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Market responses to spillovers in the energy commodity markets: evaluating short-term vs. long-term effects and business-as-usual vs. distressed phases

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Abstract

We study how market spillovers propagate within a comprehensive system of energy commodities by employing spillover analysis in the time and frequency domains. Raw materials dominate the system's connectedness, behaving as net transmitters of spillovers. However, the dynamic analysis shows that downstream commodities may also act as net transmitters but only in a few short phases. Importantly, relevant energy market episodes generate more substantial spillovers, while lower system connectedness is observed during events primarily affecting other sectors. Our main findings are substantially invariant to a series of robustness checks. These results also hold when analyzing the distribution's tails in a quantile framework that we introduce to study distressed periods. Finally, we examine a broad frequency spectrum and find high efficiency in this system, with substantial spillovers absorbed in less than two days for all commodities.

Keywords: spillovers, energy sector, commodities, connectedness.

1 Introduction

The energy sector plays a pivotal role in the economic growth of any modern economy (Shahbaz et al., 2018, Ivanovski et al., 2021). For instance, between 2000 and 2020, the European Union's (EU) Gross Domestic Product (GDP) per unit of gross available energy increased from €6.25 to €8.59 per kilogram of oil equivalent (Kgoe),[1] while, in 2021, energy costs reached 13% of global GDP.[2] Further, the low elasticity of substitution between energy and non-energy inputs underscores the specificity of the energy sector, as its inputs cannot be easily replaced by labor or capital (Medina and Vega-Cervera, 2001, Stern and Kander, 2012).

Given the central role of the energy sector in global economies, there is significant interest in understanding the key factors influencing energy-related commodity prices. Regulators, investors, and academics are particularly interested in whether upstream or downstream shocks drive energy commodity prices. Several studies have therefore analyzed financial spillovers in energy commodity systems (Green et al., 2018, Uddin et al., 2018, Kayani et al., 2024), including both raw materials and related derivatives playing a critical role in different supply chains (Eberhardt and Presbitero, 2021). Due to their strong connections with capital markets and the sharp increase in trading volumes and prices, energy-related commodities are, in fact, investigated as potential sources of shock propagation and spillovers impacting financial stability and the wider economy (Creti et al., 2013, Narayan et al., 2013, Basak and Pavlova, 2016, Flori et al., 2021).

The study of spillovers is theoretically significant since variations in energy commodity prices have both direct and indirect effects throughout the supply chain, especially in turbulent periods (Hallegatte, 2019, Guan et al., 2020). Indeed, various risk events influence the stability of the energy supply chain, potentially amplifying these effects (Zhao et al., 2023). Direct effects may occur when significant price changes in raw materials influence the preferred energy mix (Anke et al., 2020). Indirect effects involve changes in market demand and supply within related energy supply chains. For instance, a rise in oil prices might increase the demand for goods and services produced using renewable energy, thereby influencing investment and development in

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[1] Data on the energy productivity indicator, which measures economic output per unit of gross available energy, are available at: `https://ec.europa.eu/eurostat/databrowser/view/sdg_07_30/default/table?lang=en`.

[2] Source: `https://www.bnnbloomberg.ca/energy-costs-set-to-reach-record-13-of-global-gdp-this-year-1.1738500`.

that sector (De Rosa et al., 2022). This shift can accelerate the obsolescence of carbon-intensive production technologies and encourage the development of viable green alternatives (Johnson et al., 2015, Mayer et al., 2019), thus promoting a reduction in greenhouse gas (GHG) emissions. When spillovers lead to price changes in secondary energy flows, such as oil and gas derivatives, firms may need to adjust their operations, including refining processes. As a consequence, the consumption of these energy commodities and their price fluctuations can generate persistent inflationary pressures, significantly worsening the inflation-output gap trade-off and adversely affecting overall economic output (Coletti et al., 2021).

Although exploring interdependencies across energy-related commodities is crucial for understanding how disturbances propagate throughout energy supply chains and detecting whether raw materials or derivatives primarily transmit shocks, few works have analyzed how such disturbances propagate within energy supply chains. Křehlík and Baruník (2017) represent one exception, outlining how upstream shocks dominate the system's connectedness, although downstream shocks are gaining momentum in creating short-term spillovers. Yet, they only focus on the oil supply chain without including other related energy commodities, such as natural gas and coal.

We propose to investigate the connectedness within a wide system encompassing eight commodities, namely Brent Oil, Gasoline, Heating Oil, Natural Gas, Propane, Coal, Ethanol, and European Union Allowances (EUAs). These commodities represent a comprehensive set for the entire energy sector. Specifically, we aim to determine which raw materials or derivatives dominate in generating spillovers. To achieve this, we utilize the approaches of Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík (2018), which enable us to study the system's connectedness in both the time and frequency domains by exploiting the forecast-error variance decomposition (FEVD) associated with a generalized vector autoregressive framework. From a theoretical perspective, these approaches allow us to disentangle how the price dynamics of energy commodities are influenced by multiple bilateral interdependencies. Furthermore, this framework allows us to investigate how shock transmission mechanisms might occur between upstream and downstream commodities, thereby identifying the main channels through which instability propagates within the energy system. Understanding these channels is essential for monitoring the overall system stability and assessing the vulnerability of each energy commodity to spillovers.

The spillover static analysis demonstrates that raw materials dominate the spillover propagation, both at the aggregate level and in the short- and long-term. The dynamic analysis validates such findings since in 73.28% of observations, raw materials have a higher net connectedness in absolute value than derivatives and tend to behave as net transmitters, whereas their derivatives act as net receivers despite frequent changes in their transmission behavior.

Importantly, these findings tend to be confirmed during crisis episodes, with few exceptions. Events directly affecting the energy sector tend to raise the system's total connectedness. The Russia-Ukraine war is a notable example, which also caused a decrease (increase) in the connectedness of upstream (downstream) commodities. Similarly, we experience a 13% increase in total spillovers in the first two months after the breakout of the Israeli-Palestinian conflict, mainly driven by upstream commodities. By contrast, events not directly connected with this sector, such as the COVID-19 pandemic, reduce spillovers.

Additionally, we outline that most spillovers are generated in the short-term, providing relevant insights into the temporal connectedness generated among energy commodities. These results provide crucial policy implications, demonstrating that policymakers should carefully supervise spillover effects among energy commodities in relation to relevant events. Hence, they may implement appropriate hedging strategies or improve the security of supply to reduce adverse short-term interdependences.

We complement our main findings by applying different robustness checks, allowing us to address some limitations of standard approaches. First, through the quantile connectedness method proposed by Ando et al. (2022), we relax the assumption that the prevailing relationships at the conditional mean of the returns' distribution can be generalized to the entire conditional distribution. This approach highlights the idiosyncratic component of shocks disentangled from the systematic one by including several factors in the vector autoregression (VAR), which would otherwise suffer from the omitted variable bias. Second, we study the system's connectedness along different frequency values, thus identifying the spectral band that generates the maximum value of shock propagation and its stability. In so doing, we propose an approach that empirically investigates the theoretical hypothesis of market efficiency by measuring the ability of commodity markets to fully and instantaneously incorporate all available information into market prices. An in-depth examination of the system is therefore crucial for uncovering how the evolving relationships between the commodity series can generate variations in their market dynamics, which may, in turn, lead to instability (Barberis et al., 2005, Scheffer et al., 2009).

Our quantile analysis corroborates the results obtained in the dynamic analysis at the median of the shock distribution while pointing out significant differences for extreme percentiles. Notably, below the 5^{th} quantile, the net connectedness of downstream commodities is significantly more than that of upstream. In addition, we show heterogeneous shock transmission behaviors with solid variations of commodities' net connectedness across different frequency bands. Such differences better emerge when analyzing single commodities. Lastly, we notice a substantial homogeneity in the frequency band maximizing net connectedness amid commodities, highlighting that commodity markets are relatively efficient in absorbing shocks.

The remainder of the paper is organized as follows. We report the literature review in Section 2, while Section 3 presents the methodologies and Section 4 describes our dataset. In Section 5, we present and discuss the main findings of the analysis. Finally, Section 6 reports the conclusion.

2 Literature review

The scrutiny of spillovers among energy commodities has recently gained momentum due to the several sources of risk that may affect the stability of energy systems (Lin and Li, 2015, Zhang and Sun, 2016, Wu et al., 2020, Yuan and Yang, 2020, Gong et al., 2021, Zeng et al., 2021, Ding et al., 2022, Zhang et al., 2022). For example, oil and its derivatives are primary transmitters of return and volatility spillovers to various asset classes, such as agricultural commodities (Tiwari et al., 2022), precious metals (Iqbal et al., 2022), and market indices (Tan et al., 2020). Natural gas has also been identified as a net transmitter of spillovers to metal and agricultural commodity indices (Rehman and Vo, 2021, Wang et al., 2022). In contrast, coal has typically acted as an information recipient in systems including oil, natural gas, EUA, and clean energy (Ji et al., 2018, Ding et al., 2022). Similarly, the carbon market tends to behave as a net receiver against oil (Wang and Guo, 2018) and the stock market (Ji et al., 2019, Dong et al., 2024).

Despite extensive research on connectedness among energy commodities, few studies have analyzed how disturbances propagate within energy supply chains. Křehlík and Baruník (2017) provide an exception, arguing that upstream shocks dominate connectedness in the oil markets. However, their focus on the oil supply chain excludes other related commodities, such as natural gas and coal. Our research fills this gap by studying upstream and downstream spillovers in a comprehensive system of energy commodities, including raw materials (Brent oil, natural gas, and coal) and derivatives (gasoline, heating oil, propane, and ethanol). We also consider European Union Allowances, which are tradable certificates permitting the emission of one metric tonne of carbon dioxide. These certificates can be traded in financial markets by participants in the European Union Emissions Trading System (EU ETS). Established in 2005, the EU ETS is designed to regulate the most significant energy-intensive industries, which contribute to approximately 40% of the European Union's GHG emissions (European Commission, 2022). The choice of including EUA is justified by its significant impact on firms' environmental outcomes related to energy production and consumption. The "switching" effect, which occurs when there is a substitution between different fuel sources with varying carbon emission levels, is theorized to be one of the most significant drivers of carbon prices, closely linked to the market dynamics of raw energy series (Mansanet-Bataller et al. 2011, Fleschutz et al. 2021). The carbon price thus serves as a regulatory mechanism designed to encourage reductions in carbon emissions, influencing the adopted technology of energy production and prioritizing types of energy, such as favoring renewable sources over fossil fuels. Our analysis is innovative in incorporating EUA within the point of view of the energy supply chain, offering an assessment of the most relevant upstream and downstream transmission channels influencing carbon market dynamics.

Due to the recent crisis episodes affecting our society, spillovers have also been studied in a dynamic analysis framework, particularly useful during periods of market distress as connectedness is highly event-dependent (Dong et al., 2024). Previous works generally highlight increased connectedness during crisis episodes (Feng et al., 2023). Notable examples include the Global Financial Crisis (Kang et al., 2017, Ferrer et al., 2018, Nasreen et al., 2020), the 2014 oil price drop (Ferrer et al., 2018, Balli et al., 2019, Nasreen et al., 2020), and the onset of the Russia-Ukraine war (Adekoya et al., 2022, Wang et al., 2022, Lin et al., 2024, Polat et al., 2024). Conversely, research on energy commodities' spillovers during the COVID-19 pandemic yielded mixed results. Some studies reported a decrease in the connectedness of returns series (Costola and Lorusso, 2022, Tiwari et al., 2022), while others noted a sharp increase in volatility spillovers at the pandemic's onset (Jebabli et al., 2022, Huang et al., 2023). Notably, during this period, commodities often reversed their usual shock transmission behavior, as evidenced by Corbet et al. (2021) in a system comprising West Texas Intermediate (WTI), Brent, heating oil, natural gas, gasoline, and some stock indices.

By studying spillovers in energy commodity markets in relation to several crisis episodes from 2012 to 2024, our study integrates the literature on connectedness regarding the COVID-19 pandemic (Shahzad et al., 2021, Si et al., 2021, Yarovaya et al., 2021, Aharon and Demir, 2022, Lu et al., 2024), the Russia-Ukraine war (Fang and Shao 2022, Hoque et al. 2023, Jin et al. 2023, Roy et al. 2023, Wang et al. 2023, Zhang et al. 2023), and the few research on connectedness during the Israeli-Palestinian conflict (Cui and Maghyereh, 2024, Lin et al., 2024). In particular, we complement available studies by highlighting the heterogeneous transmission behavior of financial assets depending on whether the crisis episode is directly linked to the energy industry or originates from different sectors.

Eventually, our research also contributes to the literature on connectedness from a methodological perspective. Numerous studies have explored shock transmission among financial assets using the spillover index developed by Diebold and Yilmaz (2012, 2014) to estimate static and dynamic connectedness in the time domain (see, e.g., Wang and Guo (2018), Ji et al. (2019), Ferrer et al. (2021), Zhang et al. (2022), Dong et al. (2024), Kayani et al. (2024)). In this context, Baruník and Křehlík (2018) introduced a framework for estimating the spillover index in the frequency domain, differentiating between short- and long-term connectedness. Ando et al. (2022) further expanded the field by proposing the quantile connectedness method, which relaxes the assumption that relationships observed at the conditional mean of returns' distribution apply across the entire distribution, an assumption that may not hold during extreme market phases (Saeed et al., 2021, Ando et al., 2022, Chen et al., 2022, Chatziantoniou et al., 2022, Farid et al., 2022, Rizvi et al., 2022, Tiwari et al., 2022, Yousaf et al., 2022). For instance, asymmetric spillovers have been identified in the upper and lower tails of the shock distribution (Ji et al., 2019, Xia et al., 2019, Naeem et al., 2021), with higher levels of connectedness during positive disturbances (Iqbal et al., 2022, Ghosh et al., 2023).

Our research advances this literature by applying the methodologies of Diebold and Yilmaz (2012, 2014), Baruník and Křehlík (2018), and Ando et al. (2022). In addition, we apply the recent framework developed by Chatziantoniou et al. (2022), which enables the computation of short- and long-term quantile connectedness. This method allows us for a nuanced understanding of spillovers beyond the average effects, particularly under varying market conditions. Finally, we expand the framework proposed by Baruník and Křehlík (2018) introducing an approach enabling us to further study the connectedness over a wide range of frequency bands. In this way, we provide evidence on the stability of the transmission behavior of energy commodities on a large band spectrum, and we fuel the discussion on market efficiency in absorbing shocks (Lillo and Mantegna, 2003, Sornette, 2009) by highlighting the frequency maximizing net connectedness for each energy commodity.

3 Material and methods

This Section describes the empirical methodologies employed to address our research objectives. Our empirical analysis focuses on Europe, whose energy consumption and carbon dioxide emissions account for around 10% and 8% worldwide, respectively.[3]

Section 3.1 introduces the time-domain analysis to understand whether upstream or downstream commodities prevail in shock transmission. In Section 3.2, we describe the approach for the frequency domain analysis to discern the contribution of short- and long-term components in generating spillovers. We also explain the robustness checks we employ to assess the stability of our main findings. In Sections 3.2.1 and 3.2.2, we discuss how we examine variations in individual commodities' transmission behavior and the efficiency of our assets in absorbing and transmitting spillovers. Finally, in Section 3.3, we outline the quantile analysis applied to evaluate the transmission behavior across the entire shock distribution.

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[3] European Commission, Directorate-General for Energy, EU energy in figures: statistical pocketbook 2021, Publications Office of the European Union, 2021, `https://data.europa.eu/doi/10.2833/511498`.

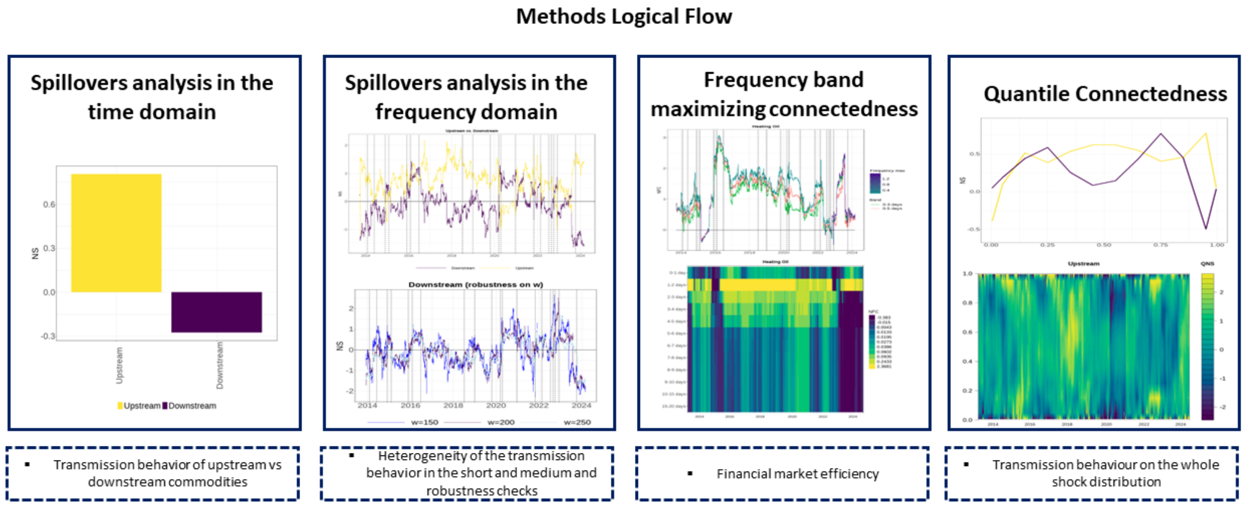

Figure 1: We describe the logical flow of the Methods section to address our research objectives.

3.1 Spillovers in the time domain

We measure the contribution of shocks on our commodity indices to the forecast error variances through the spillover index introduced by Diebold and Yilmaz (2012, 2014) (hereinafter DY). Such connectedness measure is based on the variance decomposition of a VAR(P) model with P lags and K endogenous variables, approximating a covariance stationary process:

$$Y_t = \sum_{i=1}^{P} \Phi_i Y_{t-i} + \epsilon_t = \Phi(L) Y_t + \epsilon_t \tag{1}$$

where $Y_t = (Y_{1,t}, Y_{2,t}, ..., Y_{K,t})'$ is a Kx1 vector of daily returns at time t, $\Phi(L) = [I_K - \Phi_1 L - ... - \Phi_P L^P]$ a $(K \times K)$ matrix of polynomials in the lag operator L, with I_K being the identity $K \times K$ matrix, and $\epsilon_t \sim (0, \Sigma)$ a shock vector with covariance matrix Σ possibly non-diagonal.

The returns of each commodity are thus regressed on P lags of all series in the system (including the underlying variable itself). Such a system can be rewritten through a moving average representation with infinite order, VMA(∞), of the VAR system $Y_t = \sum_{j=0}^{\infty} \Psi_j \epsilon_{t-j}$, where coefficient matrices Ψ_j are recursively defined as $\Psi_j = \Phi_1 \Psi_{j-1} + \Phi_2 \Psi_{j-2} + ... + \Phi_p \Psi_{j-p}$ with $\Psi_0 = I$ and $\Psi_j = 0$ for $j < 0$.

To ensure our results are invariant to the ordering of the variables in the system, we employ the Koop et al. (1996) and Pesaran and Shin (1998) (hereinafter KPPS) generalized vector autoregressive framework to compute variance decompositions. Following this approach, we compute KPPS H-step-ahead forecast error variance decomposition as:

$$\theta_{jk}(H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} (e_j' \Psi_h \Sigma e_k)^2}{\sum_{h=0}^{H-1} (e_j' \Psi_h \Sigma \Psi_h' e_j)} \tag{2}$$

where Σ is the covariance matrix of ϵ, σ_{kk} is the k^{th} diagonal element of Σ, and e_k is a selection vector equal to one for the k^{th} element and zeros otherwise. Element $\theta_{jk}(H)$ represents the contribution of the k^{th} commodity to the forecast error variance of the j^{th} commodity at the horizon H.

Own (terms of $\theta(H)$ on the main diagonal) and cross-variable (off-diagonal terms of $\theta(H)$) variance contributions do not necessarily sum to one. Based on DY, we thus normalize each entry of the variance decomposition matrix by its row sum as follows:

$$\tilde{\theta}_{jk}(H) = \frac{\theta_{jk}(H)}{\sum_{k=1}^{K} \theta_{jk}(H)} \tag{3}$$

with $\sum_{k=1}^{K} \tilde{\theta}_{jk}(H) = 1$ and $\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(H) = K$ by construction.

We compute total directional spillovers received by variable j from all other variables k in percentage terms as:

$$TDS_{j\leftarrow\bullet}(H) = \frac{\sum_{k=1,k\neq j}^{K} \tilde{\theta}_{jk}(H)}{K} \cdot 100 \tag{4}$$

Consistently, we measure total directional spillovers from variable j to all other variables k as:

$$TDS_{\bullet\leftarrow j}(H) = \frac{\sum_{k=1,k\neq j}^{K} \tilde{\theta}_{kj}(H)}{K} \cdot 100 \tag{5}$$

More in general, the total spillover index provides a system-wide measure of connectedness. In formula:

$$TS(H) = \frac{\sum_{j,k=1,j\neq k}^{K} \tilde{\theta}_{jk}(H)}{K} \cdot 100 \tag{6}$$

Such a measure summarizes the (cross) contribution of spillovers from shocks to all variables to the total forecast error variance.

In addition, we compute the net directional spillovers between commodity j and all the other variables of the system as $NS_j(H) = TDS_{\bullet\leftarrow j}(H) - TDS_{j\leftarrow\bullet}(H)$. They represent the difference between shocks transmitted from variable j to the system and shocks received by j from all other variables. A positive value of $NS_j(H)$ suggests that the variable j is a net transmitter, while a negative value outlines a net receiver role.

3.2 Spillovers in the frequency domain

3.2.1 Frequency decomposition

As a second step, we apply the spectral decomposition strategy introduced by Baruník and Křehlík (2018) (hereinafter BK) to assess the connectedness in the short- and long-term frequencies. In this way, we evaluate whether shocks to one variable generate persistent (lower frequencies) connectedness in the system or immediate (higher frequencies) spillovers.

We compute the frequency response function $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h}\Psi_h$ by means of a Fourier transform of the coefficients Ψ_h. More specifically, the spectrum density of series Y_t over the specific frequency ω is equal to:

$$S_Y(\omega) = \sum_{h=0}^{\infty} E(Y_t Y_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega h})\Sigma\Psi'(e^{+i\omega h}) \tag{7}$$

where $i^2 = -1$ is the imaginary unit. $S_Y(\omega)$ models the distribution of the variance of Y_t over the frequency domain.

The generalized causation spectrum allows us to compute the extent to which shocks to the k^{th} variable affect the portion of the spectrum of the j^{th} variable in correspondence with a specific frequency $\omega \in (-\pi, \pi)$:

$$\theta_{jk}(\omega) = \frac{\sigma_{kk}^{-1}[(\Psi(e^{-i\omega})\Sigma)_{jk}]^2}{(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}))_{jj}} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{\infty}(\Psi(e^{-i\omega h})\Sigma)_{jk}^2}{\sum_{h=0}^{\infty}(\Psi(e^{-i\omega h})\Sigma\Psi'(e^{+i\omega h}))_{jj}} \tag{8}$$

where h, Σ, and σ_{jj} have the same meanings described in Equation 2. Element $\theta_{jk}(\omega)$ represents the within-frequency causation for a given value ω.

Coherently with the analysis on the time domain, $\theta_{jk}(\omega)$ is row-normalized for the K commodities in the system as follows:

$$\tilde{\theta}_{jk}(\omega) = \frac{\theta_{jk}(\omega)}{\sum_{k=1}^{K}\theta_{jk}(\omega)} \tag{9}$$

Frequency bands of specific interest can be obtained by integration. In this way, by calculating the cumulative connectedness over a frequency band $d = (a, b) : a, b \in (-\pi, \pi)$ and $a < b$, we can estimate the short- and long-term connectedness as:

$$\tilde{\theta}_{jk}(d) = \int_a^b \tilde{\theta}_{jk}(\omega) d\omega \tag{10}$$

Finally, the *within* connectedness on band d is:

$$WC(d) = \left(1 - \frac{Tr\{\tilde{\theta}_{jk}(d)\}}{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(d)}\right) \cdot 100 \tag{11}$$

where $Tr\{\cdot\}$ constitutes the trace of the variance decomposition matrix.

Alternative frequency bands d can contribute differently to the overall system connectedness. In particular, the weight of a given frequency band d to the aggregate spillover is:

$$\Gamma(d) = \frac{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(d)}{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(\infty)} = \frac{1}{K} \sum_{j,k=1}^{K} \tilde{\theta}_{jk}(d) \tag{12}$$

Therefore, we can compute the *frequency* connectedness representing the contribution of the frequency band d to the overall system connectedness as:

$$FC(d) = WC(d) \cdot \Gamma(d) = \frac{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(d) - Tr\{\tilde{\theta}_{jk}(d)\}}{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(\infty)} \cdot 100 \tag{13}$$

Overall, the sum of the FC(d) over disjointed bands covering the whole frequency spectrum is equal to the total spillover measure proposed by DY. Even for BK's approach, we define similar directional measures of connectedness:

$$FDC_{j \leftarrow \bullet}(d) = \sum_{k=1, k \neq j}^{K} \tilde{\theta}_{jk}(d) \cdot \frac{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(d)}{\sum_{j,k=1}^{K} \tilde{\theta}_{jk}(\infty)} \cdot 100 \tag{14}$$

$$FDC_{\bullet \leftarrow j}(d) = \sum_{k=1, k \neq j}^{K} \tilde{\theta}_{kj}(d) \cdot \frac{\sum_{j,k=1}^{K} \tilde{\theta}_{kj}(d)}{\sum_{j,k=1}^{K} \tilde{\theta}_{kj}(\infty)} \cdot 100 \tag{15}$$

Consequently, the net frequency connectedness is $NFC_j(d) = FDC_{\bullet \leftarrow j}(d) - FDC_{j \leftarrow \bullet}(d)$.

To estimate the parameters required by the approaches of Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík (2018), we first set the order P of the VAR equal to the value which minimizes the Schwarz information criterion (SIC), as done by Yuan and Yang (2020), Ferrer et al. (2021), and Naeem et al. (2021). Precisely, we set $P = 1$. Second, we use 10-day ($H = 10$) and 100-day ($H = 100$) ahead forecast errors for the time and frequency domains, respectively, as in Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). Third, for the static analysis in the frequency domain, we divide the time horizon into the short-term ($d_1 \in [0, 5]$ days) and the long-term ($d_2 \in (5, +\infty)$ days), following Nasreen et al. (2020), Yuan and Yang (2020), and Naeem et al. (2021). Lastly, for the dynamic analysis in the time and frequency domains, we consider a rolling window of 200 days ($w = 200$) in line with Diebold and Yilmaz (2012), Baruník and Křehlík (2018), Yuan and Yang (2020), and Ferrer et al. (2021).

Section 5.5 assesses the robustness of our choices on the hyperparameters required for the Diebold and Yilmaz (2012, 2014)'s dynamic analysis. In Section 5.5.1, we exhibit our main results in case we set the order P of the VAR equal to the value that minimizes the Hannan-Quinn (HQ, $P = 1$) and Akaike (AIC, $P = 5$) information criteria. In Section 5.5.2, we halve ($H = 5$) and double ($H = 20$) the number of steps ahead. In Section 5.5.3, we decrease ($w = 150$) and increase ($w = 250$) the rolling window length by 50 days.

3.2.2 Transmission behavior over a wide range of frequency bands

We enrich the framework proposed by Baruník and Křehlík (2018) by studying the net directional connectedness of our system of commodities over a wide set of frequency values to assess if the transmission behavior of a specific commodity is stable or significantly affected by the considered spectrum bands.

First, we identify the frequency band b that maximizes (in absolute value) the net directional connectedness of each commodity k over a spectrum covering all bands from 0-1 to 0-20 days by adding 1 day one by one (e.g., $b = [0, 1]$, $b = [0, 2]$, $b = [0, 3]$, ..., $b = [0, 20]$). Since net connectedness over a frequency band b is equal to the sum of the net connectedness in all sub-bands $sub - b$ which cover the underlying spectrum b (e.g., $NFC(b = [0, 3]) = NFC(sub - b = [0, 1]) + NFC(sub - b = [1, 2]) + NFC(sub - b = [2, 3])$), this analysis provides information about the stability of the commodities in the spillover behavior as either transmitters or receivers over the different sub-bands of 1 day. Indeed, stable net transmitters or receivers tend to show the same sign of their net connectedness measured over the different sub-bands.

We assess the stability in the frequency maximizing net connectedness across different frequency bands b through the following dispersion indicator:

$$Frequency\ dispersion_{k,b} = \frac{\sum_{t=1}^{T} \left(freq_{max,k,t,b} - \overline{freq}_{max,k,b}\right)^2}{T} \tag{16}$$

where $freq_{max,k,t,b}$ is the frequency maximizing net connectedness of commodity k at a certain date t, across frequency bands b, T is the total number of observed days, and $\overline{freq}_{max,k,b} = \frac{\sum_{t=1}^{T} freq_{max,k,t,b}}{T}$.

As a second step, we analyze the frequency maximizing net connectedness for each commodity by considering the inter-day variation in net connectedness for spectral sub-bands, ranging from 0 to 20 days (e.g., $sub-b = [0, 1]$, $sub-b = [1, 2]$, $sub-b = [2, 3]$, ..., $sub-b = [19, 20]$). By covering all sub-periods of 1 day in the range of 1-20 days, this analysis complements our previous indicators introduced in Equation 16 since it enables us to assess the market efficiency in terms of the time required to absorb the largest portion of spillovers. In particular, we summarize the variation in the frequency maximizing net connectedness across different sub-bands $sub-b$ through the following dispersion indicator:

$$Frequency\ dispersion_{k,sub-b} = \frac{\sum_{t=1}^{T} \left(freq_{max,k,t,sub-b} - \overline{freq}_{max,k,sub-b}\right)^2}{T} \tag{17}$$

where $freq_{max,k,t,sub-b}$ is the frequency maximizing net connectedness of commodity k at a certain date t, across frequency sub-bands $sub-b$, and $\overline{freq}_{max,k,sub-b} = \frac{\sum_{t=1}^{T} freq_{max,k,t,sub-b}}{T}$.

Lastly, we compute the variability of the net connectedness across different sub-bands:

$$NFC\ dispersion_{k,sub-b} = \frac{\sum_{t=1}^{T} \sum_{sub-b} (NFC_{t,sub-b} - \overline{NFC}_t)^2}{T \cdot F} \tag{18}$$

where $NFC_{t,sub-b}$ is the net frequency connectedness computed at time t and sub-band $sub-b$, $\overline{NFC}_t = \frac{\sum_{sub-b} NFC_{t,sub-b}}{F}$, and F the overall number of sub-bands.

3.3 Quantile Connectedness

Connectedness introduced in Sections 3.1-3.2 provides information on spillovers generated at the mean of the conditional distribution of commodities' returns $Y_t|Y_{t-1}, Y_{t-2}, ..., Y_{t-p}$. Such measures are thus based on the assumption that the relationships observed in correspondence with the conditional mean can be generalized to the entire conditional distribution.

This assumption may not hold, especially during extreme market phases, as evidenced in several studies (see, e.g., Saeed et al. (2021), Ando et al. (2022), Chen et al. (2022), Chatziantoniou et al. (2022)). For this reason, we rely on the method introduced by Ando et al. (2022), who propose a quantile connectedness measure to assess connectedness at the tails of the conditional distribution. The quantile connectedness allows us to disentangle the idiosyncratic components of the error process from the systematic component. This approach accurately captures the value of spillovers in correspondence with extreme occurrences, potentially asymmetric and different from the mean or median relationships.

To do so, we first estimate the following quantile VAR (QVAR):

$$Y_t = \mu(\tau) + \sum_{i=1}^{P} \Phi_i(\tau) Y_{t-i} + \epsilon_t(\tau) \tag{19}$$

with τ representing the quantile, μ a $K \times 1$ conditional mean vector, and the other quantities in line with Equation 1. Exploiting the Wold's Theorem, we transform the QVAR(P) into its QVMA (∞): $Y_t = \mu(\tau) + \sum_{i=1}^{P} \Phi_i(\tau) Y_{t-i} + \epsilon_t(\tau) = \mu(\tau) + \sum_{j=o}^{\infty} \Psi_j(\tau)\epsilon_{t-j}$. Finally, we define analog measures of connectedness as those introduced in sections 3.1-3.2.

This framework distinguishes the impacts of rare events from those associated with business-as-usual scenarios. Moreover, it enables us to detect whether time-varying connectedness changes asymmetrically across the upper and lower tails of the shock distribution. This means that large positive or negative idiosyncratic shocks might generate heterogeneous levels of connectedness. We also decompose quantile connectedness into the short-term and long-term components by relying on Chatziantoniou et al. (2022)'s method, enabling us to detect which between the two prevails in magnitude.

4 Data description

4.1 Energy commodities system

We collect the daily closing prices of eight energy commodities from Thompson Reuters Eikon. The sample comprises 2,925 observations, beginning on December 17, 2012, and ending on

March 1, 2024. Specific futures contracts are listed in Table A1 in Appendix A.[4]

To facilitate the interpretation of the transmission channels, we opt to label those commodities more likely to be placed at the top of the energy production system as the upstream commodities while defining the others as downstream commodities. The former are raw materials and include *Brent oil*, *natural gas*, and *coal*. In contrast, the latter are relevant derivatives and are composed of *gasoline*, *heating oil*, *propane*, and *ethanol*.

Our system aims to provide a representative overview of key energy commodities significantly contributing to satisfying European energy production and consumption patterns. Indeed, as of 2020, oil and petroleum products (e.g., gasoline and heating oil), natural gas, and solid fossil fuels (i.e., coal) accounted for approximately 70% of the gross available energy in the EU. Moreover, such commodities play a key role in the overall energy consumption regarding final usage. In 2020, they covered about 60% of total consumption, with oil and petroleum products, and natural gas constituting the leading fuel sources with 35% and 22%, respectively.[5]

Our upstream commodities are widely employed in energy production as oil, gas, and coal account for portions equal to around 34%, 24%, and 12%, respectively. Consistently, our downstream commodities are widely representative of derivatives obtained from upstream raw materials. Specifically, about 49% of a typical barrel of crude oil is refined into gasoline, whereas 26% is turned into distillate fuel oil (heating oil and diesel fuel).[6]

Additionally, including coal and gasoline in our system allows us to account for production linkages with ethanol. Indeed, despite being mainly obtained from agricultural commodities, such as corn (50.4%), wheat (21.8%), sugar (14.5%), and other cereals and starch-rich crops (3%),[7] ethanol might also be extracted from coal (Li and Cheng, 2020, Liu et al., 2022). Moreover, gasoline is linked with ethanol since up to 5% (10%) of E5 (E10) fuel[8] contains some

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[4] When available, our data refer to the futures price of commodities listed on a European exchange (e.g., Brent oil) instead of those quoted on an extra-EU financial market (e.g., WTI).

[5] Information related to fuels contribution in terms of gross available energy and final energy consumption in Europe is available at the following link: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview`

[6] We are forced to exclude diesel fuel due to unavailable data. Additionally, our analysis does not comprehend other minor crude oil derivatives, such as kerosene-type jet fuel, petroleum coke, still gas, hydrocarbon gas liquids, asphalt and road oil, petrochemical feedstocks, residual fuel oil, and lubricants and other products, which, however, account for less relevant percentages of crude oil production (8%, 4%, 3%, 3%, 2%, 1%, 1%, 1%, and 1%, respectively) (source: `https://www.eia.gov/energyexplained/oil-and-petroleum-products/refining-crude-oil-inputs-and-outputs.php`).

[7] Source: `https://www.epure.org/wp-content/uploads/2022/09/220905-DEF-PR-ePURE-Key-figures-2021-1.pdf`.

[8] The E10 petrol was introduced in the EU by a European Fuel Quality Directive (DIRECTIVE 2009/30/EC) starting from 2011 (Source: `https://eur-lex.europa.eu/eli/dir/2009/30/oj`). However, the EU required

ethanol as a biofuel additive.[9] Lastly, we include propane since it is a widely employed lower-emission alternative transport fuel and is a relevant derivative obtained from both oil and gas (in comparable proportions).[10] Indeed, propane can be supplied from the oil refinery or based on the recovery of liquid components of natural gas, such as butane and ethane, as well as heavier hydrocarbons.

Due to the relevance of energy-related emissions in the acceleration of climate change and natural disasters, in 2005, the European Commission (EC) introduced the EU ETS, constituting the world's largest carbon trading market covering the most relevant energy-intensive industries that account for around 40% of EU greenhouse gas emissions (European Commission, 2022).[11] In this context, a European Union Allowance is a tradable certificate that allows the emission of one metric tonne of carbon dioxide and can be traded in financial markets among EU ETS participants to promote cost-effective carbon abatement targets (Ellerman et al., 2016).

For example, the differential between coal and gas prices (or the associated dark/spark spreads) represents a short-term driver for power producers to switch from coal to natural gas as the main fuel feedstock (Mansanet-Bataller et al. 2011, Fleschutz et al. 2021). Consequently, relevant connectedness emerges between energy fossil fuels and carbon price (Ren et al., 2024), with important implications for the proper balance between economic growth and environmental conservation (Ji et al., 2018, Wang and Guo, 2018, Tan et al., 2020). For such reasons, we also add the EUA price to our system of commodities.

Section 5.5.4 assesses the robustness of the total connectedness index computed on our energy commodity system by alternatively excluding either EUA or ethanol plus propane.

4.2 Descriptive statistics of the energy commodities system

From the daily closing prices P_t at t, we compute the natural logarithmic returns, which are plotted in Figure 2, as $r_t = \ln(P_t) - \ln(P_{t-1})$.[12] Table 1 shows descriptive statistics for the

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that its member states continue to ensure that sufficient volumes of today's petrol are accessible for vehicles that are only compatible with the usage of E5 petrol.

[9] Source: `https://www.eni.com/en_FR/products-services/fuels/petrol/super-95-E10/super-95-E10.shtml`

[10] Source: `https://afdc.energy.gov/fuels/propane_production.html`.

[11] In 2019, around 75% of total GHG emissions in the EU were generated by energy production (European Environment Agency, 2019).

[12] We consider prices in euros to avoid possible biases related to currency appreciation or depreciation when computing returns.

entire sample period.

As a general result, we find that commodities have, on average, a null daily performance, with a significant standard deviation (on average, around 2.8%). All commodities, except natural gas, appear to be left-skewed. This means that most observations are above the mean, while long left tails with negative returns may result from the strong downturn of commodity prices in correspondence with the global commodity markets crisis of 2014-2015 and the start of the COVID-19 pandemic. On the other hand, the right-skewness of natural gas may be due to the significant increase in the price of this commodity after the start of the Russia-Ukraine war. Furthermore, the kurtosis is greater than three, meaning a leptokurtic distribution, typical for financial assets, characterizes the analyzed commodities.

We reject the null hypothesis of normal distribution (Shapiro-Wilk and Jarque-Bera tests) at the 1% significance level for all time series. The Augmented Dickey-Fuller and the Phillips-Perron tests provide strong evidence in favor of the stationarity of our system of commodities since we reject the null hypothesis at the 1% significance level. Lastly, for all time series except Brent and heating oil, the Ljung-Box Q rejects the null hypothesis at the 1% level for up to the 5^{th} order serial correlation, evidencing significant serial autocorrelations in the returns. Compared to the other energy commodities, we notice slightly lower evidence of serial autocorrelation for up to the 20^{th} order for heating oil as the null is rejected with a 95% confidence.

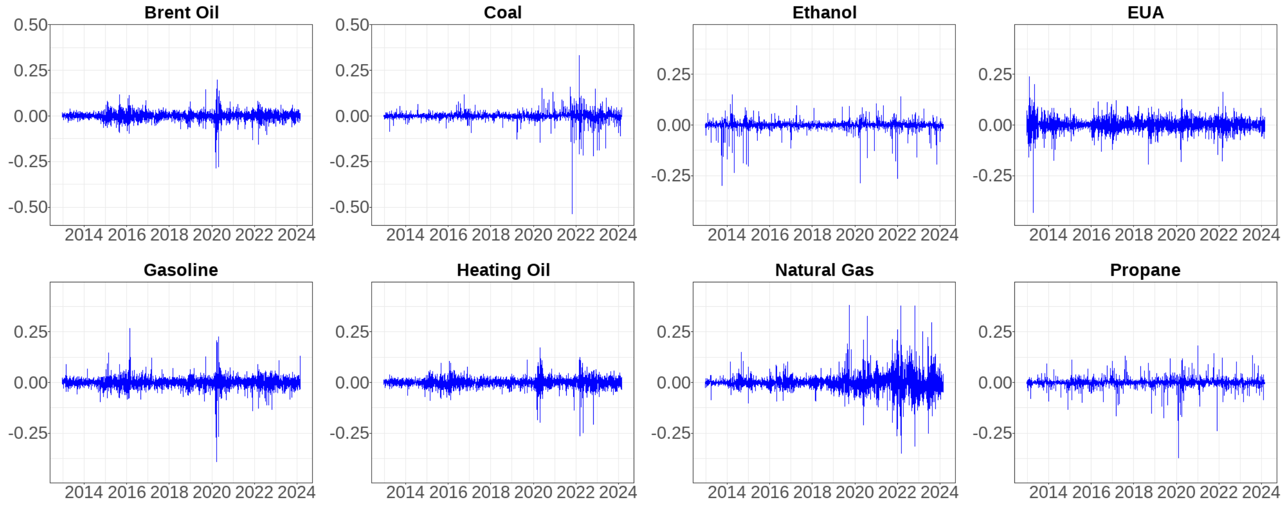

Figure 2: Commodity daily log-returns.

Commodity	mean	median	std.dev	skewness	kurtosis	SW	JB	ADF	PP	LB (5)	LB (20)
Brent Oil	0.000	0.000	0.024	−0.922	17.789	0.883***	38,969.950***	−14.336***	−2,875.802***	1.271	45.782***
Coal	0.000	0.000	0.026	−2.658	96.233	0.594***	1,131,724.000***	−14.227***	−2,902.438***	60.364***	97.054***
Ethanol	0.000	0.000	0.022	−4.466	53.003	0.607***	351,992.200***	−13.296***	−2,695.346***	27.966***	47.279***
EUA	0.001	0.000	0.032	−1.003	16.359	0.910***	33,093.060***	−15.223***	−2,903.443***	15.476***	63.160***
Gasoline	0.000	0.001	0.028	−1.186	28.547	0.836***	99,967.490***	−13.801***	−3,105.279***	15.265***	96.494***
Heating Oil	0.000	0.000	0.024	−1.112	16.143	0.881***	32,350.580***	−14.245***	−2,849.948***	7.474	35.891**
Natural Gas	0.000	0.000	0.044	0.881	15.541	0.817***	29,802.990***	−13.848***	−2,887.041***	24.717***	61.809***
Propane	0.000	0.000	0.021	−2.549	50.444	0.688***	313,183.400***	−12.570***	−2,801.856***	20.058***	39.949***

Table 1: Descriptive statistics of time series. SW and JB columns report the statistics of the Shapiro and Wilk (1965) and Jarque and Bera (1980) tests for the null hypothesis of Gaussian distribution, respectively. ADF and PP denote the statistics of the Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests, respectively. LB (l) is the Ljung and Box (1978) p-value for up to the l^{th} order serial correlation.
*p<0.10; **p<0.05; ***p<0.01

5 Empirical results

5.1 Static analysis

We explore the shock transmission mechanisms by exploiting the spillover framework introduced in Sections 3.1-3.2 on the representative system of energy commodities described in Section 4.1.

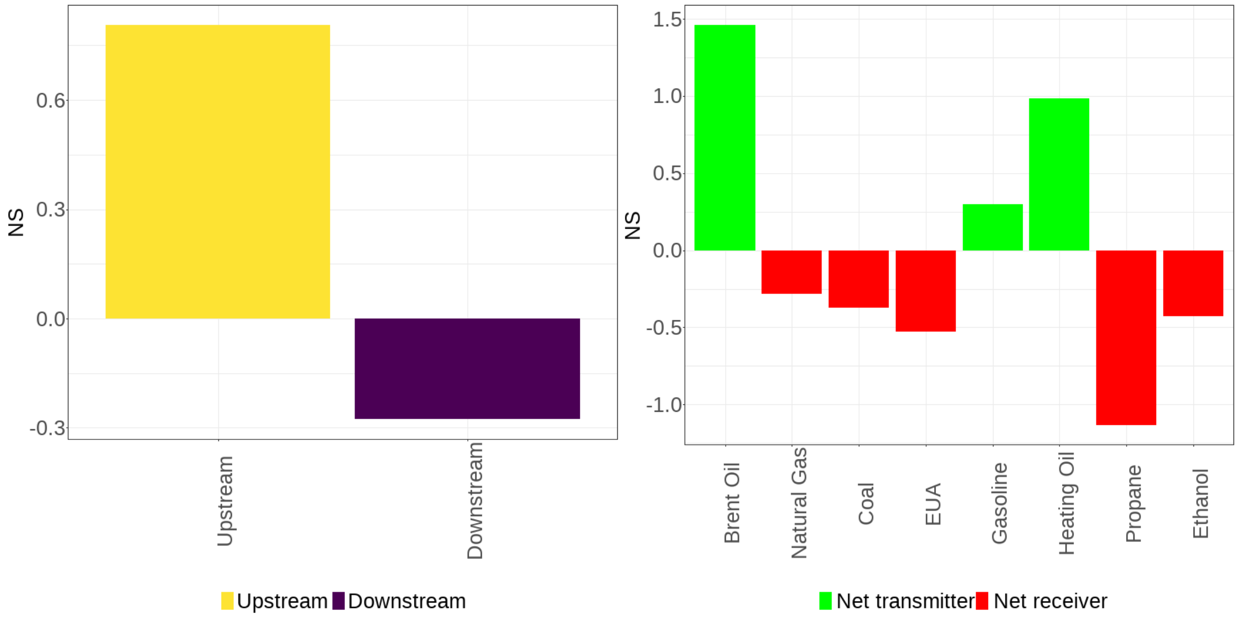

Figure 3: Net spillovers in the time domain. In the left bar plot, upstream commodities are colored yellow and downstream are violet. Downstream commodities do not include EUA. In the right bar plot, net transmitters are colored green and net receivers red.

We first analyze the aggregate groups of upstream and downstream commodities. Upstream commodities behave as net transmitters with an aggregate net connectedness of 0.81 (see the left panel in Figure 3 and Table 2). However, this results from heterogeneous dynamics between the different raw materials of our systems (see the right panel in Figure 3 and Table 2). Indeed, Brent oil is the leading net transmitter with a net connectedness of about 1.46, whereas natural gas (-0.28) and coal (-0.37) behave as net receivers. We find instead that, in the aggregate, downstream commodities are slightly net receivers (-0.28). Nonetheless, oil derivatives such as gasoline (0.30) and heating oil (0.98) behave as net transmitters, whereas propane (-1.13) and ethanol (-0.43) are characterized by negative values of net connectedness, constituting two major net receivers.

Commodity	Short-Term Net Connectedness	Long-term Net Connectedness	Total Net Connectedness
Upstream	0.783	0.024	0.807
Downstream	-0.249	-0.028	-0.277
Brent Oil	1.282	0.178	1.460
Coal	-0.232	-0.140	-0.372
Ethanol	-0.250	-0.176	-0.427
EUA	-0.534	0.004	-0.530
Gasoline	0.122	0.175	0.297
Heating Oil	0.794	0.190	0.984
Natural Gas	-0.267	-0.015	-0.281
Propane	-0.915	-0.217	-1.131

Table 2: Commodities' net connectedness in the time and frequency domains. Short- and long-term spillovers are computed by using Baruník and Křehlík (2018)'s method. Downstream commodities do not include EUA.

These results corroborate extant evidence on the core position of oil in the whole commodity markets (Ji and Fan, 2012) and pointing to oil and its derivatives as main transmitters of return and volatility spillovers (Tan et al., 2020, Iqbal et al., 2022, Tiwari et al., 2022). For instance, Kayani et al. (2024) find that Brent oil is the leading net transmitter in a system including WTI, gasoline, heating oil, carbon emissions, and natural gas. Conversely, all other commodities behave as net receivers. Such findings are consistent with existing literature on coal (Ji et al., 2018, Ding et al., 2022). However, this result differs from previous findings, where natural gas mainly acts as a transmitter of shocks on a more extensive commodities system, also including metals and agricultural indices (Rehman and Vo, 2021, Wang et al., 2022).

We finally observe that EUA (−0.53) absorbs shocks from other commodities.[13] Wang and Guo (2018) also prove that the carbon market plays the role of a receiver in return spillovers within a system composed of EUA, WTI oil, Brent oil, and natural gas markets. Analogously, Ji et al. (2019) confirm that carbon price is a net spillover recipient from returns of power sector companies. The net receiver behavior of EUA in energy commodity systems may have important economic implications for the functioning of the EU ETS as previous studies demonstrated the significant influence of carbon price on the trend of companies' carbon abatement and environmental innovation (Lin and Jia, 2019, Adamolekun, 2024). Moreover, our findings fuel the theoretical and empirical discussion on the drivers impacting EUA (Alberola et al., 2008, Bredin and Muckley, 2011, Creti et al., 2012, Lutz et al., 2013, Bai and Okullo, 2023), including energy and commodity prices (Keppler and Mansanet-Bataller, 2010, Ji et al., 2018), fundamentals (Lovcha et al., 2022), weather conditions (Eslahi and Mazza, 2023), as well as speculation and price bubbles in correspondence with energy announcements (Creti and Joëts, 2017, Hartvig et al., 2023).

These roles are confirmed mainly even when focusing on the short- and long-term net connectedness, with the former displaying a much more relevant impact (see first and second columns of Table 2). Nevertheless, we find a few noteworthy differences between the time and frequency domain analyses. In the long-term, EUA is characterized by a slightly positive net connectedness (around 0.004). Interestingly, gasoline is the only commodity whose net connectedness (in absolute value) is larger in the long-term than in the short-term. In contrast, all other commodities experience a significant drop in the connectedness level. Křehlík and Baruník (2017) also evidence the dominance of long-term spillovers with respect to gasoline in the period 2009-2011.

Notably, the spillover analysis shows that, although the upstream group of commodities behaves like a transmitter, significant differences emerge, with oil dominating the transmission channels while coal and natural gas act as receivers. Similarly, although, on average, the downstream group is a weak receiver of spillovers, it still has some relevant transmitter commodities, thus revealing heterogeneous patterns within it. To further investigate how such system-wide roles emerge from bilateral transmission channels, particularly those related to links between raw materials and the corresponding downstream demand, we report the pairwise relationships

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[13] Given the peculiarity of EUA, we do not include it in the downstream group.

Commodities	Short-Term Pairwise Connectedness	Long-Term Pairwise Connectedness	Total Pairwise Connectedness
Upstream-Downstream	−0.500	−0.037	−0.537
Propane-Heating Oil	0.259	0.086	0.345
Coal-Heating Oil	0.136	0.077	0.213
Natural Gas-Heating Oil	0.179	0.001	0.180
Gasoline-Heating Oil	0.173	-0.020	0.153
Ethanol-Gasoline	0.082	0.070	0.152
EUA-Gasoline	0.143	0.004	0.146
Ethanol-Heating Oil	0.078	0.038	0.116
EUA-Heating Oil	0.107	0.007	0.114
Coal-Brent Oil	0.093	0.020	0.113
Coal-Gasoline	0.062	0.026	0.087
Natural Gas-Gasoline	0.053	0.007	0.060
Ethanol-Propane	0.026	0.008	0.033
Coal-Natural Gas	-0.014	0.045	0.032
Natural Gas-Propane	-0.004	0.029	0.024
EUA-Ethanol	0.002	0.000	0.002
EUA-Propane	-0.001	-0.001	-0.002
Natural Gas-Ethanol	0.006	-0.008	-0.002
Coal-Propane	0.005	-0.014	-0.008
Coal-Ethanol	-0.004	-0.015	-0.019
Coal-EUA	-0.046	0.001	-0.045
Natural Gas-EUA	-0.080	0.018	-0.061
Brent Oil-Ethanol	-0.068	-0.038	-0.106
Brent Oil-Natural Gas	-0.099	-0.012	-0.112
Brent Oil-Heating Oil	-0.138	0.001	-0.138
Brent Oil-EUA	-0.158	-0.005	-0.163
Brent Oil-Gasoline	-0.305	0.011	-0.293
Gasoline-Propane	-0.260	-0.038	-0.298
Brent Oil-Propane	-0.421	-0.114	-0.535

Table 3: Pairwise connectedness across commodities. Short- and long-term spillovers are computed by using Baruník and Křehlík (2018)'s method. Each number represents spillovers generated from the commodity on the right to the commodity on the left. Hence, a negative sign suggests that the second commodity is a net receiver from the first and, vice versa, a positive sign indicates a net transmitter. Upstream-downstream pairwise connectedness is calculated by summing up pairwise spillovers between upstream (on the left) and downstream (on the right) commodities (we do not consider spillovers including EUA or between pairs of commodities that are both upstream or downstream). Pairs in the table are in decreasing order with respect to the magnitude of the total pairwise connectedness.

in Table 3.

Table 3 corroborates that downstream commodities are, in general, net receivers of connectedness at the aggregate level (−0.54) as well as in the short- (−0.50) and long-term (−0.04). The highest pairwise spillovers occur between Brent oil and propane (−0.54), Propane-heating oil (0.35), gasoline-propane (−0.30), and Brent oil-gasoline (−0.29), thus suggesting significant spillovers even among commodities not directly related in a supply chain and even between commodities on the same upstream/downstream level. For EUA, we find that its lowest connectedness in absolute value is with commodities referring to propane and ethanol. In contrast, stronger links are observed with Brent oil, heating oil, gasoline, and coal. These findings align with previous research that found a higher dependence of EUA with crude oil and coal (Chevallier, 2009, Ortas and Álvarez, 2016, Uddin et al., 2018). The high spillovers have relevant implications for the structure of alternative energy-related supply chains since energy costs and fuel prices are key drivers of the optimal energy mix (Thangavelu et al., 2015, Deng and Lv, 2020). In particular, the stability of the transmission behavior and the volatility of connectedness of the analyzed commodities should be taken into account for cost-effective and low-emissions energy planning activities (Vidal-Amaro et al., 2015, Wierzbowski et al., 2016).

These findings are substantially confirmed in the short- (Figure B1 in Appendix B) and long-run (Figure B2 in Appendix B), with the former prevailing over the latter: around 81% of total spillovers are generated in the short-run. The literature highlights that spillovers are primarily generated by short-term factors (Bondia et al., 2016, Reboredo et al., 2017, Chen et al., 2022, Zheng et al., 2023). The heterogeneity in the size of spillovers across different frequencies has relevant implications for market participants with distinct investment time horizons. Indeed, traders, brokers, and speculators characterized by short-term investments may exploit short-term connectedness to optimize their portfolio strategy. Conversely, financial actors with potentially longer investment perspectives, such as institutional investors, may consider that financial market dynamics are mainly affected by their own fundamentals in the long term, with a lower incidence of spillovers (Ferrer et al., 2018, Cui et al., 2021).

5.2 Dynamic analysis: the impact of crisis episodes on the system's connectedness

Section 5.1 refers to a static spillover analysis that may hide relevant variations in the temporal dimension. To further investigate how stable commodities are in receiving or transmitting spillovers, we discuss the dynamic evolution of connectedness in relation to significant events occurring in the system, which are summarized in Table C1 (Appendix C). Figure 4 confirms that the short-term component is the primary driver of net connectedness. Moreover, it outlines that the magnitude of spillovers is highly event-dependent (Dong et al., 2024), with the system's total connectedness typically rising after major crisis episodes (Feng et al., 2023). For instance, between June 2014 and February 2015, a series of industry-specific, macroeconomic, and financial events led to a 38% decline in global commodity prices. During this period, the system's total connectedness increased by 32%, with short-term growth of 23% and long-term growth of 79%. Consistent with these findings, Balli et al. (2019) report an increase in total connectedness within their commodity system during the 2014 oil price collapse, while Wen et al.

(2021) observe a similar trend from 2014 to 2016, noting a significant rise in the total spillover index associated with the Chinese stock market crash. In contrast, the 2015 Paris Agreement does not appear to have caused noticeable spikes in the system's total connectedness.

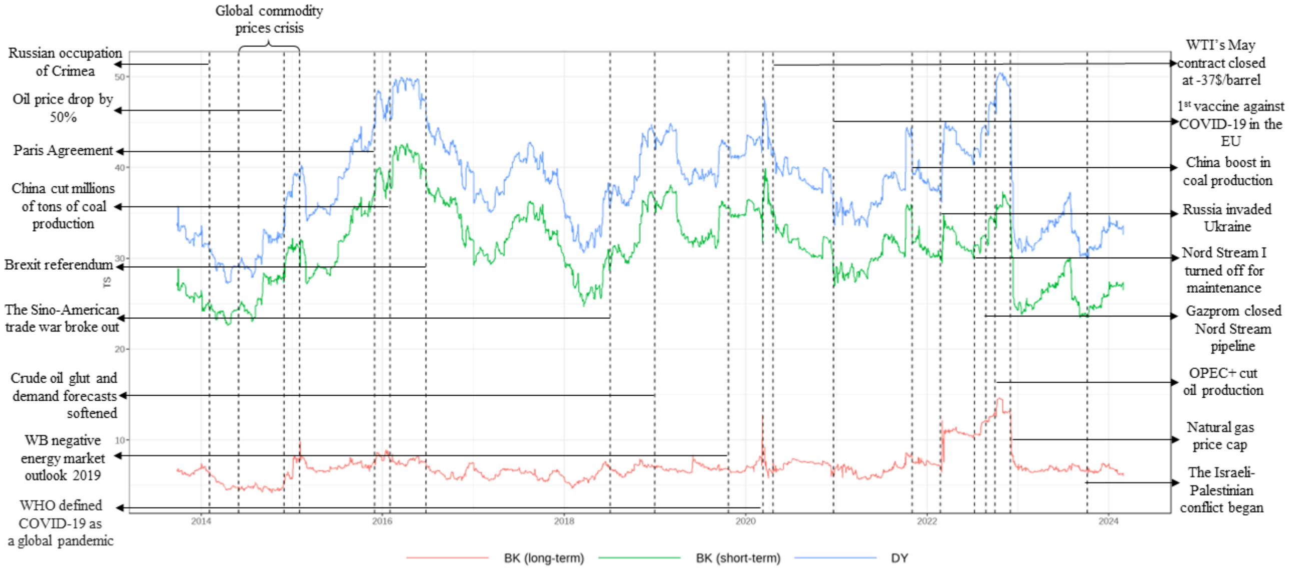

Figure 4: System's total connectedness. The results are based on a VAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 10-step-ahead (100-step-ahead) generalized forecast error variance decomposition for the time (frequency) domain. The dashed vertical lines are drawn in correspondence with the most relevant events, directly or indirectly linked to the energy sector, which have occurred over the decade, as shown in Table C1.

Additionally, Figure 5 suggests that, over time, the upstream commodities tend to be characterized by higher levels of net connectedness with respect to downstream. Indeed, in 73.28% of daily observations, raw materials display larger net spillovers in absolute value than derivatives. Moreover, upstream commodities mostly behave as net transmitters, whereas downstream are mainly net receivers, although they frequently change their transmission behavior.

During major crisis events, the level of connectedness is strongly affected in magnitude. For instance, the net spillovers of derivatives sharply collapsed at the end of February 2014 after the Russian intervention in Crimea, when they became net receivers. Meanwhile, the net spillovers of raw materials increased by 53.72% in just one week. By contrast, the net connectedness of downstream peaked at around 0.60 in December 2014, following the great oil price bust of 2014. In this case, the connectedness of upstream commodities sharply dropped to around −0.56. The Brexit referendum may have contributed to amplifying commodities' transmission behavior. Indeed, the net spillovers of raw materials more than doubled between June and September 2016, while the net connectedness of derivatives collapsed.

At the end of 2018, American crude oil production grew more rapidly than anticipated, resulting in a crude oil surplus, stagnant demand expectations, and geopolitical instability in

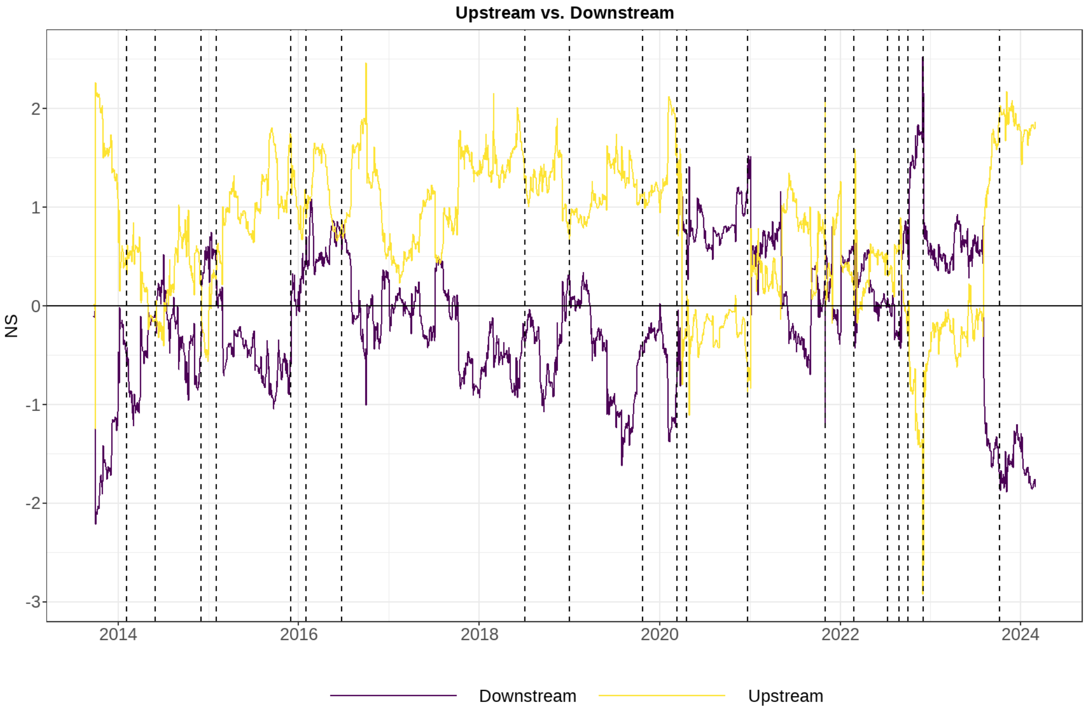

Figure 5: Net connectedness in the time domain (Upstream vs. Downstream). The results are based on a VAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 10-step-ahead generalized forecast error variance decomposition.

the energy sector. As a result, total connectedness peaked at 42.88 in December 2018, after hitting a low of 31.37 in May. During the same period, net spillovers of downstream commodities rose from -0.53 to 0.29, while the net connectedness of upstream commodities decreased by approximately 59.36%. These findings align with the analysis by Akyildirim et al. (2022), which reports an increase in total connectedness in a system of agricultural commodities during the Sino-American trade war.

Notice how downstream commodities maintained a net transmitting behavior for 287 trading days (between April 2020 and May 2021). This may result from the contraction in real global economic activity during the first phase of the pandemic. We confirm the results by Costola and Lorusso (2022) and Tiwari et al. (2022) in relation to the connectedness of energy markets during the COVID-19 pandemic: after an initial spike in March 2020, the system's total connectedness slowly but steadily decreased in the following months. For instance, from March 18, 2020, to December 24, 2020, the system's connectedness fell from 47.35 to 33.64.

Moreover, upstream and downstream commodities inverted their usual shock transmission behavior during the healthcare emergency. As an example, net spillovers of upstream shrank from 1.95 to -0.29 in just one month (March-April 2020), assuming negative values for the following twelve months until April 2021. Our findings are reasonable and justified by the deep contraction in the demand for raw materials (especially crude oil) and the storage issues experienced during the first lockdown. On the other hand, net spillovers of downstream commodities remained higher than upstream's during the first year of the healthcare emergency. Further, on November 1, 2021, we observed a significant positive spike in the net connectedness of upstream commodities, coinciding with China's announcement to increase coal production, which helped lower power prices across Europe.[14] Our findings are consistent with existing literature. For example, Iqbal et al. (2022) demonstrate that heating oil acted as a net receiver during some brief periods of the pandemic, although it primarily served as a net transmitter. Similarly, Corbet et al. (2021) find that crude oil exhibited unstable transmission behavior in April 2020. Additionally, Wang et al. (2022) highlight that, following the pandemic outbreak, crude oil shifted from positive to negative net connectedness in a system encompassing energy, agricultural commodities, and metals.

At the onset of the Russia-Ukraine war, we observed a notable rise in connectedness. Starting on February 24, 2022, the system's total spillovers grew by 13% in just one week. Our findings are consistent with those of Kayani et al. (2024), who report significant total spillovers in energy commodities at the beginning of the conflict, with a peak value of 83.33 compared to an average of 36.63. Similarly, Jiang and Chen (2022) argue that overall connectedness among seven representative sectoral commodity futures indices became more pronounced after the war began, increasing from 23.50 to 41.81. Additionally, Wang et al. (2022) provide evidence that the total volatility spillover index for commodities rose from 35 before the war to 85 by late March 2022. Finally, Polat et al. (2024) find that total connectedness between agricultural and energy commodities peaked in April 2022, shortly after the conflict began. This increase in connectedness appears persistent, with the total spillover index up by about 60% at the end of October 2022 compared to the pre-war period.

After the Russia-Ukraine war, several events hit natural gas prices, impacting commodities' transmission behavior. Indeed, the net connectedness of upstream commodities dropped from 1.08 on January 3, 2022, to -0.52 approximately a month after the beginning of the Russia-Ukraine war. On the other hand, the spillovers of derivatives sharply rose in the same period from -0.11 to 0.87. Interestingly, following Gazprom's decision to close the Nord Stream I

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[14] `https://www.bloomberg.com/news/articles/2021-11-01/european-coal-price-drops-below-100-as-china-boosts-output`

pipeline, the upstream spillovers peaked at around 0.41, and the downstream dropped at -0.10. Conversely, we observe an opposite pattern after the decision of OPEC+ to cut oil production by two million barrels per day in October 2022 and the introduction of a cap on the natural gas prices in the EU to reduce the volatility created by Russia in the gas market. Indeed, downstream commodities reached an all-time high of 2.52 in our sample, and the spillovers generated by upstream commodities assumed values even lower than those observed in the first phase of the pandemic (-2.93). Lastly, we observe a 13% increase in total spillovers in the first two months after the breakout of the Israeli-Palestinian conflict, mainly driven by upstream commodities. Our result complements the limited research pointing out how such a conflict has greatly intensified the spillovers across financial and commodity markets (Cui and Maghyereh, 2024, Lin et al., 2024).

Overall, the study highlights the significant impact of external events on market dynamics, contributing to a broader understanding of how economic and geopolitical crises influence energy markets. A pertinent example is the outbreak of the Russia-Ukraine war, which drove wholesale electricity prices in European markets to record highs in 2022, causing severe production imbalances (European Commission, 2023). The European Power Benchmark averaged €230/MWh, marking a 121% increase compared to 2021, with an unprecedented peak in August. This surge led to significant increases in energy prices and heightened uncertainty regarding supply. This was due to the fact that the EU enacted a ban on the import of Russian coal and oil (with some limited exceptions) and introduced a price cap on Russian crude oil and petroleum products. Consequently, the share of renewables in the energy mix rose to 39%, and installed renewable capacity grew by 16% in 2022 compared to the previous year. Notably, despite EUA prices rising to €80/tCO2 in 2022, these levels were insufficient to drive a shift from coal to gas in power generation due to persistently high gas prices throughout most of the year. Although natural gas was not directly sanctioned, Russia significantly reduced its exports to EU markets. In response, the EU implemented a temporary market correction mechanism to potentially cap gas prices. To bolster its energy security, the EU launched the REPowerEU plan in May 2022. This plan complemented national and collective policy decisions by establishing a comprehensive EU-level framework, focusing on diversifying supply sources, reducing demand, enhancing energy efficiency, and increasing renewable energy production.[15]

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[15] Source: `https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/739362/EPRS_BRI(2023)739`

Such insights are critical for developing theories related to global market stability and crisis management. Specifically, our dynamic analysis suggests that crisis episodes affecting the energy sector raise the system's total connectedness, whereas events not directly connected with this sector (e.g., the COVID-19 pandemic) reduce spillovers. Notice how the pandemic and the war in Ukraine generate high heterogeneity in upstream and downstream commodities' spillover propagation behavior, which may shift from net transmitters to receivers and vice versa in short sub-periods. By contrast, during several other events in our sample, commodities on the same side of the supply chain keep stable their role of net transmitters or net receivers with respect to previous business-as-usual scenarios (Balli et al., 2019, Akyildirim et al., 2022, Wang et al., 2022). Consistent patterns are observed in the short-term analysis (see Figure C1 in Appendix C), whereas more pronounced variations occur in the long-term net connectedness (see Figure C2 in Appendix C). Understanding how upstream and downstream commodities transmit or receive shocks helps optimize supply chain strategies, especially during periods of instability. This is particularly relevant for energy planning and maintaining a balanced energy mix to minimize costs and ensure reliability. The inversion of usual transmission behaviors during events such as the COVID-19 pandemic underscores the necessity for flexibility and adaptability in supply chain management.

5.3 Frequency analysis

To further investigate the role of upstream and downstream commodities in the transmission channels, we propose to study the system's connectedness along different frequency values, highlighting the spectral band that generates the maximum value of spillover propagation.

As a first step, we compute the dispersion of the frequency band that maximizes the net connectedness of each commodity over a wide spectrum ranging from 0 to 20 days, as shown in Equation 16 of Section 3.2.2. We highlight that upstream commodities reached maximum net connectedness for a higher frequency band (0.55) than downstream (0.47), corresponding to about 6 $(\frac{\pi}{0.55})$ and 7 $(\frac{\pi}{0.47})$ days (see Table 4). Such a result might be due to the heterogeneity in the mean maximum frequency band of raw materials, with Brent oil displaying the highest value (9 days) with respect to natural gas and coal (around 5 days) (see Table 4).

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Indeed, upstream commodities experience higher frequency dispersion (0.29) than downstream commodities (0.22). Several episodes that have hit upstream commodities over 2012-2024, as discussed in Section 5.2, may justify these findings.

In addition, we highlight a strong homogeneity in the frequency sub-bands of 1 day that lead to maximum spillovers. We notice that most of the shocks are absorbed within the first two days, regardless of the transmission behavior of commodities (1.51 for upstream and 1.48 for downstream), which is in line with the efficient market hypothesis. The occurrence of a shock to an asset price or return may heighten the likelihood of subsequent shocks leading to phases of market instability (Spelta et al., 2020, 2021). For example, the market response of several different asset classes to an initial shock often exhibits a power-law decay (Lillo and Mantegna, 2003, Sornette, 2009), where shocks are quickly absorbed over time. This pattern is evident even during significant events such as Brexit or the COVID-19 pandemic (De Giuli et al., 2022, Spelta et al., 2023). Consistently, analyzing single commodities, most of the highest (in absolute value) inter-day variations gather on the second frequency sub-band (see Figures E1, E2, and E3 in Appendix E), and the corresponding frequency dispersion is very low. Our findings align with those of Wang (2022), which reveal a relationship between market efficiency and connectedness, specifically noting that efficient markets act as net transmitters of information to less efficient markets. However, our research indicates that commodity prices react quickly to unexpected events, confirming that available information is swiftly incorporated into these markets (Ortiz-Cruz et al., 2012). This further contributes to the work of Kristoufek and Vosvrda (2014), who employed the Efficiency Index (Kristoufek and Vosvrda 2013) to show that energy commodity markets are quite efficient.

We instead observe larger differences regarding the magnitude of the maximum net connectedness and its variability. We find that upstream commodities display a larger mean maximum connectedness than downstream (0.20 vs. −0.02) with a similar level of dispersion (both around 0.04), confirming their more decisive role in shock propagation. Specifically, the maximum value in transmission is achieved by Brent oil (1.07), whereas derivatives, such as ethanol and propane, are the most affected commodities as receivers (−0.45 and −0.58). Further, the only other positive values of net connectedness are achieved by heating oil and gasoline, confirming the oil supply chain prevails as a transmitter channel.

Furthermore, notice how upstream commodities experience a higher number of changes in the transmission behavior with respect to downstream (57 vs. 23), mainly due to coal (107). Brent oil and heating oil are the most stable commodities in their role of transmitters, with just a few episodes of change in the direction of their spillovers over the period. For instance, the former appeared to be a net receiver only during the COVID-19 pandemic outbreak between April 6, 2020, and April 20, 2020, reaching a minimum of −0.67 on April 9, 2020 (see Figure E1 in Appendix E). Analogously, the latter was a receiver between March 3, 2015, and July 30, 2015, with the lowest amount of connectedness being −0.41 on March 16, 2015 (see Figure E1 in Appendix E). Figures E2 and E3 in Appendix E illustrate details for the remaining set of commodities.

The other commodities, both on the upstream and downstream sides, feature frequent changes in the sign, suggesting that it is unclear whether they behave as stable transmitters or receivers within the system. For instance, gasoline and coal experienced, respectively, 43 and 107 shifts in the shock propagation direction, respectively. Amid receivers, the most stable behavior is accounted for by propane, which only experienced 12 sign changes of net connectedness concentrated between August and November 2015 and over the first half of 2020.

Although some differences emerge within commodities on the same side of the supply chain, we confirm that upstream commodities display a more stable transmission behavior, translating into fewer sign changes.

Commodity	Mean max freq b	Frequency dispersion b	Mean max freq sub-b	Frequency dispersion sub-b	Mean max connectedness sub-b	Net connectedness dispersion sub-b	Number of sign changes
Upstream	0.555	0.287	1.506	0.030	0.197	0.044	57
Downstream	0.474	0.221	1.476	0.041	−0.015	0.039	23
Brent Oil	0.353	0.153	1.568	0.001	1.069	0.102	2
Coal	0.642	0.340	1.498	0.038	−0.192	0.013	107
Ethanol	0.334	0.093	1.485	0.038	−0.454	0.027	21
EUA	0.651	0.247	1.533	0.020	−0.559	0.047	47
Gasoline	0.682	0.351	1.460	0.046	0.202	0.015	43
Heating Oil	0.437	0.247	1.504	0.032	0.773	0.069	14
Natural Gas	0.671	0.367	1.452	0.051	−0.285	0.018	61
Propane	0.442	0.193	1.456	0.050	−0.581	0.044	12

Table 4: Frequency and net connectedness dispersion.

5.4 Quantile connectedness

We also investigate whether the results observed in Section 5.2 hold across the whole spillover distribution. We thus contribute to a broad literature on the asymmetric impact of positive and negative shocks to the system's connectedness (Ji et al., 2019, Xia et al., 2019, Naeem et al., 2021). Figure 6 (upper-left panel) suggests that for upstream and downstream commodities, net connectedness varies along different quantiles of the spillover distribution. Notice how upstream commodities experience a higher net connectedness with respect to downstream around the median, while such a relationship is reverted in the lower tail of the distribution.

As for raw materials, the highest quantile net spillovers (QNS) gather in the upper part of the distribution. Conversely, derivatives achieve the lowest net spillovers at the extreme upper tail. Such results are also confirmed based on the relative tail dependence (RTD), calculated as the difference between total spillovers at the 95^{th} and 5^{th} quantiles (see the upper-right plot in Figure 6). Indeed, we tend to observe positive (negative) values for upstream (downstream) commodities.

The dynamic quantile analysis (see the lower-left and right panels in Figure 6) shows that upstream commodities mainly behave as net transmitters. Their quantile net connectedness increases in correspondence with shocks involving global commodity prices (June 2014-February 2015), the Sino-American trade war, and the second phase of the pandemic. In contrast, it decreases during the first lockdown and the Russia-Ukraine war. When focusing on single commodities (see Figure D1 in Appendix D), we see that such behavior is similar to that of Brent oil (its average QNS across all quantiles fell from 1.159 to 0.095 between February 24, and November 24, 2022). Interestingly, natural gas, hard hit by the war in Ukraine, was slightly a net receiver around the median and lower tail of the distribution (its average QNS at the 55^{th} and 5^{th} quantiles are -0.425 and -0.325, respectively). In contrast, its net transmitter nature emerged at the upper tail (its average QNS at the 95^{th} quantile are 0.125). Further, natural gas was a net recipient during normal circumstances and in almost all quantiles under study, as evidenced by Iqbal et al. (2022) over a more extensive system of commodities, including energy, agricultural, and metal indices, from 2010 to 2020. Regarding coal, we find that it generally behaved as a net receiver during the whole period and across different quantiles (its average QNS are -0.485). Nonetheless, we observe two episodes in which it transmitted shocks to the

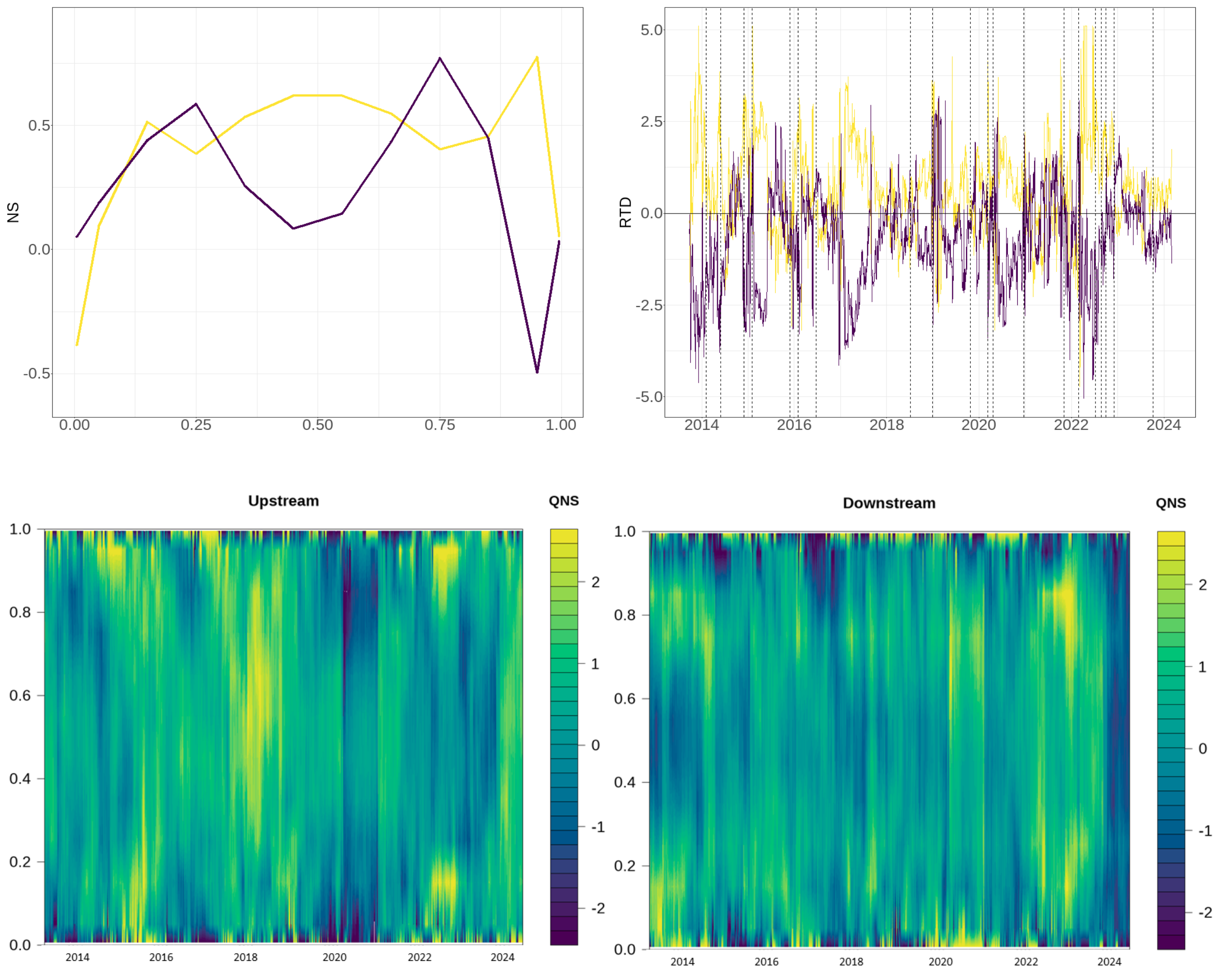

Figure 6: Quantile net spillovers (QNS). Upstream vs. downstream. The upper-left figure presents the mean of net spillovers (NS) of upstream (in yellow) and downstream (in violet) commodities across quantiles. The upper-right plot shows the relative tail dependence (RTD) of upstream and downstream commodities, namely the difference between their NS at the 95^{th} and 5^{th} quantiles, computed on the dynamic quantile connectedness with a rolling window of 200 days ($w = 200$). The lower-left and lower-right plots display the QNS of upstream and downstream commodities across quantiles (y-axis), respectively. The color represents the magnitude of commodities' QNS.

other commodities within the system, namely at the end of 2015 and after the outbreak of the war in Ukraine.

When focusing on derivatives, we observe that the quantile connectedness frequently changes sign at the extreme tails. Furthermore, downstream commodities display a net receiver behavior in the central part of the distribution until 2016 (their average QNS at the 55^{th} quantile are -0.287), and during the second phase of the pandemic (their average QNS at the 55^{th} quantile is -0.241), which is reversed during the Russia-Ukraine war (their average QNS at the 55^{th} quantile is 1.024 between February 24, and September 23, 2022). Yet, some differences emerge if we analyze single commodities. For instance, the average quantile net connectedness of heating oil shrank from 1.419 to -0.821 in the same subperiod discussed above for Brent oil. As for gasoline, we notice some periods in which this commodity behaves as a net receiver, especially for shocks in correspondence with the distribution median, observed at the end of 2013, in 2017, and at the beginning of 2018. We highlight the net transmitter behavior of ethanol, affected mainly by the commodity price crisis in 2015 and the Sino-American trade war, emphasizing its nature as a receiver of spillovers (its average QNS across all quantiles are -0.920). Propane was also mainly characterized by a negative net connectedness over the analyzed time frame (its average QNS across all quantiles are -0.738).

In summary, the quantile analysis indicates that taking into account connectedness only in correspondence with the conditional mean of the spillovers might not fully represent the direction and magnitude of the transmission behavior (see also Figure D2 in Appendix D). However, these results confirm that upstream commodities tend to behave as net transmitters, whereas downstream commodities are net receivers along a relevant portion of the spillover distribution.

The quantile connectedness analysis findings result from heterogeneous patterns that emerge when decomposing the short- and long-term quantile connectedness component employing Chatziantoniou et al. (2022)'s method. Figure D3 in Appendix D.1 relates to short-term quantile spillovers and substantially confirms the above findings. On the other hand, Figure D4 provides evidence that long-term quantile connectedness experiences quite the opposite pattern. Nevertheless, such Figures demonstrate how short-term connectedness prevails over the long-term component along multiple quantiles of shock distribution, which justifies the results on quantile connectedness at the aggregate level. Additionally, we confirm the results of Sections 5.1-5.2 concerning the prevalence of short-term connectedness over the long-term component.

5.5 Robustness check

In this Section, we test for the robustness of our dynamic results on upstream and downstream net connectedness with respect to the hyperparameters involved when estimating Diebold and Yilmaz (2012, 2014)'s approach. Thus, we change P, H, and w one at a time by letting each assume two more distinct values in addition to those presented in Section 5.2. We also estimate the total connectedness of our energy system, excluding either EUA or propane plus ethanol.

5.5.1 Robustness on P

First, we test for the robustness of our results by computing the dynamic upstream and downstream net connectedness with respect to different criteria for estimating the VAR order in Equation 1, namely the Hannan-Quinn (HQ, $P = 1$) and Akaike (AIC, $P = 5$) information criterion. Such time series are compared to the results reported in Section 5.2, where we employ the SIC ($P = 1$). Interestingly, HQ and SIC return the same VAR order. Figure 7 reveals some heterogeneity when comparing SIC with AIC. Notably, downstream commodities show lower mean and maximum differences between the time series (see Table 5).

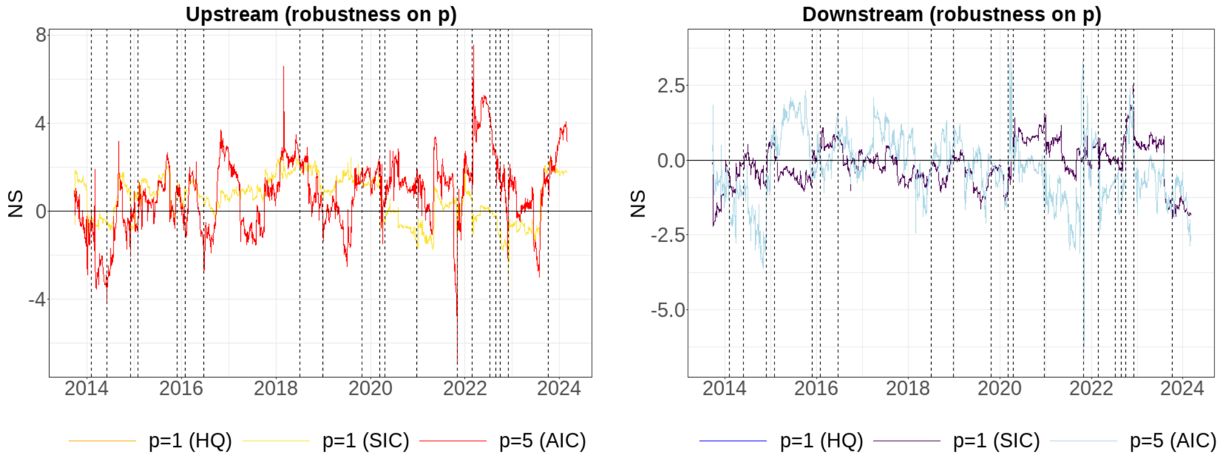

Figure 7: Upstream vs. downstream. Robustness on P.

	Mean (Upstream)	Max (Upstream)	Mean (Downstream)	Max (Downstream)
SIC ($P = 1$) vs. HQ ($P = 1$)	0.000	0.000	0.000	0.000
SIC ($P = 1$) vs. AIC ($P = 5$)	1.371	8.570	0.959	6.660

Table 5: Robustness on P. By letting the parameter vary, we compute the mean and maximum difference between the upstream and downstream net connectedness time series for which P is found by minimizing the SIC ($P = 1$) and those for which P equals 1 (HQ) and 5 (AIC).

5.5.2 Robustness on H

Second, we assess the robustness of our results by computing dynamic upstream and downstream net connectedness with respect to five ($H = 5$) and twenty ($H = 20$) steps ahead. Such time series are evaluated in terms of difference compared to the result reported in Section 5.2, where we set $H = 10$. Figure 8 plots such time series differences and reveals that the net connectedness of upstream and downstream is very stable regardless the value of H. Table

6 confirms such a finding, displaying negligible mean and maximum differences between the upstream and downstream commodities lines.

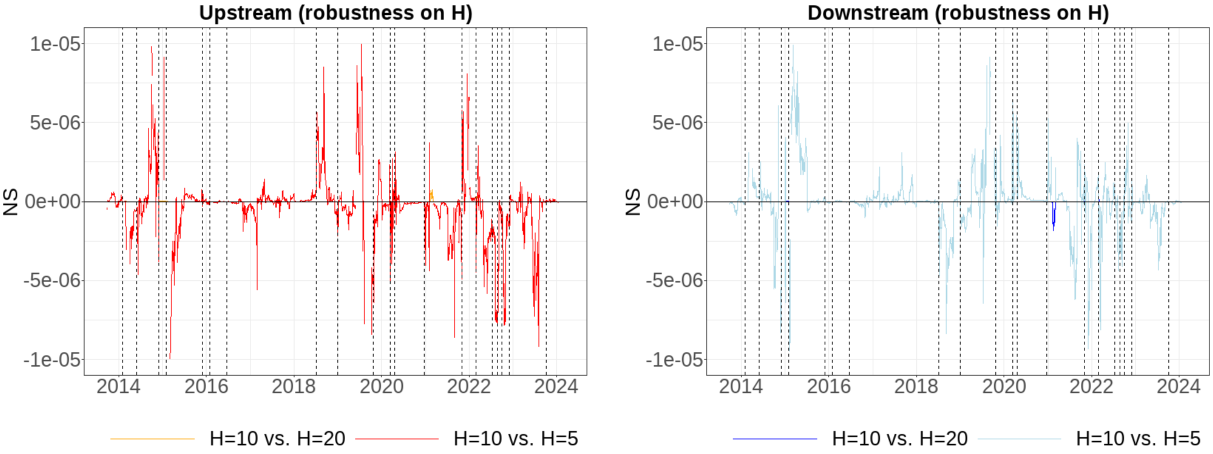

Figure 8: Upstream vs. downstream. Robustness on H (difference between time series).

	Mean (Upstream)	Max (Upstream)	Mean (Downstream)	Max (Downstream)
$H = 10$ vs. $H = 5$	0.000	0.001	0.000	0.001
$H = 10$ vs. $H = 20$	0.000	0.000	0.000	0.000

Table 6: Robustness on H. By letting the parameter vary, we compute the mean and maximum difference between the upstream and downstream net connectedness time series for which $H = 10$ and those for which H equals 5 and 20.

5.5.3 Robustness on w

Third, we assess the robustness of our results by computing the dynamic upstream and downstream net connectedness with respect to a 150- ($w = 150$) and 250- ($w = 20$) day rolling window size. Such time series are compared to one reported in Section 5.2, where we set $w = 200$. Figure 9 reveals low heterogeneity. Indeed, the net connectedness of upstream and downstream appears stable even regardless of the value of w. Downstream commodities show lower mean and maximum differences between the time series (see Table 7).

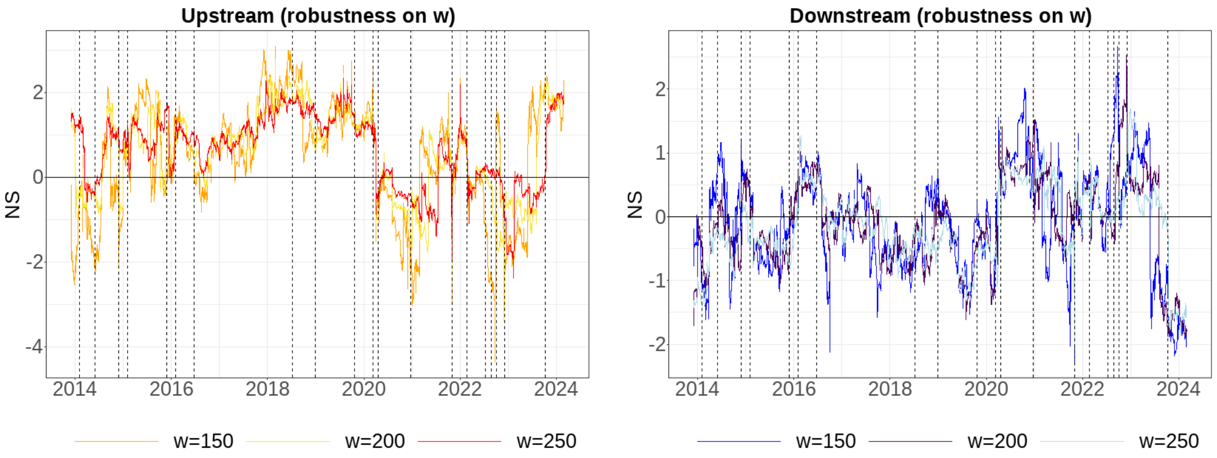

Figure 9: Upstream vs. downstream. Robustness on w.

	Mean (Upstream)	Max (Upstream)	Mean (Downstream)	Max (Downstream)
$w = 200$ vs. $w = 150$	0.624	3.742	0.427	2.311
$w = 200$ vs. $w = 250$	0.423	2.444	0.315	1.685

Table 7: Robustness on w. By letting the parameter vary, we compute the mean and maximum difference between the upstream and downstream net connectedness time series for which $w = 200$ and those for which w equals 150 and 250.

5.5.4 Robustness excluding some commodity series

Finally, we test for the robustness of our system's total connectedness by excluding alternatively EUA or propane and ethanol when computing the spillovers. Figure 10 proves that even excluding some assets from the energy system, the trend in total connectedness remains very similar (see Table 8 for further details on the mean and maximum deviations between the lines).

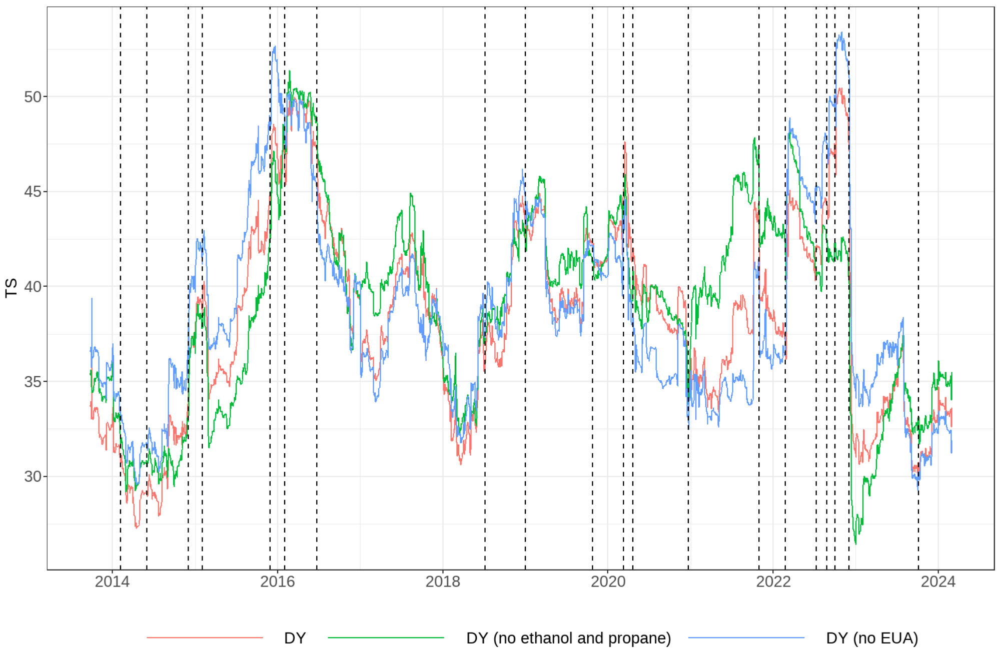

Figure 10: System's total connectedness. We compare our system's total connectedness with one excluding either EUA or ethanol plus propane.

	Mean	Max
Without EUA	1.956	5.363
Without ethanol and propane	2.062	8.777

Table 8: Robustness on total connectedness. We compute the mean and maximum difference between the total connectedness time series for the complete energy system described in Section 4.1 and the connectedness in an energy system excluding alternatively EUA or propane and ethanol.

6 Conclusion

To verify the financial stability of a representative energy system, we investigate transmission mechanisms by employing the spillover analysis based on the approaches of Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík (2018). We prove that upstream and downstream commodities behave, respectively, as net transmitters and receivers of spillovers. These considerations hold both in the time and in the frequency domains. We also employ a quantile analysis on different portions of the spillover distribution to corroborate our findings.

Such results have relevant implications for different economic actors regarding investment strategies and policy sustainability. For instance, understanding that oil plays a dominant role in spillover transmission, while coal and natural gas are often net receivers, can inform investors on how to structure their portfolios to optimize returns and mitigate risks. Investors can also enhance their financial strategies by leveraging these insights to balance energy-related raw materials and derivatives. Policymakers can utilize spillover information to minimize short-term interlinkages among energy commodity systems, thereby enhancing energy supply security. Focusing on assets less susceptible to price shocks can lead to more sustainable energy policies and infrastructure planning.

Our dynamic analysis shows how shocks directly affecting the energy sector, such as the Russia-Ukraine war, tend to raise the system's total connectedness. By contrast, less energy-specific relevant events, including the COVID-19 pandemic, reduce the system's connectedness. Moreover, the analysis of single specific frequency bands provides evidence of market efficiency since the main shocks are absorbed in less than two days, both for upstream and downstream commodities. Nonetheless, single commodities may assume heterogeneous shock transmission behaviors.

Such evidence can guide portfolio managers in developing tailored hedging strategies based on the sector affected by the crisis and the anticipated behavior of commodity prices. Additionally, managers should consider the responsiveness of specific energy-related commodities to price fluctuations in other assets when designing these strategies.

References

Adamolekun, G. (2024). Carbon price and firm greenhouse gas emissions. *Journal of Environmental Management 349*, 119496.

Adekoya, O. B., J. A. Oliyide, O. S. Yaya, and M. A. S. Al-Faryan (2022). Does oil connect differently with prominent assets during war? analysis of intra-day data during the Russia-Ukraine saga. *Resources Policy 77*, 102728.

Aharon, D. Y. and E. Demir (2022). Nfts and asset class spillovers: Lessons from the period around the covid-19 pandemic. *Finance Research Letters 47*, 102515.

Akyildirim, E., O. Cepni, L. Pham, and G. S. Uddin (2022). How connected is the agricultural commodity market to the news-based investor sentiment? *Energy Economics 113*, 106174.

Alberola, E., J. Chevallier, and B. Chèze (2008). Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy 36*(2), 787–797.

Ando, T., M. Greenwood-Nimmo, and Y. Shin (2022). Quantile connectedness: Modeling tail behavior in the topology of financial networks. *Management Science 68*(4), 2401–2431.

Anke, C.-P., H. Hobbie, S. Schreiber, and D. Möst (2020). Coal phase-outs and carbon prices: Interactions between EU emission trading and national carbon mitigation policies. *Energy Policy 144*, 111647.

Bai, Y. and S. J. Okullo (2023). Drivers and pass-through of the EU ETS price: evidence from the power sector. *Energy Economics 123*, 106698.

Balli, F., M. A. Naeem, S. J. H. Shahzad, and A. de Bruin (2019). Spillover network of commodity uncertainties. *Energy Economics 81*, 914–927.

Barberis, N., A. Shleifer, and J. Wurgler (2005). Comovement. *Journal of Financial Economics 75*(2), 283–317.

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

Basak, S. and A. Pavlova (2016). A model of financialization of commodities. *The Journal of Finance 71*(4), 1511–1556.

Bondia, R., S. Ghosh, and K. Kanjilal (2016). International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. *Energy 101*, 558–565.

Bredin, D. and C. Muckley (2011). An emerging equilibrium in the EU emissions trading scheme. *Energy Economics 33*(2), 353–362.

Chatziantoniou, I., E. J. A. Abakah, D. Gabauer, and A. K. Tiwari (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production 361*, 132088.

Chatziantoniou, I., D. Gabauer, and F. P. de Gracia (2022). Tail risk connectedness in the refined petroleum market: A first look at the impact of the covid-19 pandemic. *Energy Economics*, 106051.

Chen, Y., X. Zhu, and J. Chen (2022). Spillovers and hedging effectiveness of non-ferrous metals and sub-sectoral clean energy stocks in time and frequency domain. *Energy Economics*, 106070.

Chevallier, J. (2009). Carbon futures and macroeconomic risk factors: A view from the eu ets. *Energy Economics 31*(4), 614–625.

Coletti, D., R. Lalonde, P. Masson, D. Muir, and S. Snudden (2021). Commodities and monetary policy: Implications for inflation and price level targeting. *Journal of Policy Modeling 43*(5), 982–999.

Corbet, S., Y. G. Hou, Y. Hu, and L. Oxley (2021). Volatility spillovers during market supply shocks: the case of negative oil prices. *Resources Policy 74*, 102357.

Costola, M. and M. Lorusso (2022). Spillovers among energy commodities and the Russian stock market. *Journal of Commodity Markets*, 100249.

Creti, A. and M. Joëts (2017). Multiple bubbles in the European Union emission trading scheme. *Energy Policy 107*, 119–130.

Creti, A., M. Joëts, and V. Mignon (2013). On the links between stock and commodity markets' volatility. *Energy Economics 37*, 16–28.

Creti, A., P.-A. Jouvet, and V. Mignon (2012). Carbon price drivers: Phase I versus Phase II equilibrium? *Energy Economics 34*(1), 327–334.

Cui, J., M. Goh, and H. Zou (2021). Information spillovers and dynamic dependence between china's energy and regional cet markets with portfolio implications: New evidence from multi-scale analysis. *Journal of Cleaner Production 289*, 125625.

Cui, J. and A. Maghyereh (2024). Higher-order moment risk spillovers across various financial and commodity markets: Insights from the israeli–palestinian conflict. *Finance Research Letters 59*, 104832.

De Giuli, M. E., A. Flori, D. Lazzari, and A. Spelta (2022). Brexit news propagation in financial systems: multidimensional visibility networks for market volatility dynamics. *Quantitative Finance 22*(5), 973–995.

De Rosa, M., K. Gainsford, F. Pallonetto, and D. P. Finn (2022). Diversification, concentration and renewability of the energy supply in the european union. *Energy 253*, 124097.

Deng, X. and T. Lv (2020). Power system planning with increasing variable renewable energy: A review of optimization models. *Journal of Cleaner Production 246*, 118962.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association 74*(366a), 427–431.

Diebold, F. X. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting 28*(1), 57–66.

Diebold, F. X. and K. Yılmaz (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics 182*(1), 119–134.

Ding, Q., J. Huang, and H. Zhang (2022). Time-frequency spillovers among carbon, fossil energy and clean energy markets: The effects of attention to climate change. *International Review of Financial Analysis 83*, 102222.

Dong, Q., Y. Zhao, X. Ma, and Y. Zhou (2024). Risk spillover between carbon markets and stock markets from a progressive perspective: Measurements, spillover networks, and driving factors. *Energy Economics 129*, 107228.

Eberhardt, M. and A. F. Presbitero (2021). Commodity prices and banking crises. *Journal of International Economics 131*, 103474.

Ellerman, A. D., C. Marcantonini, and A. Zaklan (2016). The European Union emissions trading system: ten years and counting. *Review of Environmental Economics and Policy*.

Eslahi, M. and P. Mazza (2023). Can weather variables and electricity demand predict carbon emissions allowances prices? Evidence from the first three phases of the EU ETS. *Ecological Economics 214*, 107985.

European Commission (2023). Quarterly report on european electricity markets with focus on price developments in 2022.

European Commission, E. (2022). EU Emissions Trading System (EU ETS). `https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en`.

European Environment Agency, E. (2019). How are emissions of greenhouse gases in the EU evolving? `https://ec.europa.eu/eurostat/cache/infographs/energy/bloc-4a.html`.

Fang, Y. and Z. Shao (2022). The Russia-Ukraine conflict and volatility risk of commodity markets. *Finance Research Letters 50*, 103264.

Farid, S., M. A. Naeem, A. Paltrinieri, and R. Nepal (2022). Impact of covid-19 on the quantile connectedness between energy, metals and agriculture commodities. *Energy economics 109*, 105962.

Feng, H., J. Zhang, and N. Guo (2023). Time-varying linkages between energy and stock markets: Dynamic spillovers and driving factors. *International Review of Financial Analysis 89*, 102714.

Ferrer, R., S. J. H. Shahzad, R. López, and F. Jareño (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics 76*, 1–20.

Ferrer, R., S. J. H. Shahzad, and P. Soriano (2021). Are green bonds a different asset class? evidence from time-frequency connectedness analysis. *Journal of Cleaner Production 292*, 125988.

Fleschutz, M., M. Bohlayer, M. Braun, G. Henze, and M. D. Murphy (2021). The effect of price-based demand response on carbon emissions in european electricity markets: The importance of adequate carbon prices. *Applied Energy 295*, 117040.

Flori, A., F. Pammolli, and A. Spelta (2021). Commodity prices co-movements and financial stability: A multidimensional visibility nexus with climate conditions. *Journal of Financial Stability 54*, 100876.

Ghosh, B., L. Pham, T. Teplova, and Z. Umar (2023). Covid-19 and the quantile connectedness between energy and metal markets. *Energy Economics 117*, 106420.

Gong, X., R. Shi, J. Xu, and B. Lin (2021). Analyzing spillover effects between carbon and fossil energy markets from a time-varying perspective. *Applied Energy 285*, 116384.

Green, R., K. Larsson, V. Lunina, and B. Nilsson (2018). Cross-commodity news transmission and volatility spillovers in the german energy markets. *Journal of Banking & Finance 95*, 231–243.

Guan, D., D. Wang, S. Hallegatte, S. J. Davis, J. Huo, S. Li, Y. Bai, T. Lei, Q. Xue, D. Coffman, et al. (2020). Global supply-chain effects of covid-19 control measures. *Nature Human Behaviour 4*(6), 577–587.

Hallegatte, S. (2019). Disasters' impacts on supply chains. *Nature Sustainability 2*(9), 791–792.

Hartvig, Á. D., Á. Pap, and P. Pálos (2023). Eu climate change news index: forecasting eu ets prices with online news. *Finance Research Letters 54*, 103720.

Hoque, M. E., L. Soo-Wah, and M. Billah (2023). Time-frequency connectedness and spillover among carbon, climate, and energy futures: Determinants and portfolio risk management implications. *Energy Economics 127*, 107034.

Huang, J., B. Chen, Y. Xu, and X. Xia (2023). Time-frequency volatility transmission among energy commodities and financial markets during the covid-19 pandemic: A novel tvp-var frequency connectedness approach. *Finance Research Letters*, 103634.

Iqbal, N., E. Bouri, O. Grebinevych, and D. Roubaud (2022). Modelling extreme risk spillovers in the commodity markets around crisis periods including covid19. *Annals of Operations Research*, 1–30.

Ivanovski, K., A. Hailemariam, and R. Smyth (2021). The effect of renewable and non-renewable energy consumption on economic growth: Non-parametric evidence. *Journal of Cleaner Production 286*, 124956.

Jarque, C. M. and A. K. Bera (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters 6*(3), 255–259.

Jebabli, I., N. Kouaissah, and M. Arouri (2022). Volatility spillovers between stock and energy markets during crises: A comparative assessment between the 2008 global financial crisis and the covid-19 pandemic crisis. *Finance Research Letters 46*, 102363.

Ji, Q. and Y. Fan (2012). How does oil price volatility affect non-energy commodity markets? *Applied Energy 89*(1), 273–280.

Ji, Q., T. Xia, F. Liu, and J.-H. Xu (2019). The information spillover between carbon price and power sector returns: Evidence from the major European electricity companies. *Journal of Cleaner Production 208*, 1178–1187.

Ji, Q., D. Zhang, and J.-b. Geng (2018). Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production 198*, 972–978.

Jiang, W. and Y. Chen (2022). Time-frequency connectedness among commodities in pre-and post-russia-ukraine war periods. *Available at SSRN 4143276*.

Jin, Y., H. Zhao, L. Bu, and D. Zhang (2023). Geopolitical risk, climate risk and energy markets: A dynamic spillover analysis. *International Review of Financial Analysis 87*, 102597.

Johnson, N., V. Krey, D. L. McCollum, S. Rao, K. Riahi, and J. Rogelj (2015). Stranded on a low-carbon planet: Implications of climate policy for the phase-out of coal-based power plants. *Technological Forecasting and Social Change 90*, 89–102.

Kang, S. H., R. McIver, and S.-M. Yoon (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics 62*, 19–32.

Kayani, U., A. Hasnaoui, M. Khan, N. Zahoor, and F. Nawaz (2024). Analyzing fossil fuel commodities' return spillovers during the russia and ukraine crisis in the energy market. *Energy Economics 135*, 107651.

Keppler, J. H. and M. Mansanet-Bataller (2010). Causalities between CO2, electricity, and other energy variables during Phase I and Phase II of the EU ETS. *Energy Policy 38*(7), 3329–3341.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics 74*(1), 119–147.

Křehlík, T. and J. Baruník (2017). Cyclical properties of supply-side and demand-side shocks in oil-based commodity markets. *Energy Economics 65*, 208–218.

Kristoufek, L. and M. Vosvrda (2013). Measuring capital market efficiency: Global and local correlations structure. *Physica A: statistical mechanics and its applications 392*(1), 184–193.

Kristoufek, L. and M. Vosvrda (2014). Commodity futures and market efficiency. *Energy Economics 42*, 50–57.

Li, J. and W. Cheng (2020). Comparison of life-cycle energy consumption, carbon emissions and economic costs of coal to ethanol and bioethanol. *Applied Energy 277*, 115574.

Lillo, F. and R. N. Mantegna (2003). Power-law relaxation in a complex system: Omori law after a financial market crash. *Physical Review E 68*(1), 016119.

Lin, B. and Z. Jia (2019). Impacts of carbon price level in carbon emission trading market. *Applied energy 239*, 157–170.

Lin, B. and J. Li (2015). The spillover effects across natural gas and oil markets: Based on the vec–mgarch framework. *Applied Energy 155*, 229–241.

Lin, Y. R., Y. Wang, et al. (2024). The impact of russia–ukraine war on volatility spillovers. *International Review of Financial Analysis*, 103194.

Lin, Z.-L., W.-P. Ouyang, and Q.-R. Yu (2024). Risk spillover effects of the israel-hamas war on global financial and commodity markets: A time-frequency and network analysis. *Finance Research Letters*, 105618.

Liu, D., H. Lyu, J. Wang, C. Cui, and J. Sun (2022). Comparison of coal-to-ethanol product separation strategies. *Separation and Purification Technology 301*, 121968.

Ljung, G. M. and G. E. Box (1978). On a measure of lack of fit in time series models. *Biometrika 65*(2), 297–303.

Lovcha, Y., A. Perez-Laborda, and I. Sikora (2022). The determinants of CO2 prices in the EU emission trading system. *Applied Energy 305*, 117903.

Lu, X., N. Huang, and J. Mo (2024). Time-varying causalities from the covid-19 media coverage to the dynamic spillovers among the cryptocurrency, the clean energy, and the crude oil. *Energy Economics 132*, 107442.

Lutz, B. J., U. Pigorsch, and W. Rotfuß (2013). Nonlinearity in cap-and-trade systems: The eua price and its fundamentals. *Energy Economics 40*, 222–232.

Mansanet-Bataller, M., J. Chevallier, M. Hervé-Mignucci, and E. Alberola (2011). Eua and scer phase ii price drivers: Unveiling the reasons for the existence of the eua–scer spread. *Energy Policy 39*(3), 1056–1069.

Mayer, J., G. Bachner, and K. W. Steininger (2019). Macroeconomic implications of switching to process-emission-free iron and steel production in Europe. *Journal of Cleaner Production 210*, 1517–1533.

Medina, J. and J. A. Vega-Cervera (2001). Energy and the non-energy inputs substitution: evidence for Italy, Portugal and Spain. *Applied Energy 68*(2), 203–214.

Naeem, M. A., O. B. Adekoya, and J. A. Oliyide (2021). Asymmetric spillovers between green bonds and commodities. *Journal of Cleaner Production 314*, 128100.

Narayan, P. K., S. Narayan, and S. S. Sharma (2013). An analysis of commodity markets: what gain for investors? *Journal of Banking & Finance 37*(10), 3878–3889.

Nasreen, S., A. K. Tiwari, J. C. Eizaguirre, and M. E. Wohar (2020). Dynamic connectedness between oil prices and stock returns of clean energy and technology companies. *Journal of Cleaner Production 260*, 121015.

Ortas, E. and I. Álvarez (2016). The efficacy of the european union emissions trading scheme: Depicting the co-movement of carbon assets and energy commodities through wavelet decomposition. *Journal of Cleaner Production 116*, 40–49.

Ortiz-Cruz, A., E. Rodriguez, C. Ibarra-Valdez, and J. Alvarez-Ramirez (2012). Efficiency of crude oil markets: Evidences from informational entropy analysis. *Energy Policy 41*, 365–373.

Pesaran, H. H. and Y. Shin (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters 58*(1), 17–29.

Phillips, P. C. and P. Perron (1988). Testing for a unit root in time series regression. *biometrika 75*(2), 335–346.

Polat, O., H. M. Ertuğrul, B. Sakarya, and A. Akgül (2024). Tvp-var based time and frequency domain food & energy commodities connectedness an analysis for financial/geopolitical turmoil episodes. *Applied Energy 357*, 122487.

Reboredo, J. C., M. A. Rivera-Castro, and A. Ugolini (2017). Wavelet-based test of comovement and causality between oil and renewable energy stock prices. *Energy Economics 61*, 241–252.

Rehman, M. U. and X. V. Vo (2021). Energy commodities, precious metals and industrial metal markets: A nexus across different investment horizons and market conditions. *Resources Policy 70*, 101843.

Ren, X., Y. Xiao, K. Duan, and A. Urquhart (2024). Spillover effects between fossil energy and green markets: Evidence from informational inefficiency. *Energy Economics 131*, 107317.

Rizvi, S. K. A., B. Naqvi, N. Mirza, and M. Umar (2022). Safe haven properties of green, islamic, and crypto assets and investor's proclivity towards treasury and gold. *Energy Economics 115*, 106396.

Roy, A., A. Soni, and S. Deb (2023). A wavelet-based methodology to compare the impact of pandemic versus russia–ukraine conflict on crude oil sector and its interconnectedness with other energy and non-energy markets. *Energy Economics 124*, 106830.

Saeed, T., E. Bouri, and H. Alsulami (2021). Extreme return connectedness and its determinants between clean/green and dirty energy investments. *Energy Economics 96*, 105017.

Scheffer, M., J. Bascompte, W. A. Brock, V. Brovkin, S. R. Carpenter, V. Dakos, H. Held, E. H. Van Nes, M. Rietkerk, and G. Sugihara (2009). Early-warning signals for critical transitions. *Nature 461*(7260), 53–59.

Shahbaz, M., M. Zakaria, S. J. H. Shahzad, and M. K. Mahalik (2018). The energy consumption and economic growth nexus in top ten energy-consuming countries: Fresh evidence from using the quantile-on-quantile approach. *Energy Economics 71*, 282–301.

Shahzad, S. J. H., M. A. Naeem, Z. Peng, and E. Bouri (2021). Asymmetric volatility spillover among chinese sectors during covid-19. *International Review of Financial Analysis 75*, 101754.

Shapiro, S. S. and M. B. Wilk (1965). An analysis of variance test for normality (complete samples). *Biometrika 52*(3/4), 591–611.

Si, D.-K., X.-L. Li, X. Xu, and Y. Fang (2021). The risk spillover effect of the covid-19 pandemic on energy sector: Evidence from china. *Energy economics 102*, 105498.

Sornette, D. (2009). *Why stock markets crash: critical events in complex financial systems.* Princeton university press.

Spelta, A., A. Flori, N. Pecora, S. Buldyrev, and F. Pammolli (2020). A behavioral approach to instability pathways in financial markets. *Nature communications 11*(1), 1707.

Spelta, A., A. Flori, N. Pecora, and F. Pammolli (2021). Financial crises: Uncovering self-organized patterns and predicting stock markets instability. *Journal of Business Research 129*, 736–756.

Spelta, A., N. Pecora, A. Flori, and P. Giudici (2023). The impact of the sars-cov-2 pandemic on financial markets: a seismologic approach. *Annals of Operations Research 330*(1), 639–664.

Stern, D. I. and A. Kander (2012). The role of energy in the industrial revolution and modern economic growth. *The Energy Journal 33*(3).

Tan, X., K. Sirichand, A. Vivian, and X. Wang (2020). How connected is the carbon market to energy and financial markets? a systematic analysis of spillovers and dynamics. *Energy Economics 90*, 104870.

Thangavelu, S. R., A. M. Khambadkone, and I. A. Karimi (2015). Long-term optimal energy mix planning towards high energy security and low ghg emission. *Applied energy 154*, 959–969.

Tiwari, A. K., E. J. A. Abakah, A. O. Adewuyi, and C.-C. Lee (2022). Quantile risk spillovers between energy and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Energy Economics 113*, 106235.

Uddin, G. S., J. A. Hernandez, S. J. H. Shahzad, and A. Hedström (2018). Multivariate dependence and spillover effects across energy commodities and diversification potentials of carbon assets. *Energy Economics 71*, 35–46.

Vidal-Amaro, J. J., P. A. Østergaard, and C. Sheinbaum-Pardo (2015). Optimal energy mix for transitioning from fossil fuels to renewable energy sources–the case of the mexican electricity system. *Applied Energy 150*, 80–96.

Wang, K.-H., Z.-S. Wang, M. Yunis, and B. Kchouri (2023). Spillovers and connectedness among climate policy uncertainty, energy, green bond and carbon markets: A global perspective. *Energy Economics 128*, 107170.

Wang, X. (2022). Efficient markets are more connected: An entropy-based analysis of the energy, industrial metal and financial markets. *Energy Economics 111*, 106067.

Wang, Y., E. Bouri, Z. Fareed, and Y. Dai (2022). Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. *Finance Research Letters 49*, 103066.

Wang, Y. and Z. Guo (2018). The dynamic spillover between carbon and energy markets: New evidence. *Energy 149*, 24–33.

Wen, F., J. Cao, Z. Liu, and X. Wang (2021). Dynamic volatility spillovers and investment strategies between the chinese stock market and commodity markets. *International Review of Financial Analysis 76*, 101772.

Wierzbowski, M., W. Lyzwa, and I. Musial (2016). Milp model for long-term energy mix planning with consideration of power system reserves. *Applied Energy 169*, 93–111.

Wu, Q., M. Wang, and L. Tian (2020). The market-linkage of the volatility spillover between traditional energy price and carbon price on the realization of carbon value of emission reduction behavior. *Journal of Cleaner Production 245*, 118682.

Xia, T., Q. Ji, D. Zhang, and J. Han (2019). Asymmetric and extreme influence of energy price changes on renewable energy stock performance. *Journal of Cleaner Production 241*, 118338.

Yarovaya, L., A. H. Elsayed, and S. Hammoudeh (2021). Determinants of spillovers between islamic and conventional financial markets: exploring the safe haven assets during the covid-19 pandemic. *Finance Research Letters 43*, 101979.

Yousaf, I., R. Nekhili, and M. Umar (2022). Extreme connectedness between renewable energy tokens and fossil fuel markets. *Energy Economics 114*, 106305.

Yuan, N. and L. Yang (2020). Asymmetric risk spillover between financial market uncertainty and the carbon market: A gas–dcs–copula approach. *Journal of Cleaner Production 259*, 120750.

Zeng, S., J. Jia, B. Su, C. Jiang, and G. Zeng (2021). The volatility spillover effect of the European Union (EU) carbon financial market. *Journal of Cleaner Production 282*, 124394.

Zhang, J., K. Hassan, Z. Wu, and D. Gasbarro (2022). Does corporate social responsibility affect risk spillovers between the carbon emissions trading market and the stock market? *Journal of Cleaner Production*, 132330.

Zhang, W., X. He, and S. Hamori (2023). The impact of the covid-19 pandemic and russia-ukraine war on multiscale spillovers in green finance markets: Evidence from lower and higher order moments. *International Review of Financial Analysis 89*, 102735.

Zhang, Y.-J. and Y.-F. Sun (2016). The dynamic volatility spillover between european carbon trading market and fossil energy market. *Journal of Cleaner Production 112*, 2654–2663.

Zhao, Z.-Y., Y.-X. Hao, R.-D. Chang, and Q.-C. Wang (2023). Assessing the vulnerability of energy supply chains: Influencing factors and countermeasures. *Sustainable Energy Technologies and Assessments 56*, 103018.

Zheng, J., B. Wen, Y. Jiang, X. Wang, and Y. Shen (2023). Risk spillovers across geopolitical risk and global financial markets. *Energy Economics 127*, 107051.

A Data

Table A1 lists the futures contracts we consider in our empirical analysis.

Commodity	Contract	Description
Brent Oil	LCOc1	ICE - Brent Oil TRc1
Coal	ATWMc1	ICE - Coal Rotterdam TRc1
Ethanol	NEVCS01	NYMEX - Chicago Ethanol Platts Continuous LTDT
EUA	CFI2Zc1	ICE ENDEX - European Union Allowance
Gasoline	LHUCS01	ICE - NYH Gasoline (RBOB) Continuous LTD
Heating Oil	LHOCS01	ICE - Heating Oil Continuous LTD
Natural Gas	TRNLTTFMc1	ICE - Natural Gas TRc1
Propane	A7Ec1	NYMEX - Argus Propane Far East Index TRc1

Table A1: The description of commodity variables as defined in Thomson Reuters Eikon.

B Connectedness

Figures B1 and B2 show net spillovers in the frequency domain over short- and long-term horizons.

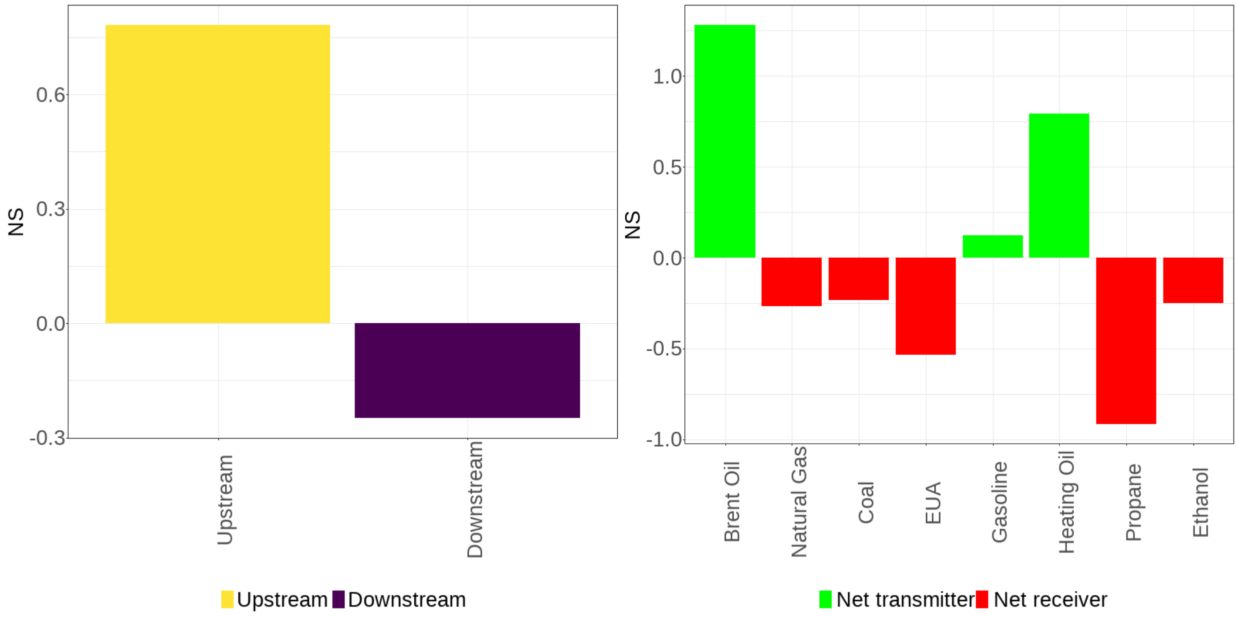

Figure B1: Net spillovers in the frequency domain (short-term). In the left bar plot, upstream commodities are colored yellow and downstream are violet. In the right bar plot, net transmitters are green and net receivers red.

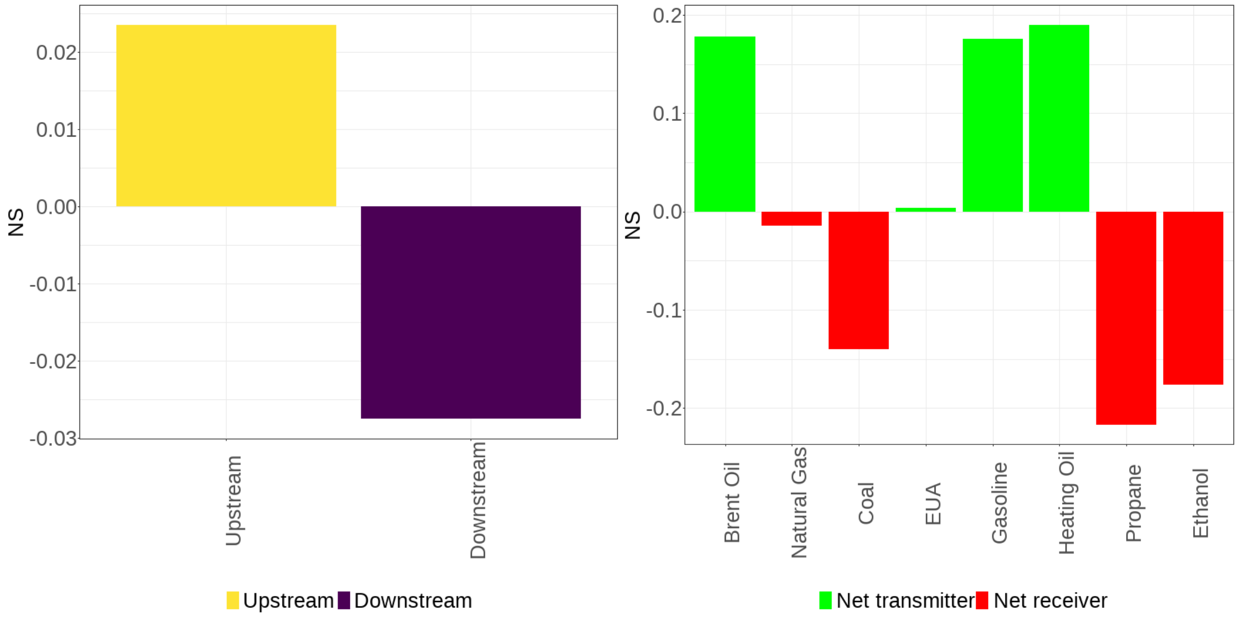

Figure B2: Net spillovers in the frequency domain (long-term). In the left bar plot, upstream commodities are colored yellow and downstream are violet. In the right bar plot, net transmitters are green and net receivers red.

C Dynamic analysis

Figures C1 and C2 highlight net connectedness in the dynamic analysis over the frequency domain for the short- and long-term scenarios. Furthermore, Table C1 describes the main crisis episodes, directly or indirectly related to the energy sector, that we consider in our analysis to justify the observed spillover across commodities in the dynamic analysis.

Date	Description
February 20, 2014	Russian occupation of Crimea began.
Between June 2014 and February 2015	A host of industry-specific, macroeconomic, and financial factors came together to cause global commodity prices to fall by 38% (e.g., in December 2014, the oil price was down 50% since April 2014). Amongst these, the transition of China's economy to more sustainable levels of growth and the shale-energy boom in the US were the dominant demand-side and supply-side factors governing the downturn in global commodity prices.
November 30, 2015-December 12, 2015	The Paris Agreement took place.
February 2016	The State Council issued a policy stating China would cut up to 1,000 million tons of coal production capacity in the following 3–5 years starting from 2016.
June 23, 2016	The Brexit referendum took place.
July 6, 2018	The Sino-American trade war broke out, but tensions have been running high since January 22, 2018.
End of 2018	American crude output was growing more quickly than expected and caused a crude oil glut, demand forecasts softened, and geopolitics roiled the energy complex.
October 25, 2019	The World Bank reported a negative energy and metal commodity prices outlook due to weak global growth.
March 11, 2020	WHO declared the novel coronavirus (COVID-19) outbreak a global pandemic.
April 20, 2020	The COVID-19 pandemic reduced demand along with storage issues. WTI's May contract closed at -$37/barrel while Brent closed at $26/barrel.
December 21, 2020	The EC authorized the first vaccine against COVID-19, mRNA BNT162b2 (Comirnaty), produced by Pfizer and Biontech.
November 1, 2021	China announced a boost in coal production.
February 24, 2022	Natural gas prices have been substantially increasing worldwide after the invasion of Ukraine as Russia has economically weaponized its exportations of natural gas via pipelines, which Europe is very dependent on. This has made coal more competitive in many markets, and some nations have resorted to coal as a substitute.
July 11, 2022	Nord Stream I was turned off supposedly for maintenance reasons.
August 26, 2022	Natural gas prices hit a record of 316 euros per MWh, more than ten times as much as the price a year before, following the decision by Gazprom to temporarily close the Nord Stream pipeline.
October 1, 2022	OPEC+ cut oil production by two million barrels per day.
December 3, 2022	The EU agreed to cap the price of natural gas to reduce the volatility created by Russia in the gas market.
October 7, 2023	The Israeli-Palestinian conflict began.

Table C1: Events directly or indirectly related to the energy sector (2014-2023).

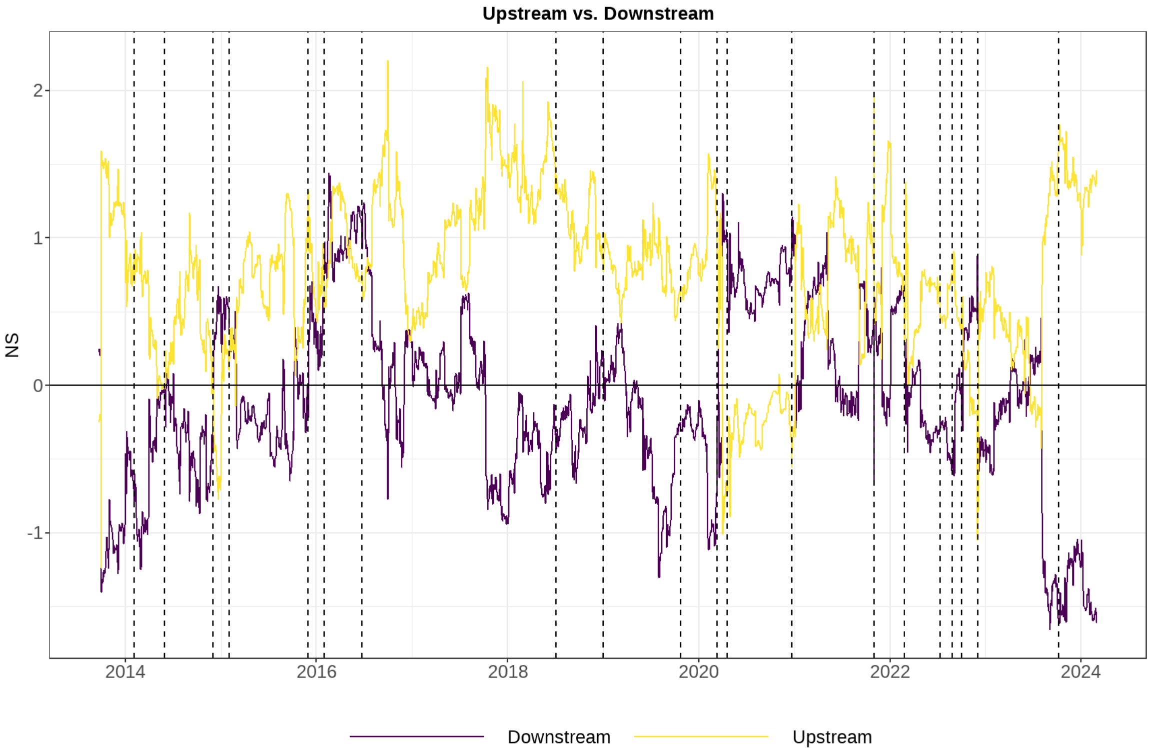

Figure C1: Net connectedness in the frequency domain, short-term (upstream vs. downstream). The results are based on a VAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 100-step-ahead generalized forecast error variance decomposition.

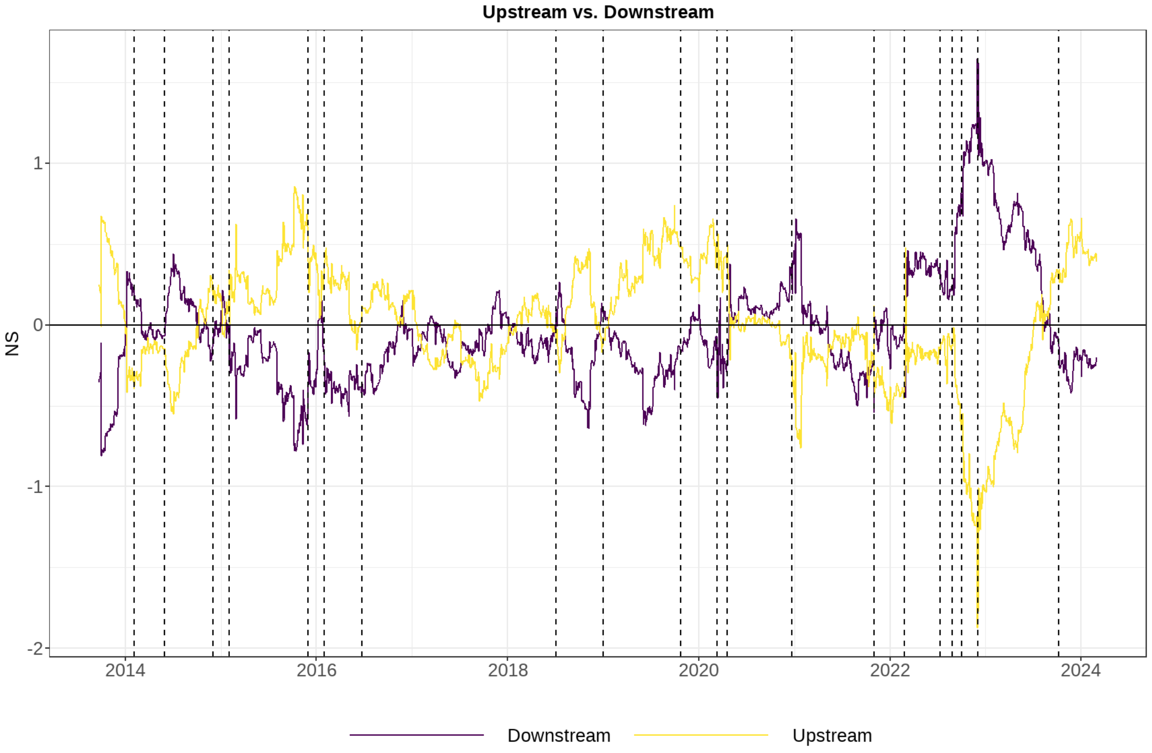

Figure C2: Net connectedness in the frequency domain, long-term (upstream vs. downstream). The results are based on a VAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 10-step-ahead generalized forecast error variance decomposition.

D Quantile Connectedness

Figure D1 highlights the net quantile connectedness for each commodity. Figure D2 shows the total quantile connectedness of the system as explained in section 3.3.

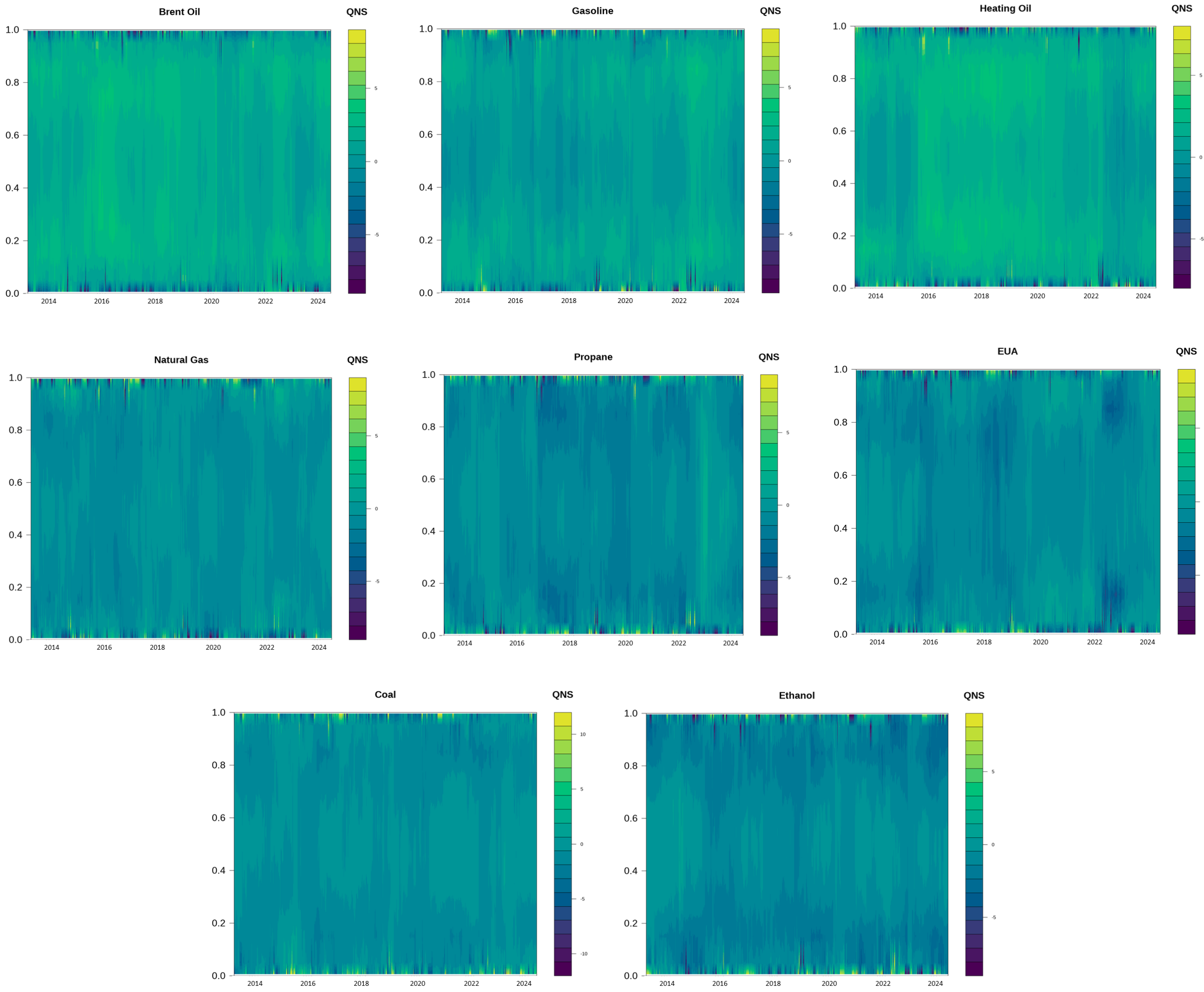

Figure D1: Commodities' quantile net spillovers (QNS). The results are based on a QVAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 100-step-ahead generalized forecast error variance decomposition. We represent quantiles along the y-axis, whereas the color represents the magnitude of commodities' QNS.

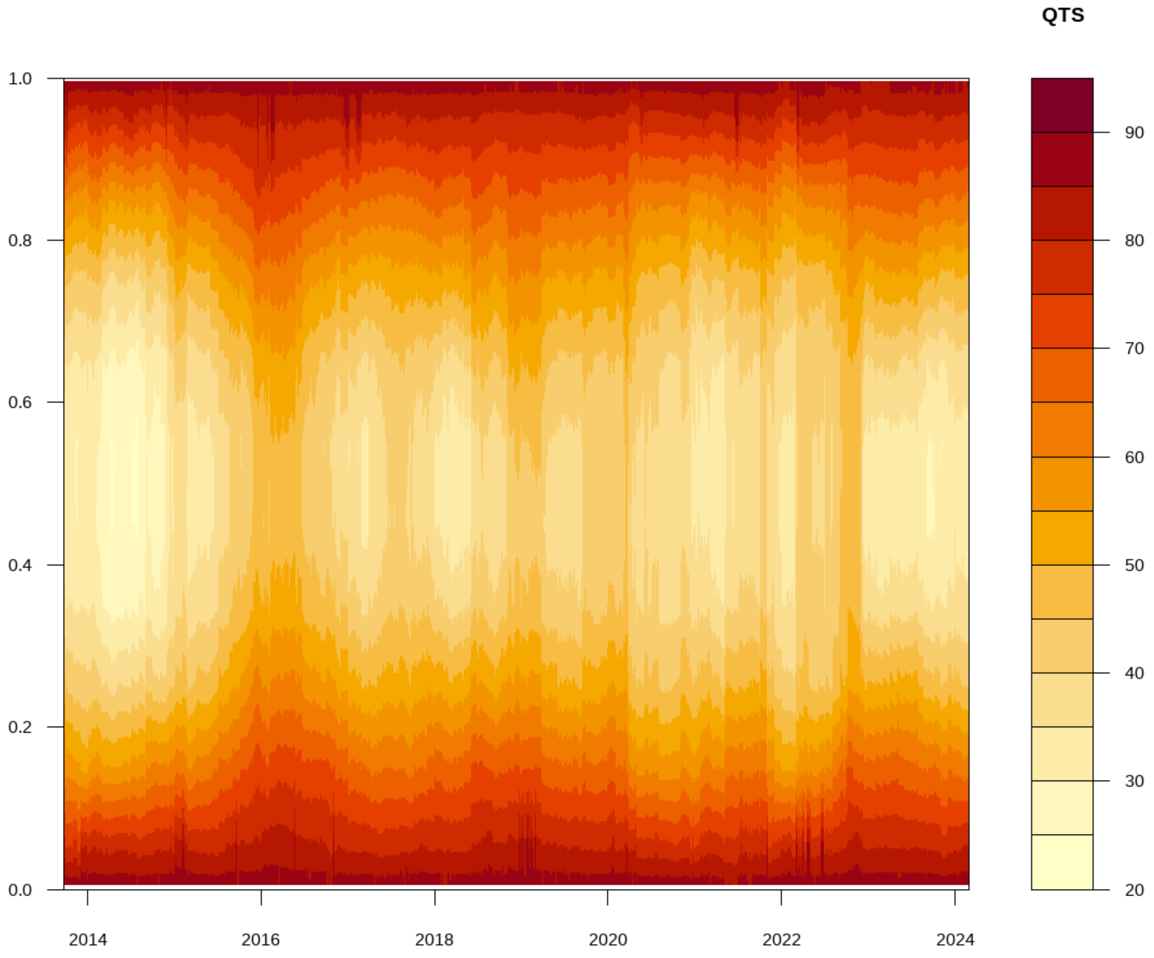

Figure D2: Total quantile connectedness. The results are based on a QVAR model with a 200-day rolling window size, a lag length of order one (SIC), and a 100-step-ahead generalized forecast error variance decomposition. We represent the quantiles along the y-axis, whereas the color represents the magnitude of the system's quantile total spillovers (QTS).

D.1 Quantile frequency connectedness

Figures D3 and D4 report the short- and long-term net quantile connectedness for upstream and downstream commodities, also pointing out their mean across quantiles and relative tail dependence.

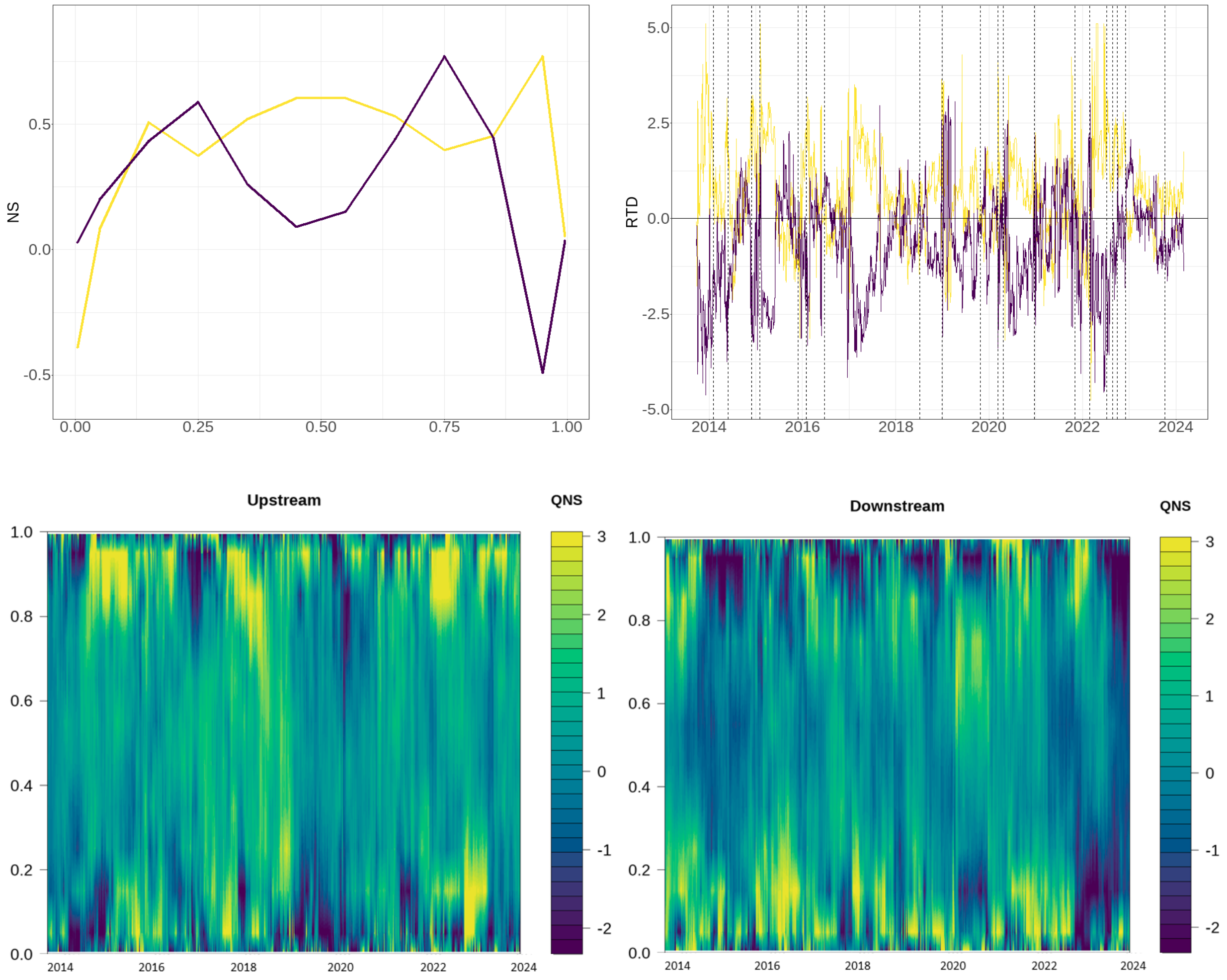

Figure D3: Quantile net spillovers (QNS) in the short-term. Upstream vs. downstream. The upper-left figure presents the mean of net spillovers (NS) of upstream (in yellow) and downstream (in violet) commodities across quantiles. The upper-right plot shows the relative tail dependence (RTD) of upstream and downstream commodities, namely the difference between their NS at the 95^{th} and 5^{th} quantiles, computed on the dynamic quantile connectedness with a rolling window of 200 days ($w = 200$). The lower-left and lower-right plots display the QNS of upstream and downstream commodities across quantiles (y-axis), respectively. The color represents the magnitude of commodities' QNS.

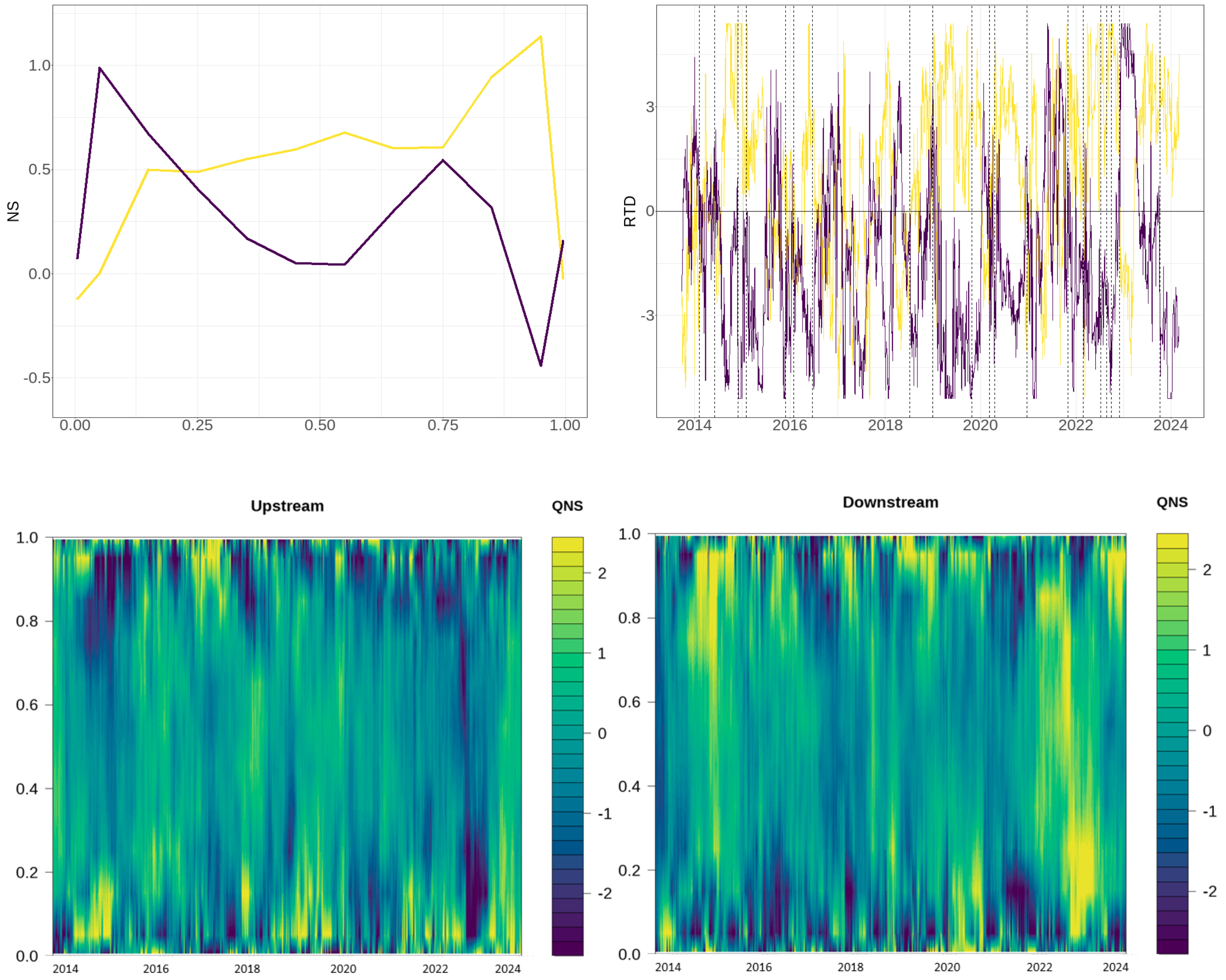

Figure D4: Quantile net spillovers (QNS) in the long-term. Upstream vs. downstream. The upper-left figure presents the mean of net spillovers (NS) of upstream (in yellow) and downstream (in violet) commodities across quantiles. The upper-right plot shows the relative tail dependence (RTD) of upstream and downstream commodities, namely the difference between their NS at the 95^{th} and 5^{th} quantiles, computed on the dynamic quantile connectedness with a rolling window of 200 days ($w = 200$). The lower-left and lower-right plots display the QNS of upstream and downstream commodities across quantiles (y-axis), respectively. The color represents the magnitude of commodities' QNS.

E Frequency analysis

The right panel of Figures E1, E2, and E3 shows commodities' maximum net connectedness. On the left panel, we plot maximum net connectedness along a number of frequency bands against net connectedness associated with two precise frequencies (0-3 days and 0-5 days).

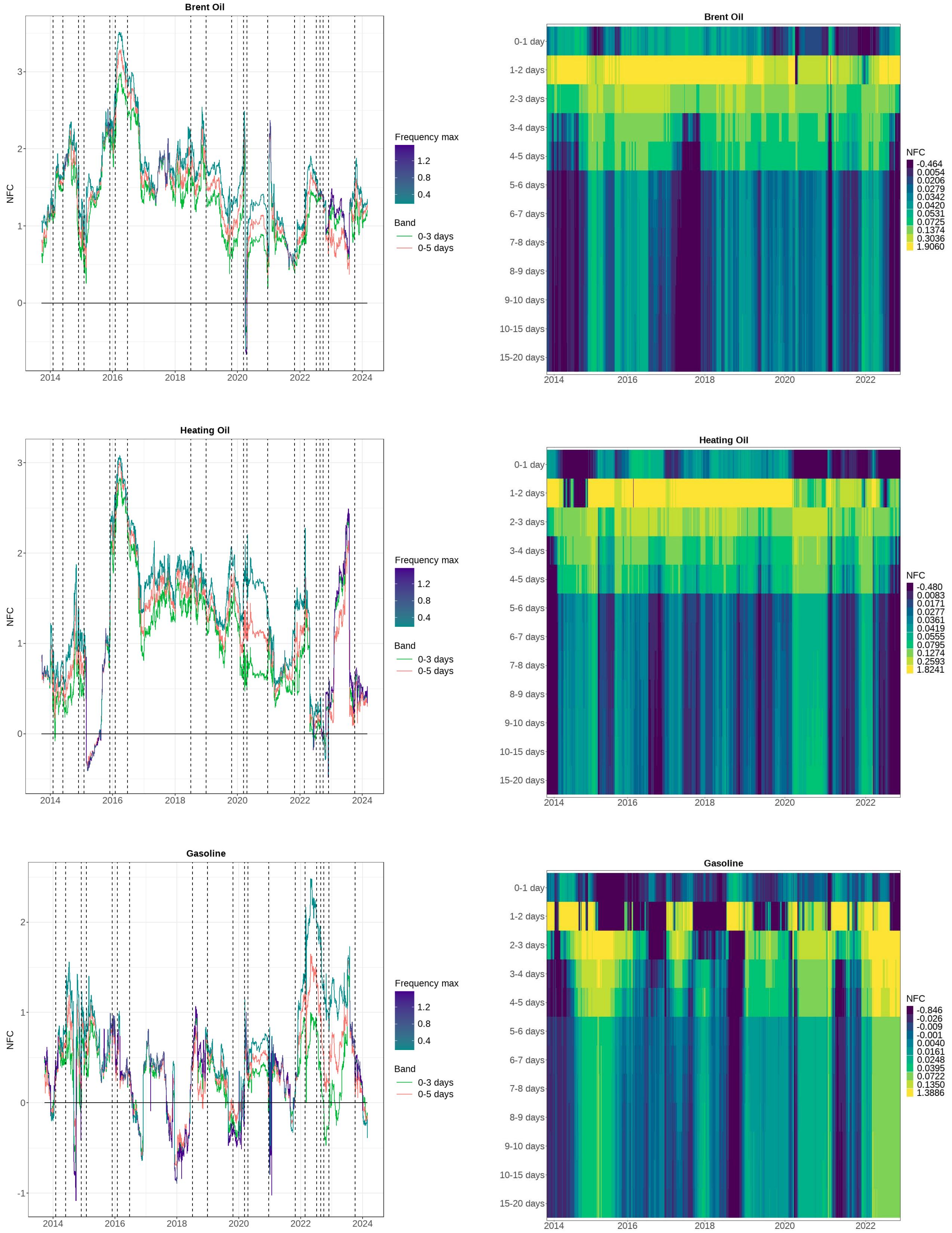

Figure E1: Maximum net connectedness of Brent oil, heating oil, and gasoline. On the left, we plot maximum net connectedness along several frequency bands against net connectedness associated with two precise frequencies (0-3 days and 0-5 days). On the right, the y-axis represents the chosen frequency sub-bands. On the z-axis, we display the inter-day net spillovers.

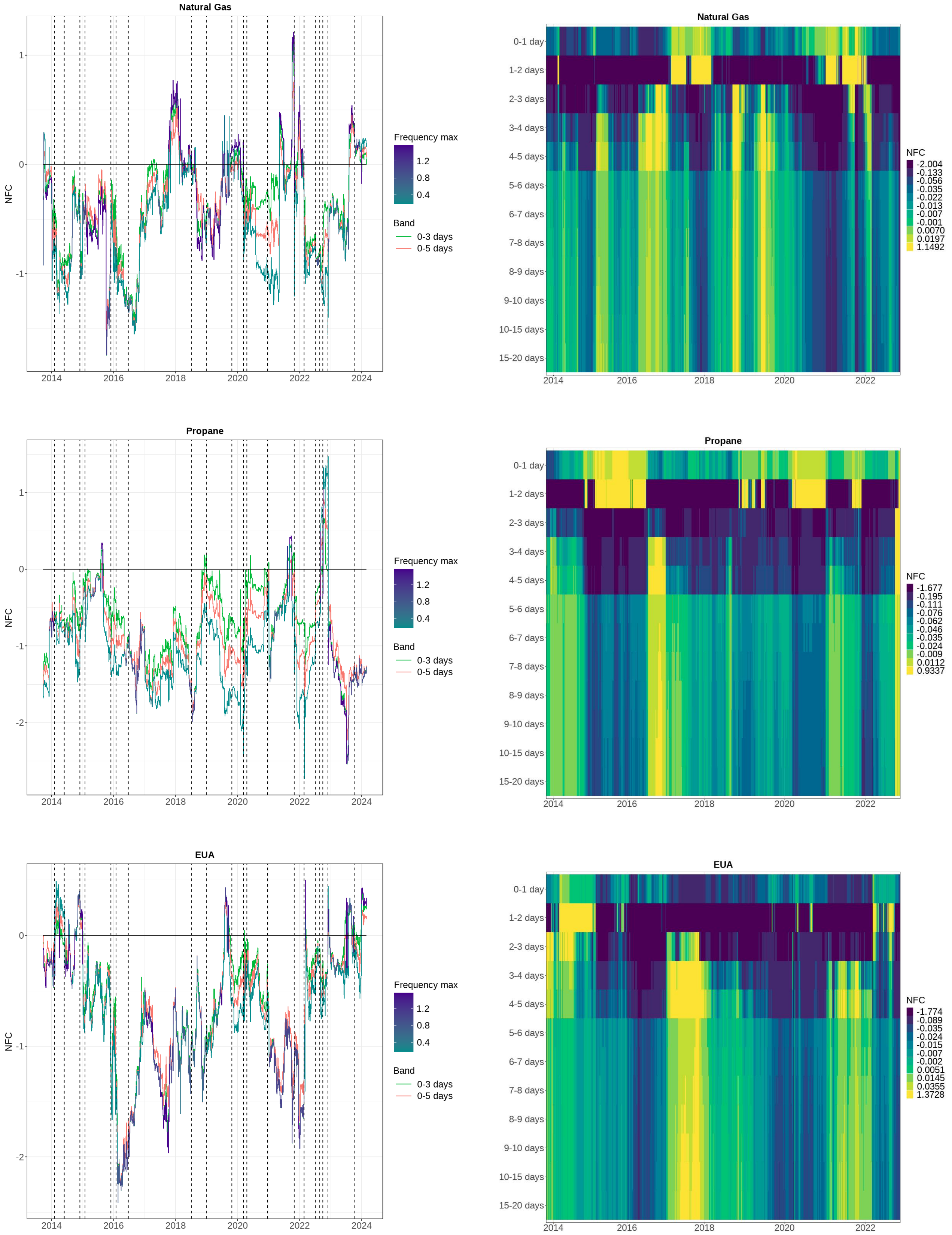

Figure E2: Maximum net connectedness of natural gas, propane, and EUA. On the left, we plot maximum net connectedness along several frequency bands against net connectedness associated with two precise frequencies (0-3 days and 0-5 days). On the right, the y-axis represents the chosen frequency bands. On the z-axis, we display the inter-day net spillovers.

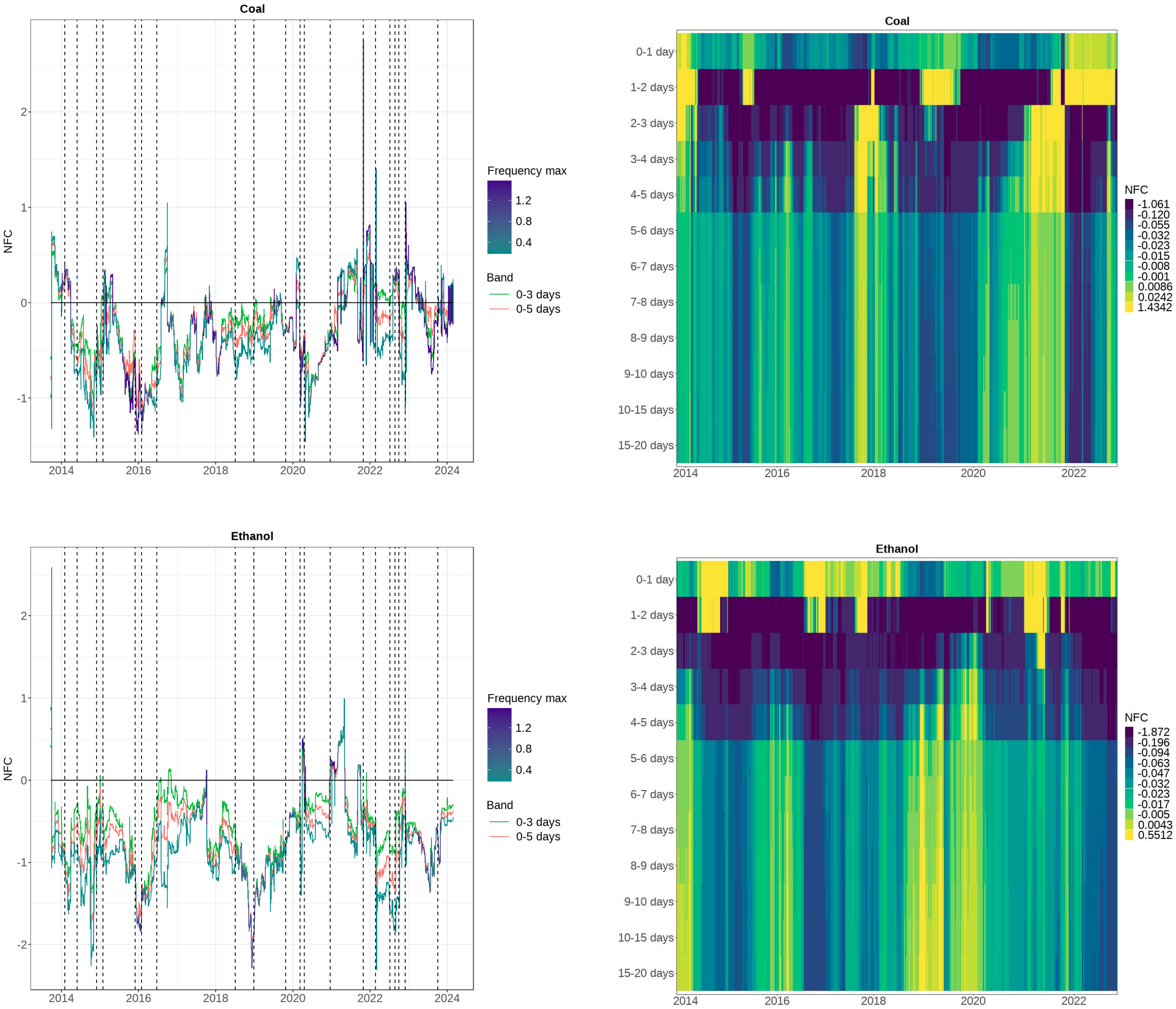

Figure E3: Maximum net connectedness of coal and ethanol. On the left, we plot maximum net connectedness along several frequency bands against net connectedness associated with two precise frequencies (0-3 days and 0-5 days). On the right, the y-axis represents the chosen frequency bands. On the z-axis, we display the inter-day net spillovers.