



# Contemporaneous and lagged $R^2$ decomposed connectedness approach: New evidence from the energy futures market

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## ABSTRACT

In this study, we investigate the return propagation mechanism across six energy futures, namely, Crude Oil, Heating Oil, Gasoline, Natural Gas, Kerosene, and Propane ranging from November 21st, 2014 until April 6th, 2023 by using a novel  $R^2$  decomposed connectedness approach. This framework allows to efficiently decompose connectedness measures into contemporaneous and lagged components. We find that the dynamic total connectedness is heterogeneous over time and economic-event dependent. Furthermore, the empirical results highlight that the contemporaneous effects are more pronounced on average while a significant amount of lagged spillovers occur in the case of Kerosene and Propane. We find that Heating Oil is the main net transmitter of shocks followed by Gasoline and Crude Oil while the main net receiver of shocks is Kerosene followed by Propane and Natural Gas. Finally, robust  $R^2$  connectedness measures are provided.

## 1. Introduction

Over the past couple of decades, global energy trading volumes and energy demand have witnessed significant increases, leading to higher fluctuation within the global energy market (He et al., 2018). Energy futures prices have experienced substantial fluctuations and usually witness jumps after important breakdowns in the markets (Liu and Tu, 2012). Previous studies suggest a substantial increase in commodities' prices might lead to amplified speculation within the futures markets (Fan and Xu, 2011; Chevillon and Riffart, 2009; Beckmann et al., 2014). Wu et al. (2011) argue that volatility transmission across various futures markets might reveal a view of price volatility spillovers amongst commodities. Since information from futures contract prices propagates to all economic agents (i.e., both producers and physical traders), futures markets are assumed to dominate spot markets (Nicolau and Palomba, 2015). Bouri et al. (2021) find that more complex interdependence among commodity futures leads to instability in the market and causes higher difficulties in portfolio management. Hence, investigating the propagation mechanism in the energy futures market is of crucial relevance for policymakers, investors, and traders. Among the many, Diebold et al. (2017) (VAR connectedness), Chatziantoniou et al. (2022c) (TVP-VAR connectedness), Jena et al. (2022) (quantile connectedness), Chatziantoniou et al. (2022a) (quantile-frequency connectedness), and Antonakakis et al. (2023) (DCC-GARCH connectedness) used different connectedness frameworks to adequately examine the energy market transmission mechanism. Nevertheless, none of the papers investigated the difference between contemporaneous and lagged connectedness effects. Thus, to the best of our knowledge, we are

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the first to investigate the contemporaneous and lagged interdependencies across energy futures by means of a novel  $R^2$  decomposed connectedness approach to get more in-depth insights concerning the transmission mechanism.

Since the introduction of the connectedness approach (Diebold and Yilmaz, 2009, 2012, 2014), researchers predominantly focused on investigating the transmission mechanism using different kinds of VAR models (see, Demiret et al., 2018; Antonakakis et al., 2020; Gabauer et al., 2020; Chatziantoniou et al., 2022b). However, increased interest is paid to the investigation of contemporaneous spillovers only. Recently, Baur and Hoang (2020) differentiate between contemporaneous and lagged spillover effects by proposing a two-step procedure, including estimating the contemporaneous contribution of the dynamic total connectedness in the first step and the lagged contribution of the dynamic total connectedness in the second step. The drawback of this approach is that only the FROM total directional connectedness measures can be computed. Recently, Zhang et al. (2023) proposed the  $R^2$  decomposed connectedness approach to solve those shortcomings. Even though this framework solves the drawback of Baur and Hoang (2020), it might suffer from some issues, including computational problems and the biased computation of  $R^2$  contributions. Hence, in this paper, we propose a novel approach that solves the aforementioned issues.

The contribution of our study is threefold. *First*, we propose a novel  $R^2$  decomposed connectedness approach that distinguishes between the contemporaneous and lagged spillovers, which might effectively compensate for the deficiency of existing studies only focusing on contemporaneous spillover effects. This method provides unbiased estimation results and is computationally more efficient than the approach of Zhang et al. (2023). Specifically, our proposed  $R^2$  decomposed connectedness approach rests on the theoretical framework of Gabauer et al. (2023) which combines the generalized forecast error variance decomposition (GFEVD) with the  $R^2$  goodness-of-fit measure as well as on the  $R^2$  decomposition concept of Genizi (1993). Consequently, our proposed framework can be seen as a generalization of the contemporaneous  $R^2$  decomposed connectedness approach of Naeem et al. (2023). *Second*, we propose two robust  $R^2$  decomposed connectedness approaches that are less sensitive to outliers. *Third*, to the best of our knowledge, our study is the first to investigate both contemporaneous and lagged spillover effects within the energy futures market. Given that return and volatility transmission across commodity futures becomes amplified during crises (Kang et al., 2017), our study might help investors identify which spillovers (i.e., contemporaneous and lagged spillovers) play a dominant role when there are big jumps or during extreme conditions so that they could optimize their risk management and investment portfolios.

Our findings illustrate that the dynamic total connectedness is heterogeneous over time and economic-event dependent. Furthermore, the findings indicate that contemporaneous spillovers are substantially larger compared to their lagged counterparts. In addition, among energy futures, Heating Oil is considered as the main net transmitter of shocks followed by Gasoline and Crude Oil while the main net receiver of shocks is Kerosene followed by Propane and Natural Gas.

The rest of the paper is organized as follows. Section 2 introduces our proposed methodology while Section 3 describes the employed dataset. In Section 4, the empirical results are presented and discussed. Finally, Section 5 concludes the study.

## 2. Methodology

We start with the  $R^2$  decomposed connectedness approach by outlining a VAR(p) with contemporaneous effects:

$$y_t = \sum_{i=0}^p B_i y_{t-i} + u_t \quad u_t \sim N(0, \Sigma) \tag{1}$$

where  $y_t$ ,  $y_{t-i}$ , and  $u_t$  are  $K \times 1$  dimensional demeaned vectors in time  $t$ , and  $B_i$  as well as  $\Sigma$  are  $K \times K$  dimensional matrices where  $diag(B_0) = 0$  – thus the left-hand side (LHS) variable is dropped from the right-hand side (RHS) variables. It should be noted that if  $p = 0$ , the model collapses to the contemporaneous  $R^2$  decomposed connectedness approach of Naeem et al. (2023). Alternatively, the outlined model can be formulated as:  $y_{k,t} = b_k x_t + u_{k,t}$  where  $x_t = [y_t, y_{t-1}, \dots, y_{t-i}, \dots, y_{t-p}]$  is an  $K(p+1) \times 1$  dimensional vector and  $b_k$  is an  $1 \times K(p+1)$  dimensional vector with zero on the  $k$ th position.

In general, the sum of the  $R^2$  contributions – using bivariate linear regressions (BLRs) – is only equal to the  $R^2$  goodness-of-fit measure of a multivariate linear regression (MLR) if all RHS variables are uncorrelated with each other. Therefore, we need to find a mapping that transforms the correlated series  $x_{k,t}$ <sup>1</sup> into orthogonal series. This can be done by using principal component analysis (PCA) where the number of latent factors is equal to the number of RHS variables. Thus, the  $R^2$  decomposition for an MLR can be computed by:

$$R_{xx} = VAV' = CC' \tag{2}$$

$$C = V\Lambda^{1/2}V' \tag{3}$$

$$R^{2,d} = C^2(C^{-1}R_{yx})^2 \tag{4}$$

where  $V$ ,  $\Lambda = diag(\lambda_1, \dots, \lambda_{K(p+1)-1})$ , and  $R_{xx}$  represent  $[K(p+1)-1] \times [K(p+1)-1]$  eigenvector, eigenvalue, and Pearson correlation matrices, respectively, while  $R_{yx}$  and  $R^{2,d}$  illustrate  $[K(p+1)-1] \times 1$  Pearson correlation and  $R^2$  contribution vectors, respectively. In more detail,  $R_{xx}$  refers to Pearson correlation coefficients across RHS variables and  $R_{yx}$  to Pearson correlation coefficients between the LHS and RHS variables. The first  $K-1$  values of  $R^{2,d}$  represent the contemporaneous  $R^2$  contributions while the remaining highlight the lagged  $R^2$  contributions. Consequently, the vector sum of  $R^{2,d}$  is equal to the MLR  $R^2$  goodness-of-fit measure. Next, we stack the  $R^{2,d}$  contribution of all  $K$  MLRs to obtain the  $K \times K(p+1)$  dimensional  $R^{2,d}$  decomposition matrix,  $[R_0^{2,d}; \dots; R_i^{2,d}; \dots; R_p^{2,d}]$ .

<sup>1</sup>  $x_{k,t}$  is equivalent to  $x_t$ , but excludes the LHS variable.

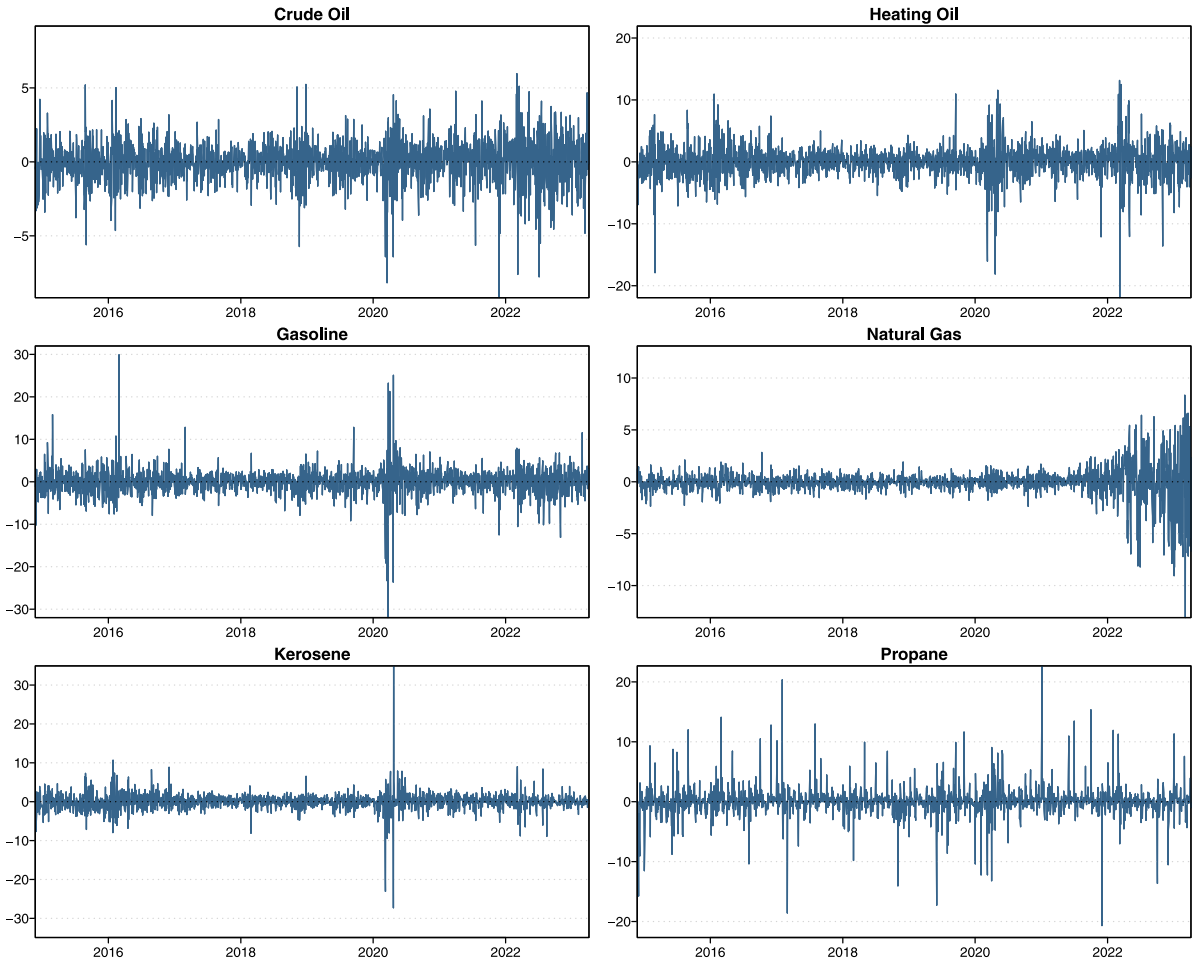


Fig. 1. Percentage changes of energy futures.

$R_0^{2,d2}$  can be interpreted as the contemporaneous spillovers ( $R_C^{2,d}$ ) while the sum of the lagged values ( $R_L^{2,d} = R_1^{2,d} + \dots + R_i^{2,d} + \dots + R_p^{2,d}$ ) stand for the lagged spillovers.

With respect to the connectedness approach of Diebold and Yilmaz (2012, 2014),  $R_C^{2,d}$  and  $R_L^{2,d}$  replace the scaled GFEVD matrix. This implies that the total connectedness index (TCI) is equal to the average  $R^2$  of the  $k$  MLRs<sup>3</sup>:

$$TCI = \frac{1}{K} \sum_{k=1}^K R_k^2 \tag{5}$$

As  $R_k^2$  is within zero and unity, TCI also lies within the same range avoiding the connectedness normalization problem (see, Lastrapes and Wiesen, 2021; Chatziantoniou and Gabauer, 2021; Gabauer, 2021). Using our proposed methodology allows us to investigate the contemporaneous and lagged TCI

$$TCI = \frac{1}{K} \sum_{k=1}^K R_k^2 \tag{6}$$

$$= \left( \frac{1}{K} \sum_{k=1}^K \sum_{j=1}^K R_{C,k,j}^{2,d} \right) + \left( \frac{1}{K} \sum_{k=1}^K \sum_{j=1}^K R_{L,k,j}^{2,d} \right) \tag{7}$$

$$= TCI^C + TCI^L \tag{8}$$

where  $TCI^C$  and  $TCI^L$  represent the contemporaneous and lagged TCI, respectively.

<sup>2</sup> It is worth mentioning that  $diag(R_0^{2,d}) = \mathbf{0}$ .

<sup>3</sup> This concept is identical to Baur and Hoang (2020).

**Table 1**  
Summary Statistics.

	Crude oil	Heating oil	Gasoline	Natural gas	Kerosene	Propane
Mean	0.007 (0.828)	0.038 (0.496)	0.062 (0.352)	-0.029 (0.329)	0.017 (0.713)	0.030 (0.569)
Variance	1.957***	6.517***	9.206***	1.804***	4.451***	5.705***
Skewness	-0.570*** (0.000)	-0.613*** (0.000)	-0.184*** (0.001)	-1.205*** (0.000)	0.493*** (0.000)	0.206*** (0.000)
Ex.Kurtosis	3.850*** (0.000)	8.290*** (0.000)	20.375*** (0.000)	14.750*** (0.000)	57.031*** (0.000)	20.288*** (0.000)
JB	1415.734*** (0.000)	6168.350*** (0.000)	36475.359*** (0.000)	19619.139*** (0.000)	285770.836*** (0.000)	36167.823*** (0.000)
ERS	-18.893*** (0.000)	-18.976*** (0.000)	-13.728*** (0.000)	-8.902*** (0.000)	-21.424*** (0.000)	-19.649*** (0.000)
Q(20)	26.492*** (0.001)	22.446*** (0.006)	16.452* (0.072)	90.692*** (0.000)	36.051*** (0.000)	41.306*** (0.000)
Q <sup>2</sup> (20)	296.830*** (0.000)	483.252*** (0.000)	478.741*** (0.000)	2475.192*** (0.000)	409.938*** (0.000)	8.571 (0.663)
Kendall rank correlation coefficients						
Crude oil	1.000***	0.474***	0.462***	0.064***	0.012	0.292***
Heating oil	0.474***	1.000***	0.570***	0.050***	0.056***	0.360***
Gasoline	0.462***	0.570***	1.000***	0.043***	0.056***	0.339***
Natural gas	0.064***	0.050***	0.043***	1.000***	0.040***	0.029**
Kerosene	0.012	0.056***	0.056***	0.040***	1.000***	0.058***
Propane	0.292***	0.360***	0.339***	0.029**	0.058***	1.000***

Notes: Skewness: D’Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test; Q(20) and Q<sup>2</sup>(20): Fisher and Gallagher (2012) weighted Portmanteau test statistics.

\*Denote significance at 10% significance level while values in parentheses represent p-values.

\*\*Denote significance at 5% significance level while values in parentheses represent p-values.

\*\*\*Denote significance at 1% significance level while values in parentheses represent p-values.

Finally, the same concept can be applied to the total directional connectedness TO and FROM others as well as the net total directional connectedness measures

$$TO_j = \sum_{k=1}^K R_{C,k,j}^{2,d} + \sum_{k=1}^K R_{L,k,j}^{2,d} \tag{9}$$

$$= TO_j^C + TO_j^L \tag{10}$$

$$FROM_j = \sum_{k=1}^K R_{C,j,k}^{2,d} + \sum_{k=1}^K R_{L,j,k}^{2,d} \tag{11}$$

$$= FROM_j^C + FROM_j^L \tag{12}$$

$$NET_j^C = TO_j^C - FROM_j^C \tag{13}$$

$$NET_j^L = TO_j^L - FROM_j^L \tag{14}$$

$$NET_j = NET_j^C + NET_j^L. \tag{15}$$

While the  $TO_j$  ( $TO_j^C/TO_j^L$ ) total directional connectedness illustrates how much of the overall (contemporaneous/lagged) variance in all LHS variables is explained by series  $j$ , the  $FROM_j$  ( $FROM_j^C/FROM_j^L$ ) total directional connectedness demonstrates how much all RHS variables explain of the overall (contemporaneous/lagged) variance in series  $j$  – equal to  $R^2$  of the  $k$  MLR. If the  $NET_j > 0$  ( $NET_j < 0$ ), series  $j$  is considered as a net transmitter (receiver) of shocks indicating that it can explain more (less) of the variation in others than vice versa. The contemporaneous and lagged connectedness measures can be interpreted in the same fashion.

### 3. Data

This study employs a daily dataset covering six energy futures, namely, Crude Oil, Heating Oil, Gasoline, Natural Gas, Kerosene, and Propane which spans over the period from November 21st, 2014 to April 6th, 2023 retrieved from *Datastream*.

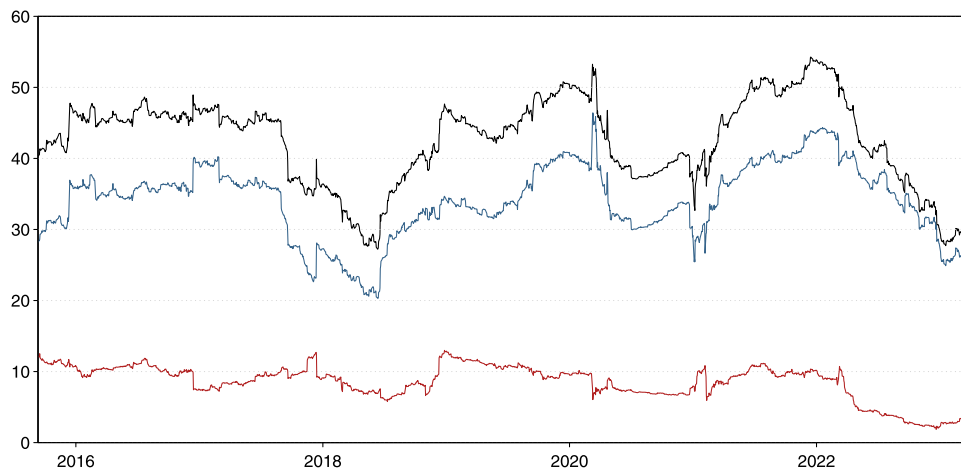
As the raw series are non-stationary according to the Elliott et al. (1996) unit-root test, we compute percentage changes for each series by  $y_t = \frac{z_t - z_{t-1}}{z_{t-1}}$  which are shown in Fig. 1.

The summary statistics are shown in Table 1. We find that Gasoline has the largest mean as well as variance, followed by Heating Oil while on the contrary the lowest mean and variance is observed for Natural Gas. This is interesting as Fig. 1 highlights that the volatility of Natural Gas has increased substantially since 2022 which is caused by the Russo-Ukrainian conflict. Furthermore,

**Table 2**  
Averaged Connectedness.

	Crude oil	Heating oil	Gasoline	Natural gas	Kerosene	Propane	FROM
Crude oil	0.66 (0.00, 0.66)	30.36 (29.51, 0.85)	20.83 (20.03, 0.80)	1.43 (0.80, 0.64)	1.16 (0.62, 0.54)	3.61 (3.30, 0.31)	57.39 (54.25, 3.14)
Heating oil	27.82 (27.30, 0.52)	0.73 (0.00, 0.73)	30.88 (29.95, 0.93)	0.65 (0.37, 0.28)	1.83 (1.17, 0.66)	7.46 (7.10, 0.37)	68.64 (65.89, 2.75)
Gasoline	20.30 (19.88, 0.43)	32.14 (31.79, 0.35)	0.49 (0.00, 0.49)	0.88 (0.61, 0.27)	0.92 (0.52, 0.41)	5.45 (5.08, 0.38)	59.70 (57.87, 1.83)
Natural gas	1.78 (1.05, 0.73)	1.10 (0.57, 0.53)	1.38 (0.79, 0.58)	1.50 (0.00, 1.50)	1.37 (0.79, 0.58)	0.79 (0.52, 0.27)	6.41 (3.72, 2.69)
Kerosene	10.07 (0.75, 9.32)	16.08 (1.45, 14.63)	9.24 (0.60, 8.64)	0.92 (0.62, 0.30)	1.66 (0.00, 1.66)	2.78 (0.67, 2.11)	39.08 (4.09, 34.99)
Propane	4.35 (3.51, 0.83)	9.38 (8.23, 1.15)	8.21 (5.35, 2.86)	0.93 (0.47, 0.46)	1.17 (0.81, 0.36)	1.26 (0.00, 1.26)	24.04 (18.37, 5.67)
TO	64.31 (52.49, 11.82)	89.05 (71.55, 17.50)	70.54 (56.72, 13.82)	4.81 (2.86, 1.95)	6.45 (3.91, 2.54)	20.10 (16.66, 3.44)	TCI ( $TCI^C$ , $TCI^L$ )
NET	6.92 (-1.77, 8.69)	20.41 (5.66, 14.75)	10.84 (-1.15, 11.99)	-1.60 (-0.86, -0.74)	-32.63 (-0.18, -32.45)	-3.94 (-1.71, -2.23)	42.54 (34.03, 8.51)

Notes:  $R^2$  decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (BIC). Values in parentheses represent contemporaneous and lagged effects, respectively.



**Fig. 2.** Dynamic total connectedness. Notes: The black line visualizes the overall dynamic total connectedness while the dynamic contemporaneous and lagged connectedness are illustrated in blue and red, respectively. Peaks can be associated with the COVID-19 pandemic (2020) and the Russo-Ukrainian war (2022).

we find that Crude Oil, Heating Oil, and Gasoline are significantly left-skewed while Kerosene and Propane are significantly right-skewed. Additionally, all series are leptokurtic and non-normally distributed according to the [Jarque and Bera \(1980\)](#) normality test. Besides, all series are stationary, autocorrelated, and exhibit ARCH errors — except Propane. Finally, we find that almost all series are significantly correlated on the 1% significance level. Therefore, using a rolling-window VAR model with contemporaneous effects appears to be an adequate modeling choice.

#### 4. Empirical results

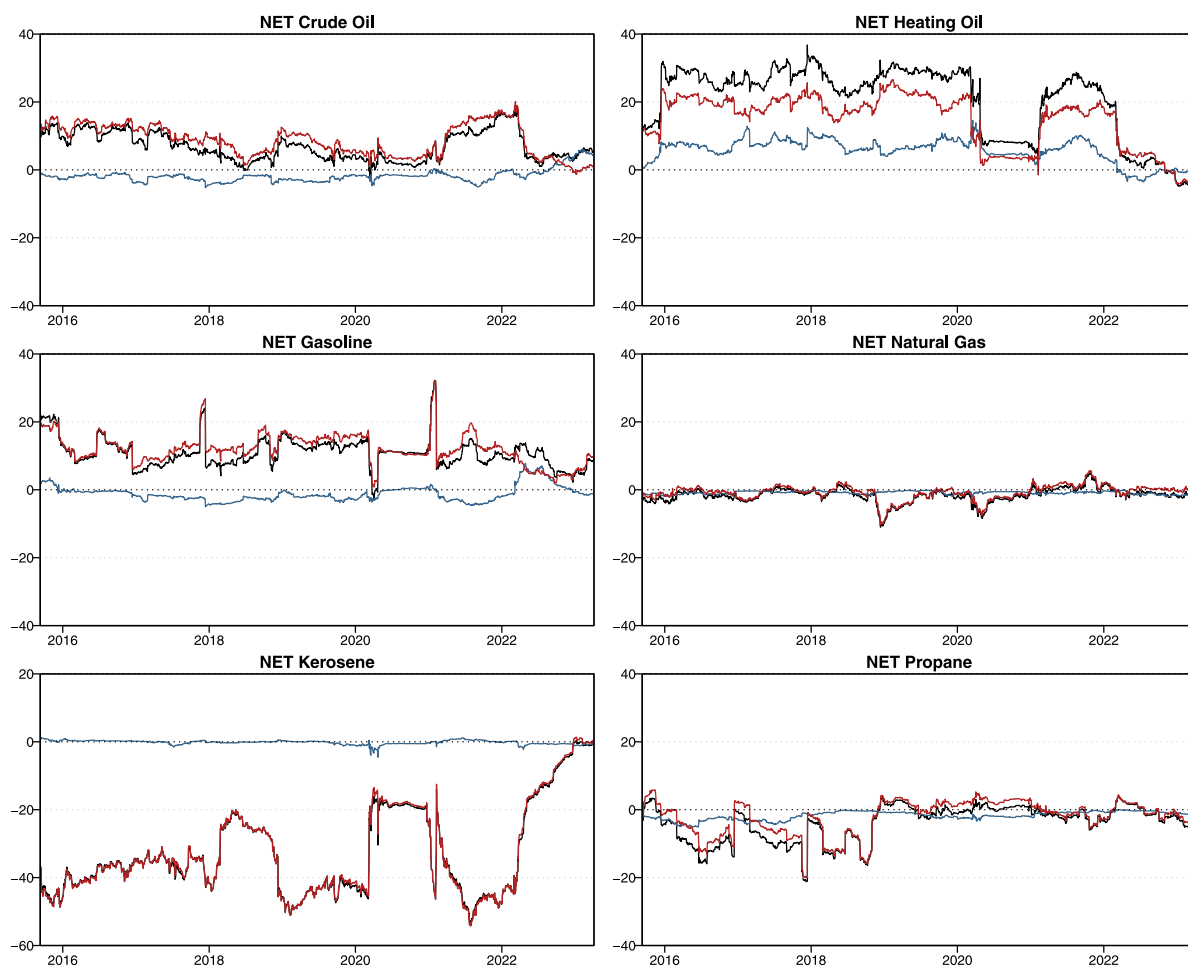
We start with interpreting the averaged connectedness measures which are shown in [Table 2](#). The presented values demonstrate the overall  $R^2$  decomposed measures while values in parentheses illustrate the contemporaneous and lagged  $R^2$  decomposed measures, respectively. We find that on average the TCI is equal to 42.54% which means that on average 42.54% of the variance of the LHS variables can be explained by the RHS variables. By decomposing this metric into its contemporaneous and lagged components, we observe that 34.03% are caused by contemporaneous dynamics while only 8.51% are related to lagged interdependencies.

Notably, all contemporaneous FROM and TO connectedness measures are substantially higher than their lagged counterparts with the exception of Kerosene where the lagged FROM measure (34.99%) is higher than the contemporaneous FROM measure (4.09%). Furthermore, we find that the main net transmitter of shock is Heating Oil (20.41%), followed by Gasoline (10.84%), and Crude Oil (6.92%) while the main net receiver of shocks is Kerosene (-32.63%), followed by Propane (-3.94%), and Natural Gas (-1.60%).

As averaged connectedness measures might conceal their time-varying behavior, we also focus on dynamic connectedness plots.

[Fig. 2](#) highlights two main peaks. The first one is observed in 2020 caused by the COVID-19 pandemic while the second one can be attributed to the Russo-Ukrainian war. Moreover, it should be noted that the contemporaneous interdependencies are more pronounced than the lagged interdependencies as they account for most of the market risk dynamics. Interestingly, the dynamic total connectedness decreased to an all-time low at the end of the sample period.

Next, we will briefly describe [Fig. 3](#) which demonstrates the time-varying net total directional connectedness. We find that Crude Oil, Heating Oil, and Gasoline are almost always net transmitters of shocks while Kerosene is throughout the sample period a net receiver of shocks. In the case of Natural Gas and Propane, we see that they are often at the net transmitting and net receiving end of shock spillovers.



**Fig. 3.** Net total directional connectedness. Notes: Black lines visualize the net total directional connectedness while the net contemporaneous and net lagged directional connectedness measures are illustrated in blue and red, respectively. Net transmitters of shocks are Crude Oil, Heating Oil, and Gasoline while Natural Gas, Kerosene, and Propane are mainly net receivers of shocks.

Moreover, we illustrate the averaged contemporaneous, lagged, and overall network connectedness measures in Fig. 4, respectively. It is shown that Crude Oil, Heating Oil, and Gasoline have a high degree of contemporaneous interdependencies while Kerosene and Propane have more pronounced lagged effects compared to the others. Interestingly, Natural Gas appears to be rather independent of the other energy futures. This is also depicted in Table 2 as only 6.41% of the variance of Natural Gas can be explained by the contemporaneous and lagged LHS variables. Thus, Natural Gas might be a suitable asset for energy portfolio diversification.

Finally, Fig. 5 provides robustness checks based on the dynamic total connectedness. By doing so we replace the Pearson correlation coefficients ( $R_{xx}$  and  $R_{yx}$ ) with the Spearman and Kendall rank correlation coefficient which are less outlier sensitive. As the results are quantitatively similar we conclude that our empirical results are robust.

## 5. Concluding remarks

In this study, we have introduced a novel and efficient  $R^2$  decomposed connectedness approach that allows us to differentiate between contemporaneous and lagged connectedness components. This novel framework has been used in order to investigate the return transmission mechanism across six energy futures, namely, Crude Oil, Heating Oil, Gasoline, Natural Gas, Kerosene, and Propane. The empirical findings suggest that the dynamic total connectedness is heterogeneous over time and economic-event dependent. Moreover, we find that contemporaneous spillover effects are more pronounced than lagged spillovers. Finally, Heating Oil appears to be the main net transmitter of shocks followed by Gasoline and Crude Oil while the main net receiver of shocks is Kerosene followed by Propane and Natural Gas. As our study focuses solely on the interconnectedness of the energy market, future studies might focus on different financial assets as well as extending the network with further commodity markets such as agricultural, livestock, industrial, and precious metal markets.

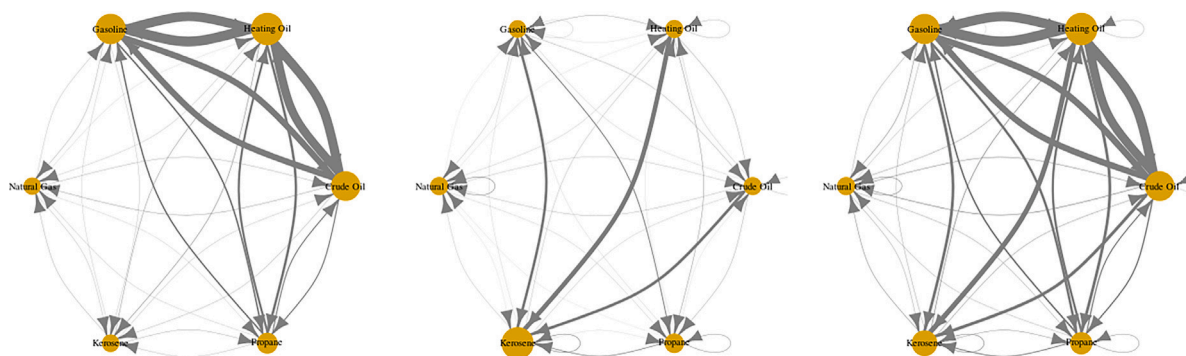


Fig. 4. Network connectedness. Notes: Contemporaneous (left), lagged (center), and overall (right) network connectedness. Crude Oil, Heating Oil, and Gasoline have a high degree of contemporaneous interdependencies while Kerosene and Propane have more pronounced lagged interdependencies.



Fig. 5. Robustness check: Dynamic total connectedness. Notes: The black line visualizes the overall dynamic total connectedness while the dynamic contemporaneous and lagged connectedness are illustrated in blue and red, respectively. The contemporaneous, lagged, and overall connectedness dynamics appear to be quantitatively similar across correlation coefficients.

## Data availability

Data will be made available on request.

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