Resources Policy 73 (2021) 102172

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

# Dynamic frequency relationships and volatility spillovers in natural gas, crude oil, gas oil, gasoline, and heating oil markets: Implications for portfolio management

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ARTICLE INFO

*JEL classification:*
G14

*Keywords:*
Energy futures markets
crises
Spillovers
Frequencies

ABSTRACT

This paper examines the dynamic frequency co-movements and volatility spillovers between crude oil, gas oil, gasoline, heating oil, and natural gas futures markets during the global financial crisis and European crisis (GFC & ESDC), recent oil price crash, and COVID-19 pandemic crisis. We apply the spillover index by Diebold and Yilmaz (2012) and wavelet methods. The results show significant risk spillovers among the leading energy futures markets. Moreover, the spillovers are intensified during the financial crisis, oil crisis and COVID-19 outbreak. WTI crude oil is the highest net contributor of volatility spillovers to the other markets, whereas the other energy markets are net receivers of spillovers for the different sub periods, with the exception of natural gas before the GFC and during COVID-19 as well as Brent oil during COVID-19. Furthermore, the results show significant integration and multiscale co-movements among energy futures. Natural gas asset offers better diversification benefits to crude oil, heating oil, gasoline and gas oil under short term. Finally, the diversification gains diminish as scales rise. The optimal weight, hedge ratios and hedging effectiveness are time varying and crises-sensitive. These findings have significant implications for energy traders and policymakers to inform their decision-making.

## 1. Introduction

The rapid financialization of energy commodities attracts the attention of energy market participants. Energy commodity futures –West Texas Intermediate (WTI) crude oil, Europe Brent crude oil, gas oil, gasoline, heating oil, and natural gas– become an alternative investment for investors and traders. On the other hand, energy prices are extremely volatile and unstable. The prices are vulnerable to international economic and political shocks, including among others the economic slowdown of big economies (China, US, and European Union), the oil supply and demand, the political conflict in Middle East region, Iran sanction and the trade tension between US and China. Recently, the outbreak of COVID-19 has intensified the instability of energy market where the oil prices decline to less than $ 20 barrel despite that the OPEC, Russia and other oil-producing countries decide to cut the production of crude oil by 10 million barrels a day, representing 10% of global supply. All these factors intensify the co-movements and spillovers among energy futures markets which have repercussions on the financial markets and economic growth. Thus, modeling the integration, contagion, spillovers, and co-movements among main energy futures are of special importance for market participants which provide them useful information to enhance their investment strategies in energy markets.

Natural gas suffered by regionality and the absence of a global integrated natural gas markets. Therefore, natural gas pricing is divergent around the globe (Li et al., 2014). The liquefied natural gas (LNG) plays a fundamental role in market integration because of its flexibility in terms of delivery (Barnes and Bosworth, 2015). Albeit a limited number of points, LNG may be delivered to multiple. In terms of energy market cointegration across different regions, an earlier work by Villar and Joutz (2006) highlight the presence of long-run relationship between West Texas Intermediate (WTI) and Henry Hub prices. According to Panagiotidis and Rutledge (2007), there exists a long-run cointegrating

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https://doi.org/10.1016/j.resourpol.2021.102172
Received 22 November 2020; Received in revised form 11 May 2021; Accepted 11 May 2021
Available online 18 June 2021
0301-4207/

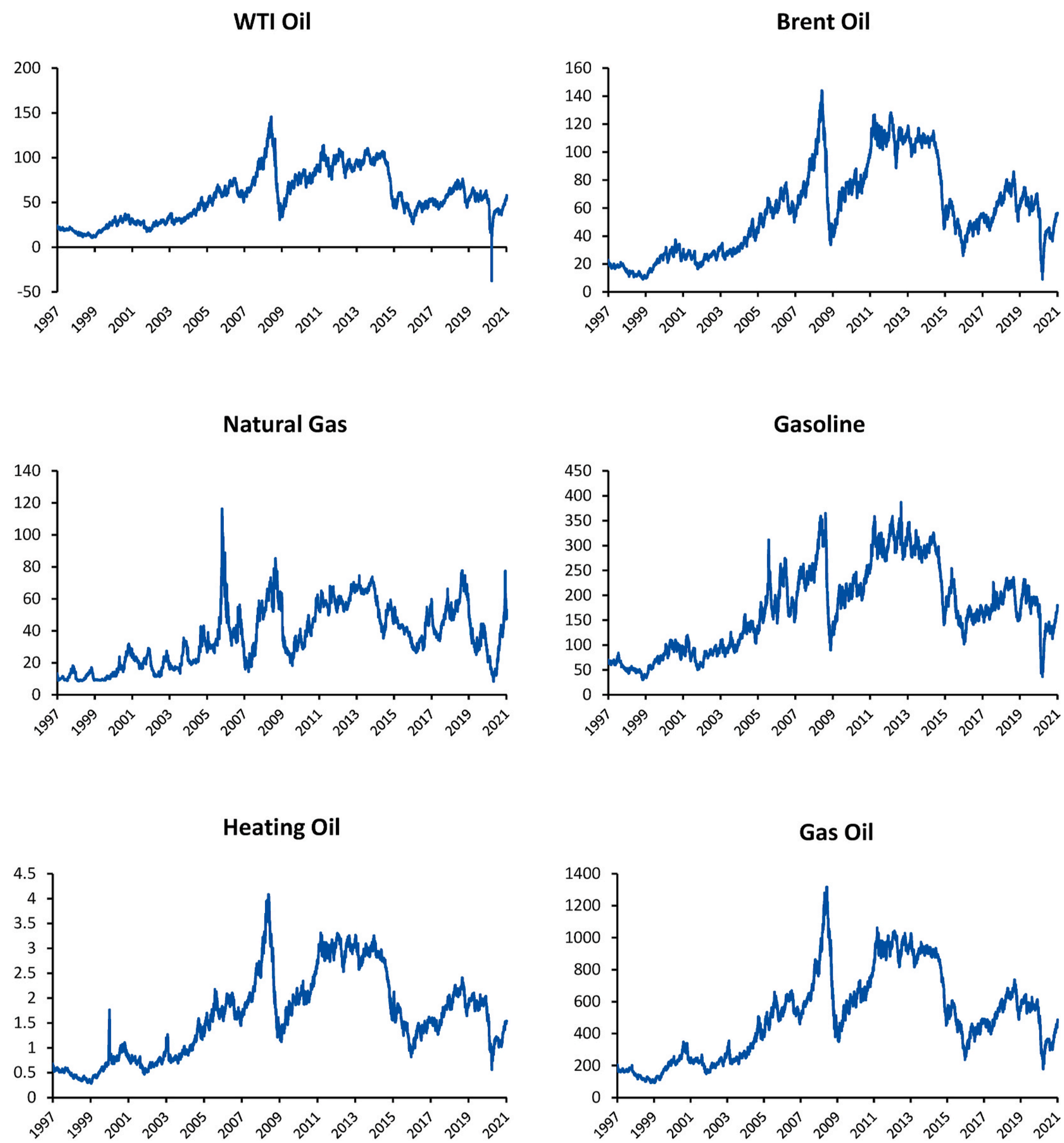



**Fig. 1.** Time variations of energy futures prices.

relationship between Brent crude oil and UK natural gas prices. In another work, Hartley et al. (2008) report the presence of long-run relationship between crude oil and natural gas market. Nick and Thoenes (2014) report the presence of structural VaR and suggest that the German natural gas gets affected by the coal prices in long-run period. Later, Geng et al. (2017) highlight the presence of non-linear relationship between regional gas and the crude oil. According to Zhang et al. (2018), gas prices are less sensitive to demand and supply factors than the oil prices in Germany and Japan however, for the US energy market, these factors are more important for gas prices compared with the oil prices.

Despite the huge number of empirical studies examining the information transmission (volatility and returns transmission) among commodity markets, only few works investigate the co-movements and directional spillovers across various frequencies under different turbulent periods (Mensi et al., 2020). Serra (2011) examines the relationship between crude oil, ethanol and sugar prices in Brazil economy. The author finds a significant impact of crude oil and sugar prices on ethanol price instability. Karali and Ramirez (2014) examine the volatility spillovers between energy markets and the determinants of the potential spillovers. The authors find evidence of volatility spillovers between crude oil and natural gas as well as between heating oil and natural gas. Moreover, the political, economic, and natural events intensify the volatility of crude oil market. Mensi et al. (2014) use different dynamic conditional correlations (DCC) GARCH model to investigate the transmission of returns and volatility between cereal and energy markets. The authors account for the OPEC news announcements. The authors find substantial evidence of volatility transmission between energy and cereal markets and that OPEC news intensify the transmission channels. Combining wavelet and copula approaches, Mensi et al. (2017) examine average as well as tail dependence between the implied volatility indexes of corn, wheat and oil. The authors show evidence of asymmetric extreme tail dependence between corn and wheat and between oil and the two cereals at multiple time horizons. More recently, Guhathakurta et al. (2020) examine the volatility spillovers between oil, agricultural and metal commodities using the spillovers index methodology of Diebold and Yilmaz (2012, 2014, 2016). The authors find spillovers between oil and other commodity markets where the peak of spillovers occurs during the oil boom in 2008 and great oil depression in 2014. They also show better hedging effectiveness for oil-metals portfolio than for oil-agro commodity portfolio.

This study investigates the co-movements, integration, contagion, and spillovers between energy futures market (West Texas Intermediate (WTI) crude oil, Europe Brent crude oil, gas oil, heating oil, gasoline, and

**Table 1**
Preliminary analysis.

| | WTI Crude Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil |
|---|---|---|---|---|---|---|
| **Panel A: Whole period** | | | | | | |
| Mean | 0.00025 | 0.00027 | 0.00024 | 0.00021 | 0.00017 | 0.00018 |
| Maximum | 0.30023 | 0.41202 | 0.47770 | 0.27196 | 0.22954 | 0.13759 |
| Minimum | −0.38829 | −0.25518 | −0.28132 | −0.51244 | −0.47012 | −0.19687 |
| Std. Dev. | 0.02646 | 0.02493 | 0.03535 | 0.02716 | 0.02490 | 0.02129 |
| Skewness | −0.09657 | 0.58896 | 2.42175 | −1.15651 | −1.23356 | −0.10879 |
| Kurtosis | 24.35802 | 28.01168 | 28.49824 | 31.53672 | 37.14503 | 7.91831 |
| Jarque-Bera | 119050*** | 163614*** | 175787*** | 213906*** | 305835*** | 6325*** |
| ADF | −80.3146*** | −18.1691*** | −57.4863*** | −80.1856*** | −80.6028*** | −79.5392*** |
| PP | −80.3366*** | −79.5615*** | −75.0854*** | −80.8874*** | −80.6323*** | −79.5747*** |
| Zivot-Andrews | −33.6212** | −38.7560*** | −42.6110*** | −33.3907** | −35.9392* | −38.5078 |
| **Panel B: Pre-GFC** | | | | | | |
| | WTI Crude Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil |
| Mean | 0.00047 | 0.00047 | 0.00058 | 0.00055 | 0.00048 | 0.00050 |
| Median | 0.00000 | 0.00000 | −0.00053 | 0.00000 | 0.00000 | 0.00000 |
| Maximum | 0.15873 | 0.16256 | 0.47770 | 0.16885 | 0.22954 | 0.13759 |
| Minimum | −0.17217 | −0.19891 | −0.28132 | −0.16187 | −0.47012 | −0.13481 |
| Std. Dev. | 0.02346 | 0.02328 | 0.04003 | 0.02688 | 0.02764 | 0.02169 |
| Skewness | −0.24430 | −0.15893 | 2.68677 | −0.00673 | −1.77538 | −0.06801 |
| Kurtosis | 6.83310 | 7.22216 | 28.51926 | 5.80337 | 46.47391 | 5.75332 |
| Jarque-Bera | 1884.47*** | 2262.62*** | 85835.3*** | 991.879*** | 240123*** | 959.095*** |
| ADF | −40.9395*** | −54.1472*** | −40.3450*** | −53.2916*** | −30.9794*** | −55.3145*** |
| PP | −55.0752*** | −54.1481*** | −52.3201*** | −53.2699*** | −55.7547*** | −55.3175*** |
| Zivot-Andrews | −41.0585** | −54.2528** | −29.6316*** | −53.370** | −26.0690*** | −55.4559** |
| **Panel C: During GFC & ESDC** | | | | | | |
| | WTI Crude Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil |
| Mean | −0.00009 | 0.00014 | −0.00016 | −0.00015 | 0.00004 | 0.00000 |
| Median | 0.00000 | 0.00009 | −0.00049 | 0.00000 | 0.00000 | 0.00000 |
| Maximum | 0.21277 | 0.18130 | 0.35777 | 0.14730 | 0.10536 | 0.07781 |
| Minimum | −0.13065 | −0.16832 | −0.10884 | −0.12451 | −0.09936 | −0.11794 |
| Std. Dev. | 0.02800 | 0.02397 | 0.03034 | 0.02482 | 0.02098 | 0.02081 |
| Skewness | 0.38610 | 0.00161 | 2.16056 | −0.23699 | −0.25091 | −0.47617 |
| Kurtosis | 9.62935 | 10.46686 | 24.30260 | 6.57437 | 5.63935 | 6.03721 |
| Jarque-Bera | 2080.60*** | 2604.18*** | 22068.4*** | 607.244*** | 337.142*** | 473.229*** |
| ADF | −34.8026*** | −33.9525*** | −31.9439*** | −32.9553*** | −33.8179*** | −34.0038*** |
| PP | −34.8050*** | −33.9489*** | −31.9690*** | −32.9548*** | −33.8230*** | −34.0138*** |
| Zivot-Andrews | −15.7234** | −34.5753** | −20.0206*** | −33.9986 | −34.3831*** | −15.4482*** |
| **Panel D: Economy recovery** | | | | | | |
| | WTI Crude Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil |
| Mean | 0.00041 | 0.00008 | −0.00104 | 0.00006 | −0.00013 | −0.00007 |
| Median | 0.00048 | 0.00019 | −0.00051 | 0.00024 | 0.00000 | 0.00000 |
| Maximum | 0.03200 | 0.04178 | 0.09426 | 0.07612 | 0.04360 | 0.02805 |
| Minimum | −0.03206 | −0.03192 | −0.07983 | −0.08824 | −0.06475 | −0.03671 |
| Std. Dev. | 0.01095 | 0.01021 | 0.01422 | 0.01413 | 0.01190 | 0.00965 |
| Skewness | −0.10407 | −0.02031 | 0.50774 | −0.48414 | −0.38714 | −0.24074 |
| Kurtosis | 3.15798 | 3.79525 | 12.65086 | 9.14678 | 5.87139 | 3.91138 |
| Jarque-Bera | 1.07829 | 10.0130*** | 1487.11*** | 611.461*** | 139.668*** | 16.7776*** |
| ADF | −18.9182*** | −18.9179*** | −19.7861*** | −19.7875*** | −19.1712*** | −19.5178*** |
| PP | −18.9163*** | −18.9436*** | −19.8066*** | −19.7833*** | −19.1732*** | −19.5227*** |
| Zivot-Andrews | −19.1232** | −19.3125*** | −9.5520*** | −19.9818** | −19.6123*** | −20.1562*** |
| **Panel E: Oil price crash** | | | | | | |
| | WTI Crude Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil |
| Mean | −0.00046 | −0.00039 | 0.00001 | −0.00036 | −0.00029 | −0.00035 |
| Median | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Maximum | 0.13694 | 0.11070 | 0.36451 | 0.11851 | 0.14863 | 0.11979 |
| Minimum | −0.10726 | −0.08083 | −0.12261 | −0.17767 | −0.12708 | −0.10487 |
| Std. Dev. | 0.02378 | 0.02165 | 0.02829 | 0.02235 | 0.02167 | 0.01964 |
| Skewness | 0.11622 | 0.33233 | 2.02122 | 0.00468 | 0.27893 | 0.46461 |
| Kurtosis | 5.91109 | 5.36262 | 26.89549 | 8.77720 | 9.23883 | 7.03047 |
| Jarque-Bera | 506.378*** | 357.659*** | 34873.1*** | 1981.71*** | 2329.53*** | 1015.80*** |
| ADF | −41.3717*** | −36.8620*** | −37.9366*** | −40.9362*** | −41.4144*** | −38.0826*** |
| PP | −41.3036*** | −36.9267*** | −38.2418*** | −40.8240*** | −41.2933*** | −38.0905*** |
| Zivot-Andrews | −41.6902*** | −37.2368*** | −28.2639*** | −41.1600*** | −29.4683*** | −18.5443*** |
| **Panel F: COVID-19 outbreak** | | | | | | |
| | WTI Crude Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil |
| Mean | 0.00248 | 0.00207 | 0.00100 | 0.00105 | 0.00010 | 0.00048 |
| Median | 0.00000 | 0.00058 | 0.00000 | 0.00111 | 0.00000 | 0.00000 |
| Maximum | 0.30023 | 0.41202 | 0.21607 | 0.27196 | 0.11186 | 0.13291 |
| Minimum | −0.38829 | −0.25518 | −0.17253 | −0.51244 | −0.17738 | −0.19687 |
| Std. Dev. | 0.05657 | 0.05401 | 0.04848 | 0.05566 | 0.03393 | 0.03333 |
| Skewness | −0.33021 | 1.11666 | 0.28999 | −2.69352 | −0.65942 | −0.44737 |
| Kurtosis | 18.86114 | 21.17635 | 4.98025 | 31.47264 | 8.19532 | 9.41707 |
| Jarque-Bera | 3244.66*** | 4317.86*** | 54.8186*** | 10811.3*** | 369.908*** | 540.483*** |
| ADF | −5.3176*** | −18.3147*** | −14.7876*** | −18.7414*** | −16.6276*** | −17.3027*** |
| PP | −16.9275*** | −18.4073*** | −14.6476*** | −18.7655*** | −16.6192*** | −17.3371*** |
| Zivot-Andrews | −7.2636*** | −16.2397*** | −15.6290*** | −20.3961*** | −18.0767*** | −18.6106*** |

**Notes:** ***, ** and * indicates significance level at 1,5 and 10 percent.

**Table 2**
Unconditional correlations among energy price returns.

| | *WTI Crude Oil* | *Brent Oil* | *Natural Gas* | *Gasoline* | *Heating Oil* | *Gas Oil* |
|---|---|---|---|---|---|---|
| **Panel A: Whole period** | | | | | | |
| WTI crude Oil | 1 | | | | | |
| Brent Oil | 0.5887*** | 1 | | | | |
| Natural Gas | 0.0537*** | 0.0810*** | 1 | | | |
| Gasoline | 0.5921*** | 0.4705*** | 0.0475*** | 1 | | |
| Heating Oil | 0.6294*** | 0.4883*** | 0.0773*** | 0.5665*** | 1 | |
| Gas Oil | 0.6046*** | 0.6351*** | 0.0835*** | 0.5052*** | 0.6601*** | 1 |
| **Panel B: Pre-GFC** | | | | | | |
| WTI crude Oil | 1 | | | | | |
| Brent Oil | 0.5766*** | 1 | | | | |
| Natural Gas | 0.0390** | 0.0528*** | 1 | | | |
| Gasoline | 0.6293*** | 0.4096*** | 0.0333* | 1 | | |
| Heating Oil | 0.6415*** | 0.4231*** | 0.0581*** | 0.5516*** | 1 | |
| Gas Oil | 0.5436*** | 0.6857*** | 0.0515*** | 0.4395*** | 0.5191*** | 1 |
| **Panel C: During GFC & ESDC** | | | | | | |
| WTI crude Oil | 1 | | | | | |
| Brent Oil | 0.5833*** | 1 | | | | |
| Natural Gas | 0.0771*** | 0.1041*** | 1 | | | |
| Gasoline | 0.6202*** | 0.5136*** | 0.0632** | 1 | | |
| Heating Oil | 0.7348*** | 0.6367*** | 0.0948*** | 0.7367*** | 1 | |
| Gas Oil | 0.7221*** | 0.6140*** | 0.1338*** | 0.6871*** | 0.9009*** | 1 |
| **Panel D: Economy recovery** | | | | | | |
| WTI crude Oil | 1 | | | | | |
| Brent Oil | 0.5972*** | 1 | | | | |
| Natural Gas | 0.0771 | 0.1238** | 1 | | | |
| Gasoline | 0.4894*** | 0.4108*** | 0.0178 | 1 | | |
| Heating Oil | 0.6434*** | 0.5924*** | 0.0156 | 0.5232*** | 1 | |
| Gas Oil | 0.6938*** | 0.6529*** | 0.0802 | 0.5920*** | 0.8274*** | 1 |
| **Panel E: Oil price crash** | | | | | | |
| WTI crude Oil | 1 | | | | | |
| Brent Oil | 0.6090*** | 1 | | | | |
| Natural Gas | 0.0920*** | 0.1511*** | 1 | | | |
| Gasoline | 0.6167*** | 0.4398*** | 0.0411 | 1 | | |
| Heating Oil | 0.6935*** | 0.5642*** | 0.1011*** | 0.6037*** | 1 | |
| Gas Oil | 0.7181*** | 0.6199*** | 0.1137*** | 0.5953*** | 0.7708*** | 1 |
| **Panel F: COVID-19 outbreak** | | | | | | |
| WTI crude Oil | 1 | | | | | |
| Brent Oil | 0.6008*** | 1 | | | | |
| Natural Gas | 0.0433 | 0.0917 | 1 | | | |
| Gasoline | 0.4984*** | 0.5937*** | 0.1013* | 1 | | |
| Heating Oil | 0.5287*** | 0.5507*** | 0.1454** | 0.4793*** | 1 | |
| Gas Oil | 0.5458*** | 0.5742*** | 0.1373** | 0.4414*** | 0.8735*** | 1 |

**Notes:** ***, ** and * indicates significance level at 1,5 and 10 percent.

natural gas) under different crises periods. Our sample is carefully considered and motivated by their high volatilities which affect the financial markets, non-energy commodity markets (metals and agricultural markets), and the economic growth. More importantly, energy futures markets are large and a significant portion of trading is made in that market. Figure A1 depicts the number of energy futures and option contracts traded globally in 2018. It exhibits that Brent crude oil is widely traded in futures markets followed by WTI oil. We notice that natural gas is considered as a substitute input for crudes in the industrial and electrical domains (Adhikati and Putnam, 2020). Gasoline is obtained after refining WTI and Brent crude. Heating oil and natural gas are seen as a substitute. The rapid internationalization process has increased the consumption of these physical assets. These markets are a barometer for the economic growth and development (Cai et al., 2019). On the other hand, energy firms usually use the futures contracts to hedge their position against future price instability and uncertainty. Speculators operating in energy futures markets earns a higher risk-return investment vehicle. On the other hand, the spread of the coronavirus (COVID-19) pandemic has been increasingly impacting the energy markets. For the first time, the WTI oil contract costs minus $37 per barrel on April 20, 2020. Despite the efforts of OPEC+, the outbreak of COVID-19 has decreased significantly the global oil demand. The US International Energy Agency estimates that the global oil demand declines by 30% of demand in April 2020, followed by a second important year-on-year decline of 26 million barrels/day in May 2020.[1] Thus, the linkages among these markets are evident and the price instability of one market can affect the others.

This paper contributes to the related literature in three important ways. First, we measure volatility spillovers at different economic events using the methodology proposed by Diebold and Yilmaz (2012). This empirical method enriches our understanding on volatility spillovers by accounting for the magnitude and the directional spillovers among markets over time which is important for speculators and energy traders to be interested in short-term spillovers and for policy makers to implement the regulations. In addition, we examine the spillovers under different markets conditions: (i) Before GFC (January 2, 1997–September 14, 2008), (ii) during GFC and ESDC (September 15, 2008–December 31, 2012), (iii) Economy recovery (January 2, 2013–June 14, 2014), (iv) during oil crisis (June 15, 2014–November 30, 2019), and (v) during COVID-19 outbreak (December 2019–February 17, 2021). This analysis can provide us information set

[1] https://www.bruegel.org.

**Table 3**
Results of total volatility spillover.

| | WTI Oil | Brent Oil | Natural Gas | Gasoline | Heating Oil | Gas Oil | From Others |
|---|---|---|---|---|---|---|---|
| **Panel A: Whole period** | | | | | | | |
| WTI Oil | 99.2 | 0.1 | 0 | 0.3 | 0.1 | 0.2 | 0.8 |
| Brent Oil | 38.3 | 58.1 | 0 | 2.4 | 1.1 | 0 | 41.9 |
| Natural Gas | 0.3 | 0.3 | 99.3 | 0.1 | 0 | 0 | 0.7 |
| Gasoline | 35.3 | 2.9 | 0.1 | 61.6 | 0 | 0.1 | 38.4 |
| Heating Oil | 41.1 | 3.4 | 0.1 | 4.1 | 50.9 | 0.3 | 49.1 |
| Gas Oil | 39 | 11 | 0.1 | 2.1 | 7.8 | 40 | 60 |
| To others | 154.1 | 17.8 | 0.4 | 9 | 9.1 | 0.6 | 190.9 |
| Own | 253.3 | 75.9 | 99.6 | 70.6 | 60 | 40.6 | **31.80%** |
| Net | 153.3 | −24.1 | −0.3 | −29.4 | −40 | −59.4 | |
| **Panel B: Pre-GFC** | | | | | | | |
| WTI Oil | 99.2 | 0.2 | 0.2 | 0.2 | 0.1 | 0.1 | 0.8 |
| Brent Oil | 41.9 | 55.9 | 0.1 | 1.1 | 0.7 | 0.2 | 44.1 |
| Natural Gas | 0.2 | 0.1 | 99.6 | 0 | 0 | 0 | 0.4 |
| Gasoline | 39.4 | 0.5 | 0.2 | 59.8 | 0 | 0.1 | 40.2 |
| Heating Oil | 41.3 | 0.8 | 0.2 | 3.3 | 54.1 | 0.3 | 45.9 |
| Gas Oil | 33.4 | 15.2 | 0.1 | 1.9 | 4.4 | 45.1 | 54.9 |
| To others | 156.2 | 16.8 | 0.8 | 6.5 | 5.2 | 0.7 | 186.2 |
| Own | 255.4 | 72.7 | 100.4 | 66.3 | 59.3 | 45.8 | **31.00%** |
| Net | 155.4 | −27.3 | 0.4 | −33.7 | −40.7 | −54.2 | |
| **Panel C: During GFC & ESDC** | | | | | | | |
| WTI Oil | 98 | 0 | 0.2 | 0.2 | 1.1 | 0.5 | 2 |
| Brent Oil | 36.4 | 55.5 | 0 | 3.5 | 3.6 | 1 | 44.5 |
| Natural Gas | 0.8 | 0.7 | 96.9 | 0.2 | 0.4 | 1.1 | 3.1 |
| Gasoline | 38 | 5.9 | 0.3 | 54.5 | 0.5 | 0.9 | 45.5 |
| Heating Oil | 53.4 | 9.9 | 0.3 | 7 | 28.2 | 1.3 | 71.8 |
| Gas Oil | 52.5 | 8.2 | 0.5 | 5.4 | 17.6 | 15.8 | 84.2 |
| To others | 181 | 24.7 | 1.2 | 16.3 | 23.2 | 4.7 | 251.2 |
| Own | 279 | 80.2 | 98.1 | 70.8 | 51.4 | 20.5 | **41.90%** |
| Net | 179 | −19.8 | −1.9 | −29.2 | −48.6 | −79.5 | |
| **Panel D: Economy recovery** | | | | | | | |
| WTI Oil | 98.2 | 0.4 | 0.1 | 0.6 | 0.3 | 0.3 | 1.8 |
| Brent Oil | 36.6 | 53 | 0.5 | 4.4 | 3.8 | 1.6 | 47 |
| Natural Gas | 1.6 | 1.4 | 96.2 | 0.1 | 0.4 | 0.4 | 3.8 |
| Gasoline | 23.4 | 5.2 | 0.2 | 69.8 | 1.1 | 0.4 | 30.2 |
| Heating Oil | 40.3 | 7.8 | 0.5 | 4.7 | 46.6 | 0.1 | 53.4 |
| Gas Oil | 47.2 | 11.2 | 0.1 | 6.5 | 13.1 | 21.8 | 78.2 |
| To others | 149 | 26 | 1.5 | 16.3 | 18.7 | 2.8 | 214.3 |
| Own | 247.2 | 79 | 97.7 | 86.1 | 65.3 | 24.7 | **35.70%** |
| Net | 147.2 | −21 | −2.3 | −13.9 | −34.7 | −75.4 | |
| **Panel E: Oil price crash** | | | | | | | |
| WTI Oil | 96.4 | 0.8 | 0.3 | 0.1 | 0 | 2.4 | 3.6 |
| Brent Oil | 43.7 | 51.6 | 0.1 | 0.6 | 1 | 3.1 | 48.4 |
| Natural Gas | 1 | 1.4 | 97.4 | 0 | 0 | 0.2 | 2.6 |
| Gasoline | 35.5 | 2.6 | 0.5 | 59.8 | 0.1 | 1.5 | 40.2 |
| Heating Oil | 45.4 | 4 | 0.2 | 3.9 | 43.2 | 3.4 | 56.8 |
| Gas Oil | 53.8 | 5.9 | 0.3 | 2.9 | 9.2 | 28 | 72 |
| To others | 179.3 | 14.7 | 1.3 | 7.5 | 10.4 | 10.6 | 223.7 |
| Own | 275.7 | 66.2 | 98.6 | 67.3 | 53.5 | 38.6 | **37.30%** |
| Net | 175.7 | −33.7 | −1.3 | −32.7 | −46.4 | −61.4 | |
| **Panel F: COVID-19 outbreak** | | | | | | | |
| WTI Oil | 90.3 | 0.7 | 0.1 | 6.6 | 2.1 | 0.2 | 9.7 |
| Brent Oil | 27.2 | 57.3 | 0.9 | 13.6 | 0.4 | 0.6 | 42.7 |
| Natural Gas | 0.8 | 0.3 | 98.2 | 0.4 | 0.1 | 0.2 | 1.8 |
| Gasoline | 26.9 | 16.8 | 0.2 | 55.7 | 0.2 | 0.1 | 44.3 |
| Heating Oil | 34.3 | 12.6 | 1 | 3.8 | 47.8 | 0.5 | 52.2 |
| Gas Oil | 33.5 | 14.7 | 0.8 | 3.6 | 26.1 | 21.2 | 78.8 |
| To others | 122.7 | 45.1 | 3 | 28 | 29 | 1.6 | 229.4 |
| Own | 213.1 | 102.3 | 101.1 | 83.8 | 76.8 | 22.9 | **38.20%** |
| Net | 113 | 2.4 | 1.2 | −16.3 | −23.2 | −77.2 | |

**Note:** The second last row in each sub panel represents the net effect of each energy market towards other markets whereas last row highlights its own contribution.

on the asymmetric spillovers which is important for portfolio design.

Second, it explores the integration in energy markets by quantifying the correlation ranks at different time scales. To examine frequencies, we use the maximal overlap discrete wavelet transform (MODWT). This method gains high attention in modern finance due to their ability to transform a raw series into coefficients to variations over a set of scales (Percival and Walden, 2000). We notice that MODWT is not impacted by the circular shifting of the input variable (Cornish et al., 2006). By decomposing the raw series, we account for market heterogeneity hypothesis. In fact, we are interested in the interactions among futures across various frequencies.

Third, we make use of wavelet correlation matrix, wavelet multiple correlation, and wavelet multiple cross-correlations. The differences in market expectations and risk appetite are controlled using the wavelet approach as some investors are interested in the relationships at high frequencies (short-term) and the others are interested in the low frequencies (long-term).

With the aim to achieve our objectives, we carry different econometric methods, including spillovers index of Diebold and Yilmaz (2012), the wavelet correlation, the correlation ranks matrix, the

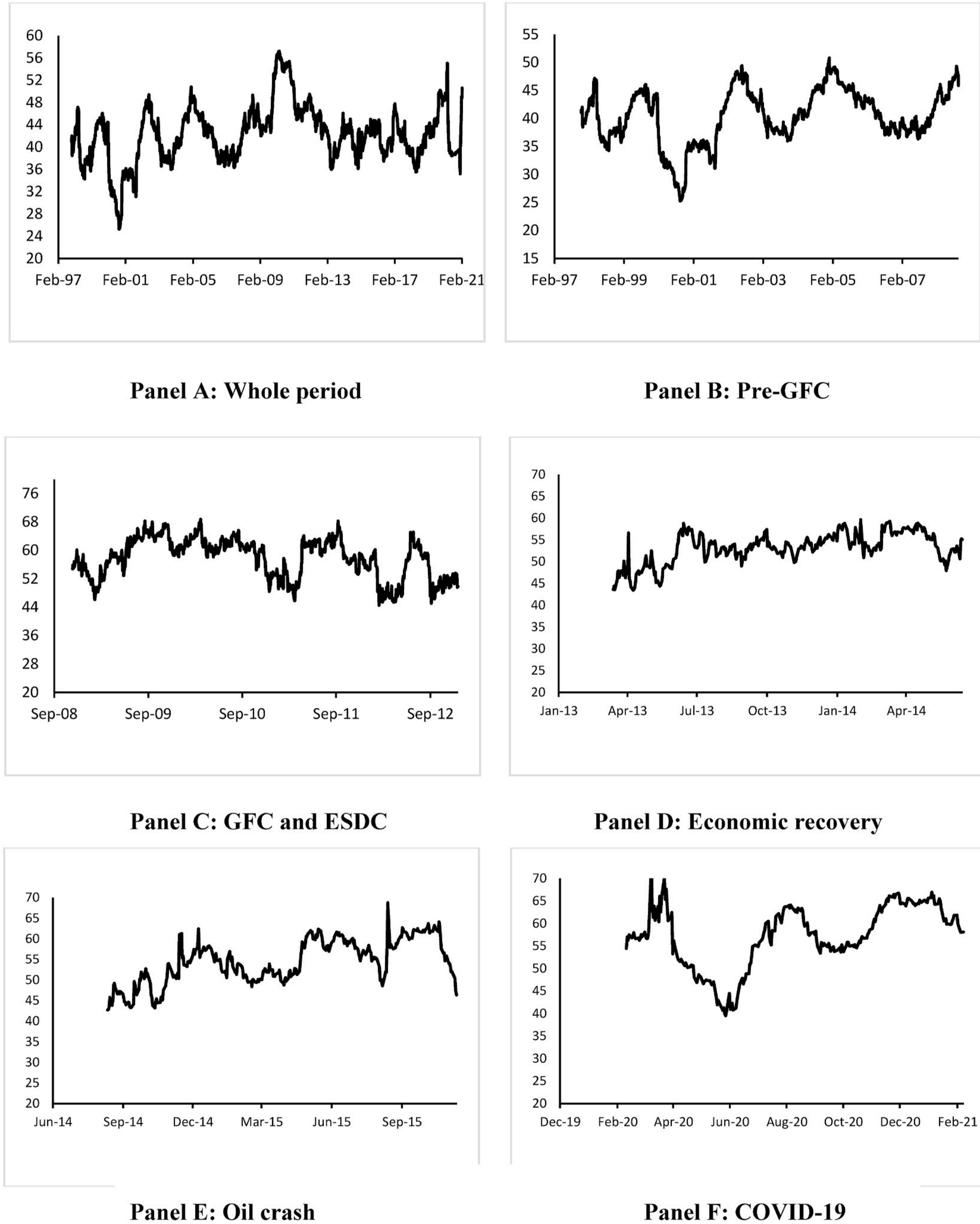



**Fig. 2.** Time variations of total volatility spillover among energy futures.

wavelet multiple correlation, and wavelet multiple cross-correlations. We apply the Maximal Overlap Discrete Wavelet Transformation (MODWT) to decompose raw series into decomposed series to account for frequencies. More interestingly, we account for recent economic events by decomposing the entire period into three sub periods: (i) Before GFC (from January 3, 1997 to September 15, 2008), (ii) Before oil crisis (September 16, 2008 to June 15, 2014, and (iii) during oil crisis (from June 16, 2014 to February 17, 2020).

The results show volatility spillovers among energy futures, which is increased during times of the financial crises, oil crash and COVID-19 pandemic outbreak. Among all energy markets, WTI oil is the most significant contributor of volatility to other markets regardless of the different sub periods. In addition, Gas oil is the least contributor of volatility spillovers to the other markets before the GFC and the COVID-19 crisis, while natural gas contributes at a minimum level to volatility spillovers during the financial and oil crises. On the other hand, gas oil is the highest receiver of volatility spillovers from the other energy markets, particularly from WTI oil irrespective of the sub-periods. More importantly, the volatility spillover among energy markets is extremely influenced by the 1998 Asian crisis, 2003 Gulf War, 2008 GFC, great oil bust and COVID-19 outbreak. Using the rolling window correlation method, we show high dynamic correlations between WTI and Brent oil. In addition, the correlations between Brent oil futures and other energy markets are similar to those of WTI oil. Overall, we find evidence of contagion among energy futures markets with the exception of natural gas which is weakly dependent to energy markets, supporting the decoupling hypothesis. The degree of integration among energy futures is high and increases with the wavelet scale. A portfolio risk analysis shows that hedging effectiveness and hedge ratio is time varying and crises-sensitive.

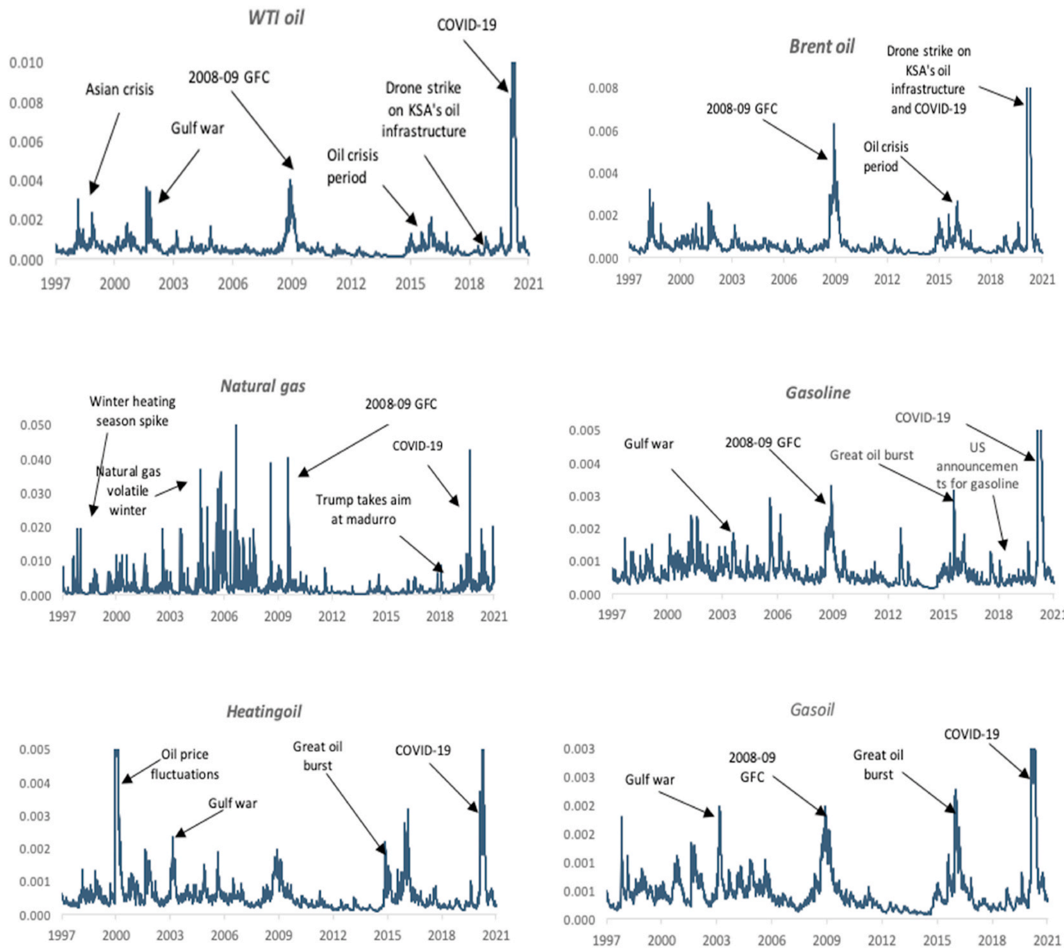



**Fig. 3.** Time variations in energy market conditional volatility. N**otes:** The conditional volatility of energy markets is calculated through GARCH (1, 1) model. We use the Akaike Information Criteria (AIC) is used to select the optimal lag orders.

We structure the remainder of our work in the following sequence. Section 2 explains methodology of our study. Section 3 explains data and its sources. Section 4 provides discussion on empirical results. Finally, section 5 concludes our work with implications.

## 2. Literature review

The interactions among energy markets have attracted a special attention in the last few years. A first strand of literature has examined the relationships among energy markets in different market places. Lin and Tamvakis (2001) examine the spillover effects between the New York Mercantile Exchange (NYMEX) and the London's International Petroleum Exchange (IPE). The authors find evidence of significant spillover mean returns in the IPE morning section, where up to two lag days' NYMEX information has significant effects. Moreover, the authors show substantial bidirectional volatility spillovers between NYMEX and IPE markets. Using the methodology of Hong (2001), Feng-bin (2008) investigate the Granger causality and spillover effects among crude oil markets (Dubai oil, London, NYMEX WTI, IPE Brent, as well as Tapis and Minas in Southeast Asia). The authors find that the role of London and New York futures markets in information spillover is significant. WTI crude oil futures has a slight edge over Brent crude oil futures in information transmission.

A second strand of literature examined the linkages between spot and futures energy markets Alizadeh et al. (2008); Chen et al. (2014); Sheu and Lee (2014; Silvapulle and Moosa, 1999). Bekiros and Diks (2008) examine the nonlinear causality between sport and futures (one, two, three and four months) WTI crude oil markets. The authors find a causal linkage from spot to futures markets. Moreover, if nonlinear effects are accounted for, neither market leads or lags the other consistently, indicating a position of leads and lags are time varying. Using the spillover index by Diebold and Yilmaz (2014), Magkonis and Tsouknidis (2017) examine the volatility spillovers between sport and futures energy markets (crude oil, heating oil and gasoline contracts). The authors find significant volatility spillovers between sport and futures markets. In addition, crude oil is the large contributor of spillovers in the system. Hedging pressures and trading volumes transmit large spillovers to both spot and futures markets of crude oil and heating oil-gasoline markets. Chang and Lee (2020) find asymmetric spillover effects from futures to spot energy markets. More importantly, the transition probabilities is strongly associated to the volatility of the futures markets.

A third strand of literature studied the relationships between different energy assets.[2] Brown et al. (2002) find a significant long-term cointegration between oil and natural gas prices and that crude oil prices lead those of U.S. natural gas prices. In contrast, Batten et al. (2017) show the natural gas price leads the crude oil prices. Baruník et al. (2015) account for asymmetric stylized fact to measure the volatility spillovers in crude oil, heating oil and gasoline markets. The authors find increasing volatility spillovers among petroleum markets after the 2008 global financial crisis. More interestingly, the authors find a decline in asymmetries in spillovers (total and directional spillovers) after the 2008 GFC. The total volatility spillovers due to negative returns dominate the volatility spillovers due to positive returns. Browm and Yucel

[2] See Mensi et al. (2021a,b); Rehman et al. (2019).

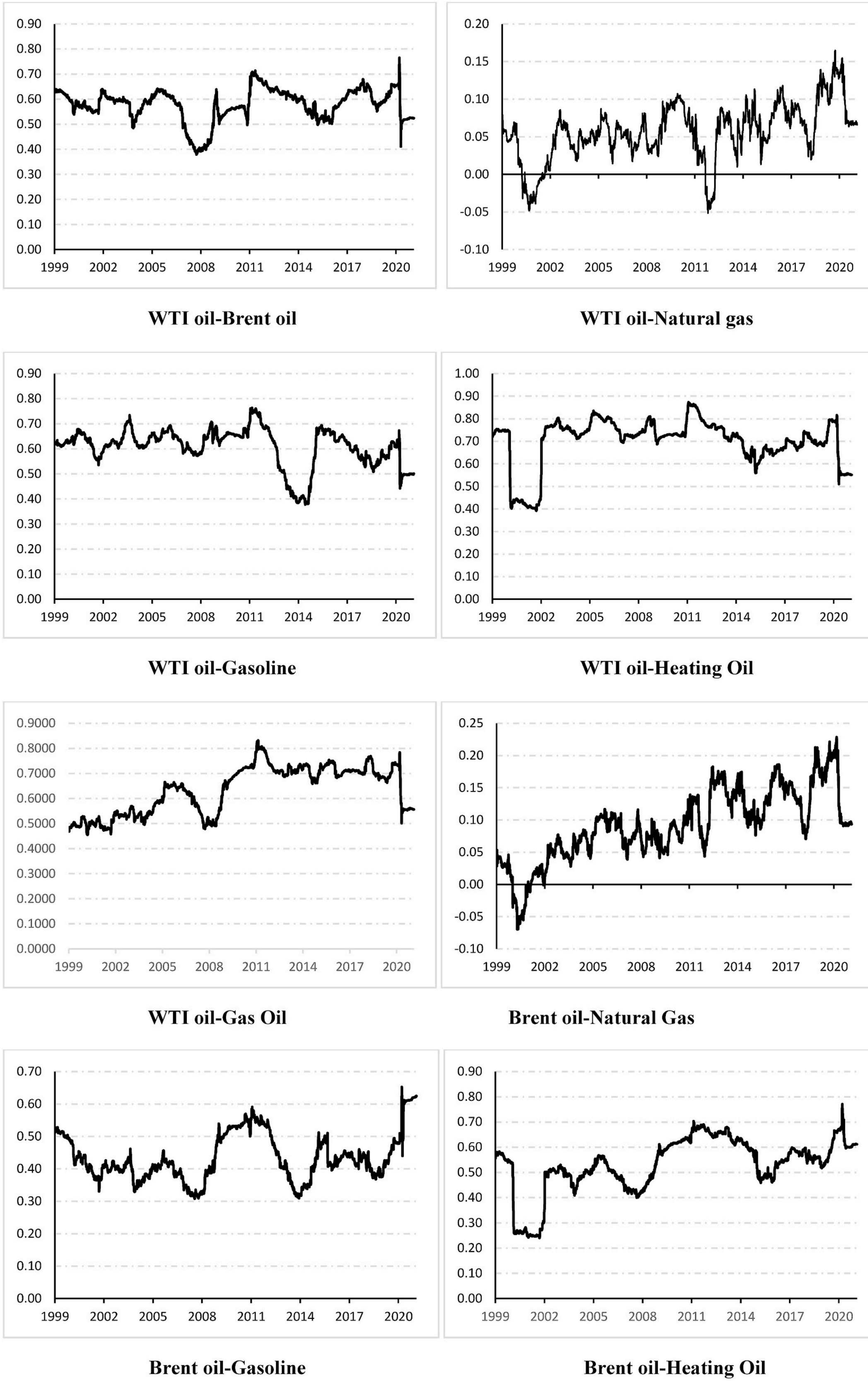
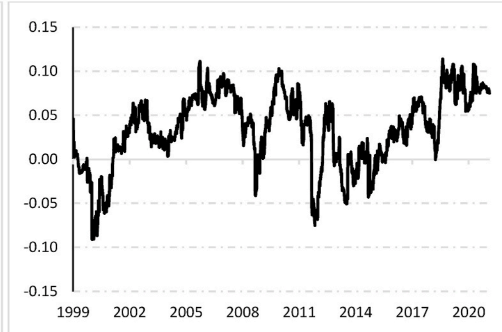



**Fig. 4.** Rolling window correlation (24-months).


**Brent oil-Gas Oil**



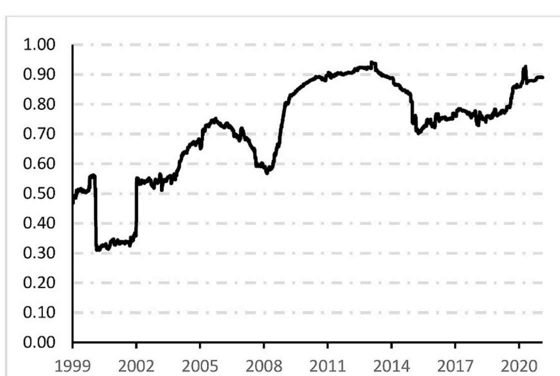

**Natural Gas-Gasoline**


**Natural Gas-Heating Oil**


**Natural Gas-Gas Oil**


**Gasoline-Heating Oil**


**Gasoline-Gas Oil**




**Heating Oil- Gas Oil**

**Fig. 4.** (*continued*).


**Fig. 5.** Wavelet Correlation Matrix. **Notes**: C1= WTI Oil; C2= Brent Oil; C3=Natural Gas; C4= Gasoline; C5= Heating Oil; C6= Gas Oil. The x-axis represents coefficients for estimating the wavelet correlation however time period for different wavelet scales is highlighted on y-axis, corresponding to 2j, where superscript represents scale. Strength of the correlation coefficient is highlighted color of the blocks where color changes from red to blue in case the correlation ranges from high to low coefficient. The y-axis stands for wavelet scales. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

(2008) and Mu (2007) find that oil price shocks influence the natural gas prices because crude oil is a substitute for natural gas. Broadstock et al. (2020) examine the integration among natural gas market across Europe countries. Using the Diebold and Yilmaz (2009) methodology, the results show heterogeneous connectedness in price spillovers and a complex lead-lag relation. More importantly, the authors find an increasing pattern of natural gas market integration. Lahiani et al. (2017) examine the relationships between WTI crude oil, gasoline, diesel, heating and Henry Hub natural gas. The authors find evidence of cointegration between the considered markets. Furthermore, crude oil prices serve as a predictor of gasoline, diesel, heating and natural gas markets in the short term. Li et al. (2019) analyze the spillovers effects between WTI crude oil and Henry Hub natural gas using a hybrid model based on the bivariate empirical mode decomposition, Fine-to-Coarse algorithm and the Grey correlation degree. The results show significant risk spillovers at multiple time-scales between markets under investigation. Mensi et al. (2021a,b) examine the sensitivity of oil exporting and oil importing economies to energy commodity pricing and report that oil exporting countries are more sensitive to energy prices than oil importing countries. According to Rehman et al. (2019), energy futures provide more optimal returns by combining with non-energy commodities. Lovcha and Perez-Laborda (2020) examine the evolving frequency spillovers and connectedness between crude oil and natural gas markets. They find a significant low-frequency connectedness between both markets even after the shale gas revolution. Chiou-Wei et al. (2020) examine the WTI oil and Henry Hub natural gas in spot and futures markets. The authors find that accounting for macro news announcements influence the co-movements between markets under study and enhance the hedging effectiveness. More recently, Li and Su (2021) find that COVID-19 pandemic crisis intensified the spillovers and connectedness among energy markets (WTI crude oil, gasoline, heating oil, propane and natural gas).

From the above literature, we claim that analyzing the spillover transmission strengths and directional in energy commodity markets especially during extreme risk periods like the 2008 GFC, oil price crash, and COVID-19 pandemic crisis is of great significance to policymakers and investors. It helps policymakers to monitor and control market risk and maintain a sustainable financial stability and economic growth. We contribute to the existing literature by investigating the time-frequency patterns in the relationship between energy market volatility during different major crises (financial, energy, and health system crises). Further, we carry a portfolio risk analysis under different turbulent periods.

## 3. Methodology

### 3.1. Wavelet decomposition method

Before applying the application of our wavelet correlation and wavelet cross correlation techniques as our principal methodology, we

**Table 4**
**Correlation ranking under different time scales.**

| Rank | 2–4 days | 4–8 days | 8–16 days | 16–32 days | 32–64 days |
|---|---|---|---|---|---|
| 1 | Natural Gas – Gas Oil (0.11) | Brent Oil-Natural Gas (0.15) | Crude Oil-Natural Gas (0.18) | Crude Oil-Natural Gas (0.2) | Natural Gas-Gasoline (0.21) |
| 2 | Brent Oil-Natural Gas (0.18) | Natural Gas – Gas Oil (0.16) | Brent Oil-Natural Gas (0.2) | Natural Gas-Gasoline (0.22) | Brent Oil-Natural Gas (0.23) |
| 3 | Natural Gas-Gasoline (0.2) | Crude Oil-Natural Gas (0.16) | Natural Gas-Gasoline (0.2) | Natural Gas – Gas Oil (0.23) | Crude Oil-Natural Gas (0.25) |
| 4 | Crude Oil-Natural Gas (0.22) | Natural Gas-Gasoline (0.17) | Natural Gas – Gas Oil (0.23) | Brent Oil-Natural Gas (0.23) | Natural Gas – Gas Oil (0.3) |
| 5 | Natural Gas-Heating Oil (0.27) | Natural Gas-Heating Oil (0.2) | Natural Gas-Heating Oil (0.26) | Natural Gas-Heating Oil (0.29) | Natural Gas-Heating Oil (0.33) |
| 6 | Gasoline-Gas Oil (0.37) | Gasoline-Gas Oil (0.5) | Crude Oil-Gasoline (0.6) | Crude Oil-Gasoline (0.66) | Gasoline-Heating Oil (0.69) |
| 7 | Crude Oil-Gas Oil (0.43) | Crude Oil-Gas Oil (0.58) | Crude Oil-Gas Oil (0.62) | Crude Oil-Heating Oil (0.68) | Gasoline-Gas Oil (0.7) |
| 8 | Brent Oil-Gas Oil (0.49) | Crude Oil-Gasoline (0.59) | Crude Oil-Heating Oil (0.65) | Crude Oil-Gas Oil (0.7) | Crude Oil-Heating Oil (0.77) |
| 9 | Heating Oil- Gas Oil (0.5) | Brent Oil-Gas Oil (0.63) | Gasoline-Gas Oil (0.66) | Gasoline-Heating Oil (0.72) | Crude Oil-Gas Oil (0.79) |
| 10 | Crude Oil-Gasoline (0.69) | Brent Oil-Gasoline (0.64) | Gasoline-Heating Oil (0.69) | Gasoline-Gas Oil (0.73) | Brent Oil-Gasoline (0.82) |
| 11 | Brent Oil-Gasoline (0.7) | Gasoline-Heating Oil (0.65) | Crude Oil-Brent Oil (0.71) | Brent Oil-Gasoline (0.75) | Crude Oil-Gasoline (0.83) |
| 12 | Gasoline-Heating Oil (0.7) | Heating Oil- Gas Oil (0.7) | Brent Oil-Heating Oil (0.74) | Brent Oil-Heating Oil (0.79) | Brent Oil-Heating Oil (0.85) |
| 13 | Crude Oil-Brent Oil (0.73) | Crude Oil-Heating Oil (0.72) | Brent Oil-Gas Oil (0.75) | Crude Oil-Brent Oil (0.83) | Brent Oil-Gas Oil (0.88) |
| 14 | Brent Oil-Heating Oil (0.73) | Brent Oil-Heating Oil (0.72) | Brent Oil-Gasoline (0.76) | Brent Oil-Gas Oil (0.83) | Crude Oil-Brent Oil (0.92) |
| 15 | Crude Oil-Heating Oil (0.74) | Crude Oil-Brent Oil (0.74) | Heating Oil- Gas Oil (0.85) | Heating Oil- Gas Oil (0.87) | Heating Oil- Gas Oil (0.96) |

**Note:** C1= Crude Oil; C2= Brent Oil; C3=Natural Gas; C4= Gasoline; C5= Heating Oil; C6= Gas Oil. The first column represents ranking of correlation from its lowest to highest value. Rank 1 highlights the lowest correlation value whereas rank 15 represents highest correlation coefficient. A coefficient with lower value is assigned higher rank in a situation where two correlation values appear in a single scale. For the purpose of clarity, we present correlation coefficient in parenthesis.

make use of the unique wavelet decomposition approach known as a maximal overlap discrete wavelet transform (MODWT). Since the methodology behind wavelet correlation works on the interaction of wavelet covariances [*x(t), y(t)*] with wavelet variances [*x(t)*] and [*y(t)*], the process of MODWT is defined as follows:

$$\rho xy(\lambda j) = \mathrm{Corr}(wij,twij,t) = \mathrm{Cov}(wij,twij,t)varwij,\ tvar(wij,t) \tag{1}$$

where $w_{ij,t}$ represents wavelet coefficients and λj obtained by applying the MODWT framework. The process of Daubechies least asymmetric (LA) wavelet filter with length 8 is used for decomposing our sampled time series into six components i.e. from $D_1$ to $D_6$. In these decomposed series, the respective frequencies are represented through number of days.

### 3.2. Wavelet cross correlations and multiple correlations

The application of wavelet correlation is used extensively in the finance literature to measure connectedness between equity markets across time-frequency space. However, applications of Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross Correlation (WMCC) are presented as an extension of traditional wavelet methodologies. Fernandez-Macho (2012) introduces the Wavelet Multiple Correlation and Wavelet Multiple Cross Correlation techniques to remove limitations experienced under pairwise correlation and cross correlation.

The process of MODWT defines wavelet coefficients Wjt=(w1,jtw2, jt, …,wnjt) for each λj scale under a multivariate stochastic process Xt=(x1t, x2t, …,xnt) for respective xit series. The expression WMC ϕX(λj) highlights the multi-scale correlation estimated from Xt. For variables with linear combination, i.e. w1,jt, where $i = 1, \ldots, n$, we estimate regression to give maximum value of the square root of coefficient of determination. However, for variables with zk, k≠ i, coefficient of determination for a set of variables zi is given as R2 = 1-1ρii, where ρii represents the ith diagonal element from inverse correlation matrix. The expression for wavelet multiple correlation ϕX(λj) is therefore given as,

$$\phi X(\lambda j) = 1\text{-}1maxdiag\ Pj\text{-}1 \tag{2}$$

Equation (2) presents Pj as a correlation matrix [n X n] of Wjt. However, expression for the largest element in argument diagonal is given as maxdiag(.). For remaining variables, regression of zi is equal to the coefficient of determination, which is equivalent to the correlation square values between observed (zi) and the fitted (zi) regression coefficient values. Therefore, the equation of wavelet multiple correlation WMC ϕX(λj) is best defined as:

$$\phi X(\lambda j) = \mathrm{Corr}(wij,twij,t) = \mathrm{Cov}(wij,t,wij,t)varwij,\ tvar(wij,t) \tag{3}$$

We also present expressions for variances and co-variances as follows:

$$\mathrm{Var}(wij,t) = \delta j2 = 1Tj\ t = :j\text{-}1T\text{-}1Wij,t2 \tag{4}$$

$$\mathrm{Var}(wij,t) = \zeta j2 = 1Tj\ t = :j\text{-}1T\text{-}1Wij,t2 \tag{5}$$

$$\mathrm{Cov}(Wij,t,\ Wij,t) = \gamma j2 = 1Tj\ t = :j\text{-}1T\text{-}1Wij,t,\ Wij,t \tag{6}$$

In the above expressions, for [Wkj, k ≠ 1], Wij leads towards maximization of the coefficient of determination, whereas Wij represent the corresponding fitted values. The number of wavelet coefficients such as Lj = 2j-1L-1+1 is affected by the associated boundary of wavelet filter with scale λj and length L. Expression for the unaffected coefficient number with boundary conditions is given as Tj = Lj+1.

We also allow a lag value of τ for each scale λj between the observed and fitted values of the criterion variable. The expression, based on the above discussion, is presented as follows:

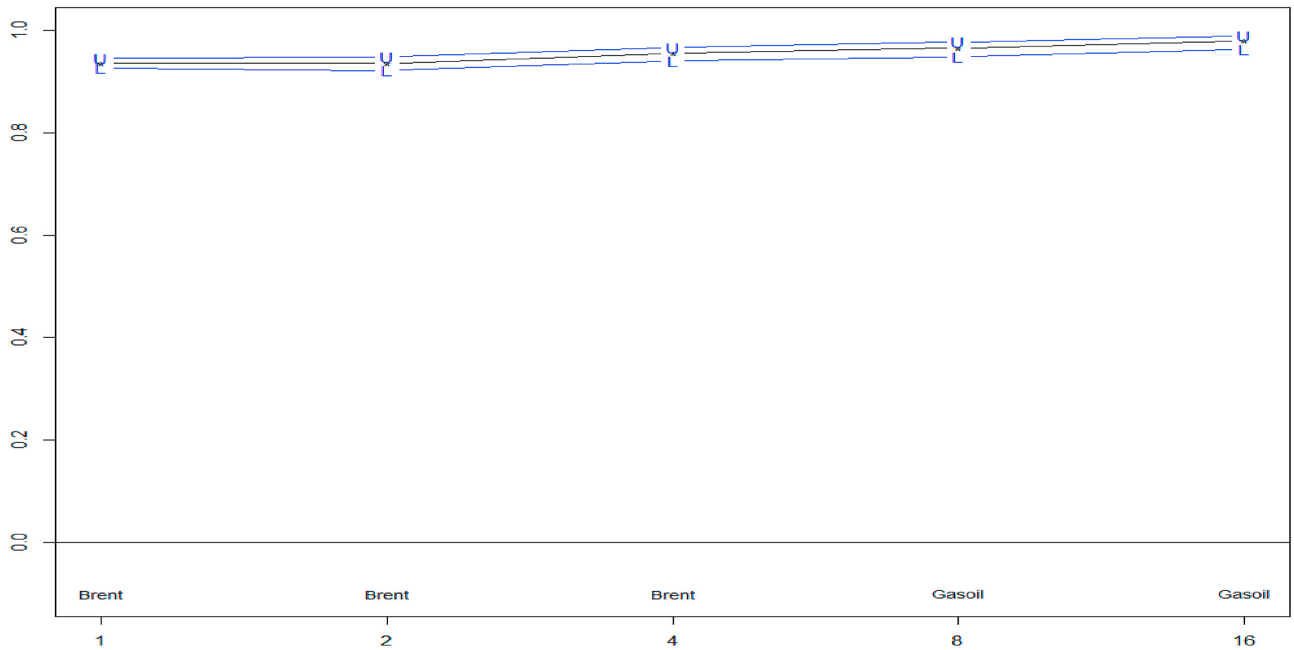
$$\phi X,\ \tau(\lambda j) = \mathrm{Corr}\ Wij,t,\ Wij,t+\tau = \mathrm{Cov}(wij,t,wij,t+\tau)varwij,\ tvar(wij,t+\tau) \tag{7}$$

For the purpose of constructing a confidence interval, we suppose X=(X1, …,XT) which represents multivariate stochastic Gaussian process (Equation (7)). We further apply Jth order MODWT to all the sampled univariate series (xi1, …,xiT) for $i = 1 \ldots$ to obtain wavelet coefficient vector.

$$wj = Wjo \ldots Wj,T\text{-}1 = w1j,o \ldots wnjo, \ldots, W1j,T2j\text{-}1,\ j\text{-}1 \ldots J \tag{8}$$

Finally, the confidence interval for the sample wavelet correlation coefficient is presented as

$$CI1\text{-}\alpha\phi x\lambda j = \tanh[zj \pm \varnothing 1\text{-}\alpha 2\text{-}1/\ T2j\text{-}3] \tag{9}$$




**Notes**: Figure 6 presents light blue lines corresponding towards upper and lower bounds at 95% confidence interval.

**Fig. 6.** Wavelet Multiple Correlation. Not**es:** Fig. 6 presents light blue lines corresponding towards upper and lower bounds at 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

### 3.3. Spillover framework

To measure returns spillover, we make use of Diebold and Yilmaz (2012) spillover approach which employs generalized vector auto-regression i.e. GVAR. For computation, let's suppose a returns series Xt following a covariance stationary VAR p process as appended below.

$$\mathrm{Xt} = \mathrm{i} = 1\mathrm{P}\Phi\mathrm{iXt\text{-}i}+\varepsilon\mathrm{t}, \tag{10}$$

In the above equation, Xt denotes a vector of $N \times 1$ endogenous variable, $\Phi$i as $N \times N$ AR coefficient matrices whereas $\varepsilon\sim 0,\Sigma$ represents vector with independent and identical disturbance distribution with zero and $\Sigma$ covariance matrix. The resultant VAR process is expressed as follows.

$$\mathrm{Xt} = \mathrm{i} = 1\infty\mathrm{Bi}\varepsilon\mathrm{t\text{-}i}, \tag{11}$$

Bi as a $N \times N$ coefficient matrix follows recursion as $\mathrm{Bi} = \Phi1\mathrm{Bi\text{-}1}+\Phi2\mathrm{Bi\text{-}2}+\cdots+\Phi\mathrm{pBi\text{-}p}$, where B0 represents $N \times N$ identity matrix whereas Bi = 0 for $i < 0$. We define cross-variance and self-variance components based on the *H*-step ahead forecasting error variance decomposition (FEVD) (see Koop et al., 1996; Pesaran and Shin, 1998). The cross-variance components represent spillover index θijH as is presented below.

$$\theta\mathrm{ijH} = \sigma\mathrm{jj\text{-}1h} = 0\mathrm{H\text{-}1ei'Bh}\ \Sigma\ \mathrm{ej2h} = 0\mathrm{H\text{-}1ei'Bh}\ \Sigma\ \mathrm{Bh'ei}, \tag{12}$$

In the above equation, $\Sigma$ denotes covariance matrix of the vector of errors ε, ei represents selection vector, σjj highlights the standard deviation of residual of jth equation and finally ith is equal to one with remaining elements having zero value. The standardization of the spillover index measured above is presented below.

$$\theta\mathrm{ijH} = \theta\mathrm{ij(H)j} = 1\mathrm{N}\theta\mathrm{ij(H)}, \tag{13}$$

where by construction, $\mathrm{j} = 1\mathrm{N}\theta\mathrm{ijH} = 1$ and $\mathrm{ij} = 1\mathrm{N}\theta\mathrm{ijH} = \mathrm{N}$. θijH presents magnitude of directional connectedness (pairwise) directed from *j* to *i* at *H* horizon. We estimate total spillover index CH by employing contributions from the variance decomposition approach in the following equation.

$$\mathrm{CH} = \mathrm{ij} = 1,\mathrm{j}\neq\mathrm{iN}\theta\mathrm{ijHij} = 1\mathrm{N}\theta\mathrm{ijH} \times 100 = \mathrm{ij} = 1,\mathrm{j}\neq1\mathrm{N}\theta\mathrm{ijHN} \times 100, \tag{14}$$

In order to analyze the contribution from and towards each energy commodity, we aggregate "total spillover" from the "TO" and "FROM" expressions. We estimate directional connectedness Ci←*H and C*←iH from each commodity towards the other commodities as

$$\mathrm{Ci}\leftarrow{*}\mathrm{H} = \mathrm{j} = 1,\mathrm{j}\neq\mathrm{iN}\theta\mathrm{ijHij} = 1\mathrm{N}\theta\mathrm{ijH} \times 100 = \mathrm{j} = 1,\mathrm{j}\neq1\mathrm{N}\theta\mathrm{ijHN} \times 100, \tag{15}$$

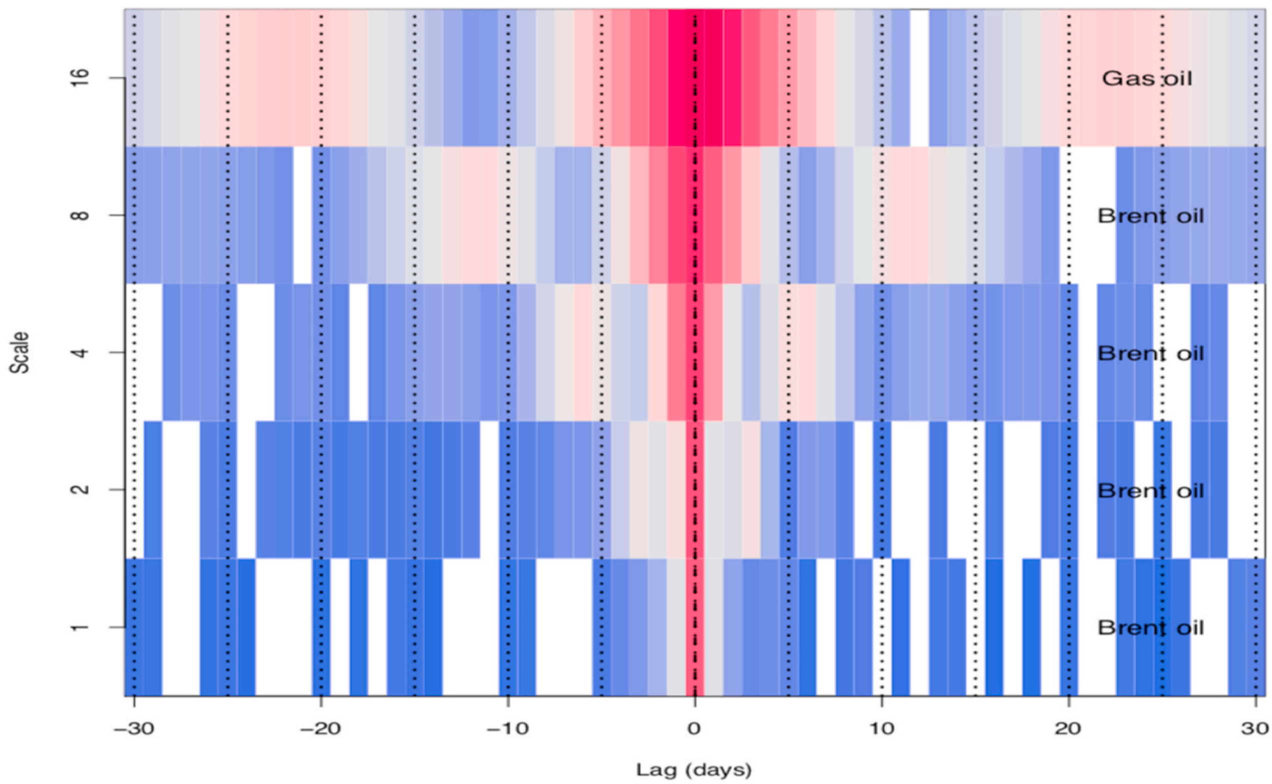
$$\mathrm{C}{*}\leftarrow\mathrm{iH} = \mathrm{j} = 1,\mathrm{j}\neq\mathrm{iN}\theta\mathrm{jiHij} = 1\mathrm{N}\theta\mathrm{jiH} \times 100 = \mathrm{j} = 1,\mathrm{j}\neq1\mathrm{N}\theta\mathrm{jiHN} \times 100, \tag{16}$$

The expression for net directional connectedness transmitted from energy commodity *i* to other commodities *j* is as follows.

$$\mathrm{CiH} = \mathrm{C}{*}\leftarrow\mathrm{iH\text{-}Ci}\leftarrow{*}\mathrm{H} \tag{24}$$

## 4. Data and descriptive statistics

We use daily closing price for six main energy futures markets, namely West Texas Intermediate (WTI) crude oil, Europe Brent crude oil, heating oil, gas oil, gasoline, and Henry Hub natural gas. The Henry Hub futures market offers market participants significant hedging activity to monitor risk in the in the highly volatile natural gas price. Henry




**Note**: The wavelet coefficients are presented at 95 percent confidence interval. We see few small white patches representing zero span zones in 95 percent of the times. We can also see vertical dashed lines at equal span that represent the localization of strong wavelet correlation. On the extreme right, the color indicator highlights strength of the correlation between different alternative energy markets.

**Fig. 7.** Wavelet Multiple Cross-Correlations. **Note**: The wavelet coefficients are presented at 95 percent confidence interval. We see few small white patches representing zero span zones in 95 percent of the times. We can also see vertical dashed lines at equal span that represent the localization of strong wavelet correlation. On the extreme right, the color indicator highlights strength of the correlation between different alternative energy markets. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Hub is the third largest physical commodity futures contacts in terms of trading volume.[3,4] The sample period spans from January 2, 1997 to February 8, 2021, totaling 6265 daily observations. The data period covers important political and economic events (e.g., 2008 GFC, 2012 ESDC, 2014 great oil bust, and China-US trade war, and COVID-19 pandemic crisis). The data are compiled from Datastream. We use the daily continuously compounded returns as the natural logarithm of two consecutive pricing values.

Fig. 1 depicts the evolution of energy futures prices along the sample period. We observe that all energy price series exhibit a structural change during the GFC. Moreover, we observe a significant oil price decline between mid-2014 and 2016, corresponding to times of great oil price bust. The trajectory of natural gas price is different from those of other energy products, which show a relatively stable trend since 2009 until 2019. It is worth noting that WTI oil prices exhibit a negative value in April 20, 2020. This is due to the effects of COVID-19 pandemic crisis leading to demand falling and storage space approaching maximum capacity. All energy prices show a downside trend during the pandemic outbreak.

Table 1 provides descriptive statistics and stationarity properties for energy price returns under the whole period and five subperiods (before the GFC, during both GFC and ESDC, during oil price crash and during COVID-19 pandemic crisis). The average returns for all energy markets are positive and nearly zero for the whole sample period (Panel A). The Brent oil has the highest average returns and heating oil the least one. We notice that the average returns is negative for WTI oil, natural gas, and gasoline during the GFC and ESDC period. After the financial crisis (Economy recovery period), natural gas, heating oil and gas oil price returns are negative. More importantly, all energy markets exhibit negative returns with the exception of natural gas whereas they are positive during COVID-19 pandemic period.

In addition, natural gas is the highest volatile market for all

[3] https://www.cmegroup.com/trading/energy/natural-gas/natural-gas_quotes_globex.html#.

[4] https://www.oxfordenergy.org/wpcms/wp-content/uploads/2020/06/2-Gas-in-Europe-Part-III-Down-Down-Deeper-and-Down.pdf.

**Table 5**
Results of portfolio design.

| Portfolios | $w_t^{WTI}$ | $\beta_t$ | HE |
|---|---|---|---|
| **Panel A**: Pre GFC (2nd Jan. 1997- Sep. 14, 2008) | | | |
| WTI/Brent oil | 0.5326 | 1.1334 | 0.0159 |
| WTI/Natural gas | 0.2847 | 0.0496 | −2.6389 |
| WTI/Gasoline | 0.3706 | 0.6310 | −0.4098 |
| WTI/Heating oil | 0.5290 | 0.7959 | −0.3766 |
| WTI/Gas oil | 0.6175 | 0.6878 | 0.1097 |
| **Panel B**: GFC and ESDC crisis (15th Sep. 2008- Dec. 31, 2012) | | | |
| WTI/Brent oil | 0.6535 | 1.3491 | 0.1924 |
| WTI/Natural gas | 0.3662 | 0.0605 | −1.2678 |
| WTI/Gasoline | 0.5286 | 0.6992 | −0.1162 |
| WTI/Heating oil | 0.8466 | 0.9533 | 0.2703 |
| WTI/Gas oil | 0.8433 | 0.9182 | 0.3275 |
| **Panel C**: Economic recovery period: (2nd Jan. 2013- Jun. 14, 2014) | | | |
| WTI/Brent oil | 0.7354 | 1.5249 | 0.3104 |
| WTI/Natural gas | 0.5025 | 0.0770 | −0.0693 |
| WTI/Gasoline | 0.3776 | 0.5941 | −0.3627 |
| WTI/Heating oil | 0.6634 | 0.8002 | 0.1191 |
| WTI/Gas oil | 0.8860 | 0.9068 | 0.3985 |
| **Panel D**: Oil crash period: (15th June 2014–Nov. 30, 2019) | | | |
| WTI/Brent oil | 0.6146 | 1.2755 | 0.1452 |
| WTI/Natural gas | 0.4567 | 0.0755 | −0.4962 |
| WTI/Gasoline | 0.5706 | 0.7092 | −0.0381 |
| WTI/Heating oil | 0.8086 | 0.8943 | 0.1787 |
| WTI/Gas oil | 0.8606 | 0.9086 | 0.3394 |
| **Panel E**: COVID-19: (1st Dec. 2019- Feb 8, 2021) | | | |
| WTI/Brent oil | 0.4643 | 0.9977 | −0.1459 |
| WTI/Natural gas | 0.2834 | 0.0603 | −3.7968 |
| WTI/Gasoline | 0.5061 | 0.6632 | −0.1101 |
| WTI/Heating oil | 0.7359 | 0.8913 | 0.2075 |
| WTI/Gas oil | 0.6549 | 0.8146 | 0.1382 |

**Note:** Table 5 provides estimates using dynamic conditional covariance between returns of energy commodities with their respected conditional variances employing DCC model. The dynamic ratio is computed using covariance between two energy markets divided by variance of the WTI returns.

subperiods with the exception of COVID-19 period, whereas gas oil is the least one irrespective of subperiods. WTI crude oil is more risk than Brent oil for the different subperiods. The energy markets are more volatile during COVID-19 period relative to other subperiod. The skewness values are different to zero, indicating evidence of asymmetric behavior. In addition, the kurtosis values are high and above the value of the normal distribution, indicating fat tails and leptokurtic behavior. The Jarque-Bera test shows non-normal distribution of all return series for all considered subperiods. The results of ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) unit tests show that all return series are stationary. Furthermore, the Zviot and Andrews (1992) (ZA) test allows for one single break under the alternative hypothesis. The ZA test statistics reject the null hypothesis, confirming that all return series are stationary.

Table 2 reports the unconditional correlations among all energy price returns and shows positive and statistically significant correlations among all pairs. The highest correlation is observed for heating oil and gas oil during different sub-periods Overall the highest correlations among energy price returns is identified during GFC and ESDC. Crude oil (WTI and Brent) are highly correlated with gas oil, heating oil, and gasoline, whereas their correlations with natural gas are low. More importantly, the natural gas is weakly correlated with the other energy markets.

Fig. 3 displays the trajectory of energy futures volatility over the sample period spanning from 1997 to 2021. The graphical evidence shows evidence of high volatility. We notice that the volatility trajectory is similar to WTI oil and Brent oil. This result is explained by the similarity of features and the high correlations between these markets. The energy markets exhibit clustered volatility which corresponds to main events as reported in Fig. 3 and hence justifies the application of GARCH model. For crude oil (Brent and WTI), we observe four important peaks occurring during 1998 Asian crisis, the Gulf war in March 2003, 2008–2009 GFC, and in 2016 corresponding to oil price decline. This result indicates that crude oil markets are vulnerable to economic and political shocks. Natural gas is also affected by Asian crisis, Gulf war, GFC and CVOID-19 crises. Gasoline is less influenced by the Asian crisis compared with the remaining energy markets. Gasoline exhibits the highest peak during Iraq war, the recent great oil bust and COVID-19 outbreak. Heating oil and gas oil are not immune against the Asian crisis, GFC, Gulf war, oil price crash, and COVID-19.

## 5. Results and discussions

### 5.1. Results of spillovers among energy markets

Table 3 presents the estimated results of total volatility spillovers among energy futures under five main economic events: before the GFC, during the GFC and ESDC, economy recovery, during the GFC and ESDC (41.9%) compared to the periods of oil price crash (37.3%) and COVID-19 outbreak (38.2%). The total volatility spillovers decreases during economy recovery period (35.7%). The rise in spillovers during both GFC and ESDC as well as the oil price crash is due to the fact that the oil prices experience two important phases: an upside trend during the GFC where the oil prices exceed $140 in summer 2008 and a downside trend during the oil crisis period where the value of one barrel decreases below $30. We note the WTI oil has a net contributing factor in risk to other markets, whereas the other markets (Brent oil, natural gas, gasoline, heating oil, and gas oil) are net recipients of risk, except for Brent oil and natural gas during COVID-19 where they serve as net contributors of spillovers. More importantly, WTI oil futures is the largest contributor of spillover in the system at different economic events. During the COVID-19 pandemic, the WTI oil contributes 27.2% on the forecasting variance for Brent oil, 0.8% for natural gas, 26.9% for gasoline, 34.3% for heating oil, and 33.5% for gas oil. In contrast, gas oil is the least contributor of volatility to the other markets before the GFC and the oil crisis, while natural gas has minimum contribution in the volatility during the GFC and ESDC, and oil crisis. On the other hand, gas oil is the higher receiver of volatility from the other energy markets, particularly from WTI oil irrespective of the considered subperiods. Similarly, heating oil receives a large portion of volatility from WTI oil. Before the GFC period, heating oil and gas oil (45.9%) are the highest receiver of volatility, followed by Brent oil (44.1) and gasoline (40.2%). WTI oil is the least receiver of volatility from other energy markets under different turbulent periods. Overall, the largest transmitters are WTI oil for all subperiods (222.9–0.7 before the GFC; 213.7–1.7 before the oil crisis; 247.5–2.1 during the oil crisis). WTI oil futures prices act as price discovery variable for the Brent oil, heating oil, gasoline, and natural gas markets. Gas oil, heating oil, gasoline and natural gas have little contribution of risk o the other markets. Moreover, all energy markets are mainly influenced by their own risk.

Although Table 2 provides a valuable information of “average” static spillovers, they do not show the changes taking place during our sample period. Fig. 2 plots the dynamic total volatility spillovers among energy futures markets during different market statuses. The graphical evidence shows that the volatility spillover is time varying and crises-sensitive. Looking at the Panel A, we find that the spillovers decreases significantly in 2000 and increases after the 2007 US subprime crisis. The total spillovers ranges between 25% and 65%. Before the GFC (Panel B), we observe a downside trend in the total volatility after 1999 where the minimum total volatility spillovers attain 25% in the last quarter of 2000. During the GFC and ESDC (Panel C), the spillover index is high and varies between 50% in October 2, 0008 and 68% in 2011. The magnitude of spillovers decreases during the economic recovery (Panel D). It stays relatively stable after July 2013. However, the spillover index jumps in summer 2015 and reaches 65% during the oil crisis (Panel E). It is worth noting that the total volatility spillover experiences a drop in 2017. The total volatility spillovers reach the maximum level during COVID-19 outbreak (Panel F) and especially in March–April

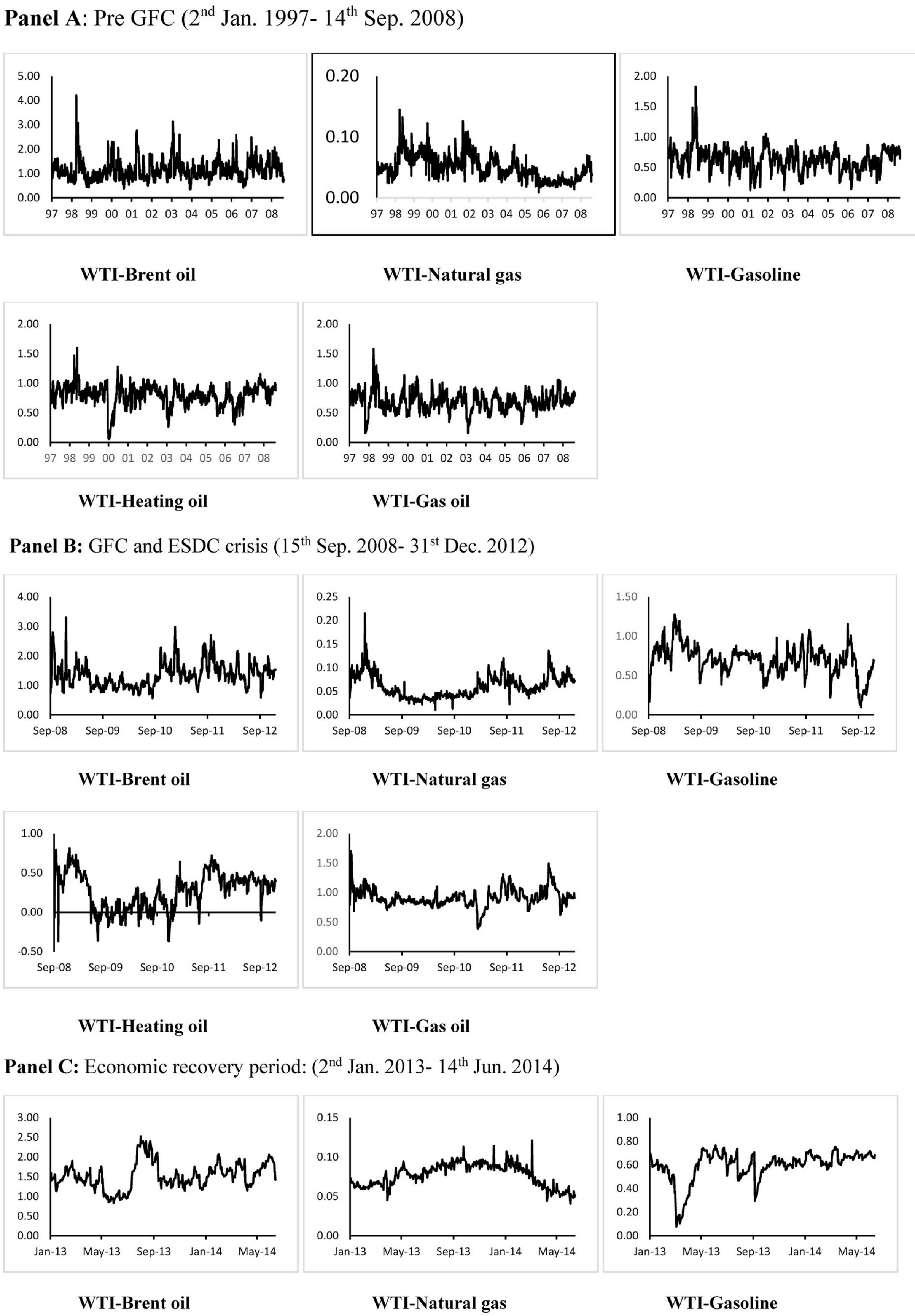
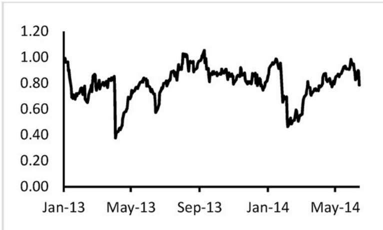
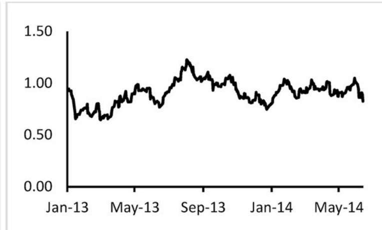



**Fig. 8.** Timeline of dynamic hedge ratio.

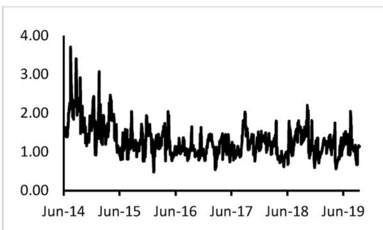



**WTI-Heating oil**

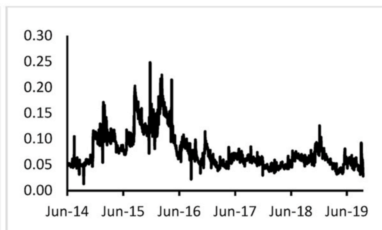



**WTI-Gas oil**

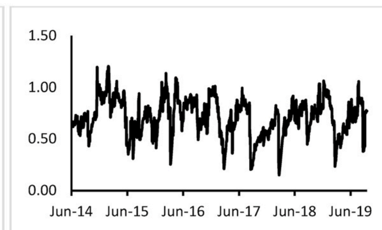
**Panel D:** Oil crash period: (15th June 2014- 30th Nov. 2019)



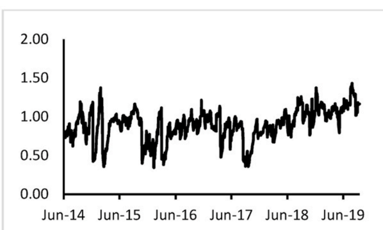

**WTI-Brent oil**



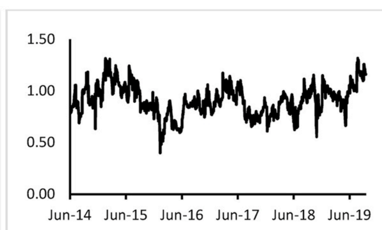

**WTI-Natural gas**




**WTI-Gasoline**

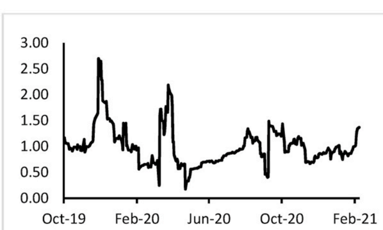



**WTI-Heating oil**

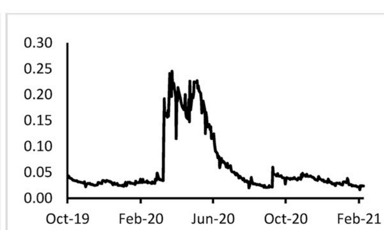



**WTI-Gas oil**

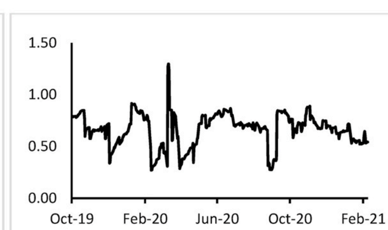
**Panel E:** COVID-19: (1st Dec. 2019- 8th Feb 2021)



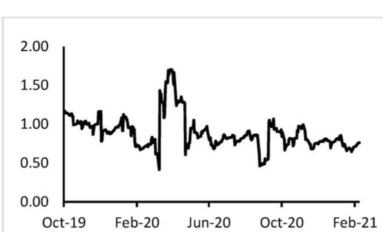

**WTI-Brent oil**



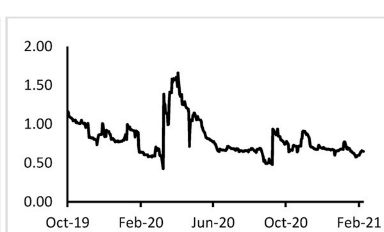

**WTI-Natural gas**




**WTI-Gasoline**




**WTI-Heating oil**




**WTI-Gas oil**

**Fig. 8.** (*continued*).

2020 (70%). This high instability in volatility spillovers due to the significant low global demand for oil due to COVID-19 lockdown and the political tension between the US and China.

We carry two robustness tests to assess the sensitivity of our spillover results (Fig. A2). Specifically, we compute the spillover index for orders 2–6 and plot the minimum, maximum, and the median values to check the choice of the order of the VAR, In addition, we illustrate the spillover index for forecast horizons varying for 2, 5 and 10 days. The graphical evidence shows that spillover indices that appear to follow similar patterns, indicating that the total spillover plot is independent to the choice of the order of the VAR or the choice of forecast horizon.

### 5.2. Contagion and energy market integration

We decompose the price returns raw series into different scales where the D1 scale reveals the highest frequency (or short-run) occurring at an interval from 2 to 4 days. D2 scale stands for the 4–8 days scale, D3 for 8–16 days, D4 for 16–32 days. D5 scale is the lowest scale that occurs between 32 and 64 days. This decomposition provides an extra information useful for energy investors in terms of risk management.

Fig. 4 depicts the evolution of rolling correlations (24 months) among energy futures markets.[5] The results exhibit time-varying correlations among all pairs. The trajectory patterns are different among all pairs. WTI oil and Brent oil show positive and high correlations along the sample period. We observe a drop in correlation during the 2003 gulf war, during 2008–2009 GFC and during COVID-19 outbreak. Looking at the correlations between WTI oil futures with both gasoline and heating oil, they exhibit different trends despite that the correlations are positive along the sample period. We note that WTI oil and heating oil correlation are very low in 2000. The degree correlations between WTI and natural gas are low compared with the other pairs. The highest correlation reaches 0.15 in 2020 and is negative during the ESDC period. This result indicates evidence of portfolio diversification benefits. The correlations among Brent oil futures and other energy markets are similar to those of WTI oil futures. We note that natural gas futures exhibit a low correlation with other energy futures. For gasoline-heating oil, gasoline-gas oil, and heating oil-gas oil pairs, we find dynamic and positive correlations. In addition, they exhibit similar trends during Asian crisis. Overall, the graphical evidence support evidence of the contagion effects among energy markets (WTI oil, Brent oil, gas oil, gasoline, and heating oil).

We use the wavelet correlation matrix to assess the integration among energy futures markets. As shown in Fig. 5, the correlations among all pairs are positive and range from 0.11 to 0.97. The correlations increase for all pairs with wavelet scales rise. More specifically, we find that WTI and Brent are highly correlated, where the correlations range between 0.73 for scale 1 to 0.92 for scale 16. The highest correlation is observed for heating oil-gas oil pair (0.96) at low scales, whereas the least correlation is for natural gas-gas oil pair (0.11) at high scale. We note that the correlations of pairs WTI oil-Brent oil, Brent oil-heating oil, WTI oil-heating oil, WTI-gas oil, Brent oil-gas oil, gasoline-heating oil, and gas oil-gasoline are high particularly for a high wavelet scale (D16). In contrast, natural gas is low correlated with all other energy markets where the highest correlation does not exceed 0.33. For example, at scale 1, it ranges between 0.11 for natural gas-gas oil pair and 0.27 for natural gas-heating oil. At scale 16, it varies between 0.21 for natural gas-gasoline and 0.33 for natural gas-heating oil pair. The natural gas futures serve as a hedging asset for energy investors, particularly for a low wavelet scale.

To evaluate the diversification benefits in energy futures markets, we estimate the correlation parameter at multiple time horizons: 2–4 days, 4–8 days, 8–16 days, 16–32 days, and 32–64 days. Several interesting results can be drawn from the diversification ranking of energy futures pairs. Table 4 presents the estimated results and shows that natural gas provides higher diversification gains. In contrast, the correlations among crude oil, heating oil, gas oil, and gasoline provide less diversification advantages. More importantly, the diversification benefits are important for short-term horizon (2–4 days) and decrease with the increase in time horizon. In addition, the magnitude of the rise in the correlation parameters is linked with an increasing scale.

We now investigate the results of the wavelet multiple correlation highlighted in Fig. 6. We find that the integration among energy markets increases with the wavelet scale. It is less than 0.9 for a low scale and close to 1 for a high scale. The results show high integration among energy futures. Thus, the prices of energy markets under investigation move proportionally over time and frequencies. The financialization and the opening of transmission networks lead to convergence of prices in different locations. The integration evidence in Brent oil and gasoline futures markets limit the possibilities of diversification and arbitrage.

The results of wavelet multiple cross-correlations, illustrated in Fig. 7, Brent oil futures take the lead statistically at both low and middle scales ranging from 1 to 8 whereas for highest scale 16 gas oil leads all the energy markets. This result indicates that Brent oil maximizes multiple correlations against the linear combination of other energy markets. This result is because Brent crude oil market is the leading and largest energy market and a benchmark for pricing of two-thirds of the world's crude oil supplies. The graphical evidence reported in Fig. 7 is consistent with the findings of Table 4.

### 5.3. Portfolio management results

Our results carry substantial implications for energy investors regarding hedging purposes. Our objective is to examine whether including WTI crude oil asset in the portfolio of energy stocks can minimize the risk of the resulting portfolio. We consider a hedged portfolio of WTI and energy stocks in which an energy investor aims to hedge exposure to energy price movements. To do so, we use the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC GARCH) model[6] which has no asymptotic properties (Engle, 2002) to measure hedge ratios, optimal weights and hedging effectiveness for our portfolio consisting of WTI oil with another energy asset including Brent oil, natural gas, heating oil, gasoline, and gas oil. We select WTI because this asset has the highest contribution of risk towards other markets. We evaluate the portfolio risk before the GFC (January 2, 1997 to September 14, 2008), during the GFC and ESDC (September 15, 2008 to December 31, 2012), economy recovery (January 2, 2013 to June 14, 2014), during the oil crisis (June 15, 2014 to November 30, 2019) and during COVID-19 pandemic crisis (December 1, 2019 to February 8, 2021). We are familiar with the structural break tests; however, we have followed the key economic events to split our sample period.

The idea is to build a portfolio with minimum risk without compromising expected return following the methodology of Kroner and Ng (1998). We compute optimal weight of WTI asset in this portfolio (wtWTI), at time $t$ as:

wtWTI = htnon-WTI-htWTI,non-WTIhtWTI-2htWTI,non-WTI + htnon-WTI, with wtWTI = 0wtWTI<0wtnon-WTI0≤wtWTI≤11wtWTI>1 (17)

where (htnon-WTI), htWTI and htWTI, non-WTI are respectively the conditional volatility of energy market other than WTI, the conditional volatility of the WTI asset and the conditional covariance between the WTI and other energy assets, respectively. The optimal budget weight invested in non-WTI oil is equal to (1-wtWTI).

[5] The results of Rolling Window Correlation under different scales are available upon request.

[6] The results of DCC GARCH model are available upon request.

Regarding risk-minimizing hedge ratios, we apply the methodology proposed by Kroner and Sultan (1993). More precisely, we consider a portfolio composed by WTI and another energy asset (WTI and non-WTI). To minimize the risk of a portfolio that is $1 long in WTI oil contract, an energy trader should short $β of the non-WTI asset. Specifically, minimum variance hedge ratio at time t is expressed as follows:

βt = htWTI,non-WTIhtWTI (18)

In the final step, we compute the hedging effectiveness ratio as follows:

HE = 1-VarhedgedVarunhedgedHE = 1-VarhedgedVarunhedged, (19)

where and are respectively the variance of the hedge (a portfolio composed by WTI and other energy asset) and unhedged portfolio (energy portfolio other than WTI). The higher HEHEHE ratio indicates a higher hedging effectiveness.

Table 5 reports the results for the optimal weights, hedge ratios, and hedging effectiveness under different turbulent periods. Looking at the period before the GFC (Panel A), we find that energy traders should hold less WTI assets in their portfolio than other energy assets with the exception of Brent oil, heating oil and gas oil. The optimal weights vary between 0.28% for WTI/Natural gas to 0.61% for WTI/gas oil. The latter pair indicates that, for each $1 dollar budget, the trader should invest $0.61 in WTI oil and the $0.265 in gas oil for minimizing risk while the expected return remains unchanged.

During GFC & ESDC period (Panel B), we observe that investors should hold more WTI futures asset than the other energy asset with the exception of natural gas futures. The optimal weights vary between 0.366 for WTI/Natural gas to 0.846 for WTI/Heating oil. We observe that the proportion invested in WTI futures asset increased during the GFC & ESDC period compared to the pre-crisis period. This is due to the high rise in oil prices during 2008–2009. The proportion invested in WTI futures continue to rise after the financial crises (Economy recover period) for all cases with the exception of gasoline (see Panel C).

This result highlights that energy investors increase their investment in WTI oil asset. During the oil crisis (Panel D), the optimal weight values decrease significantly for Brent oil, natural gas, and gas oil and increase for gasoline and heating oil. We conclude that the optimal weights are sensitive to the energy and financial shocks and investors must change their portfolio structure weights accordingly. Looking at the COVID-19 pandemic crisis (Panel E), the optimal weight values range between 0.28% for natural gas and 0.73% for heating oil. Overall, we find that energy investors should invest more in natural gas futures irrespective o$\beta_t$f sub-period.

Looking at the results of hedge ratios, the coefficient values () are high regardless of the different subperiods and for all energy assets with the exception of natural gas futures asset. The hedge ratio values oscillate between 0.049 for natural gas and 1.133 for Brent oil before the financial crisis (Panel A), between 0.060 for natural gas and 1.349 for Brent oil during the GFC &ESDC period (Panel B), between 0.077 for natural gas and 1.52 for Brent oil during the economy recovery period (Panel C), between 0.075 for natural gas and 1.524 for Brent oil during oil crash (Panel D), and between 0.060 for natural gas and 0.0997 for Brent oil during COVID-19 pandemic outbreak (Panel E). The lowest hedge ratio occurs for natural gas which constitute the cheapest hedging strategy and highest for Brent oil which is the most expensive heeding strategy. The result holds under different sub-periods.[7] The hedging effectiveness results reveal that a combined portfolio provides better risk reductions than an individual energy portfolio for the cases of Brent and gas oil before the GFC period. Under different turbulent period, we show that adding WTI future asset provides a better hedging effectiveness for the case of Brent oil, heating oil and gas oil during GFC& ESDC, economy recovery, and oil crash periods. During COVID-19, adding WTI asset to heating oil and gas oil offers higher diversification benefits. In contrast, we find that, for natural gas and gasoline, adding WTI will not provide a diversification benefit. Fig. 8 plots the hedge ratios under different subperiods. We observe that the hedge ratio is time varying and crises-sensitive. Before the financial crisis, we observe that the hedge ratio experiences a significant jump in 1998 for all cases, corresponding to financial Asian crisis period. The hedge ratio is high for the WTI-Brent oil pair compared to other pairs. This result holds for the different sub-periods. During COVID-19 pandemic crisis, we find a significant jump between March and April for all cases followed by relatively constant hedge ratios between June 2020 and February 2021.

## 6. Conclusion and policy implications

This paper examines the multiscale spillovers between 6 main energy futures namely WTI crude oil, Europe Brent crude oil, heating oil, gasoline, gas oil, and natural gas using different econometric methods, including spillovers index of Diebold and Yilmaz (2012), the wavelet correlation, the correlation ranks matrix, the wavelet multiple correlation, and wavelet multiple cross-correlations. We applied the Maximal overlap discrete wavelet transform (MODWT) to decompose raw series into decomposed series to account for frequencies. More interestingly, we account for recent economic events by decomposing the entire period into different subperiods: (i) Before GFC (January 2, 1997–September 14, 2008), (ii) during GFC and ESDC (September 15, 2008–December 31, 2012), (iii) Economy recovery (January 2, 2013–June 14, 2014), (iv) during oil crisis (June 15, 2014–November 30, 2019), and (v) COVID-19 spread (December 2019–February 17, 2021).

Our results show that energy market volatility is extremely higher during 1998 Asian crisis, 2003 Gulf War, 2008 GFC, great oil bust and COVID-19. On the other hand, we show significant volatility spillovers among energy futures, which is higher during the recent oil GFC and ESDC period. Furthermore, WTI oil remains as an active contributor of volatility to other energy commodity markets before GFC, during GFC and ESDC, before the oil crisis, during the oil crisis, and COVID-19 pandemic spread. Gas oil is the least contributor of volatility spillovers to other markets before the GFC and during the COVID-19 pandemic crisis, while natural gas is the least contributor to volatility spillovers for the whole period, during the GFC and ESDC, during the economy recover, and during the oil crisis. In addition, gas oil is the highest receiver of volatility spillovers from the other energy markets, particularly from WTI oil for all sub-periods. These results are in line with the findings of Ache et al. (2006) and Villar and Joutz '2006) who find evidence of significant cointegration between oil and gas market. Heating oil receives a large portion of volatility from WTI oil. In contrast, WTI oil is the least receiver of volatility spillovers from other energy futures markets under different turbulent periods followed by natural gas.

The results of rolling window correlation method show high correlations between WTI and Brent oil. We note that the degree correlations between WTI and natural gas is low compared to the other pairs and were negative 2000 and 2011–2012, indicating diversification opportunities. These results support the earlier results of Geng et al. (2016) who document that the prices of natural gas show deviations from crude oil prices. In addition, the correlations Brent oil futures and other energy markets are similar to those of WTI oil futures. We find dynamic and positive correlations for gasoline-heating oil, gasoline-gas oil, and heating oil-gas oil pairs. The results show evidence of contagion effects among energy futures markets. The exception occurs for natural gas which is weakly dependent to other energy markets, supporting decoupling hypothesis. Similar results are also reported by Zhang and Ji (2018) who report the presence of decoupling hypothesis for oil-gas prices in the energy markets of US, Europe and Asia. The wavelet correlation matrix reveals that WTI and Brent are highly correlated over

[7] The negative hedge ratio indicates that investors should hold short position in WTI futures asset and a long position in the energy futures asset.

different scales.

However, the degree of integration among energy futures is high and increases with the wavelet scale. Our results are supported by Geng et al. (2017) who find that the coherence pattern among different energy prices varies across time. Using the wavelet multiple cross-correlations, we find that Brent oil futures take the lead statistically at both low and middle scales ranging from 1 to 8, whereas for low scale 16, gas oil leads all the energy markets. The natural gas futures contract is low correlated with all other energy markets, suggesting that natural gas serves as a diversifier asset for different wavelet scales. A portfolio risk valuation shows that the optimal weights, hedging effectiveness and hedge ratios are dynamic, sensitive to economic, and energy events. More importantly, a mixed portfolio provides a higher diversification gain for the majority of cases.

Our analysis based on wavelet multiple cross correlation highlights the presence of returns' comovement across different investment horizons. The level of such comovement varies across different investment periods based on which different pairs of energy commodities as portfolios are arranged. The pair with weak correlation is ranked low whereas commodity pair with strongest correlation is ranked highest. Therefore, in the presence of integrated energy market, diversification is achievable only when the assets are placed in portfolio based on their low correlation. Our measures for hedging ratios and hedging effectiveness also examines the presence of any hedging opportunities which energy commodities can present together with WTI. Hence, though the energy commodities show returns coherence with each other, this coherence varies across different periods and therefore, the possibility for diversification depends on the investment horizon as well as on the level of correlation between these assets.

Our findings have some significant economic implications to energy investors and policy makers. First, energy investors may use out results to optimize the investment for optimal decision making. Energy investors may be aware that the energy markets are vulnerable not only to the law of supply and demand shocks but also to financial and pandemic crises where the spillovers effects attain their maximum level. Specifically, the COVID-19 pandemic outbreak has increased the uncertainty in the oil market. Specifically, the US crude futures fell to negative values, crashed from $18 a barrel to -$38 in April 2020, for the first time in history as stockpiles overwhelmed storage facilities, which left oil investors reeling. Second, investors should consider that the spillovers is sensitive to the time scales in order to manage appropriately their energy portfolio. The identification of the source (direction) and the magnitude of volatility spillovers provide valuable information on how commodity futures are linked under different market scenarios and time horizons. Third, investors may consider the natural gas futures for hedging purposes as it exhibits a weak integration with other energy markets. Policy makers may select the appropriate tools for reducing the economic uncertainty and make the energy markets more stable and healthy particularly under times of financial crises, oil price stress, and health system crises. Regulators should pay attention to the directional and strength of spillovers and identify which energy asset is the most contributor of volatility spillovers to the other markets to identify the risk contagion in energy markets and to predict the effective commodity policies. Policy makers should adjust their policies and rules during financial crises, oil crash and pandemic outbreak periods due their significant damage to the economy.

This research can be extended by examining the connectedness network and risk spillovers between fossil energy and biofuel under different short- and long-terms as well as before and during pandemic outbreak.

## Author statement

**Walid Mensi:** Conceptualization, Writing- Original draft preparation, Supervision, Reviewing and Editing.

**Mobeen Ur Rehman:** Data curation, Methodology, Software, Visualization.

**Xuan Vinh Vo:** Supervision, Visualization, Reviewing and Editing.

## Acknowledgement

This research is funded by the University of Economics Ho Chi Minh City, Vietnam.

## Appendix

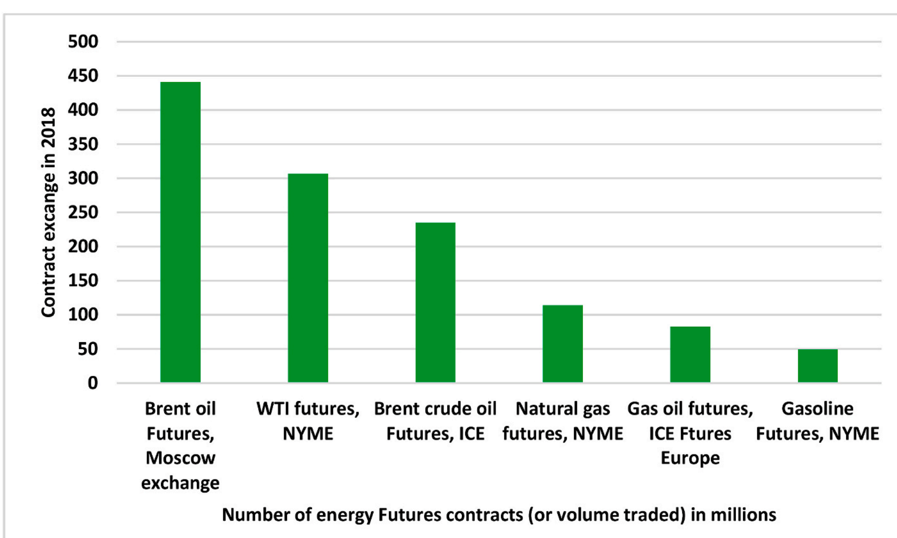



**Fig. A1.** Number of Energy Futures Contracts

**Source:** Statista 2020.

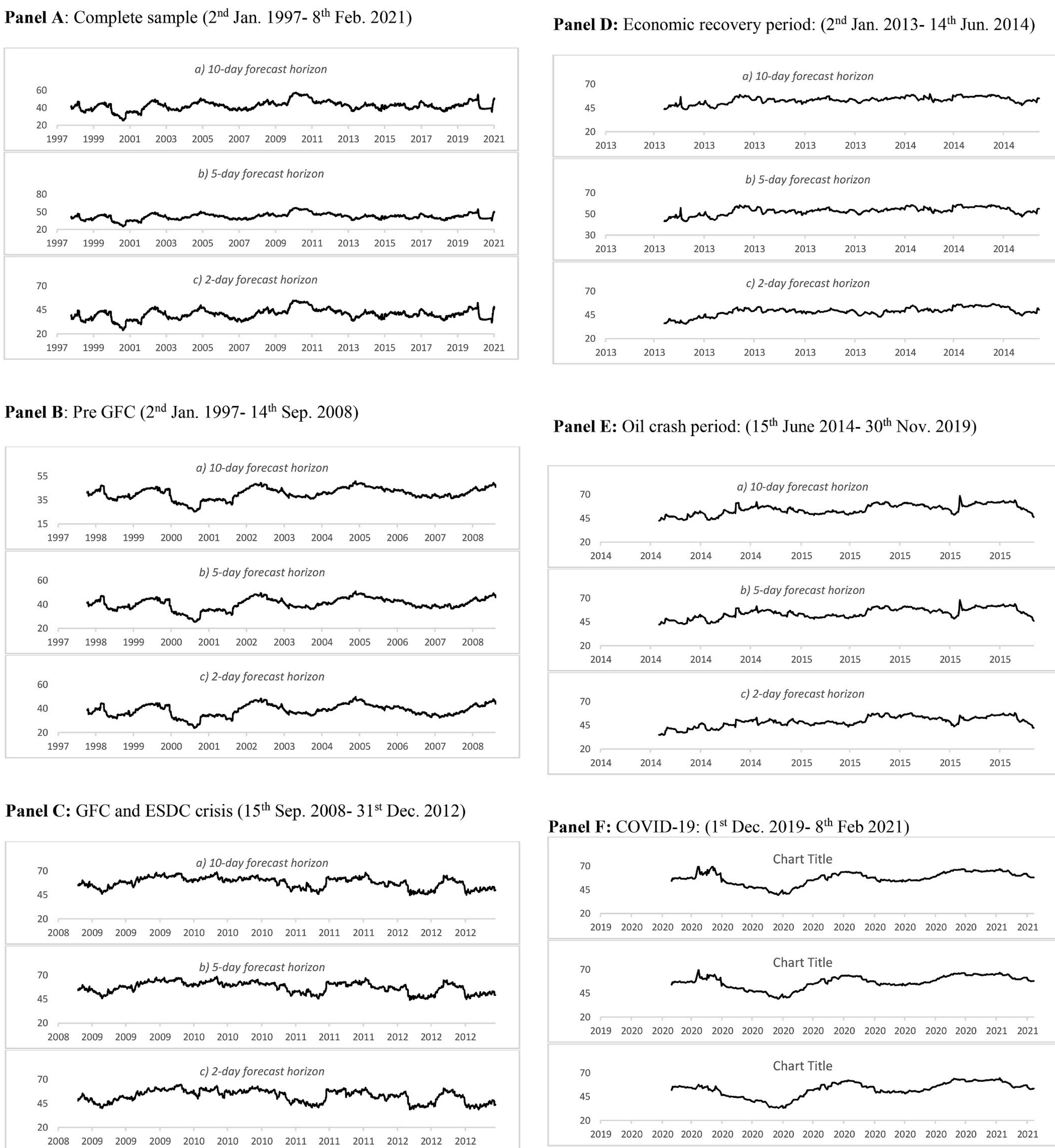



**Fig. A2.** Robustness tests.

**Notes:** (a) sensitivity of the index to the VAR lag structure (max, min, and median values of the index for VAR orders 2–6); (b) sensitivity of the index to forecast horizon (max, min, and median values over 5- to 10-day horizons). The optimal lag structure of 2 is used for estimation, the forecasting windows include 10, 5 and 2 days horizon whereas rolling window of 100 observations is used.

## References

Adhikari, R., Putnam, K., 2020. Comovement in the commodity futures markets: an analysis of the energy, grains, and livestock sectors. Journal of Commodity Markets 18, 100090.

Alizadeh, A.H., Nomikos, N.K., Pouliasis, P.K., 2008. A Markov switching approach for hedging energy commodities. J. Bank. Finance 32, 1970–1983.

Ashe, F., Osmundsen, P., Sandsmark, M., 2006. The UK market for natural gas, oil and electricity: are prices decoupled? Energy J. 27 (2), 27–40.

Barnes, R., Bosworth, R., 2015. LNG is linking regional natural gas markets: evidence from the gravity model. Energy Econ. 47, 11–17.

Baruník, J., Kočenda, E., Vácha, L., 2015. Volatility spillovers across petroleum markets. Energy J. 36, 309–329.
Batten, J.A., Ciner, C., Lucey, B.M., 2017. The dynamic linkages between crude oil and natural gas markets. Energy Econ. 62, 155–170.
Bekiros, S., Diks, C., 2008. The relationship between crude oil spot and futures prices: cointegration, linear and nonlinear causality. Energy Econ. 30, 2673–2685.
Broadstock, D., Li, R., Wang, L., 2020. Integration reforms in the European natural gas market: a rolling-window spillover analysis. Energy Econ. 91, 104939.
Brown, S.P., Yücel, M.K., 2002. Energy prices and aggregate economic activity: an interpretative survey. Q. Rev. Econ. Finance 42 (2), 193–208.
Brown, S.P., Yücel, M.K., 2008. What drives natural gas prices? Energy J. 29, 45–60.
Cai, G., Zhang, H., Chen, Z., 2019. Comovement between commodity sectors. Phys. Stat. Mech. Appl. 25, 1247, 125.
Chang, K., Lee, C., 2020. The asymmetric spillover effect of the Markov switching mechanism from the futures market to the spot market. Int. Rev. Econ. Finance 59, 374–388.
Chen, P.F., Lee, C.C., Zeng, J.H., 2014. The relationship between spot and futures oil prices: do structural breaks matter? Energy Econ. 43, 206–217.
Chiou-Wei, S., Chen, S., Zhu, Z., 2020. Natural gas price, market fundamentals and hedging effectiveness. Q. Rev. Econ. Finance 78, 321–337.
Cornish, C., Bretherton, C., Percival, D., 2006. Maximal overlap wavelet statistical analysis with application to atmospheric turbulence. Boundary-Layer Meteorol. 119, 339–374.
Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. 182, 119–134.
Diebold, F.X., Yilmaz, K., 2016. Trans-Atlantic stock volatility connectedness: U.S. and European financial institutions, 2004–2014. J. Financ. Econom. 14 (1), 81–127.
Diebold, F.X., Yilmaz, K., 2016b. Trans-Atlantic stock volatility connectedness: U.S. and European financial institutions, 2004–2014. Energy Economics 29, 46–63.
Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econ. Stat. 20 (3), 339–350.
Feng-bin, L., Yi, L., Shuan-hong, W., Shou-yang, W., 2008. Information spillovers among international crude oil markets — an empirical analysis based on CCF method and ECM. Systems Engineering - Theory & Practice 28, 25–34.
Geng, J.B., Ji, Q., Fan, Y., 2017. The relationship between regional natural gas markets and crude oil markets from a multi-scale nonlinear Granger causality perspective. Energy Econ. 67, 98–110.
Geng, J.B., Ji, Q., Fan, Y., 2016. The impact of the North American shale gas revolution on regional natural gas markets: evidence from the regime-switching model. Energy Pol. 96, 167–178.
Guhathakurta, K., Dash, S.R., Maitra, D., 2020. Period specific volatility spillover based connectedness between oil and other commodity prices and their portfolio implications. Energy Econ. 85, 104566.
Hartley, P.R., Medlock III, K.B., Rosthal, J.E., 2008. The relationship of natural gas to oil prices. Energy J. 29, 47–65.
Hong, Y., 2001. A test for volatility spillover with applications to exchange rates. J. Econom. 103, 183–224.
Karali, B., Ramirez, O.A., 2014. Macro determinants of volatility and volatility spillover in energy markets. Energy Econ. 46, 413–421.
Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. Rev. Financ. Stud. 11 (4), 817–844.
Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. J. Financ. Quant. Anal. 28 (4), 535–551.
Li, R., Joyeux, R., Ripple, R., 2014. International natural gas market integration. Energy J. 35, 159–179.
Li, X., Sun, M., Gao, C., He, H., 2019. The spillover effects between natural gas and crude oil markets: the correlation network analysis based on multi-scale approach. Phys. Stat. Mech. Appl. 524, 306–324.
Lin, B., Su, T., 2021. Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities? Res. Int. Bus. Finance 56, 101360.
Lin, S., Tamvakis, M.N., 2001. Spillover effects in energy futures markets. Energy Econ. 23, 43–56.
Lovcha, Y., Perez-Laborda, A., 2020. Dynamic frequency connectedness between oil and natural gas volatilities. Econ. Modell. 84, 181–189.
Magkonis, G., Tsouknidis, D.A., 2017. Dynamic spillover effects across petroleum spot and futures volatilities, trading volume and open interest. Int. Rev. Financ. Anal. 52, 104–118.
Mensi, W., Hammoudeh, S., Nguyen, D.K., Yoon, S.M., 2014. Dynamic spillovers among major energy and cereal commodity prices. Energy Econ. 43, 225–243.
Mensi, W., Rehman, M.U., Vo, X.V., 2020. Spillovers and co-movements between precious metals and energy markets: implications on portfolio management. Resour. Pol. 69, 101836.
Mensi, W., Rehman, M.U., Hammoudeh, S., Vo, X.V., 2021a. Spillovers between natural gas, gasoline, oil, and stock markets: evidence from MENA countries. Resour. Pol. 71, 101983.
Mensi, W., Rehman, M.U., Maitra, D., Al-Yahyaee, K.H., Vo, X.V., 2021b. Oil, natural gas and BRICS stock markets: evidence of systemic risks and co-movements in the time-frequency domain. Resour. Pol. 72, 102062.
Mensi, W., Tiwari, A., Bouri, E., Roubaud, D., Al-Yahyaee, K.H., 2017. The dependence structure across oil, wheat, and corn: a wavelet-based copula approach using implied volatility indexes. Energy Econ. 66, 122–139.
Mu, X., 2007. Weather, storage, and natural gas price dynamics: fundamentals and volatility. Energy Econ. 29 (1), 46–63.
Nick, S., Thoenes, S., 2014. What drives natural gas prices? —a structural VAR approach. Energy Econ. 45, 517–527.
Panagiotidis, T., Rutledge, E., 2007. Oil and gas markets in the UK: evidence from a cointegrating approach. Energy Econ. 29, 329–347.
Percival, D.B., Walden, T., 2000. Wavelet Methods for Time Series Analysis. Cambridge University Press, Cambridge.
Rehman, M.U., Bouri, E., Eraslan, V., Kumar, S., 2019. Energy and non-energy commodities: an asymmetric approach towards portfolio diversification in the commodity market. Resour. Pol. 63, 101456.
Serra, T., 2011. Volatility spillovers between food and energy markets: a semiparametric approach. Energy Econ. 33, 1155–1164.
Silvapulle, P., Moosa, I.A., 1999. The relationship between spot and futures prices: evidence from the crude oil market. J. Futures Mark. 19, 175–193.
Villar, J.A., Joutz, F.L., 2006. The Relationship between Crude Oil and Natural Gas Prices. Working paper.
Zhang, D.Y., Ji, Q., 2018. Further evidence on the debate of oil-gas price decoupling: a long memory approach. Energy Pol. 113, 68–75.
Zivot, E., Andrews, D.W.K., 1992. Further evidence on the great crash, the oil price shock, and the unit root hypothesis. J. Bus. Econ. Stat. 10 (3), 251–270.