong (2020), and Tang et al. (2021).

We report summary descriptive statistics of the log volatilities in Table 1. From the descriptive statistics, we can observe several interesting facts. One, natural gas is the most volatile energy commodity with the highest standard deviation of 0.0511, while other examined commodities show similar standard deviations ranging from 0.0247 to 0.0277. Two, the largest kurtosis is associated with negatively skewed natural gas (52.6597), which indicates a high level of risk for investment due to higher probabilities of negative extreme returns. Similarly, heating oil and diesel are skewed to the left. Three, crude oil and gasoline are positively skewed, indicating that most extreme values are concentrated on the right side.

Our intention is to analyze the data during different periods of economic development, with an accent on various degrees of distress. For that, following the relatively calm development of the late 1990s and early 2000s, we divide our data set into seven sub-periods: (i) the period before the Global Financial Crisis (pre-GFC), (ii) the global financial crisis period (GFC), (iii) the post-GFC period, (iv) the period of low oil prices, (v) the period of rising U.S. interest rates, (vi) the period of the Covid-19 pandemic, and (vii) the period of the Russia–Ukraine war. We employ a combination of the Bai-Perron (1998, 2003) tests to detect structural breaks in the five examined energy commodities, along with key economic events to define the critical periods.

Period one is the pre-GFC period (January 8, 1997 – June 28, 2007). This period begins with a major oil price downturn that occurred from 1997 to 1999. Consequently, the price of WTI sustainably increased between the years 2002 and 2008. This time period represents seven consecutive years in a row, with the annual average price rising year-on-year. The rise in oil prices coincided with the global commodity price boom and asset price increase, represented by real estate market bubbles in the UK and the U.S. Additionally, innovations in financial markets contributed to the sustained rise of oil prices. The positive price trend in the oil market ended in 2008 with the emergence of the GFC. Period two is the global financial crisis (June 29, 2007 – February 5, 2009), characterized by extreme stress in global financial markets and banking systems. Period three is the post-GFC period (February 6, 2009 – November 29, 2014), marked by a rise in the oil price on the back of supply risks and disruptions in the Middle East and North Africa, along with tight fundamentals. Period four (November 30, 2014 – August 9, 2017) is characterized by a collapse in oil prices. During period five, the Fed increased U.S. interest rates from 0.75-1.00% to 2.25-2.50% in response to solid gains in the U.S. economy (August 10, 2017 – December 31, 2019). Period six is the Covid-19 pandemic (January 1, 2020 - February 23, 2022). Salisu et al. (2021) state that the Covid-19 pandemic led to a global economic slowdown, causing a drop in the West Texas Intermediate oil price below zero in

April 2020. Period seven covers the first year of the Russia–Ukraine war (February 24, 2022 – February 6, 2023), which has resulted in major supply disruptions and historically higher prices for a number of commodities.

5. EMPIRICAL RESULTS

5.1 Total connectedness

The complexity of the connectedness in the U.S. energy commodity market is portrayed with the total volatility spillover plot in Figure 1, that illustrates the dynamics of the volatility spillovers among the five energy commodities over the examined time period. The index ranges from 16.58% to 69.21%, representing both calm and turbulent periods. The total volatility spillover index over the whole examined period is, on average, 39.71%. Advance with the total volatility spillover index, it exhibits higher highs and higher lows during our examined period. Continuously higher peaks of the index indicate increasing interdependencies in the commodity markets, that is related to the expanding financialization of commodities in general (Mensi et al., 2013). In other words, the shock transmission through the examined assets is more intensified over time, generating a more connected system. These spillovers may greatly affect insurance against risk and portfolio construction, as well as diversification strategies. In addition to the main rising trend identified in the total volatility spillover index described above, we can observe several sub-trends. (i) An upward trend during the global financial crisis (2006-2009). (ii) A diminishing spillover index after the GFC (2009-2015). (iii) An increasing trend from 2015 to August 2022, which is terminated by the sharp decline of the index. This last section of the index contains the Covid-19 pandemic and the Russia–Ukraine war. Notably, the beginning of the Covid-19 pandemic is for a short time period marked by a large drop in the index, possibly due to a general decrease in activity linked to severe economic limits imposed worldwide.[10] Lin and Su (2021) explain this steep decline in energy commodity connectedness by historically unique negative WTI price. Guo et al. (2021) argue that crude oil prices fluctuated dramatically because of the unbalance of supply and demand. Short after the sharp decline, the spillover index rises above previous levels.[11] The higher volatility connectedness on the energy market during the Covid-19 pandemic is subject to the substantial

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[10] Ali et al. (2020) claim that huge crude oil price swings happened partly due to the Covid-19 pandemic and partly due to political maneuvers among oil producers during the period.

[11] In March 2022, crude oil prices reached eleven-year highs of more than $120 per barrel. That is in stark contrast with crude oil's plunge in the spring of 2020 in response to the Covid-19 pandemic. At that time, the price of April West Texas Intermediate crude oil futures fell to minus $37 per barrel shortly before expiration, meaning that traders were willing to pay to avoid the physical delivery of crude oil.

mediating impact of financial panic risk (Lin and Su, 2021). The total volatility spillover index ends with a peak at the beginning of the Russia-Ukraine war, followed by a decline in market connectedness as the initial panic fades away.

The results in Table 2 present numerical calculations of the DY index for the entire period. We observe two key patterns in the total spillover index table. One is that the volatility of natural gas is chiefly affected by its own history, as demonstrated by the diagonal value ($j=k$) of 89.58%. Two, for the rest of the examined commodities, their own volatilities range between 49.60% and 58.42% of the total volatility.

The individual commodities are connected in economic terms due to existing production and substitution relationships among them. A substitution relationship exists between crude oil and natural gas in the industrial and energy sectors. The production relationship in the petroleum refining process transforms crude oil (input) into heating oil, gasoline, and diesel fuel (output). Further, heating oil can also be produced as a by-product of the "cracking" process of crude oil (input) into gasoline (output) (Casassus et al., 2013). Given these production and substitution relationships among commodities, we would expect volatility from crude oil to be quickly transmitted to its by-products (Jena et al., 2022). However, Table 2 shows a different pattern as spillovers from crude oil to gasoline, diesel, and heating oil are not so large. Very similar results are presented by Baruník et al. (2016) for a different time span, showing that crude oil is not a dominant volatility transmitter to heating oil and gasoline. In sum, our results indicate the potential diversification benefits of introducing petroleum-based products (diesel, gasoline, heating oil) into a portfolio of oil-linked assets.

Further, the analysis of individual sub-periods represented in Table 3 and Table 4 shows that the highest value of the total spillover index is demonstrated during the distress periods of the Covid-19 pandemic (55.20%) and GFC (50.88%), which enables us to reject Hypothesis 1. The pattern of increased connectedness and system-wide contagion vulnerability during different episodes of crises in the financial market aligns with Mensi et al. (2022a), Mensi et al. (2022c) and Younis et al. (2023). The last distress period we examine is the first year of the Russia-Ukraine war. The empirical analysis of the total spillover index reveals two patterns during the Russia-Ukraine war. The initial phase of the conflict is characterized by increased uncertainty and instability as a result of multiple factors, including political unrest, disrupted trade alliances, and the looming possibility of economic ramifications. During the first two months of the conflict, the total volatility spillover index surged to 53.97%, one of the highest values since 1997 (results are presented in Table 4). Such behavior is in line with the heuristics concept applied to finance by Tversky and Kahneman (1973), in which people tend to accentuate newer or easy-to-remember events instead of investigating the range of available information prior to making decisions. In this respect, the Russia-Ukraine war serves as a bold example fitting the pattern as Umar et al. (2022a) show that the impact of the war was more protracted on many commodities, including gas, oil, gasoline, and heating oil. Another theory explaining intensified volatility transmission during distress period is herding behavior. Investors are subject to herding behavior when they have insufficient information and succumb to emotional contagion. As a result, prices in various markets move simultaneously, even in the absence of direct economic links between them. Nonetheless, market participants revise their expectations as the conflict unfolds and the circumstances become more settled. They develop strategies to mitigate potential risks, resulting in a decline in both volatility and interconnectedness.[12] This is represented by the decline in the index in Figure 1. The detailed defragmentation of this process via inspecting the frequency decomposition and directional spillovers reveals that a decrease in total connectedness after the initial months of the Russia-Ukraine war can be attributed to a decline in long-term connectedness, which follows a similar pattern (Figures 3, 4 and 5). Also, we detect a decline in FROM spillovers for all energy commodities except natural gas, as well as a reduction in TO spillovers for all energy commodities after the first shock of the war dissolves (Figure 2).

The pre-GFC period is notable for the highest spike in the total spillover index, observed in August 2005, which coincided with Hurricane Katrina. The hurricane caused extensive damage to oil and gas infrastructure, leading to a surge in oil and gasoline prices. This event aligns with the findings of Baruník et al. (2016), who conclude that the increase in volatility spillovers in the energy commodity market is in parallel with rising commodity prices.

Another two spikes in the total volatility index are observed during the period of low oil prices in 2015 and 2016. The primary event during that time was the collapse of oil prices, which began in mid-2014 and continued through 2015 and 2016. The reason for the collapse was an oversupply of oil in the global market, driven by increased production from the United States shale oil industry and a decision by OPEC to maintain production levels despite weakening demand. The rapid decline in oil prices caught many market participants off guard, leading to increased market turbulence and concerns about the financial stability of oil-related companies and sectors. Geopolitical tensions in various oil-producing regions added to the

[12] Adekoya et al. (2022) demonstrate stronger connectedness among oil and other financial assets during the Russia–Ukraine war.

volatility and uncertainty in the oil market. Conflicts in the Middle East, particularly in Syria and Iraq, along with tensions between Saudi Arabia and Iran, raised concerns about potential disruptions to the oil supply.

The sub-period associated with rising interest rates in the U.S. displays the low values of the DY index (38.28%), comparing to other periods, as the own-history (diagonal) volatility increases and the off-diagonal volatility decreases. The fundamental link between oil prices and interest rates is that the real interest rate serves as the opportunity cost of oil extraction and storage (Working, 1949). A lower (higher) real interest rate results in reduced (increased) production and increased (reduced) storage. On the other hand, as the interest rate decreases, consumer borrowing goes up, and companies are encouraged to increase spending, which drives up overall oil demand. Based on the above reasoning, the low connectedness values are echoed in the earlier empirical evidence of Akram (2009), who concludes that oil prices increase with negative movements in U.S. real interest rates, or Mensi et al. (2020), who show a significant link between WTI crude oil prices and U.S. interest rates in the intermediate term.

Further, an assessment of individual effects reveals that natural gas stands in contrast to oil-based commodities. Natural gas transmits and receives the lowest portion of volatility from oil-based commodities in all examined sub-periods. Its volatility is chiefly influenced by its own history, with diagonal values above 83.37%, indicating its resistance to volatility shocks coming from oil-based commodities. Diesel exhibits similar characteristics during the pre-GFC period (90.96%). In terms of bidirectional spillovers, heating oil is the dominant commodity in terms of volatility received in each individually examined period (see Table 3). The major sources of volatility transmission vary across periods, with heating oil playing the primary role in the pre-GFC, post-GFC, and Fed rates increase periods. However, during the GFC and Covid-19 pandemic, oil takes on this role, while diesel assumes it during the period of low oil prices, and gasoline does so during the Russia-Ukraine war. Contrary, natural gas transmits the lowest proportion of volatility during all analyzed sub-periods. Additional results of bidirectional spillovers demonstrate that the largest off-diagonal volatilities are between the pairs heating oil-diesel and heating oil-crude oil.

5.2 Directional connectedness

For the purpose of detailed analysis, we further decompose the total volatility spillover index into the directional volatility spillover indices (*from*-, *to*-, and *net*-) defined in equations 5-6; the results are presented in Figure 2 (panels A-C). The decomposition clarifies the cross-commodity relationship and explains why changes in the volatility of one commodity are likely to trigger reactions in other commodities. Panel A in Figure 2 represents how the volatility spillover is transmitted from a particular commodity to other commodities (*from-*). Panel B exhibits the amount of spillover that individual commodities receive (*to-*). Panel C demonstrates *net-*spillovers, that is a difference between *from-* and *to-*spillovers. In other words, if the *net-*spillover is positive, the commodity is a "spillover giver," and if the *net-*spillover is negative, it is a "spillover receiver".

Several interesting patterns and more detailed information on the dynamics of directional spillovers are obtained from the analysis of Figure 2 (panels A-C). (i) The net spillover index of crude oil and heating oil oscillates most of the time in the positive domain (panel C), meaning that these commodities are volatility givers.[13] A detailed analysis of *from-*spillovers (panel A) demonstrates a rising trend with higher lows in volatility transmission from heating oil after the GFC. (ii) A similar pattern of a rising trend in *from-* spillovers is detected for diesel (panel A), leading to its dominance in the positive territory of *net-*spillovers after 2015 (panel C). (iii) Contrary, natural gas mostly oscillates in the negative territory as volatility receiver. (iv) Gasoline seems to have a moderate role in terms of transmitting and receiving volatility, as *net-* spillovers symmetrically alternate from positive to negative territory (panel C).

We can also document some patterns related to the Covid-19 pandemic and the Russia–Ukraine war. In Figure 2 (panel C), we present the net volatility spillovers and demonstrate that (i) natural gas is a net volatility receiver during the Covid-19 pandemic, whereas it turns into a net volatility transmitter during the Russia–Ukraine war. (ii) Crude oil became a source of volatility after the Covid-19 pandemic emerged. Additionally, heating oil and diesel became net receivers at the beginning of the Covid-19 pandemic. All the above results resonate with the general findings of Gong and Xu (2022), who document that geopolitical risk impacts the overall connectedness of commodity markets and Guo et al. (2021), who give warnings on the sensitivity of crude oil to the steps taken during the Covid-19 pandemic.

5.3 Frequency decomposition

After having analyzed the total and directional volatility connectedness in the energy market, we proceed to examine the interconnectedness at different investment horizons (different frequencies). The Diebold and Yilmaz (2014) connectedness framework extended by Baruník

[13] Ji et al. (2018) examine the dynamics of the oil WTI, heating oil, gasoline, U.S. gas, and UK gas from 2000 to 2017. Contrary to our results, they present a negative value for heating oil net directional spillovers, suggesting that heating oil is a volatility receiver during the examined period.

and Křehlík (2018) allows us to precisely assess the dynamics of the frequency decomposition of connectedness across various time periods. This is important as well as useful because various sources fueling individual and market sentiment produce short-, medium-, and long-term risk. Investors' perception of the stability of the economic and financial system often hinges upon understanding the disparities in long-term, medium-term, and short-term volatility connectedness. Therefore, when analyzing system-wide connectedness, we should also examine linkages with different degrees of persistence underlying systemic risk.

In Figures 3, 4 and 5, we present charts of the frequency connectedness among the five examined energy commodities. Short-term volatility decomposition in the upper panels of Figures 4 and 5 is of interest to various subjects in finance, economics, and risk management. For example, portfolio managers assess and manage the risk of their investment portfolios over shorter time horizons. Understanding short-term volatility changes is essential for determining option values and implied volatilities in option's pricing models. High-frequency trading and algorithmic trading firms often focus on short-term volatility patterns to make rapid trading decisions and execute strategies based on intraday price movements. Also, short-term investment horizon can be associated with the short-term investment strategies applied in technical analysis. Finally, understanding how short-term volatility affects investor behavior and decision-making is a key topic in behavioral finance. The long-run connectedness in the lower panels is primarily a subject of interest for funds and long-term investments, such as pension funds, which are concerned with managing long-term volatility to meet their financial goals. Further, economists and policy makers study long-term volatility to assess the economy's stability and make long-range forecasts. The results based on real fundamentals may help to make a proper decision in energy security, resilience, prices, and donations. The medium-term investment horizon is pictured in the middle panels.[14] Medium-term volatility decomposition is crucial for asset allocation decisions, where investors aim to balance risk and return over a horizon of several months to a few years. Economists and policymakers often consider medium-term volatility in macroeconomic indicators when making forecasts and policy decisions. Oil-based commodities are important variables for inflation forecasting. Inflation is also a key factor for pricing fixed-income securities, such as bonds. Finally, firms often evaluate medium-term volatility in cash flows and discount rates when making capital

[14] The total connectedness captures the sum through all frequency bands and corresponds to that presented in Figure 1.

budgeting decisions. Specifically, the medium-term volatility of oil-related commodities will be mainly of interest to companies operating in the energy industry.

From the charts 3, 4 and 5, we can observe three patterns: (i) In periods of pre-GFC, GFC, low oil prices, the Covid-19 pandemic, and the Russia–Ukraine war, the long-term component of connectedness dominates. This component is closely tied to the real economy. Baruník and Křehlík (2018) explain that long-term connectedness is linked to uncertainty in the financial markets, joined with uncertainty about future economic conditions. On the other hand, (ii) during the periods of post-GFC and rising U.S. interest rates, the medium-term component drives the volatility connectedness, while (iii) the short-term connectedness does not dominate in any examined sub-period. The combination of results means that shocks in the energy market primarily impact medium-term and long-term connectedness and generate medium-term and long-term responses.

Apart from the abovementioned patterns, the individually examined distress periods (the GFC, the Covid-19 pandemic, and the Russia-Ukraine war) exhibit some common patterns. In all three periods, the long-term frequency component dominates, and such domination corresponds to several economic explanations. (i) Wei et al. (2022) attribute the dominance of long-term connectedness in crude oil futures to the strong persistence in price volatility. (ii) The dominance of long-term volatility connectedness seems to be driven by economic channels. Kang et al. (2019) argue that long-term volatility connectedness is primarily influenced by economic factors, while financial channels are linked to short-run comovements. (iii) The long-term frequency component is related to unprecedented shock to the economic system. In our analysis, the GFC, the Covid-19 pandemic and the Russia-Ukraine war represent extraordinary economic events (Le et al., 2021; Zhang and Hamori, 2021; Guo et al., 2021). We show in Figures 4 and 5 that the level of long-term connectedness is by far the highest during three specific periods of distress regardless of their origin, whereas the short-term connectedness is comparatively lower. These results allow us to reject Hypothesis 2.

From an investment perspective, the effect of shocks in energy markets is most pronounced for medium-term and long-term strategies. Finally, shocks that materialize on the energy markets are also characterized by longer persistence that produces direct implications for the portfolio management and hedging strategies that we cover later in Section 5.5. The findings further stress the importance of a longer-term investment strategy when compared to a short-term one. As such, the finding hints that, according to behavioral theories, investors may overreact to new information on geopolitical risk and conflicts (Zaremba et al., 2022), but they put an accent on their long-term impact rather than on a short-one.[15] We pursue this avenue in the next section 5.4.

5.4 Drivers of volatility connectedness

In our empirical analysis, we examine the volatility relationships among five energy assets at different time frequencies. To enhance the explanatory power of our analysis and gain a deeper understanding of the factors driving volatility connectedness, we conduct an auxiliary regression analysis following the approach of Baruník and Kočenda (2019). Specifically, we regress the spillover measurements representing short-term, medium-term, and long-term connectedness on three key variables: the VIX index, which measures market "fear" on the stock market, the Geopolitical Risk Index (GPR), which captures geopolitical tensions and events, and the U.S. Dollar index.[16] These variables are selected as potential drivers of oil price volatility. In terms of long-term connectedness, our findings in Table 5 indicate that higher values of the VIX index strengthen volatility linkages in the energy market from the beginning of the GFC until the end of the examined period. Conversely, prior to the GFC, a higher VIX index is associated with decreased long-term connectedness. Analyzing each distress period individually, we bring the following results: (i) During the GFC, the significant decline in asset values, including oil prices, led to market turmoil. The VIX index reached historically high levels as investors were concerned about their portfolios. Across this period, the elevated levels of the VIX index strengthened long-term connectedness in the energy market, while reducing the transmission of volatility in the short and medium-term frequencies. (ii) Contrary to the GFC period, during the Russia-Ukraine war, the role of the VIX index in influencing the volatility spillover effect is found to be minimal. The empirical results indicate that the mechanism of shock propagation is positively associated with geopolitical risk, as measured by the GPR index, across all three frequencies. (iii) The Covid-19 pandemic initially triggered a decline in asset prices, including oil, and led to a surge in market volatility in parallel with the GFC. As the virus spread globally, industries faced severe disruptions, supply chains were disrupted, and existing economic linkages were eroded, causing uncertainty to spread

[15] Short-term strategy might be more related to extreme events potentially captured by quantile connectedness. Our study is designed to primarily quantify frequency connectedness and its inferences on varying investment horizons. For that, we do not perform quantile spillover approach that is targeted on the extreme spillovers, albeit we acknowledge that such approach is useful to assess risk at distribution tails. This avenue is left for further research, though.

[16] GPR index data are downloaded from https://www.matteoiacoviello.com/gpr.htm. Data for the U.S. Dollar and the VIX indexes are downloaded from inveting.com. We prefer to use the GPR index to the PCI index due to the weekly data availability of the GPR index.

worldwide, which is more analogous to the Russia-Ukraine war. In this context, both the VIX index and the GPR index had an impact on volatility propagation. The higher GPR index strengthened short- and medium-term connectedness, while the rise in the VIX index intensified long-term connectedness.

5.5 Hedge ratios and portfolio weights

With ongoing financialization, energy commodities gradually became important parts of portfolios (Mandaci et al., 2020). In this respect, intense volatility and the complexity of financial markets call for an accurate calculation of the optimal hedge ratios, which are expected to change over time. The hedge ratio represents the optimal number of contracts of an asset x that an investor must include in his/her portfolio to obtain the most effective protection against adverse market movements. Similar to hedge ratios, optimal portfolio weights are expected to change over time as well. For that, we examine the portfolio weights and hedge ratios among energy assets during different sub-periods. The implications of the above-mentioned results would be applicable to international portfolio diversification and risk management. We answer the question of whether and to what extent optimal diversification strategies changed during the examined sub-periods due to the volatility changes reflected in varying connectedness patterns.

We follow the approach adopted by Antonakakis et al. (2018) and Kočenda and Moravcová (2019) and estimate an asymmetric dynamic conditional correlation (ADCC). We proceed in two stages initially; we calculate best-fitting univariate GARCH models for each individual time series. In the second stage, residuals standardized by their standard deviation from the first stage are applied in the ADCC model to quantify time-varying volatilities, covariances, and correlations of various assets over time and to construct the optimal hedge ratios and portfolio weights as specified in equations 9-11.[17]

An investment portfolio is vulnerable to a range of market risks. Hedging strategies are protection used to reduce the downside risk of a portfolio. Specifically, hedging is a risk management strategy designed to offset losses in investment by taking an opposite position in a different asset. The reduction in risk is generally related to a reduction in potential profit because hedging represents costs (hedging costs) that need to be paid to protect a portfolio. To assess profitable hedging, investors should recognize that hedging strategies differ according

[17] The DCC model offers several advantages relative to a simple correlation analysis. It is parsimonious compared to many multivariate GARCH models. Further, the DCC model is flexible because it enables the estimation of time-varying volatilities, covariances, and correlations of various assets over time.

to the direction and size of spillovers. Therefore, in Table 6, we report optimal values of portfolio weights for all periods under research; for the sake of completeness, we also report hedge ratios in Table A1 in the Appendix. The results indicate that including natural gas in the oil-based portfolio brings diversification benefits and lower hedging costs.

This can be illustrated by examining the hedging effectiveness for petroleum-based commodities (crude oil, diesel, heating oil, and gasoline) and the natural gas portfolio. A 1-USD long position in all examined petroleum-based commodities can be hedged by a short position lower than 12 cents during all analyzed time periods. The lowest hedging costs demonstrate a diesel-natural gas portfolio. Specifically, to hedge a 1-USD long position in diesel, we need to sell 0.086 cents of natural gas in the pre-GFC period, 0.091 during the GFC, 0.032 in the post-GFC period, 0.014 during the period of low oil prices, 0.006 in the period of rising U.S. interest rates, and 0.019 during the Covid-19 pandemic. The hedging potential of natural gas in a financial portfolio is also documented by Jebabli et al. (2022) and Rizvi et al. (2022). They both provide evidence of the hedging effectiveness of natural gas in a stock market portfolio. The results of hedge ratios enable us to reject Hypothesis 3.

Our results imply that including natural gas in the petroleum-based portfolio has diversification benefits. Nevertheless, as depicted in Table A1, even though natural gas offers a means for hedging, the elevated volatility observed during turbulent periods tends to raise the expenses associated with hedging. Hedging costs, expressed as the number of contracts, are highest during the GFC period for all portfolios consisting of natural gas and petroleum-based commodity. Our results correspond to that of Elsayed et al. (2020), who observe an increase in hedging costs for the WTI volatility portfolio over 2008-2009. Mensi et al. (2022a) recommend that portfolio managers should continuously adjust their portfolios to different geopolitical events to mitigate the risk of significant loss. Younis et al. (2023) also suggest adjusting the asset allocation over time, especially during periods of financial distress. Yousaf (2021) demonstrates Covid-19 volatility transmission to the WTI oil market and recommends investors to WTI oil enhance portfolio diversity by incorporating safe-haven assets. A similar outcome is shown by Mensi et al. (2022b) among oil and Islamic sector stock markets during GFC and Covid-19. Hence, an active portfolio rebalancing, contrary to the static approach, is needed under different market circumstances. Our results enable us to reject Hypothesis 4.

The portfolio weights presented in Table 6 are not stable over the examined sub-periods and differ in size for each examined pair of energy assets. The lowest values are characterized for portfolios that include natural gas. For example, the average weight for a natural gas-crude oil portfolio ranges from 0.157 to 0.365, indicating that in a 1-USD portfolio, we should invest

0.052 USD in natural gas and 0.948 USD in crude oil. For other natural-gas-based portfolios, the portfolio weights range from 0.150-0.361 (diesel), 0.169-0.364 (heating oil), and 0.163-0.455 (gasoline). The lower preference for having natural gas in an energy commodity portfolio can be explained by the high price volatility quantified by the standard deviation of log returns in Table 1. On the other hand, heating oil demonstrates the highest values of portfolio weights with crude oil (0.395-0.956) and diesel (0.357-0.852). Specifically, during the period of rising U.S. interest rates, a 1-USD portfolio should allocate 0.956 USD to heating oil and only 0.044 USD to crude oil. For the same sub-period, our results also suggest adopting a large position of heating oil in a portfolio with diesel. In a 1-USD portfolio, on average, 0.852 USD should be invested in heating oil and only 0.148 USD in diesel. As suggested by our results, effective management of an energy commodity portfolio requires regular recalculation of portfolio weights. This is imperative for investors in the energy market who want to attain the maximum expected return at a certain level of risk. Additionally, it is worth noting that the optimal portfolio weights for the two-asset portfolio of gasoline and heating oil during the GFC period are close to zero (0.007), which suggests that the minimum-variance portfolio could be gained by using a single-asset portfolio.

5.5 Robustness check

In this section, we provide a robustness check of our previous analysis. The key issue in terms of volatility spillovers is the measurement of volatility. Following the approach of Liu and Gong (2020), we employ two alternative measures of volatility (range-based and conditional volatility) to calculate the total connectedness of energy commodities. The range-based volatility of Parkinson (1980) and the conditional volatility derived from the GARCH model introduced by Bollerslev (1986) are now employed instead of the realized volatility applied in the previous empirical analysis. In the same way, as in Alizadeh et al. (2002) and Diebold and Yilmaz (2012), the weekly range-based volatility is calculated as follows:

$$range\ e_t = 0.361\ x\ \left[ln\ (P_t^{max}) - ln(P_t^{min})\right]^2, \tag{13}$$

where P_t^{max} denotes the highest price observed during week *t*, while P_t^{min} represents the lowest price in the same time frame. Conditional volatility is derived in a standard way based on a GARCH (1,1) model.

The results of the robustness check are reported in a graphical form in Appendix Figure A1. The figure presents the total volatility Diebold-Yilmaz spillover index based on realized volatility, range-based volatility, and GARCH conditional volatility. Dynamics of the spillover index based on the three volatility measures yield highly comparable and not materially different results. As such, based on the robustness check, we show that our benchmark results are robust with respect to alternative measures of volatility.

6. Conclusions and implications

We analyze volatility connectedness among energy commodities in the U.S. market over 1997-2023. During the examined period, the energy market has been reshaped by several major events: a global financial crisis, a period of low oil prices (due to a boom in shale oil drilling), a period of increasing U.S. interest rates, the Covid-19 pandemic, and the first year of the Russia–Ukraine war. We capture volatility spillovers in the U.S. energy market during different periods of distress by combining two recent tools: the volatility spillover index of Diebold and Yilmaz (2009, 2012) along with its extension, which allows assessment of the time-frequency connectedness introduced by Baruník and Křehlík (2018). Finally, we estimate an ADCC model and derive optimal portfolio weights and hedge ratios to show an optimal risk-return relationship among energy commodities during different distress periods.

Over the full-time span, the total volatility spillover index gradually increases, and the pattern correlates with the progressive financialization of oil-based commodities after 2002. The rising volatility connectedness in the energy market thus reflects the rising interconnectedness of financial markets. The pattern is consistent with the observation that financial variables have become the key driving factor of energy commodity price returns, as shown by Adams et al. (2020). However, when comparing connectedness among the studied individual sub-periods, the Covid-19 pandemic is characterized by the highest systematic risk, followed by the early stage of the Russia–Ukraine war. During both periods, the value of the DY spillover index exceeds the values reached during the GFC. In this respect, connectedness linked to political distress and massive administrative measures surpasses that linked primarily to financial distress. This evidence hints at the fact that solid and chiefly non-financial phenomena are able to strongly impact the connectedness dynamics. Among the energy commodities, heating oil dominates other assets as over time it transmits as well as receives the largest amounts of volatility when measured by directional volatility spillovers. In contrast, natural gas seems to be detached from the rest of the energy commodities in that its volatility is strongly affected only by its own past volatility. Based on our evidence, economists and policymakers can gain insights into the level of connectedness among energy commodities, identify which events and assets play significant roles in transmitting shocks, and develop strategies to mitigate systemic risks during periods of instability. Further, since oil prices influence the cost of production and transportation, affecting a wide range of consumer goods and services, understanding the connectedness among oil-based commodities helps economists and policymakers anticipate potential inflationary pressures and assess the overall impact on consumers and the broader economy. This implication is important for major central banks as Aliyev and Kočenda (2023) show that the ECB policy affects fuel (oil) commodity prices.

The assessment of frequency connectedness provides evidence that the long- and medium-term components dominate U.S. energy commodity market connectedness. From a practical perspective, the values of long- and medium-term connectedness imply that investors perceive the greatest risk at longer investment horizons. This perception is most pronounced during periods of distress directly related to the energy market, such as falling oil prices, or the stressful periods of the Covid-19 pandemic, the GFC, and the early stage of the Russia–Ukraine war. The short-term component records lower values across all examined periods, with the exception for the GFC. In general, our results suggest that the U.S. energy market is characterized by a longer persistence of volatility and higher transmitting uncertainty. This evidence provides implications for investors as it indicates that the formation of investment preferences with respect to energy commodities is linked primarily to investors' longer-term concerns reflecting the most uncertain investment horizons.

Finally, we demonstrate that a portfolio consisting of oil-based commodities complemented with natural gas brings substantial diversification benefits, which provides further implications for investors. Specifically, portfolios of oil-based commodities that also include natural gas are characterized by the lowest hedging costs, albeit varying across periods and increasing during turbulent periods of the GFC and the Covid-19 pandemic. The diversification benefits should be credited primarily to the fact that natural gas volatility is chiefly influenced by its own history and is largely independent from the volatility of other examined energy assets. The financial effects of volatility on the U.S. energy market suggest that a mixed "oil and gas" portfolio provides increased stability and a valuable investment option.

Taken together, the evidence we bring underscores that studying connectedness among oil-based commodities is vital for understanding the complexities of the oil market, managing risks associated with energy price fluctuations, and formulating effective policies to address the economic and financial challenges related to the oil industry.

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Table 1: Descriptive statistics

	Natural Gas	Oil WTI	Gasoline	Heating Oil	Diesel
Mean	-0.0002	0.0004	0.0004	0.0003	0.0003
Maximum	0.7456	0.4258	0.2351	0.2468	0.2683
Minimum	-1.0251	-0.2749	-0.2533	-0.4701	-0.2531
Std. Dev.	0.0511	0.0273	0.0277	0.0263	0.0247
Skewness	-0.3754	0.7022	0.0216	-1.0216	-0.2499
Kurtosis	52.6597	27.4111	9.8866	31.8819	14.0115
LB Test (12)	85.35***	69.18***	14.88	30.48***	56.13***
JB Test	671955.9***	161625.4***	12822.98***	226666***	32841.28***
ADF Test	-63.45***	-59.06***	-79.95***	-35.63***	-42.75***

Note: ***, **, * denote rejection of the null hypothesis at 1, 5, and 10% significance levels, respectively. ADF test H_0: the data are non-stationary; JB test H_0: the data is normally distributed; LB test H_0: the data is independently distributed.

Table 2: Total volatility spillover index

Total examined period	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	89.58	1.01	2.04	2.95	4.42	2.08
Oil WTI	0.19	50.82	15.44	21.80	11.74	9.84
Gasoline	0.26	15.83	53.01	20.22	10.68	9.40
Heating Oil	1.27	18.29	14.98	49.60	15.87	10.08
Diesel	0.52	10.78	9.80	20.47	58.42	8.32
TO	0.45	9.18	8.45	13.09	8.54	**39.71**

Notes: The total volatility spillover index is based on Diebold and Yilmaz (2012) and calculated by Equations 1- 6. The column "FROM" represents directional connectedness transferred to a specific commodity FROM all other commodities in a group. The bottom row "TO" indicates the directional spillover effect TO all other examined energy commodities from a specific one.

Table 3: Total volatility spillover index for the individually examined periods

pre-GFC	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	96.34	0.69	0.67	0.73	1.57	0.73
Oil WTI	0.03	65.75	9.82	22.21	2.19	6.85
Gasoline	0.04	11.05	71.51	14.80	2.60	5.70
Heating Oil	1.57	19.17	10.33	65.70	3.23	6.86
Diesel	0.03	1.72	1.65	5.65	90.96	1.81
TO	0.33	6.53	4.49	8.68	1.92	**21.95**

GFC	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	87.46	0.87	10.88	0.44	0.35	2.51
Oil WTI	0.10	47.21	20.60	16.45	15.64	10.56
Gasoline	0.16	21.72	43.57	18.70	15.85	11.29
Heating Oil	0.09	25.08	18.35	33.06	23.41	13.39
Diesel	0.29	24.11	15.38	25.94	34.28	13.14
TO	0.13	14.36	13.04	12.31	11.05	**50.88**

post-GFC	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	92.69	0.39	0.75	2.04	4.13	1.46
Oil WTI	0.69	46.09	15.49	22.17	15.56	10.78
Gasoline	0.47	14.88	52.05	20.17	12.43	9.59
Heating Oil	2.58	16.31	14.68	41.87	24.57	11.63
Diesel	1.91	14.12	14.81	28.65	40.50	11.90
TO	1.13	9.14	9.14	14.61	11.34	**45.36**

Low oil prices	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	93.07	0.42	1.96	0.73	3.82	1.39
Oil WTI	0.41	50.05	9.55	17.01	22.99	9.99
Gasoline	0.41	20.58	46.31	16.69	16.01	10.74
Heating Oil	1.34	20.59	6.90	44.78	26.39	11.04
Diesel	0.55	18.21	7.75	17.77	55.71	8.86
TO	0.54	11.96	5.23	10.44	13.84	**42.02**

Fed Rates Increase	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	88.73	1.20	0.72	3.60	5.75	2.25
Oil WTI	0.25	55.20	12.33	18.20	14.02	8.96
Gasoline	0.81	11.99	56.71	16.18	14.30	8.66
Heating Oil	1.69	14.39	13.88	48.87	21.17	10.23
Diesel	0.29	8.13	6.51	26.00	59.07	8.19
TO	0.61	7.14	6.69	12.80	11.05	**38.28**

Covid-19	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	83.37	1.71	4.26	4.66	6.00	3.33
Oil WTI	0.21	38.49	24.82	16.66	19.82	12.30
Gasoline	0.38	22.21	38.47	18.83	20.11	12.31
Heating Oil	0.25	24.39	20.26	30.75	24.34	13.85
Diesel	0.35	23.99	20.48	22.26	32.91	13.42
TO	0.24	14.46	13.97	12.48	14.05	**55.20**

Russia-Ukraine war	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	83.90	9.12	3.41	1.22	2.34	3.22
Oil WTI	0.84	62.17	17.97	12.35	6.66	7.57
Gasoline	0.27	16.29	59.82	11.77	11.84	8.04
Heating Oil	1.76	1.05	16.73	59.91	20.55	8.02
Diesel	2.39	2.57	12.71	19.95	62.37	7.53
TO	1.05	5.81	10.16	9.06	8.28	**34.36**

Notes: The individually examined time periods are pre-GFC (from January 8, 1997 to June 2, 2007); GFC (the global financial crisis from June 29, 2007 to February 5, 2009); post-GFC (the period after the global financial crisis from February 6, 2009 to November 29, 2014); Low oil prices (period of declining oil prices from November 30, 2014 to August 9, 2017); Fed rates increase (the period of rising interest rates in the U.S. from August 10, 2017 to December 31, 2019); Covid -19 pandemic (from January 1, 2020 to February 23, 2022); Russia-Ukraine war (the first year of the war in Ukraine running from February 24, 2022 to February 6, 2023).

Table 4: Total volatility spillover index for the early stage of the Russia-Ukraine war

Russia-Ukraine war	**Natural Gas**	**Oil WTI**	**Gasoline**	**Heating Oil**	**Diesel**	*FROM*
Natural Gas	92.57	1.57	1.48	2.87	1.51	1.49
Oil WTI	2.73	31.78	12.62	30.58	22.30	13.64
Gasoline	15.07	15.33	28.00	19.32	22.28	14.40
Heating Oil	2.62	16.44	6.80	45.33	28.81	10.93
Diesel	8.62	13.38	11.05	34.51	32.45	13.51
TO	5.81	9.34	6.39	17.45	14.98	**53.97**

Note: The early stage of the Russia-Ukraine war runs from February 24, 2022, to April 4, 2022.

Table 5: Results for regression estimation on short-term, medium-term, and long-term connectedness in relation to VIX, US Dollar, and Geopolitical Risk Index (GPR)

	Short	Medium	Long
pre-GFC			
Intercept	6.3410***	11.2675***	13.2199***
VIX	-0.013027*	0.0079	-0.1122***
US Dollar	-1.6348	3.6838	20.3695
GPR	0.0001	0.0067***	0.0110***
R^2	0.0012	0.0422	0.0672
GFC			
Intercept	15.5020***	22.4021***	6.1027***
VIX	-0.0939***	-0.0599***	0.2495***
US Dollar	-24.7550	11.5209	24.7437
GPR	-0.0189***	-0.0253***	0.0087
R^2	0.2133	0.1842	0.4744
post-GFC			
Intercept	7.6706***	15.7732***	10.6277***
VIX	0.1777***	0.1818***	0.1051***
US Dollar	-2.1727	2.4542	-3.8149
GPR	-0.0126***	-0.0178***	-0.0016
R^2	0.1496	0.1584	0.0755
Low oil prices			
Intercept	9.4536***	17.5694***	10.1502***
VIX	-0.2564***	-0.2000***	0.4804***
US Dollar	-8.1497	3.0923	39.7444
GPR	0.0097***	0.0156***	-0.0031
R^2	0.2095	0.0971	0.197
Fed Rates Increase			
Intercept	9.1885***	19.8011***	12.1631***
VIX	-0.0364	-0.1438***	0.2480***
US Dollar	11.9409	24.1636	-35.7648
GPR	0.0025	-0.0014	-0.0075**
R^2	0.0034	0.0259	0.0818
Covid-19			
Intercept	11.2887***	23.6588***	19.2899***
VIX	-0.1884***	-0.3123***	0.0540***
US Dollar	72.9734***	94.2773*	-61.2900
GPR	0.0040*	0.0126***	-0.0014
R^2	0.3848	0.3452	0.0237
Russia-Ukraine war			
Intercept	3.4541***	12.4396***	6.7602**
VIX	0.0376*	-0.0425	0.2302*
US Dollar	8.6085	28.8531	43.1407
GPR	0.0020*	0.0070***	0.0336***
R^2	0.0488	0.0722	0.1642

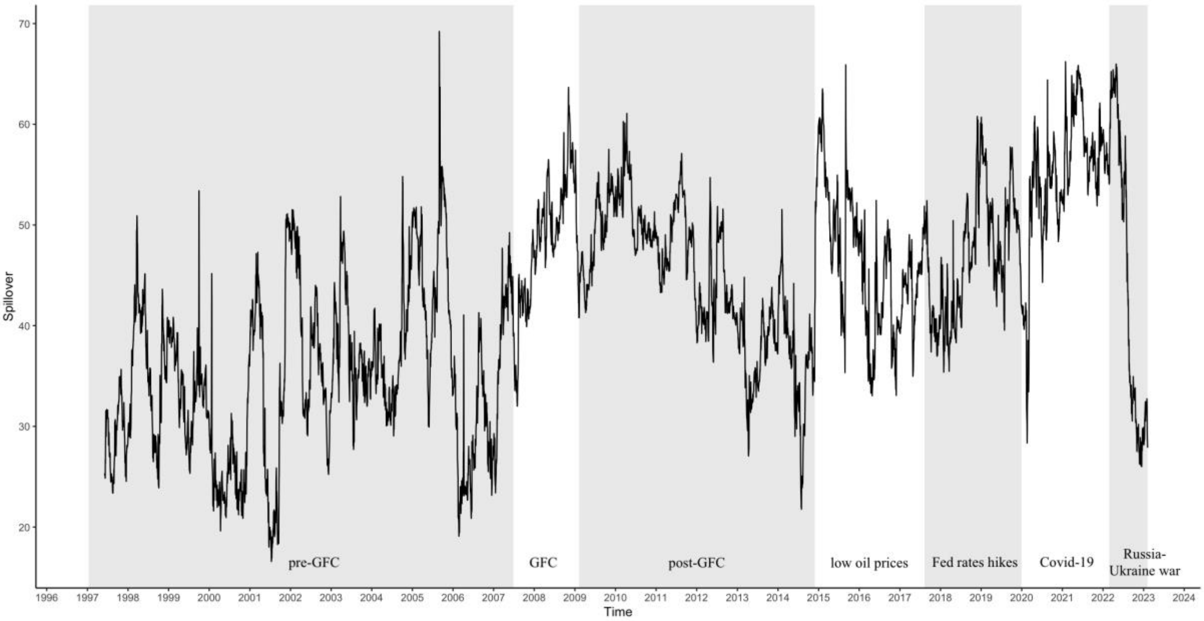
Notes: *** denotes p-value < 0.01, **p-value <0.05, *p-value < 0.10. The individually examined time periods are described in Notes of Table 2.

Table 6: Portfolio weights

	Pre-GFC period				GFC period				Post - GFC period			
Energy assets	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**
Diesel - Oil WTI	0.495	0.216	-0.08	1.006	0.707	0.403	-0.169	1.446	0.657	0.308	-0.097	1.605
Heating Oil - Oil WTI	0.395	0.316	-0.41	1.165	0.901	0.487	-0.270	1.606	0.722	0.385	-0.353	1.591
Nat. Gas - Oil WTI	0.262	0.167	-0.02	0.88	0.364	0.248	0.015	1.082	0.276	0.164	-0.020	0.739
Gasoline - Oil WTI	0.234	0.213	-0.18	1.126	0.302	0.301	-0.180	1.163	0.401	0.256	-0.226	1.116
Heating Oil - Diesel	0.477	0.23	-0.08	1.012	0.715	0.390	-0.315	1.578	0.449	0.485	-1.466	1.711
Nat. Gas - Diesel	0.253	0.193	-0.08	0.982	0.343	0.176	-0.020	0.736	0.225	0.116	-0.004	0.693
Gasoline - Diesel	0.365	0.199	-0.03	1.089	0.161	0.198	-0.462	0.711	0.243	0.217	-0.373	1.082
Nat. Gas - Heating Oil	0.256	0.193	-0.02	1.059	0.319	0.175	0.000	0.682	0.223	0.125	-0.019	0.696
Gasoline - Heating Oil	0.291	0.284	-0.31	1.207	0.007	0.249	-0.746	0.766	0.196	0.219	-0.445	1.114
Gasoline – Nat. Gas	0.647	0.174	0.161	1.017	0.545	0.206	0.076	0.928	0.678	0.150	0.246	1.014
	Low Oil Prices				**Fed Rates Increase**				**Covid-19**			
Energy assets	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**
Diesel - Oil WTI	0.577	0.282	-0.157	1.243	0.612	0.276	-0.015	1.472	0.633	0.354	-0.284	1.491
Heating Oil - Oil WTI	0.511	0.309	-0.187	1.283	0.956	0.297	0.105	1.707	0.559	0.435	-0.551	1.761
Nat. Gas - Oil WTI	0.365	0.151	0.073	0.849	0.270	0.135	-0.009	0.644	0.157	0.242	-0.029	1.006
Gasoline - Oil WTI	0.485	0.248	-0.161	1.118	0.540	0.301	-0.202	1.258	0.478	0.387	-0.387	1.493
Heating Oil - Diesel	0.462	0.339	-0.589	1.454	0.852	0.233	0.123	1.712	0.357	0.370	-0.587	1.399
Nat. Gas - Diesel	0.361	0.129	0.077	0.838	0.244	0.125	-0.010	0.607	0.150	0.173	-0.021	0.898
Gasoline - Diesel	0.443	0.244	-0.175	1.106	0.417	0.257	-0.199	0.977	0.327	0.284	-0.481	0.965
Nat. Gas - Heating Oil	0.364	0.139	0.029	0.819	0.192	0.107	-0.022	0.530	0.169	0.176	-0.020	0.849
Gasoline - Heating Oil	0.494	0.276	-0.195	1.183	0.205	0.263	-0.364	1.057	0.345	0.354	-0.554	1.147
Gasoline – Nat. Gas	0.654	0.159	0.049	0.969	0.728	0.147	0.255	0.998	0.837	0.215	-0.008	1.034

Notes: This table presents the summary statistics for the optimal portfolio weights (median, sd – standard deviation, min – minimum, max – maximum). The values are reported for individually examined time periods. For a detailed description of time periods, see the Data section or Notes below Table 1. The calculations for the Russia–Ukraine war are not provided due to the small number of observations for this period. This data sample does not exhibit the ARCH effect and, therefore, does not allow ADCC computations.

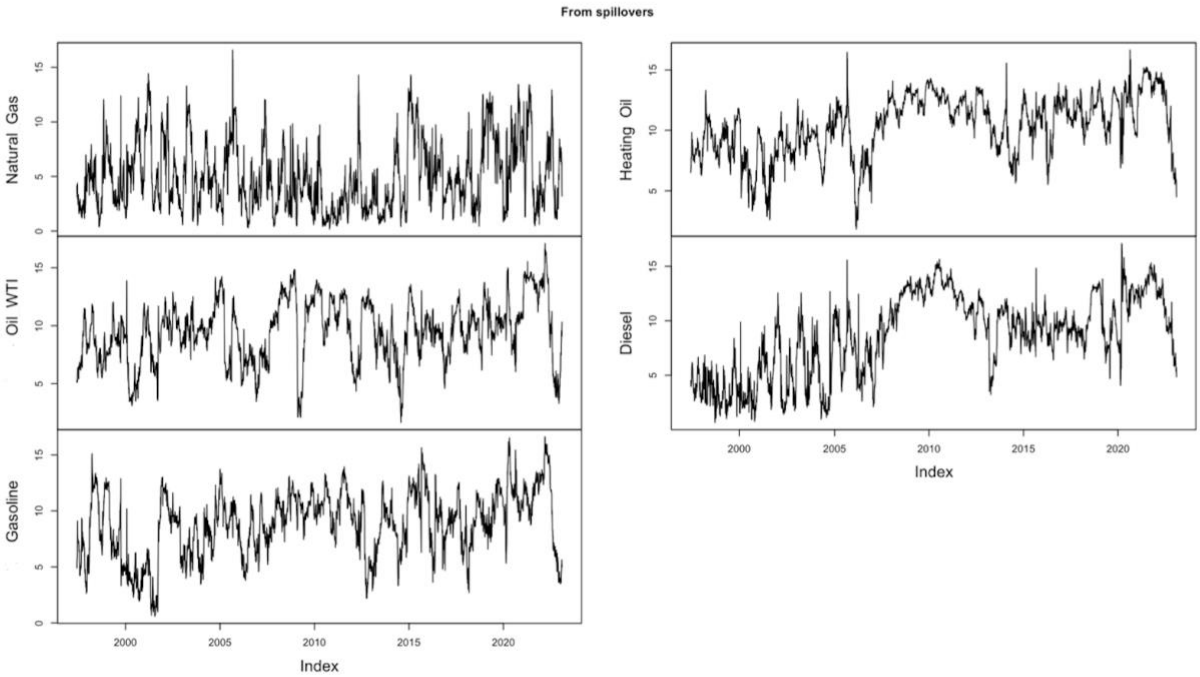
Figure 1: The total volatility connectedness of five energy commodities (natural gas, crude oil, gasoline, heating oil, diesel) over the Sample Period from January 8, 1997 to February 6, 2023



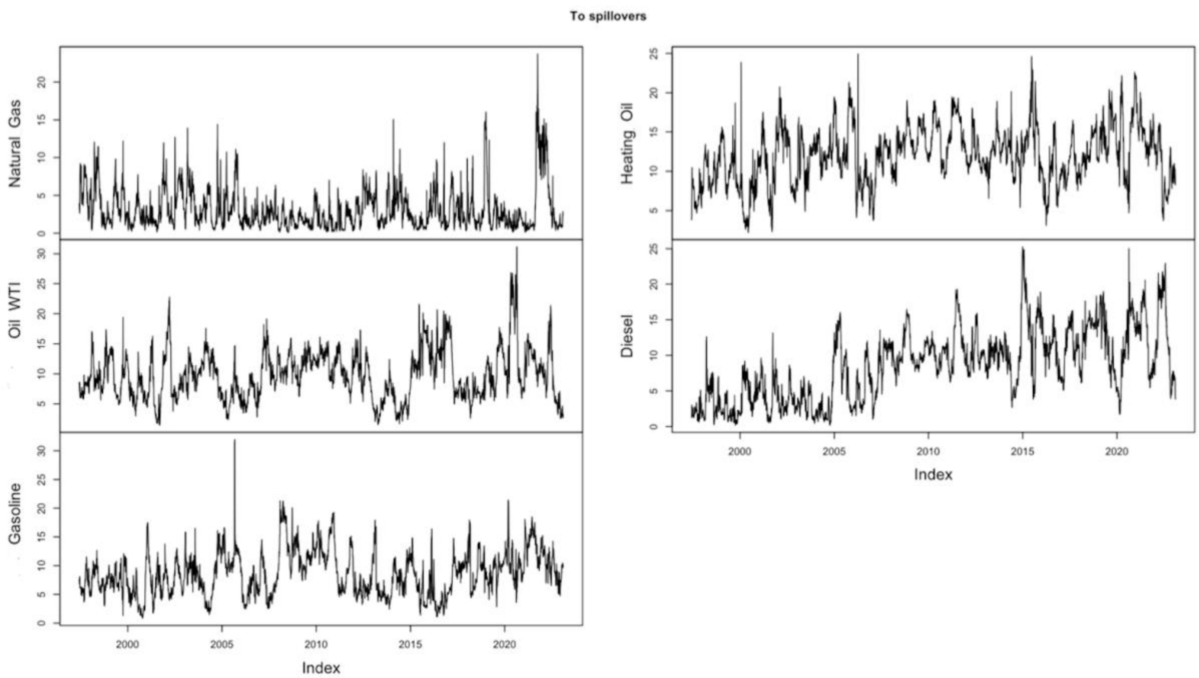
Note: The total volatility connectedness of five energy commodities

Figure 2: Directional volatility spillovers

Panel A: FROM energy commodities



Panel B: TO energy commodities



Panel C: NET spillovers

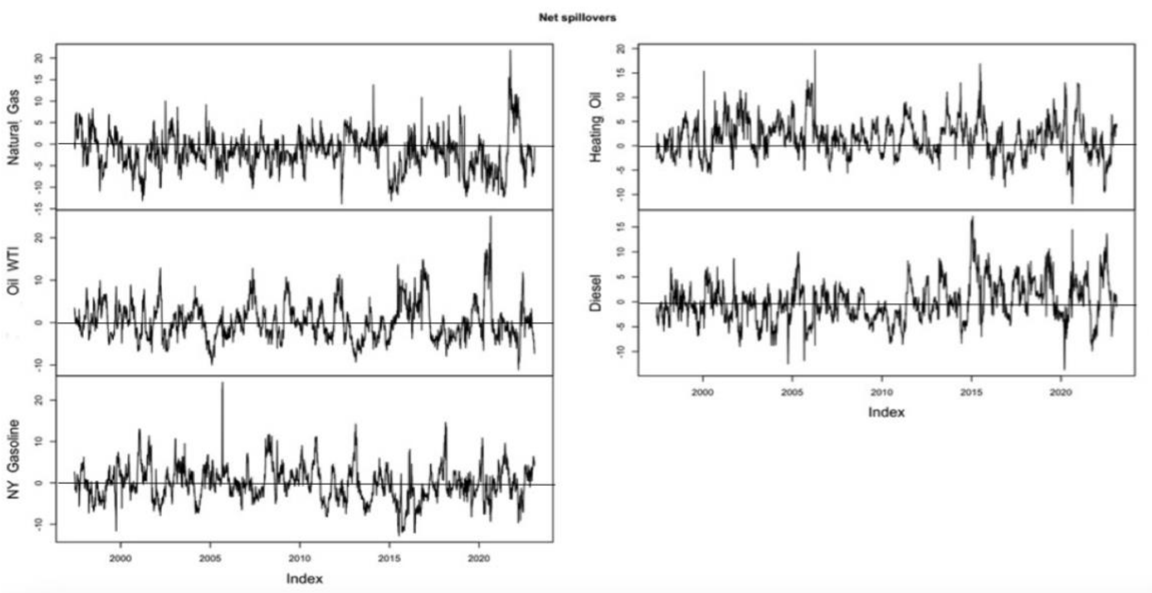
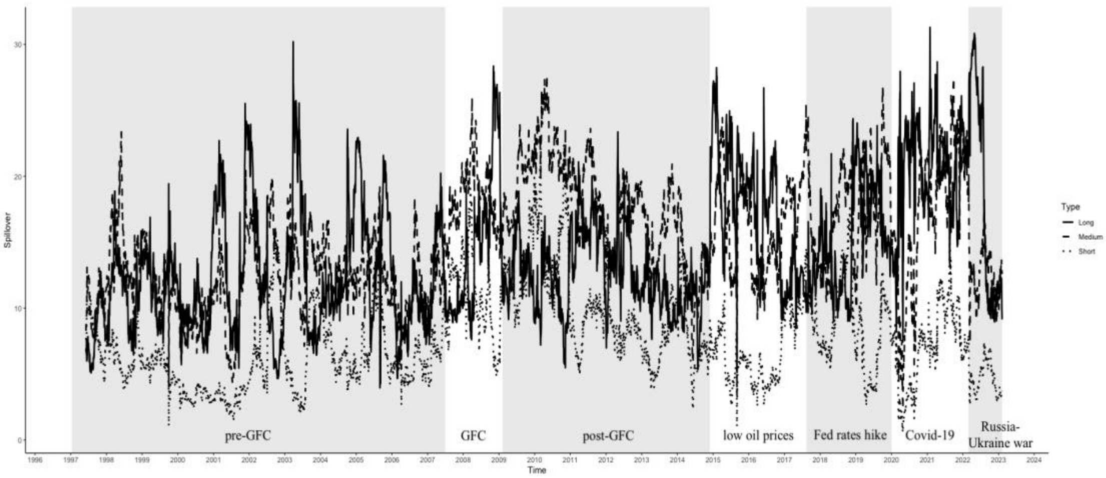
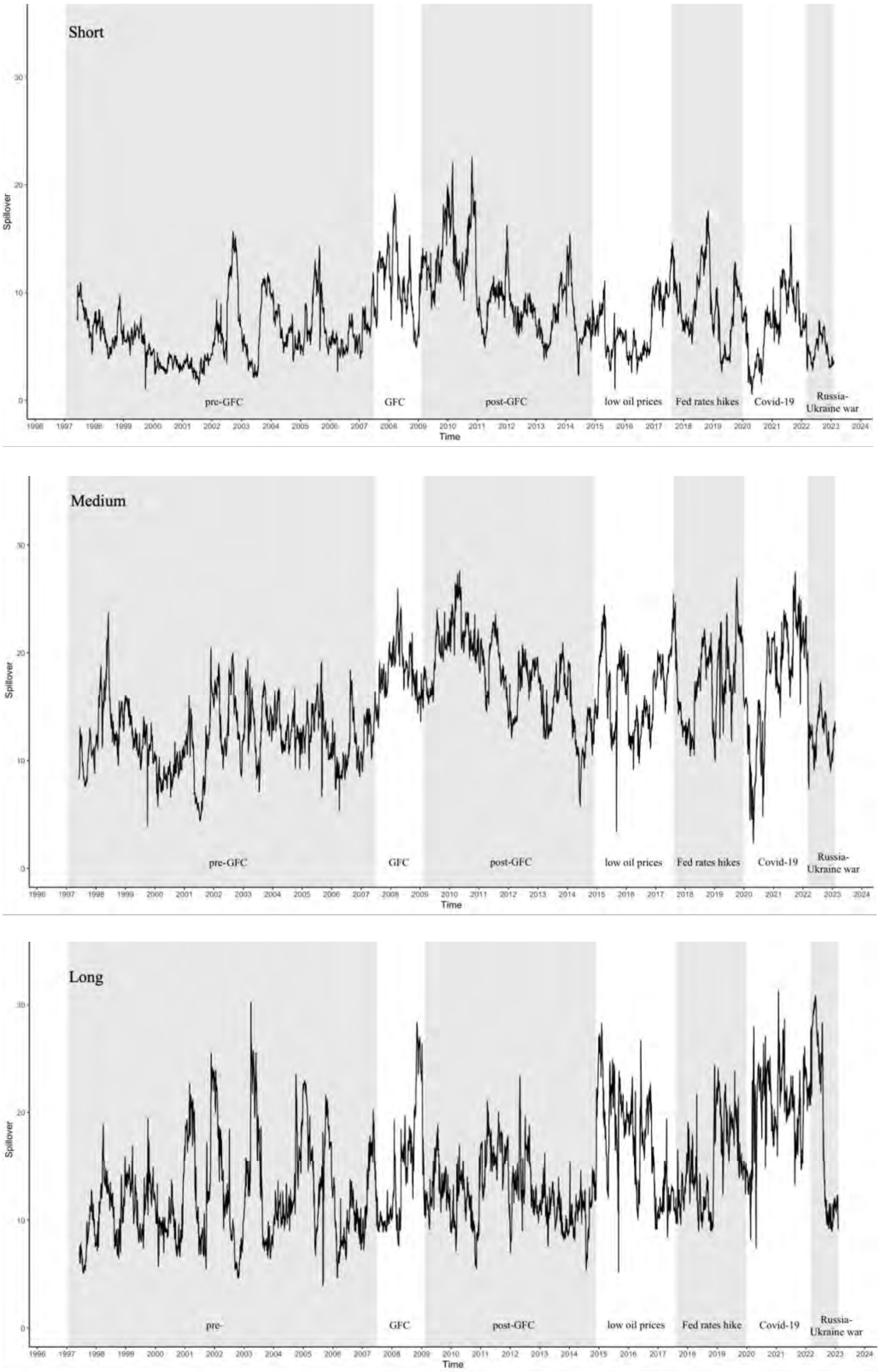


Figure 3: Dynamic frequency connectedness. The solid line represents the frequency connectedness within a long-term horizon defined at d3 ∈ (20, 200] days, the dashed line represents the frequency connectedness within a medium-term horizon defined at d2 ∈ (5, 20] days, and the dotted line represents the frequency connectedness within a short-term horizon defined at d1 ∈ [1, 5] days.



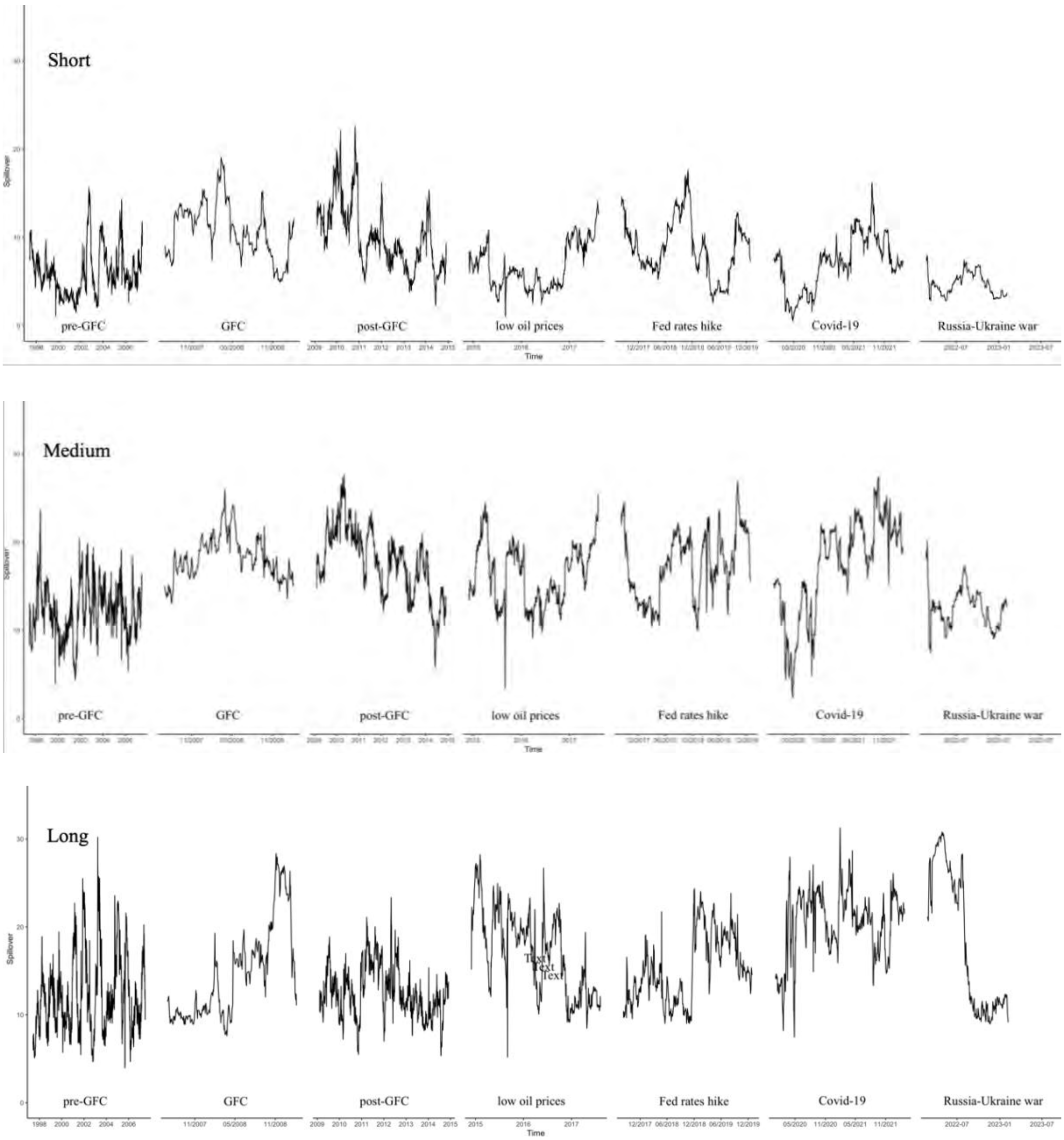
Note: The sum of all lines within each frequency band represents the total connectedness.

Figure 4: Frequency connectedness of five energy commodities (natural gas, crude oil, gasoline, heating oil, diesel) over the Sample Period from January 8, 1997 to February 6, 2023 across three investment horizons (short-term, medium-term, long-term)



Note: Dynamic frequency connectedness is divided according to investment horizons. Upper panel: frequency connectedness at the short-term horizon defined at d1 ∈ [1, 5] days. Middle panel: the medium-term horizon defined at d2 ∈ (5, 20] days. Lower panel: the long-term horizon defined at d3 ∈ (20, 200] days.

Figure 5: Frequency connectedness of commodities during individually examined sub-periods (pre-GFC, the GFC, post-GFC period, period of low oil prices, period of rising US interest rates, Covid-19 pandemic, the Russia-Ukraine war) across three investment horizons



Note: Dynamic frequency connectedness is divided according to investment horizons. Upper panel: frequency connectedness at the short-term horizon defined at d1 ∈ [1, 5] days. Middle panel: the medium-term horizon defined at d2 ∈ (5, 20] days. Lower panel: the long-term horizon defined at d3 ∈ (20, 200] days.

Appendix

Table A1: Hedge ratios

	Pre-GFC				GFC				Post - GFC			
Energy assets	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**
Diesel - Oil WTI	0.367	0.168	0.085	1.187	0.716	0.194	0.055	1.162	0.638	0.154	0.165	1.069
Heating Oil - Oil WTI	0.822	0.275	0.182	3.967	0.749	0.205	0.070	1.168	0.688	0.167	0.220	1.224
Natural Gas - Oil WTI	0.188	0.181	-0.32	1.200	0.125	0.220	-0.435	0.918	0.111	0.375	-0.546	5.398
NY Gasoline - Oil WTI	0.817	0.171	0.185	2.438	0.850	0.204	0.137	1.290	0.682	0.155	0.155	1.189
Oil WTI - Diesel	0.373	0.137	0.009	1.056	0.841	0.298	0.431	2.829	0.795	0.193	0.284	1.598
Heating Oil - Diesel	0.454	0.293	0.029	3.834	0.874	0.081	0.630	1.028	0.903	0.124	0.474	1.478
Natural Gas - Diesel	0.217	0.269	-0.54	3.101	0.153	0.227	-0.482	1.135	0.120	0.294	-2.582	1.375
Gasoline - Diesel	0.429	0.151	0.019	1.167	0.878	0.138	0.512	1.301	0.797	0.153	0.363	1.630
Oil WTI - Heating Oil	0.746	0.154	0.053	1.528	0.955	0.309	0.499	2.962	0.844	0.205	0.299	1.611
Diesel - Heating Oil	0.408	0.166	0.042	1.552	0.940	0.082	0.671	1.122	0.881	0.100	0.455	1.285
Natural Gas - Heating Oil	0.265	0.198	-0.04	1.690	0.180	0.211	-0.503	0.999	0.111	0.295	-1.706	1.776
Gasoline - Heating Oil	0.803	0.180	0.052	1.800	0.995	0.169	0.461	1.586	0.857	0.137	0.296	1.462
Oil WTI - Natural Gas	0.074	0.060	-0.05	0.571	0.080	0.239	-0.239	1.922	0.038	0.078	-0.241	0.393
Diesel - Natural Gas	0.086	0.077	-0.05	0.782	0.091	0.088	-0.114	0.352	0.032	0.059	-0.203	0.317
Heating Oil - Natural Gas	0.108	0.160	-0.03	2.538	0.091	0.090	-0.122	0.373	0.032	0.061	-0.172	0.324
Gasoline - Natural Gas	0.085	0.072	-0.06	0.540	0.114	0.160	-0.312	0.817	0.020	0.064	-0.186	0.244
Oil WTI - Gasoline	0.579	0.116	0.144	1.309	0.695	0.189	0.126	1.413	0.614	0.183	0.089	1.115
Diesel - Gasoline	0.306	0.134	0.064	1.274	0.596	0.138	0.096	0.824	0.554	0.154	0.099	1.038
Heating Oil - Gasoline	0.620	0.248	0.253	4.165	0.584	0.139	0.117	0.869	0.597	0.153	0.125	1.051
Natural Gas - Gasoline	0.162	0.182	-0.08	1.644	0.137	0.178	-0.575	0.805	0.047	0.233	-0.651	1.675

	Low Oil Prices				Fed Rates Increase				Covid-19			
Energy assets	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**	**median**	**sd**	**min**	**max**
Diesel - Oil WTI	0.714	0.135	0.415	1.405	0.632	0.108	0.308	1.033	0.696	0.162	0.159	1.257
Heating Oil - Oil WTI	0.739	0.147	0.418	1.616	0.614	0.090	0.365	0.947	0.790	0.192	0.143	1.701
Natural Gas - Oil WTI	0.054	0.107	-0.330	0.578	0.052	0.519	-1.009	5.558	0.158	0.549	-0.416	7.113
NY Gasoline - Oil WTI	0.647	0.143	0.292	1.312	0.628	0.157	0.254	1.528	0.774	0.213	0.208	1.870
Oil WTI - Diesel	0.771	0.153	0.194	1.350	0.754	0.197	0.249	1.271	0.802	0.311	0.417	2.849
Heating Oil - Diesel	0.809	0.178	0.324	2.094	0.713	0.143	0.240	0.930	0.894	0.122	0.349	1.394
Natural Gas - Diesel	0.029	0.102	-0.546	0.433	0.018	0.412	-1.241	3.489	0.107	0.643	-0.942	8.726
Gasoline - Diesel	0.618	0.178	0.145	1.730	0.676	0.206	0.089	1.788	0.820	0.246	0.344	2.695
Oil WTI - Heating Oil	0.745	0.158	0.274	1.351	0.974	0.208	0.431	1.986	0.831	0.373	0.354	3.735
Diesel - Heating Oil	0.773	0.169	0.202	2.097	0.921	0.118	0.417	1.334	0.820	0.133	0.481	1.963
Natural Gas - Heating Oil	0.072	0.110	-0.354	0.750	0.065	0.753	-1.750	7.389	0.113	0.577	-1.047	7.096
Gasoline - Heating Oil	0.654	0.204	0.171	2.236	0.839	0.207	0.403	2.306	0.858	0.268	0.427	2.964
Oil WTI - Natural Gas	0.033	0.052	-0.178	0.187	0.016	0.075	-0.127	0.459	0.032	0.144	-0.434	1.089
Diesel - Natural Gas	0.014	0.050	-0.179	0.341	0.006	0.058	-0.170	0.266	0.019	0.070	-0.083	0.550
Heating Oil - Natural Gas	0.039	0.058	-0.456	0.341	0.015	0.057	-0.127	0.250	0.022	0.069	-0.203	0.350
Gasoline - Natural Gas	0.027	0.059	-0.317	0.231	0.001	0.061	-0.180	0.234	0.051	0.142	-0.039	1.117
Oil WTI - Gasoline	0.637	0.154	0.146	1.305	0.669	0.215	0.103	1.383	0.759	0.225	0.180	2.164
Diesel - Gasoline	0.572	0.172	0.146	2.120	0.602	0.152	0.080	0.977	0.690	0.128	0.232	0.961
Heating Oil - Gasoline	0.652	0.182	0.140	2.033	0.584	0.147	0.197	1.034	0.772	0.152	0.192	1.172
Natural Gas - Gasoline	0.047	0.119	-0.553	0.807	0.005	0.228	-1.719	0.650	0.219	0.716	-0.172	8.359

Notes: This table presents the summary statistics for the optimal hedge ratios (median, sd – standard deviation, min – minimum, max – maximum). The values are reported for individually examined time periods. For a detailed description of time periods, see the Data section or Notes below Table 1. The calculations for the Russia–Ukraine war are not provided due to the small number of observations for this time period. This data sample does not exhibit the ARCH effect and, therefore, does not allow ADCC computations.

Figure A1: Total volatility spillover index of three volatilities (realized, range, and GARCH conditional volatility)