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Dynamic volatility transfer in the European oil and gas industry☆

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ABSTRACT

The study examines dynamic volatility transmissions among European energy industry participants along the production lines of Upstream, Midstream, Downstream, and Integrated Oil Gas (IOG) segments. Using Diebold-Yilmaz (2012, 2014) spillover index, during the sample period of October 2006 to June 2022, we find significant internal volatility spillover among the European energy sector participants, primarily emanating from Upstream companies. In subsamples, we show that Downstream and Midstream segments can also become volatility transmitters under certain conditions. More importantly, the large Russian IOG companies became significant volatility transmitters after 2022 with the onset of Russia's war on Ukraine, potentially causing major system instability because these IOG firms were traditionally volatility absorbers in the network. Overall, we provide insights about the interconnectedness among European energy companies during normal and extreme market conditions and highlight important system dynamics that could be useful for policy makers and investors.

1. Introduction

Today, the oil and natural gas industry plays a critical role in the global economy and the everyday life of citizens who rely on oil and gas for work, transportation, heating, and nourishment, among others. The processes, systems and the companies involved in producing and distributing oil and gas are increasingly complex, capital-intensive and continuously evolving with technological innovations (CRS, 2021). Due to the high entry barriers, the industry is characterized by an oligopolistic structure where governments often have a direct or an indirect involvement in the management of these strategically and economically important national companies. The involvements are non-negligible, since these national oil companies (NOCs) controlled over $3 trillion in assets in 2019 and produced much of the world's oil and gas, while their operations are often non-transparent to the public (IMF, 2022). With the recognition of energy risk as a new source of systemic risk, (e.g., Jang et al., 2020; Caporin et al., 2023; Yang and Hamori, 2021), there have been an increasing number of studies into oil price behaviors in relation with equity markets, debt markets and political uncertainty (e.g., Kang et al., 2017a, 2017b).

It is important to understand the link between oil and gas markets. First, the supply and demand dynamics of all energy commodities are interconnected (Al-Maamary et al., 2017). Second, as a number of companies are involved in both exploration and production of oil and gas, their financial performance can be influenced by the performance of both commodities simultaneously (George et al., 2016). While traditionally Brent, WTI, and natural gas prices are strongly correlated, gas prices seem to have decoupled recently, as government policies and environmental regulations have preferential treatment towards natural gas. For example, the European Union (EU)'s energy strategy change with shift towards gas as a "green alternative" from oil (SPGlobal, 2022) and diversification of the energy supply-chain, increase reliance on US and other non-European energy sources call for examination of oil and gas prices' together.

Globally, a few oil-rich countries are the dominant players in the oil and gas industry. While the US energy sector is privatized and therefore data is readily available, it is not the case for non-US companies (IMF, 2022). Thus energy studies tend to focus on the US market (e.g., Antonakakis et al., 2018; Zhao, 2020), in particular studies on renewable energy and clean energy sources (Ferrer et al., 2018). Apart from the US, the European continent is also a big player in the energy sector. Although the European Union produced 1.9 million Tera Joule (TJ)

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worth of natural gas in 2020 (Eurostat, 2023), it remained heavily dependent on external energy, with an over 80% increase in natural gas dependence ([import - export] / inland demand). The top gas exporters to the EU are Russia (23.3%), Norway (22.7%), Ukraine (10.2%) and Belarus (8.9%) (Eurostat, 2023).

Even without external disruptions such as Russia's war on Ukraine (Council of Europe, 2023), energy prices can be highly volatile because of the slow production/distribution process and the limited number of large production players (who can collude on supply and engage in price setting). While there are hopes that in the long run, the use of nuclear power, renewables and alternative energy sources can be exploited to reduce carbon emissions and improve energy security throughout Europe, in the short term the end users are largely dependent on traditional oil and gas producers (IMF, 2022).

In this study, we focus on the European energy market where the impact of environment and geopolitical risks on stability and sustainability are of growing concern, especially since the start of Russia's war on Ukraine. Specifically, we investigate the volatility spillover among crude oil, natural gas, unleaded gasoline prices and the stock prices of major European oil and gas companies over the period from October 2006 to June 2022. We divide our sample into different industry segments, namely Upstream, Midstream, Downstream and Integrated Gas and Oil, to analyze the flow of volatility throughout the production and distribution process.

The economic and financial studies often distinguish between fundamental versus financial excess volatility. Fundamental excess volatility of different economic entities can be interconnected through the supply chain of goods, services (including technology) and capital flows. These effects are known in the literature as spillovers (Masson, 1999), interdependence and interconnectedness (Forbes and Rigobon, 2002; Forbes, 2012), or fundamental-based contagion (Kaminsky and Reinhart, 2000). On the other hand, financial contagion is defined as shocks that can trigger crises elsewhere and spread to all or most of the system participants (Masson, 1999).

In the empirical literature, various methods have been used to measure connectedness. For example, Granger causality network by Billio et al. (2012), Conditional Value at Risk (CoVaR) by Liu et al. (2022), Marginal Expected Shortfall (MES) by Acharya et al. (2012), and VaR-GARCH model by Arouri et al. (2012). In the last decade, Diebold and Yilmaz (2012)'s generalized spillover index (DY spillover index, hereafter), using generalized forecast error variance decomposition of Pesaran and Shin (1998) and Koop et al. (1996), have gained traction in risk transmission analysis, particularly in energy sector analysis. In extensions for the model, for example, Antonakakis et al. (2023) and Ghosh et al., 2023 examine volatility transmissions, using time-varying parameter VAR variant of the connectedness approach.

The popularity of the DY spillover index can be attributed to its intuitiveness and flexibility, suitable for network analysis even in market turbulence and transition. Specifically, the model considers the dynamic nature of volatility, allowing for changing market conditions and accounting for the interaction between the market (or the network) participants. In addition, the approach can distinguish between directional spillovers, aiding the identification of the main source of potential systemic risk. The net spillover matrix is a popular tool for representing systematically important elements within the set of companies. Overall, we adopt the DY spillover index because of the above listed statistical benefits and to facilitate comparison of our results with findings in the extant energy spillover literature which extensively use this application.

In this study, we provide comprehensive network analysis of the European energy sector in relation to oil and natural gas prices using the DY spillover index. Our contribution to the literature is threefold. First, to the best of our knowledge, our work is the first comprehensive analysis of the volatility transmission dynamics across all major European oil and natural gas companies. Covering >90% of the total market capitalization of the European energy sector from October 24, 2006 to June 30, 2022. The existing literature covers only a handful of major oil companies (e.g., Antonakakis et al., 2018), and over shorter periods. Our time series coverage includes three exogenous shock periods, namely the 2008 Global Financial Crisis (GFC), the European sovereign debt crisis (ESDC), and the Covid-19 pandemic (C19).

Second, while previous studies examine volatility transmission across individual energy companies across normal and stress periods, we provide a full network approach view. By including all major European energy network participants, we seek to display the most significant net connections (i.e., edges in the network) and provide key insights into the vulnerable points of the system.

Third, by differentiating across Upstream, Downstream, Midstream, and Integrated Oil and Gas segments along the production line, we identify the emission mechanism for the idiosyncratic volatility spillover shocks in the context of European companies and identify system fragility points during stressful condition. We note that the energy market has an exposure to external impacts, such as weather, political decisions, wars, and pandemics. System instability can arise from various sources, such as Russia's war on Ukraine which has adversely affected the publicly traded European energy companies, many of which are in the IOG segment. Since the start of the war in February 2022, the IOG segment has become a significant volatility transmitter. This evidence is rather alarming since prior to the Russian conflict, the IOG segment serves as volatility receivers and absorbers and supports system stability.

In summary, this paper provides new insights into the volatility transmission mechanism in the European oil and gas industry with a unique network approach, highlighting various causes of system shifts, and show how different types of shocks (e.g., demand, supply and uncertainty) affect various groups of the energy supply chain participants.

The rest of the paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 presents the research methodology followed by data description. Section 4 provides the full sample and subsample results. Section 5 concludes.

2. Literature review

The interconnectedness of the energy commodity and the equity market has attracted much research attention over the years. Earlier studies focus on the connection between oil prices and overall stock returns, providing various conclusions. Using US stock data and crude oil prices, Sadorsky (1999), Jones and Kaul (1996) and Kling (1985) find an inverse relationship, while Chen et al. (1986) find insignificant results. Huang et al. (1996), on the other hand, examine the relationship between oil futures and US stocks and conclude that while price movements of oil futures have no impact on aggregate equity market indexes, they do influence specific stocks. In a follow up work, Sadorsky (2001) finds support for the inverse relationship between stock returns and oil prices by using interest rates and foreign exchange rates as additional explanatory variables.

In addition to the numerous studies into the linkages between oil prices and stock returns, (e.g., Cunado and de Gracia, 2003, El-Sharif et al., 2005; Kilian and Park, 2009; Wang et al., 2013), there are studies on the volatility relationship across the commodity markets (including oil) and the equity market. Mostly aggregated stock market indices are considered in studies evaluating the link between oil and stock market volatility in the USA. (e.g., Phan et al., 2016; Arouri et al., 2011a) and in major oil producing countries (Arouri et al., 2011b).

Phan et al. (2016) document positive contemporaneous relationship between trading volume, price volatility, and bid-ask spread, using crude oil, *E*-mini NASDAQ and S&P 500 index futures data. While Maghyereh et al. (2016) analyze the connections between oil and equity indices across 11 countries, their insights into European companies remain limited. Thus, a comprehensive analysis of major European oil and gas companies will be a material contribution to the literature.

Despite the numerous extant studies on the spillover between crude oil and the stock market, there are relatively few studies on natural gas and financial markets. Ewing et al. (2002) analyze the volatility spillover between oil and natural gas markets using the GARCH model, while Zhang et al. (2017) investigate the spillover effect of the stock market volatility index for crude oil and natural gas markets. Zhang et al. (2020) study the return and volatility spillover from commodity and utility sectors to equity indices in North America and Europe. Their results show that, compared to natural gas, crude oil has a greater volatility spillover on the utility stock indices. Dai and Zhu (2022) document the return volatility spillover and the dynamic connectedness of WTI crude oil futures, natural gas futures, and the Chinese stock market indices. They find a high interdependence among all analyzed asset classes, and a sharp increase in the total volatility spillover during major crisis events.

Malik and Ewing (2009) show that aggregate stock market indices may mask the heterogeneity of responses to oil price volatility in the different sectors. They examine the transmission of volatility shocks between oil prices and five US major sectors and find significant volatility transmission between the oil market and some of the examined sectors. Arouri et al. (2012) investigate the volatility transmission between oil and stock markets in Europe and the U.S.A. at a sectoral level and show significant volatility interaction between oil and stock market sectors. Interestingly Arouri et al. (2012) show that for Europe, the transmission of volatility is much more apparent from oil to stocks than from stocks to oil.

Using information from the Dow Jones Stoxx Europe 600 index and seven DJ Stoxx sector indices, Arouri et al. (2012) report significant volatility spillovers between oil prices and sector stock returns. Sadorsky (2012) on the other hand, analyzes the volatility spillovers between oil prices and the US clean energy and technology sectors, and finds that clean energy sector prices are more highly correlated with technology sector volatility than with oil price volatility. In a related study, Ferrer et al. (2018) measure the volatility and return spillover between oil prices and the returns of the green energy sector in the USA. They find that crude oil price is not a key driver of the stock market performance of renewable energy companies. In the context of the Chinese market, Wang and Wang (2019) investigate the volatility spillover between WTI and 11 Chinese equity sectors, while Dai and Zhu (2022) examine volatility spillover and the dynamic relationships among commodity futures (WTI and NG) and the Chinese sector indices linked to the Belt and Road initiative (BRI).

To our knowledge, only a handful of recent papers investigate the volatility spillover at the individual stock level in relation to oil and gas prices. Antonakakis et al. (2018) examine the volatility spillovers and co-movements among oil prices and stock prices of major oil and gas corporations. They find significant volatility spillover effects between oil, and oil and gas companies with BP, Chevron, Exxon, Shell, and Total being the major net transmitters. Corbet et al. (2020) test for the existence of volatility spillovers and co-movements among energy-focused corporations during the outbreak of the Covid-19 pandemic. They find positive and economically meaningful spillovers from falling oil prices to both renewable energy and coal markets. Wu et al. (2021) investigate the risk connectedness using a Value-at-Risk (VaR) measure within a network comprising the top 20 global energy companies. Their results show that the dynamics are mainly driven by the US stock market volatility and investors' sentiment over the full sample, while energy market risks and exchange rate movements exert significant but short-term influences.

Only a handful of studies (e.g., Antonakakis et al., 2018; Corbet et al., 2020; Wu et al., 2021) examine the oil and gas industry at the firm level. However, these studies either combine the analysis of energy commodity firms, such as coal, electric utility and renewable energy companies, or examine only a few key market players globally, or focus only on the US market. This study widens the research scope of Corbet et al. (2020) by focusing on European oil and natural gas companies, providing more insights into the sustainability and stability of the European energy market which is an acute concern for decision makers globally after 2022, with the start of Russia's war on Ukraine.

3. Data and research methodology

3.1. Data

This study focuses on the European energy market. Our sample provides a representative coverage of energy companies with a primary exchange listing on any European exchange in the *Energy - Fossil Fuels* business sector, based on the Refinitiv Business Classification (TRBC).[1] From each subsector, daily stock price, trading volume and market capitalization data are collected for the 40 companies from the following six relevant industry groups:

- *Oil and Gas Exploration and Production*
- *Oil and Gas Drilling*
- *Oil Related Services and Equipment*
- *Oil and Gas Transportation Services*
- *Oil and Gas Refining and Marketing*
- *Integrated Oil and Gas*

Following the extant energy literature (e.g., Kang et al., 2017b; Ewing et al., 2018), companies are classified into Upstream, Midstream, Downstream, and IOG segments as follows:

- *Firms in Oil and Gas Exploration and Production & Oil and Gas Drilling* → Upstream
- *Firms in Oil and Gas Transportation Services & Oil Related Services and Equipment* → Midstream
- *Firms in Oil and Gas Refining and Marketing* → Downstream
- *Firms with a mix of business, active in upstream, midstream, and downstream activities* → Integrated Oil and Gas (IOG)

From each of the four different industry segments, we choose the 10 largest European exchange listed corporations (as of June 2022) with some further constraints. Specifically, we require daily continuous stock market coverage from October 24, 2006, until the end of the sample period or until the liquidation (delisting) of the company. The start of the sample period is restricted by our data access with the intent to provide a current picture of the industry including all major players as of 2022. GALP was listed on October 24, 2006, while ROSN went public in July of the same year. The finalized sample period is from October 24, 2006, to June 30, 2022. The sample is restricted to liquid stocks, defined as stocks where the number of zero daily volatility does not exceed 20% of the observations. The start of the sample is two years of the financialization of the energy market (see Irwin and Sanders, 2011) so it is unlikely to affect our analysis.

Table 1 summarizes our sample of 40 European energy companies with relevant available data by industry segments, covering 91.7% of the total market capitalization of the European oil and gas industry. 98.6% of the market capitalization of IOG companies, 60.4% of the Upstream segment, 69.4% of the Midstream segments, and 92.2% of the Downstream segment.

We complement our daily European energy stock dataset, and include information on external assets, namely commodity futures and equity market return. We collect daily exchange listed futures information on ICE Europe Brent Crude Oil (Brent), the Dutch TTF Natural

[1] Alternative classification of companies, using the Global Industry Classification Standard (GICS), is also performed. This grouping is slightly different based on GICS, and due to the lack of data, only seven-element company groups can be created. The summary of the corporates is described in Table C.1 in the Online Appendix. There is no major difference in the results regardless of the classification standard.

Table 1
Summary of the sample companies by industry segments of Upstream, Midstream, Downstream and IOG, based on the TRBC industry classification.

Ticker	Company Name	Exchange	Industry group	Capitalization
Integrated Oil and Gas				
SHEL	Shell	UK	Integrated Oil and Gas	205,631
TTEF	TotalEnergies	France	Integrated Oil and Gas	141,241
EQNR	Equinor	Norway	Integrated Oil and Gas	113,235
GAZP	Gazprom	Russia	Integrated Oil and Gas	103,229
ROSN	Rosneft	Russia	Integrated Oil and Gas	58,363
ENI	Eni	Italy	Integrated Oil and Gas	50,832
LKOH	Lukoil	Russia	Integrated Oil and Gas	41,347
SIBN	Gazprom Neft	Russia	Integrated Oil and Gas	28,593
SNGS	Surgutneftegaz	Russia	Integrated Oil and Gas	11,618
TATN	Tatneft	Russia	Integrated Oil and Gas	12,702
Sum				**766,789**
Upstream				
NVTK	Novatek	Russia	Oil & Gas Exploration and Production	40,117
LUNE	Orron Energy	Sweden	Oil & Gas Exploration and Production	12,906
HBR	Harbour Energy	UK	Oil & Gas Exploration and Production	4106
DNO	DNO	Norway	Oil & Gas Exploration and Production	1680
TLW	Tullow Oil	UK	Oil & Gas Exploration and Production	901
MAUP	Maurel and Prom	France	Oil & Gas Exploration and Production	1002
SQZ	Serica	UK	Oil & Gas Exploration and Production	801
CNE	Capricorn Energy	UK	Oil & Gas Exploration and Production	743
TETY	Tethys Oil	Sweden	Oil & Gas Exploration and Production	256
PHARP	Pharos Energy	UK	Oil & Gas Exploration and Production	124
Sum				**62,637**
Midstream				
TENR	Tenaris	Italy	Oil Related Services and Equipment	18,588
SRG	Snam	Italy	Oil & Gas Transportation Services	18,135
ENAG	Enagas	Spain	Oil & Gas Transportation Services	5620
VOPA	Vopak	Netherlands	Oil & Gas Transportation Services	3306
VLLP	Vallourec	France	Oil Related Services and Equipment	2965
SUBC	Subsea 7	Norway	Oil Related Services and Equipment	2907
SBMO	SBM Offshore	Netherlands	Oil Related Services and Equipment	2735
TRNF	Transneft	Russia	Oil & Gas Transportation Services	2723
EUAV	Euronav	Belgium	Oil & Gas Transportation Services	2691
FLUX	Fluxys Belgium	Belgium	Oil & Gas Transportation Services	359
Sum				**60,028**
Downstream				
BP	BP	UK	Oil & Gas Refining and Marketing	97,670
NESTE	Neste	Finland	Oil & Gas Refining and Marketing	32,991
REP	Repsol	Spain	Oil & Gas Refining and Marketing	22,689
OMVV	OMV	Austria	Oil & Gas Refining and Marketing	17,660
GALP	GE SGPS	Portugal	Oil & Gas Refining and Marketing	9485
PKN	PKN Orlen	Poland	Oil & Gas Refining and Marketing	6723
MOLB	MOL	Hungary	Oil & Gas Refining and Marketing	5730
ROSNP	OMV Petrom	Romania	Oil & Gas Refining and Marketing	5319
RUBF	Rubis	France	Oil & Gas Refining and Marketing	2880
LTS	Grupa Lotos	Poland	Oil & Gas Refining and Marketing	2832
Sum				**203,980**

Note: Market capitalization is expressed in million €.

Gas (NG), the ICE Europe Low Sulphur Gasoil (Gasoil), and daily returns on FTSE All World Index (FTSEALL). Asset i price volatility (V_{it}) at time t is $V_{it} = |ln(P_{it}) - ln(P_{it-1})|$ where P_{it} is the daily closing price of asset i on day t.[2] Descriptive statistics of the volatility series are reported in Table 2 (graphs of the daily volatilities are in Figs. A.1 – A.5 in the Appendix).

Two stocks, TLW and LUNE, are outliers in terms of maximum value and return volatility. In December 2019, the CEO and the director of explorations of TLW left as the company was facing major problems across its oil and gas exploration fields in Ghana, Uganda, Kenya, and Guyana. Then almost immediately the Covid-19 pandemic struck. As for LUNE, the last day of trading in its shares on Nasdaq Stockholm was June 22, 2022, as it changed its name to Orron Energy after merging its E&P business with Aker BP, to reflect its new status as a pure-play renewables business. Prior to delisting in 2022, LUNE's stock price decreased from 444.1 SEK on June 17 to 10.2 SEK, on June 20, erasing almost 98% of the company's market capitalization.

3.2. The volatility spillover index

To examine spillovers in the volatility of major oil companies' stock prices and commodity prices, we apply the generalized version of the spillover index, introduced in Diebold and Yilmaz (2012). The DY model is based on a VAR method (Sims, 1980) with a major focus on the calculation of Forecast Error Variance Decomposition (FEVD). Given that the ordering of the variables in the VAR model is hard to justify, the generalized VAR framework (e.g., Koop et al., 1996) is used in which FEVDs are invariant to the ordering of the variables. Given the goal is to assess the magnitude of volatility spillovers rather than to identify the causal effects of structural shocks, this appears to be the preferred choice in the present context.

Under the generalized VAR framework, we consider a covariance-stationary VAR (p) model with N-variable i.e., $Y_t = \sum_{t=1}^{p} \psi_i Y_{t-1} + e_t$,

[2] Our choice of volatility measures is motivated by Forsberg and Ghysels (2007), who show that absolute returns are good volatility predictors, as they have good population performance, low sampling errors and are robust to jumps. In robustness checks, results are also replicated with GARCH(1,1) model (see Figs C.16–C.23).

Table 2
Descriptive statistics of realized volatilities of the selected companies and the external assets.

Name	Mean	Median	St. dev.	Min.	Max.	Skew.	Kurt.	Jarque-Bera	ADF	Obs.
Integrated Oil and Gas										
SHEL	0.012	0.008	0.013	0	0.194	3.755	29.301	0.16***	−8.15***	4092
TTEF	0.012	0.009	0.013	0	0.182	3.806	27.758	0.14***	−9.23***	4092
EQNR	0.013	0.010	0.014	0	0.195	2.674	14.768	0.04***	−8.09***	4092
GAZP	0.014	0.010	0.019	0	0.363	6.184	71.857	0.91***	−8.28***	4092
ROSN	0.015	0.010	0.020	0	0.451	7.517	112.242	2.19***	−9.16***	4092
ENI	0.012	0.008	0.014	0	0.234	4.435	40.979	0.30***	−8.69***	4092
LKOH	0.014	0.009	0.018	0	0.258	4.689	39.041	0.27***	−8.22***	4092
SIBN	0.013	0.008	0.017	0	0.310	4.842	44.282	0.35***	−7.92***	4092
SNGS	0.015	0.010	0.020	0	0.374	5.97	69.215	0.84***	−8.77***	4092
TATN	0.017	0.011	0.021	0	0.354	4.898	45.566	0.37***	−8.56***	4092
Upstream										
NVTK	0.016	0.011	0.019	0	0.302	4.467	39.026	0.27***	−9.04***	4092
LUNE	0.018	0.011	0.066	0	4.020	55.455	3371.658	1940***	−3.89**	4092
HBR	0.024	0.016	0.032	0	0.855	9.026	170.717	5.02***	−10.15***	4092
DNO	0.024	0.016	0.028	0	0.612	4.833	61.024	0.65***	−10.03***	4092
TLW	0.023	0.016	0.034	0	1.264	14.352	452.31	35.02***	−10.58***	4092
MAUP	0.016	0.011	0.018	0	0.306	3.021	22.536	0.09***	−8.84***	4092
SQZ	0.024	0.016	0.032	0	0.882	7.995	159.506	4.38***	−13.07***	4092
CNE	0.018	0.013	0.020	0	0.346	4.311	39.681	0.28***	−9.86***	4092
TETY	0.020	0.014	0.022	0	0.310	3.783	27.717	0.14***	−12.14***	4092
PHARP	0.019	0.013	0.023	0	0.423	4.348	42.201	0.32***	−9.16***	4092
Midstream										
TENR	0.016	0.012	0.017	0	0.241	3.192	20.142	0.08***	−9.28***	4092
SRG	0.010	0.007	0.010	0	0.213	4.382	52.184	0.50***	−10.87***	4092
ENAG	0.011	0.008	0.011	0	0.16	3.144	22.142	0.09***	−10.86***	4092
VOPA	0.012	0.008	0.013	0	0.168	3.301	20.638	0.08***	−11.09***	4092
VLLP	0.023	0.016	0.025	0	0.388	3.502	26.156	0.13***	−10.21***	4092
SUBC	0.019	0.014	0.020	0	0.237	2.652	13.013	0.03***	−8.50***	4092
SBMO	0.016	0.011	0.018	0	0.282	3.915	29.245	0.16***	−10.20***	4092
TRNF	0.016	0.010	0.021	0	0.325	4.891	44.008	0.35***	−8.77***	4092
EUAV	0.018	0.013	0.018	0	0.165	2.201	7.649	0.01***	−10.19***	4092
FLUX	0.009	0.006	0.01	0	0.151	2.807	19.227	0.07***	−12.88***	4092
Downstream										
BP	0.012	0.008	0.014	0	0.217	3.636	28.442	0.14***	−8.38***	4092
NESTE	0.016	0.011	0.016	0	0.213	2.774	14.214	0.04***	−10.28***	4092
REP	0.014	0.010	0.015	0	0.171	3.063	16.904	0.06***	−8.15***	4092
OMVV	0.015	0.011	0.016	0	0.213	3.517	23.925	0.11***	−9.35***	4092
GALP	0.014	0.010	0.016	0	0.221	3.345	22.144	0.09***	−9.20***	4092
PKN	0.016	0.012	0.015	0	0.134	1.782	5.600	0.01***	−10.49***	4092
MOLB	0.014	0.010	0.015	0	0.162	2.97	15.782	0.05***	−8.24***	4092
ROSNP	0.013	0.008	0.016	0	0.162	3.279	17.915	0.06***	−8.92***	4092
RUBF	0.011	0.008	0.012	0	0.125	2.729	12.015	0.03***	−9.69***	4092
LTS	0.016	0.012	0.016	0	0.17	2.108	8.439	0.02***	−11.11***	4092
External assets										
Gasoil	0.015	0.010	0.016	0	0.332	4.753	52.546	0.49***	−9.53***	4092
FTSEALL	0.007	0.004	0.008	0	0.100	3.712	23.283	0.10***	−7.60***	4092
NG	0.021	0.012	0.030	0	0.479	5.183	45.08	0.36***	−9.64***	4092
Brent	0.016	0.011	0.018	0	0.309	4.209	41.809	0.31***	−7.58***	4092

Notes: Jarque-Bera statistics are expressed in millions. The 1%, 5%, and 10% significance levels are indicated with ***, **, *, respectively.

where $e_t \sim i.i.d(0, \Sigma)$ is a $N \times 1$ vector of residuals. The moving average representation of VAR model takes the form of $Y_t = \sum_{j=0}^{\infty} A_j e_{t-j}$, where A_j is an $N \times N$ coefficient matrix. A_j follows a recursive pattern as $A_j = \psi_1 A_{j-1} + \psi_1 A_{j-2} + \ldots + \psi_p A_{j-p}$, A_0 is an identity matrix and $A_j = 0$ for $j < 0$. Diebold and Yilmaz (2012) apply a generalized framework of VAR model to calculate the H-step ahead generalized forecast error decomposition, as follows:

$$\Phi_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{1}$$

where σ_{ii} is the i element on the principal diagonal of Σ. Since the sum of each row of $\Phi_{ij}(H)$ is not equal to 1, each element of the matrix is normalized by taking the ratio:

$$\widetilde{\Phi}_{ij}(H) = \frac{\Phi_{ij}(H)}{\sum_{j=1}^{N} \Phi_{ij}(H)} \tag{2}$$

so that the decomposition including shocks in each market equals to unity, i.e., $\sum_{j=1}^{N} \widetilde{\Phi}_{ij}(H) = 1$ and the total decomposition of all variables sums to N, i.e., $\sum_{ij=1}^{N} \widetilde{\Phi}_{ij}(H) = N$. The total spillover index which explains the spillovers from all the assets to total FEVD is computed as

$$TS(H) = \frac{\sum_{ij=1, i \neq j}^{N} \widetilde{\Phi}_{ij}(H)}{N} \bullet 100 \tag{3}$$

The directional spillovers which measure the volatility spillover received by asset i from the universe of markets j is calculated as

$$DS_{i \leftarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\Phi}_{ij}(H)}{N} \bullet 100 \tag{4}$$

and

$$DS_{i\to j}(H) = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\Phi}_{ji}(H)}{N} \bullet 100 \tag{5}$$

Finally, the net spillovers from one variable to another for a set of variables are calculated by taking the difference of Eq. (4) and (5) as follows

$$NS_i(H) = DS_{i\to j}(H) - DS_{i\leftarrow j}(H) \tag{6}$$

4. Empirical results

4.1. Static, full sample interconnectedness analysis

We start the analysis of the volatility transmission across European energy companies, oil and gas commodity futures, and a global equity index by investigating their spillover effects. Table 3 presents key volatility spillovers results for our energy company universe, based on the full sample estimation. For brevity, Table 3 is only a subset of Table B.1 in the Appendix. Diebold and Yilmaz (2014) report a 78.3% spillover index in their investigation of the financial system, which they consider as very high. In our case the total volatility spillover index is also high, reaching 76.1%, which indicates high interconnectedness among all assets. Our spillover index is higher than that shown by Antonakakis et al. (2018) who study a handful of the world largest oil and gas companies from 2001 to 2016 and find 69.8% for the DY spillover index. In Table 3., the largest pairwise volatility spillovers (colored by magenta) can be detected from Brent to Gasoil (11.9%), from HBR to SRG (11.9%) and from HBR to CNE (10.7%).

A participant is either a net volatility transmitter (positive values in *Net* row) or receiver (negative values in *Net* row), based on the difference between emitted and taken volatilities. The net spillover indices indicate that FLUX (−77.4%) is the largest volatility receiver, followed by FTSEALL (−76.3%). Similarly, we find that Gasoil and Brent are net volatility receivers (with −32.8%, −14.1% values, respectively), suggesting that these commodity volatilities are impacted by the oil and gas companies' volatilities. Antonakakis et al. (2018) and Dai and Zhu (2022) using a small sample of global oil and gas companies and Chinese sample, respectively, find that energy commodities are net volatility receivers in their network. On the other hand, we find that NG is a net volatility transmitter (26.0%), which underlines the importance of including this commodity in the study in addition to oil.

Furthermore, all Downstream companies are net volatility receivers while Upstream companies are net transmitters (except for PHARP). Wu et al. (2021) also find that the Downstream segment is affected the most and the Upstream segment contributes the most to the volatility spillover of the energy system. Although, IOG companies tend to be volatility receivers; four Russian companies are net transmitters.

Using the connectedness table (see Table B.1), we construct a matrix containing the pairwise net directional connectedness of all pairs and provide a visual representation in Fig. 1.

An arrow from variable y_i to variable y_j denotes a positive net directional connectedness (in other words, variable y_i omits more or explains more volatility than y_j observing these two nodes in insulation). The companies are grouped and color-coded by sector. External assets are represented in one circle; however, they do not belong together thus they are colored differently. The colors of the arrows indicate the industry segment of the transmitter participant. Only those edges with the uppermost 5% magnitude of the net spillover are shown. Thicker arrows indicate connections from the top 1%, the strongest pairwise spillover connections.

In Fig. 1, the blue colored arrows dominate, indicating that the Upstream companies are the primary volatility transmitters in the system. Of the possible 114 arrows, 88 are from this segment, accounting for 77.2% of all edges. This is followed by the Midstream segment with 19.3%, then the IOG segment with 1.8%. Natural Gas and Brent both have one outgoing edge which means 0.9% each. Gasoil and FTSEALL have no outgoing edges, nor the whole Downstream segment. The distribution on the receiving side is more even. The Midstream segment has 34 arrows which is 29.8% of the possible edges, followed by the Downstream segment (29.8%), the IOG segment (20.2%) and the Upstream segment (7.9%). FTSEALL has 6.1%, Gasoil 4.4% and Brent 2.6% of the incoming edges. Natural Gas has no incoming edges.

There are a few underlying reasons for why the Upstream segment is likely the primary source of volatility emission. Companies in this segment are associated with the beginning of the production cycle and are likely to have the strongest connection with oil supply shocks. In this sense, the segment is directly linked to OPEC decisions (see Behrouzifar et al., 2019). This is consistent with King et al. (2012) who find that many Upstream companies are state-owned and publicly traded companies in this segment must coexist with the related political decisions. They also highlight that in addition to the segment's dependence on the political decision-making process in oil-exporting nations, the world supply of oil is occasionally reduced by war, terrorism, and guerrilla activity that are the result of political instability or conflict.

Despite the large number of connectedness articles, there are few written on the deeper structure of the networks and the top nodes. In the same vein, the more recent papers by Wu et al. (2021) and Dai and Zhu (2022) do not highlight the top nodes in their network analysis. To find the main drivers of the network, we use the net (out-in) and total connections. Table 4 identifies the most vulnerable points of the network, by showing the participants with the most edges. The first four columns provide the aggregated relationships, with subsequent columns representing the nodes having the most incoming and outgoing edges separately.

The participants with the most outgoing and net edges comprise of the same set of companies, HBR, TLW, DNO, VLLP, and LUNE in this order. Of these, only VLLP is from the Midstream segment while the remainder belong to the Upstream segment. Tables 3 and B.1. show that FLUX, FTSEALL, and SRG are the strongest volatility receivers, considering the spillover index. These nodes also have the highest number of incoming edges (although in a different order, FTSEALL, FLUX, and SRG). They are followed by ENAG and SHEL. The three companies, FLUX, SRG and ENAG, are from the Midstream segment, while SHEL is from the IOG segment.

Table 4 and Fig. 1 provide three insights. First, there is no asset which is concurrently volatility receivers and emitter. Second, the Upstream segment contributes the most to the volatility spillover, with a number of companies (e.g., LUNE, HBR, DNO and TLW) that are strong volatility transmitters with numerous net edges. Third, there is no such external asset on the recipient side and the incoming edges are more evenly distributed.

4.2. Dynamic, rolling-window-based interconnectedness analysis

While all industries tend to shift over time, this is especially true for the energy industry which has experienced significant changes in recent years with technological innovations and the adaptation of new alternative resources. In addition, the energy sector is sensitive to external demand and supply shocks. To address the dynamics of the European energy market, we investigate the changing connectedness in the network by adopting a rolling-window approach. Fig. 2 presents the total volatility spillover index over the sample period based on the 250-day rolling window and a 10-day ahead forecast horizon.[3]

It is interesting to note that even though the static total spillover

[3] In robustness checks, alternative rolling window sizes (500-day and 750-day), forecast horizons (20 and 30-day ahead) and confidence levels (90% and 99%) are also used. The results are consistent (see Figs C.3 – C.14).

Table 3
The strongest pairwise spillovers, top raw representing source node and left column target.

	⋯	LUNE	HBR	⋯	TLW	⋯	CNE	⋯	SRG	⋯	FLUX	Gasoil	FTSEALL	⋯	Brent	From
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
LUNE	⋯	97.3	0.2	⋯	0.2	⋯	0.1	⋯	0.0	⋯	0.0	0.0	0.0	⋯	0.0	2.7
HBR	⋯	1.5	47.2	⋯	8.5	⋯	2.9	⋯	0.4	⋯	0.1	1.2	0.2	⋯	2.1	52.8
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
TLW	⋯	1.5	9.4	⋯	54.4	⋯	1.9	⋯	0.3	⋯	0.1	1.0	0.2	⋯	1.6	45.6
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
CNE	⋯	2.2	10.7	⋯	6.9	⋯	20.8	⋯	0.5	⋯	0.1	1.1	0.5	⋯	1.9	79.2
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
SRG	⋯	3.4	11.9	⋯	5.7	⋯	3.5	⋯	9.8	⋯	0.3	1.3	0.5	⋯	2.2	90.2
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
FLUX	⋯	2.1	5.0	⋯	4.2	⋯	2.5	⋯	0.8	⋯	16.9	1.2	0.4	⋯	1.3	83.1
Gasoil	⋯	2.3	7.7	⋯	5.6	⋯	1.5	⋯	0.3	⋯	0.1	17.8	0.5	⋯	11.9	82.2
FTSEALL	⋯	3.7	5.6	⋯	4.1	⋯	3.3	⋯	0.6	⋯	0.1	1.6	3.1	⋯	2.4	96.9
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
Brent	⋯	2.6	9.8	⋯	5.9	⋯	2.1	⋯	0.4	⋯	0.1	9.0	0.5	⋯	17.5	82.5
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
To	⋯	121.2	230.2	⋯	170.4	⋯	90.9	⋯	18.5	⋯	5.7	49.4	20.6	⋯	68.4	*76.1*
Net	⋯	**118.5**	**177.4**	⋯	**124.8**	⋯	**11.7**	⋯	**−71.7**	⋯	**−77.4**	**−32.8**	**−76.3**	⋯	**−14.1**	

Note: This table is a subset of the whole spillover matrix which is represented in Table B.1.

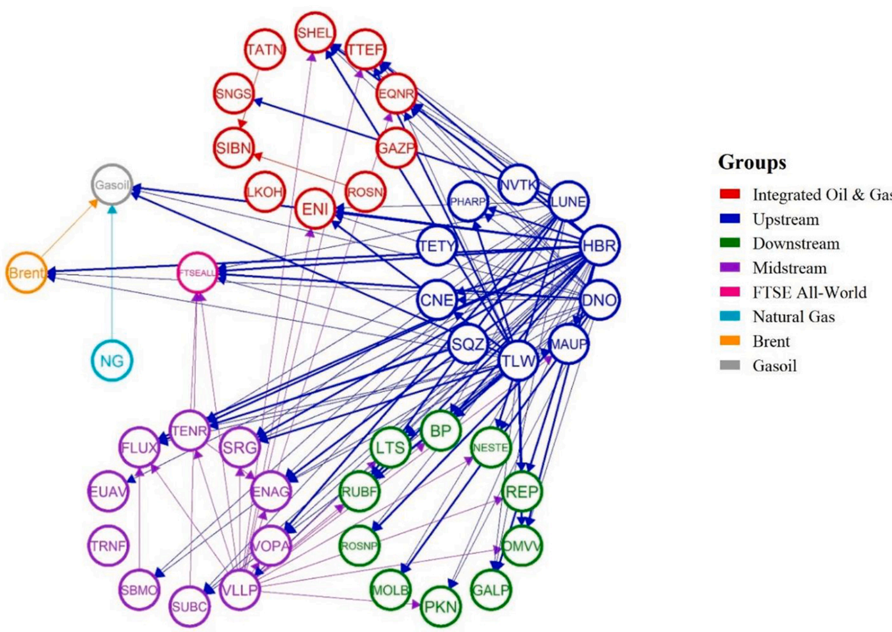


Fig. 1. Static, full-sample volatility interconnectedness network.
Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow indicates the industry segment of the transmitter asset. Thinner lines represent the strongest 5% of connections, while thicker lines show connections from the top 1%. For the figure, we use Lag = 3 and H = 10 model inputs.

Table 4
European energy market participants with most edges in the Network.

Top 5 Sum				Top 5 Incoming		Top 5 Outgoing		Top 5 net	
Node	Total	In	Out	Node	In	Node	Out	Node	Net
HBR	29	0	29	FTSEALL	7	HBR	29	HBR	29
TLW	23	0	23	FLUX	6	TLW	23	TLW	23
DNO	18	0	18	SRG	6	DNO	18	DNO	18
VLPP	18	1	17	ENAG	6	VLPP	17	VLPP	16
LUNE	16	0	16	SHEL	5	LUNE	16	LUNE	16

index is 76.04% when examined over time, it is mainly above this value and fluctuates between 73% and 93%. This is another indication that a time-varying approach provides significantly more information for energy market stakeholders compared to a static analysis.

The investigation horizon contains three periods that the Euro Area Business Cycle Dating Committee considers to be crises (EABC, 2022). These are the Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC) and the Covid-19 pandemic (C19). Fig. 2 shows the time-series trend with crisis periods marked in pink, blue, and yellow shading, respectively. Consistent with Bouri (2015) and Kang et al.

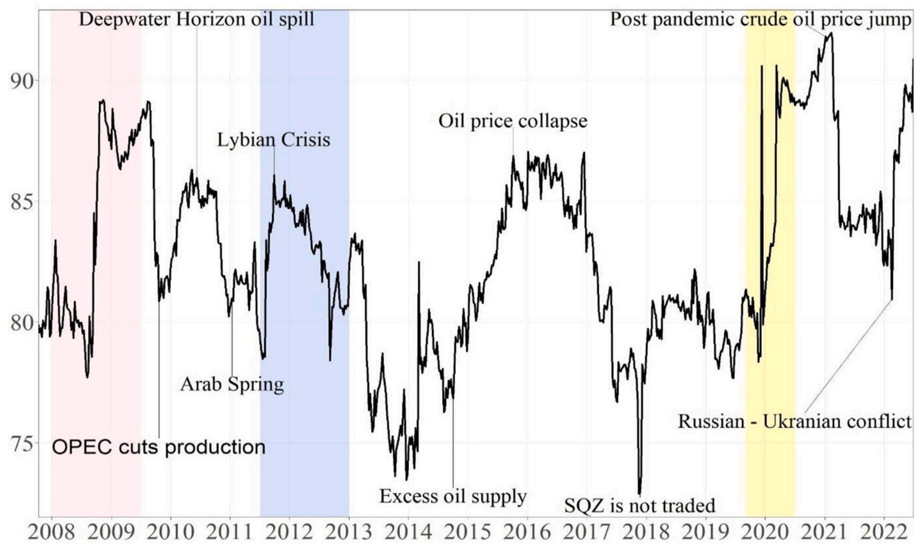


Fig. 2. Total volatility spillover over the observation horizon.
Note: The total volatility (100%) is indicated on the left axis. The shaded areas represent various crises periods, namely the GFC: January 1, 2008 – July 1, 2009 (pink area), the ESDC: July 1, 2011 – January 1, 2013 (blue area), and the C19: September 1, 2019 – July 1, 2020 (yellow area). In creating the figure, we used Lag = 3 and H = 10 as model parameters with window size of 250 days.

(2017a) who study volatility spillover during the GFC, we find that the volatility spillover increases during turbulent periods. However, the spillover effect did not fade out immediately after the end of the GFC but persisted until mid-2010. A plausible explanation for the persistence is the April 2010 Deepwater Horizon oil spill in the Gulf of Mexico that was caused by a BP oil rig.

The second phase of high spillover of about 85% is observed during the period between mid-2011 to 2014, before they collapsed to below 75% at the end of 2014. These spillovers reflect the uncertainty in the energy market due to the 2011 Arab Spring, the Libyan political unrest, the turbulence in Bahrain, Egypt, and Yemen, as well as the Syrian Civil War in the post-2011 period. Additionally, these events overlap with the ESDC, which increased uncertainty in the PIIGS country. Figs. B1 – B4 show the heightened volatility index values for companies from these countries. The third phase of increased spillover was evident from 2015 when oil prices hovered around $50. It is noteworthy that before the oil price declined from mid-2014 to 215, volatility spillovers reached a local minimum. Fantazzini (2016) suggests that there was a negative bubble in 2014–2015, which decreased oil price beyond the level justified by economic fundamentals, and that might explain the low volatility spillovers.

The Covid-19 pandemic paralyzed real economic activity around the world. Oil prices experienced unprecedented decline because of plummeting demand due to reduced economic activity, limited international travel, and implementation of lockdowns. By June 30, 2022, there were over 600 million confirmed Covid-19 cases and 6.5 million confirmed deaths globally. Despite the decline in oil prices, the high spillover index persisted. There are a few publications on volatility spillovers in the oil industry during the Covid-19 pandemic (e.g., Ghorbel and Jeribi, 2021; Mensi et al., 2022; Shahzad et al., 2021) which all show similar results.

In 2022, Russia started an offensive against Ukraine. The eight Russian companies (GAZP, ROSN, LKOH, SIBN, SNGS, TATN, NVTK, and TRNF) within the observed universe accounted for 26.66% of the total market capitalization. The connectedness index is particularly sensitive to these companies. On February 24, 2022, following the start of a full-scale invasion of Ukraine by Russia, the Moscow Exchange (MOEX) suspended trading and foreign clients were banned from selling any securities. On March 23, 2022, it was announced that trading of 33 Russian Ruble securities would resume on March 24 for residents of Russia, but foreign investors remained restricted to repo and derivative deals. Between February 22, 2022, and June 30, 2022, the MOEX index dropped to 2204.85 from 3084.74. Although Western sanctions further sank the Russian stock market, revenues collected through the oil and gas industries, which accounted for about 40% of the Russian government state budget, remained largely the same (Sturm and Menzel, 2022).

4.3. Spillover effects in crisis periods

While the impact of crises on the energy market is well documented in the empirical literature, it is less common to compare different turbulent periods. Several studies (e.g., Wu et al., 2021) examine tranquil and turbulent periods, with narrow focus on large global energy companies. We provide a more comprehensive analysis of European energy companies using a network approach to identify system vulnerability points. For additional insights into different market turbulences, we perform a static spillover analysis on three separate turbulent periods, namely the GFC, ESDC, and C19. Figs. 3a – 3c show that the strongest net volatility transmitters differ across the subsample periods, and different underlying effects move the market during these turbulent periods.

The IOG segment becomes significant volatility emitter during the GFC. This effect can be connected to Russian companies as 36% of the significant edges originate from the six Russian IOG companies. This ratio increases to 52% if NVTK (Upstream) and TRNF (Midstream) are also considered. Political anxieties following the conflict with Georgia and the sharp decline in the price of Urals heavy crude oil (Kuboniwa, 2014) contributed to the 2008–2009 subprime crisis in Russia, resulting in the 2008 Russian market crash, wiping out more than $1 trillion in value.

During the ESDC crisis, the Upstream companies' volatility emission significantly declined but one Downstream company, NESTE, was a volatility emitter. In NESTE's 2012 annual financial report, serious intermittent production problems in the main facility are mentioned, exacerbated by the escalating the ESDC and the deepening crisis between Iran and the West.[4] While crude oil prices peaked in early spring

[4] Source: NESTE 2012 Annual report, https://www.neste.com/sites/default/files/attachments/corporate/investors/agm/review_by_the_board_of_directors_2012.pdf.

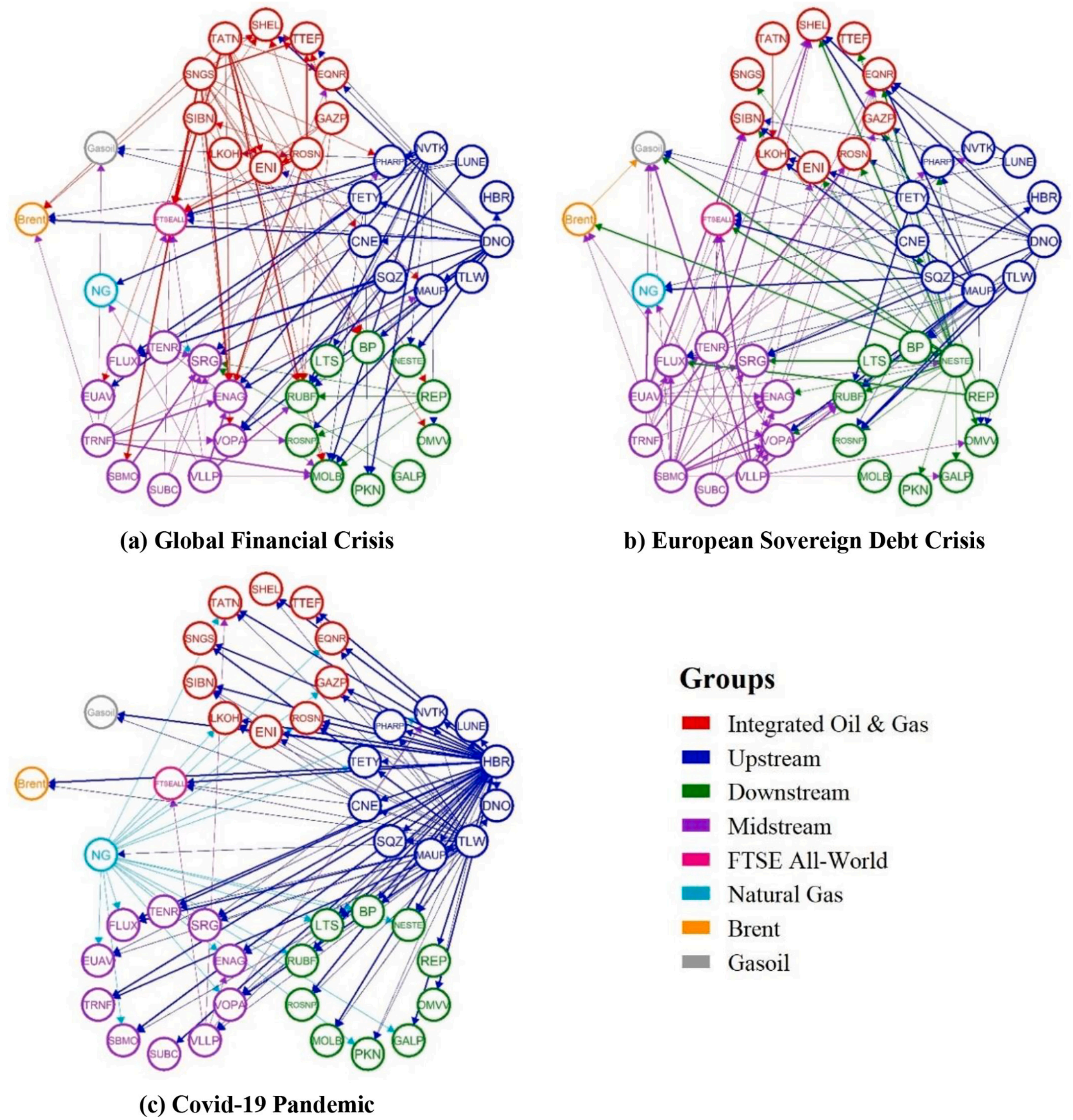


Fig. 3. Network model of volatility spillover in European oil and gas industry in different sub-periods.
Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow denotes the asset from which it originates. Thinner lines represent the strongest 5% of connections, while thicker lines show the top 1% strongest connections. For the figure, we use Lag = 3 and H = 10 model inputs. The three crisis periods: the Global Financial Crisis (GFC) from January 1, 2009, to July 1, 2009; the European Sovereign Debt Crises (ESDC) from July 1, 2011 to January 1, 2013; and the Covid-19 pandemic (C19) from September 1, 2019 to July 1, 2020.

at $125/bbl amid concerns of a deepening crisis between Iran and the West, the recession fears in Europe pushed oil prices back down to $90. Midstream companies increased their investments in the 2006–2012 period to adopt new production methods, build new pipelines for shale production and transport LNG. In 2012, it was estimated that another $250 billion in capital investment would be required over the next 20 years. This put extreme pressure on Midstream companies and their investors in view of the demand decline due to ESDC and the increase in supply from US shale oil. [5]

In the C19 period, 89% of the edges originated from three nodes, name HBR, TLW and NG. Global gas demand slumped in Q1 2020 with

[5] Deloitte, 2012 Deloitte Oil & Gas Conference A new world of opportunity, https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Energy-and-Resources/dttl-ER-The-rise-of-the-midstream.pdf.

the implementation of C19 lockdowns. The pandemic hit an already declining gas demand due to historically mild temperatures over the first few months of the year. In February 2020, the TTF month-ahead fell to a 10-year low and in the second quarter, the economic stress pushed prices further down into unchartered territories. With record low prices, even small price movements had a relatively high impact on volatility. The demand slump for NG had an indirect effect on the volatility of HBR and TLW as they have high exposure to gas exploration and extraction.[6]

4.4. Distribution of imported and emitted volatility over time

Previously, in the static plot, it was highlighted that imported volatility is evenly distributed among the four sets of companies while external assets receive way less. Fig. 4a proves that this statement is persistent in time. It shows the distribution of the most powerful linkages, as seen in the network plot of Fig. 1. The same rolling window method is utilized here.

In Fig. 4b, the persistent presence of blue shaded area and purple shaded are imply consistent volatility emission from the Upstream segment and the Midstream segment, respectively. In addition, various idiosyncratic shocks can be identified. For example, the top section of the graph (with red spikes) shows that the IOG segment becomes a significant volatility importer three times during our sample period. All these cases can be connected to Russian companies. The first spike is identical with the results of Fig. 3a during the GFC, the second spike around Crimea annexation, and the third spike coincides with the Russia-Ukraine war which started in February 2022.

The steep devaluation of the Russian Ruble that started in the second half of 2014 added to the financial crisis (Viktorov and Abramov, 2020). Investors sold off their Russian assets, which further decreased the value of the Ruble and raised concerns of a possible financial disaster. At least two significant causes contributed to the loss of trust in the Russian economy. First is the decrease in oil prices, a significant export for Russia, in 2014 by about 50%. Second is the implementation of international economic sanctions on Russia in response to its annexation of Crimea and the war in Donbas (Frye, 2019).

There are five different idiosyncratic volatility spillover periods driven by Natural Gas. According to Growitsch et al. (2015), the volatility of TTF increased during the final quarter of 2007, but decreased from the first quarter of 2008 to the third quarter of 2009. The change can partly be explained by the decline in crude oil prices. The price of gas in continental Europe is frequently index linked to the price of crude oil (Zhang and Ji, 2018). Brent Crude Oil peaked on July 11, 2008, and reached its local minimum on December 24, 2008. TTF behaves very similarly, with a longer price decreasing period, and reaching its local minimum on September 3, 2009.

Two significant events in 2011 were particularly noteworthy in terms of natural gas supply and consumption. The supply side was impacted by the revolution against powerful regimes in the Middle East and in North Africa. These two regions are important natural gas providers to European companies (Del Sarto, 2016). On the demand side, the Fukushima nuclear accident that followed the tsunami which hit Japan on March 11, 2011, had a huge impact on the energy discussion in the European Union and the region's projected demand for natural gas (Hayashi and Hughes, 2013). In reaction to widespread protests against nuclear power, politicians started researching alternatives, with gas acting as an essential safety net.

The third spillover shock connected to natural gas is related to the Crimea annexation period. As a form of pressure, Russia announced two consecutive price increases for retail gas in Ukraine through Gazprom in April 2014. As a result of the lack of advance payments, tensions increased and on June 16, 2014, Russia cut off the gas supply to Ukraine. An interim deal was struck at the end of March 2015 following several months of negotiations and the assistance of the European Union (Reuters, 2015).

The natural gas market instability was already evident during the Covid-19 pandemic, driven by an initial decline in demand and rapid price rise in the summer of 2021 (Fulwood, 2022). When Russia's aggression against Ukraine in the first few months of 2022 raised concerns about the safety of Europe's gas supply and the unpredictability of gas prices on the continent, the situation deteriorated further. In the first quarter of 2022, the EU spent a projected €78 billion on gas imports, €27 billions of which came from Russia. EU's net gas imports had increased by 10% over this time, while imports of liquefied natural gas (LNG) had increased by 72% year on year (EC DG-Energy, 2020, 2022).

During 2006–2022, two discernible Brent-related volatility spillover spikes occurred, the first of which happened in 2017. OPEC and non-OPEC members decided to execute a nine-month production cut on May 25, 2017. Russia, a major non-OPEC oil producer, and OPEC agreed to renew their oil supply curbs through the end of 2018 (Bloomberg, 2017). The spillover became apparent once more in late 2021, this time due to the Omicron form of the Covid-19 virus. The revelation that other European nations are imposing travel restrictions on the UK as it manages a growing wave of the highly transmissible virus added new pressure to demand and spurred a sell-off. The front-month futures price for Brent fell by 12% on November 26 after the World Health Organization classified the SARS-CoV-2 Omicron as a variant of concern. A little more than a month later, oil prices rose on hopes that the omicron virus version would be milder, calming worries about the demand forecast (Reuters, 2022).

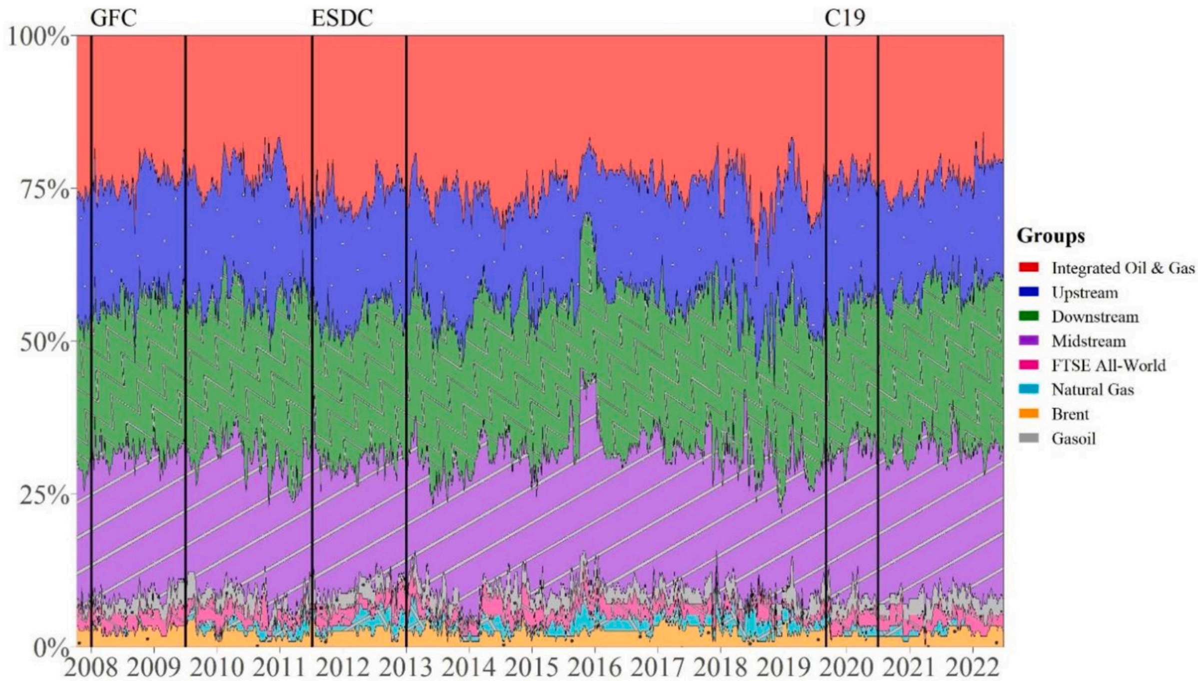
5. Conclusion

This study examines the co-movements and spillovers in volatility between the stock prices of key European oil and gas companies and the prices of oil and gas commodities in the period from October 24, 2006 to June 30, 2022. To the best of our knowledge, this is the first empirical study that examines volatility co-movements and spillovers utilizing company-level data from 40 oil and gas companies clustered to distinct segments, in a network setting.

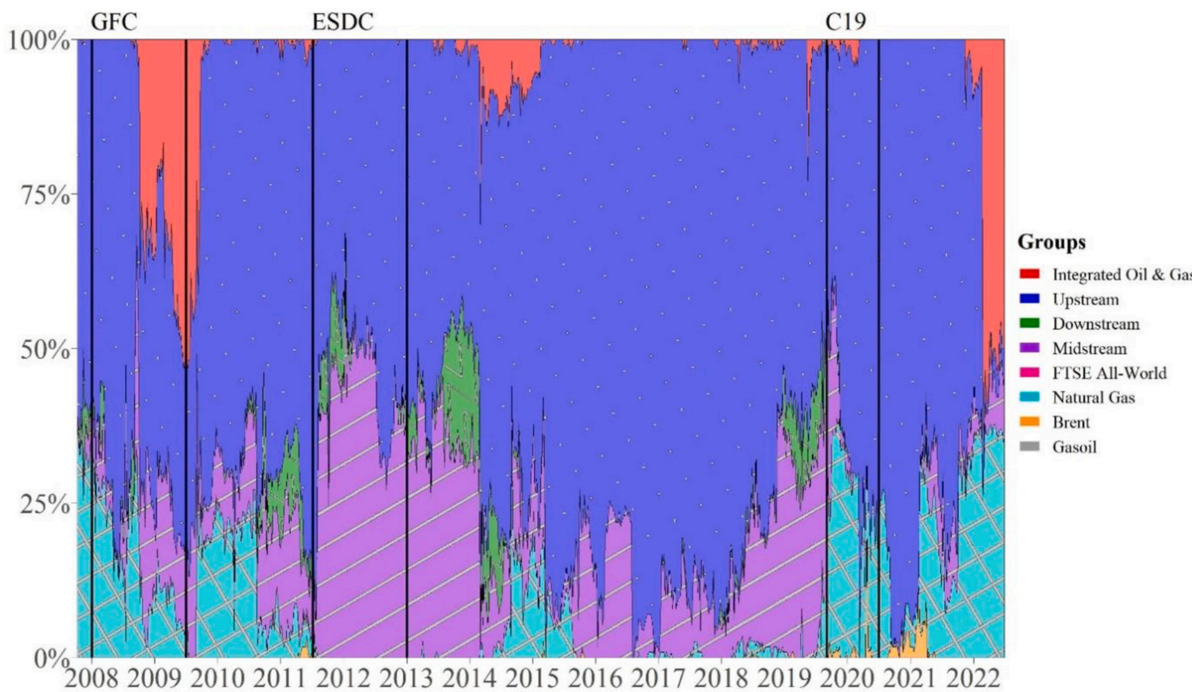
The results of this study offer fresh and distinctive perspectives on this dynamic and continuously evolving sector, as it moves from relying primarily on traditional continental oil to shale oil production and natural gas. We show that the Upstream companies are the major volatility transmitters during our sample period. During the European Sovereign Debt crisis (ESDC) and the Covid-19 pandemic, the volatility transmission mechanisms were altered. During the ESDC, the volatility emission from the Upstream segment declined even as the Midstream segment came under stress conditions. More importantly, during the Global Financial Crisis and recently with the Ukraine invasion, the IOG companies have become major volatility transmitters. This latter effect is alarming because the large IOG companies traditionally were volatility absorbers and system stability providers.

For investors seeking to diversify across the energy sector, it is critical to understand the companies' vulnerability of companies within the system and to external factors. Our results provide new insights into the key European energy sector network, their overall network risk, and the time-varying network fragility due to external shocks. We believe that the unique insights into the various crisis situations during our sample period offer interesting scenario analysis and information for regulators and policy makers to ensure crisis preparedness. Specifically, the over-reliance on traditional oil and gas companies, highlighted by the dominance of the Upstream companies' volatility transmission stresses the pressing need for energy diversification. Europe's ongoing energy crisis management should consider diversification along the supply chain at least as long as alternatives or renewable energy sources are not yet available in large volume to replace the oil and gas energy source.

[6] In robustness test, we also examined alternative time period definitions for the Covid-19 pandemic, using the extended time period reflecting Asian travel restriction in Fig. C.2. of the Online Appendix.



(a) Distribution of imported volatility from the various energy sectors and commodities over time



(b) Distribution of emitted volatility from the various energy sectors and commodities over time

Fig. 4. Distribution of imported and emitted volatility over time.
Note: Panel (a) displays distribution of imported volatility over time, while Panel (b) shows distribution of emitted volatility over time. For both figures, in the model input we use Lag = 3 and H = 10, with window size of 250 days and we display the strongest 5% of edges.

CRediT authorship contribution statement

Zsuzsa R. Huszár: Conceptualization, Supervision, Formal analysis, Writing – original draft. **Balázs B. Kotró:** Data curation, Formal analysis, Methodology, Software, Visualization. **Ruth S.K. Tan:** Formal analysis, Writing – review & editing.

Appendix A. Realized volatilities

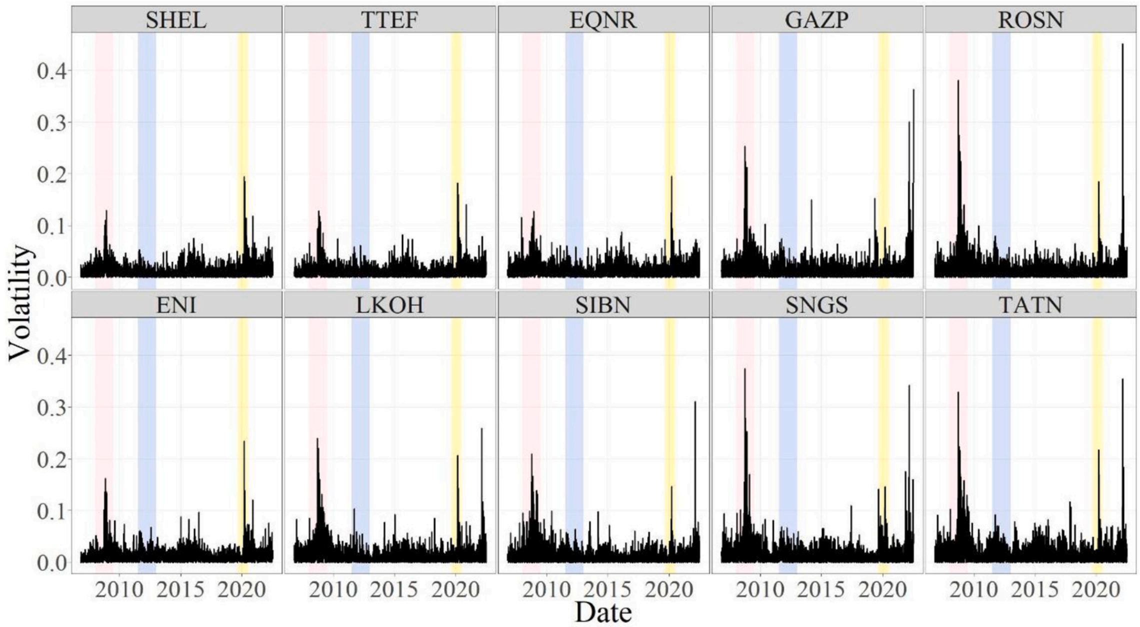


Fig. A.1. Realized volatilities of the European energy companies from the Integrated Oil and Gas segment over the period from October 2006 to June 2022.

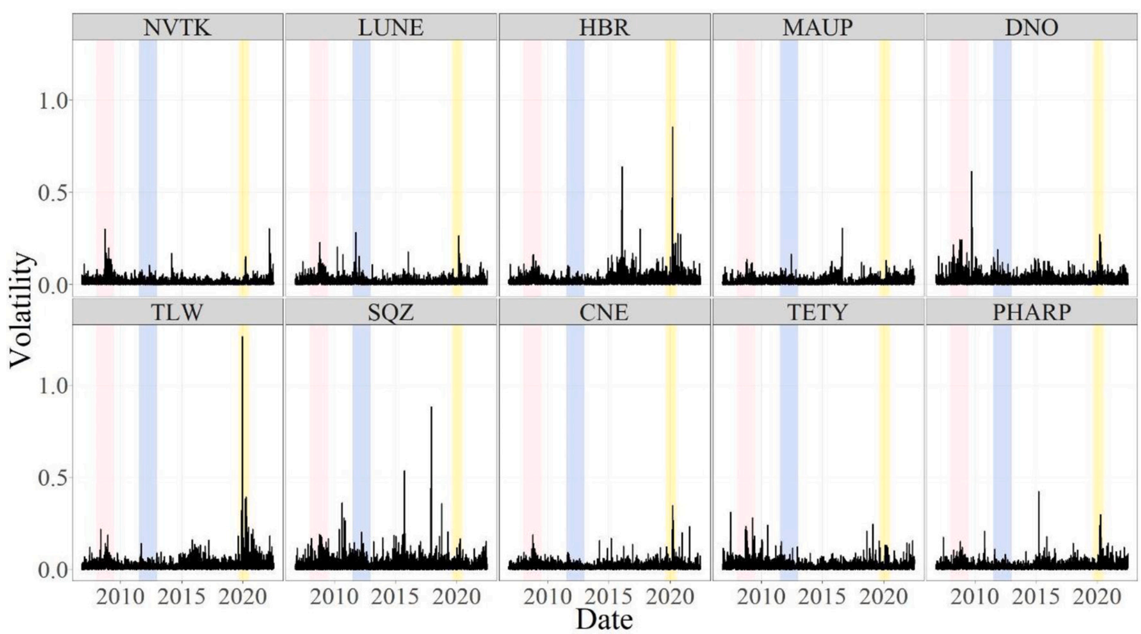


Fig. A.2. Realized volatilities of the European energy companies from the Upstream segment over the period from October 2006 to June 2022.

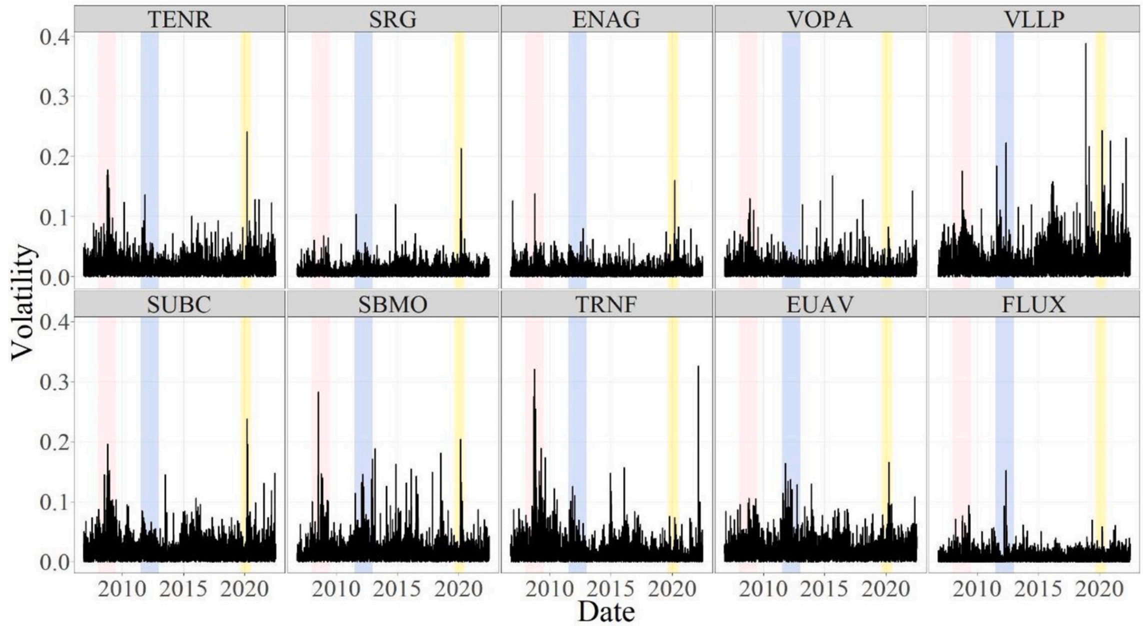


Fig. A.3. Realized volatilities of the European energy companies from the Midstream segment over the period from October 2006 to June 2022.

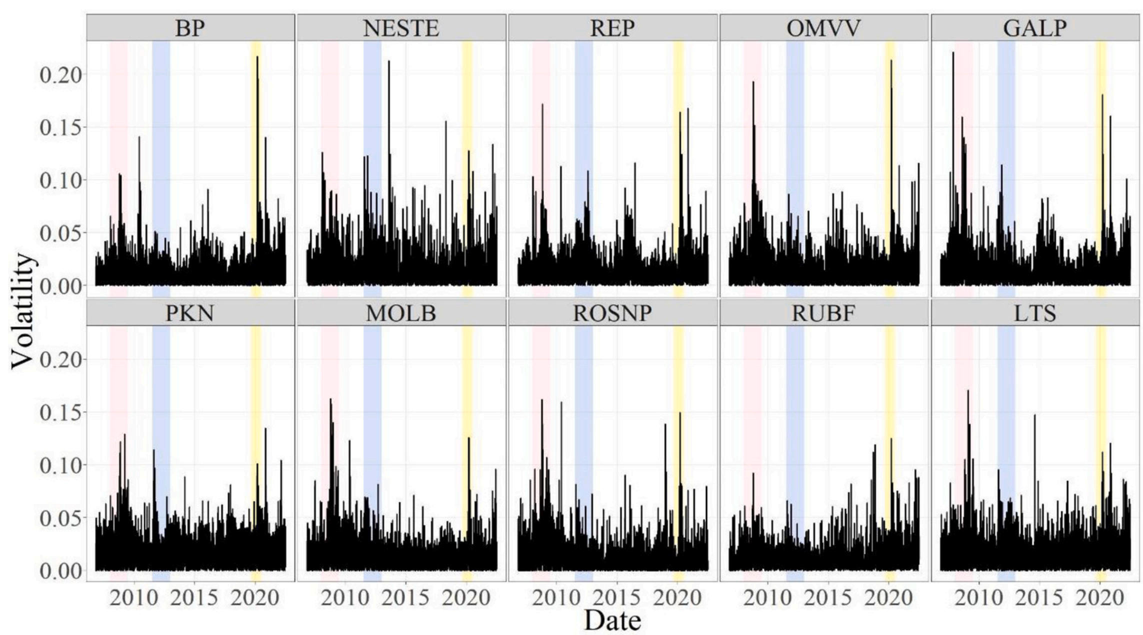


Fig. A.4. Realized volatilities of the European energy companies from the Downstream segment over the period from October 2006 to June 2022.

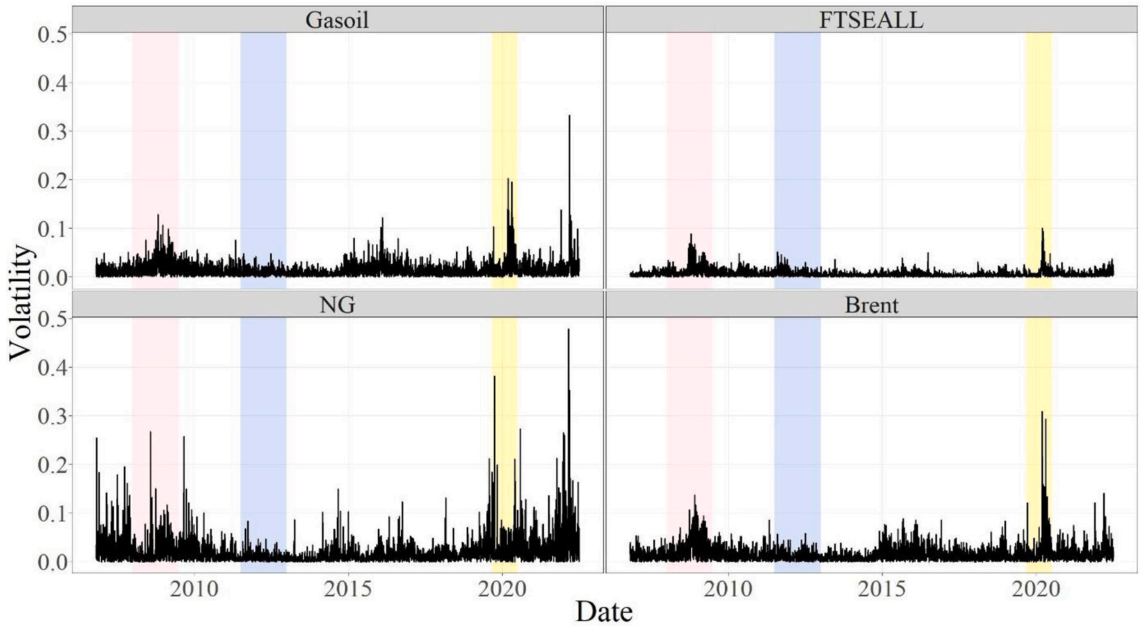


Fig. A.5. Realized volatilities of the ICE Europe Brent Crude Oil 1 M futures, the Dutch TTF Natural Gas 1 M futures, the ICE Europe Low Sulphur Gasoil 1 M futures and the FTSE All World Index over the period from October 2006 to June 2022.

Appendix B. Volatility spillovers

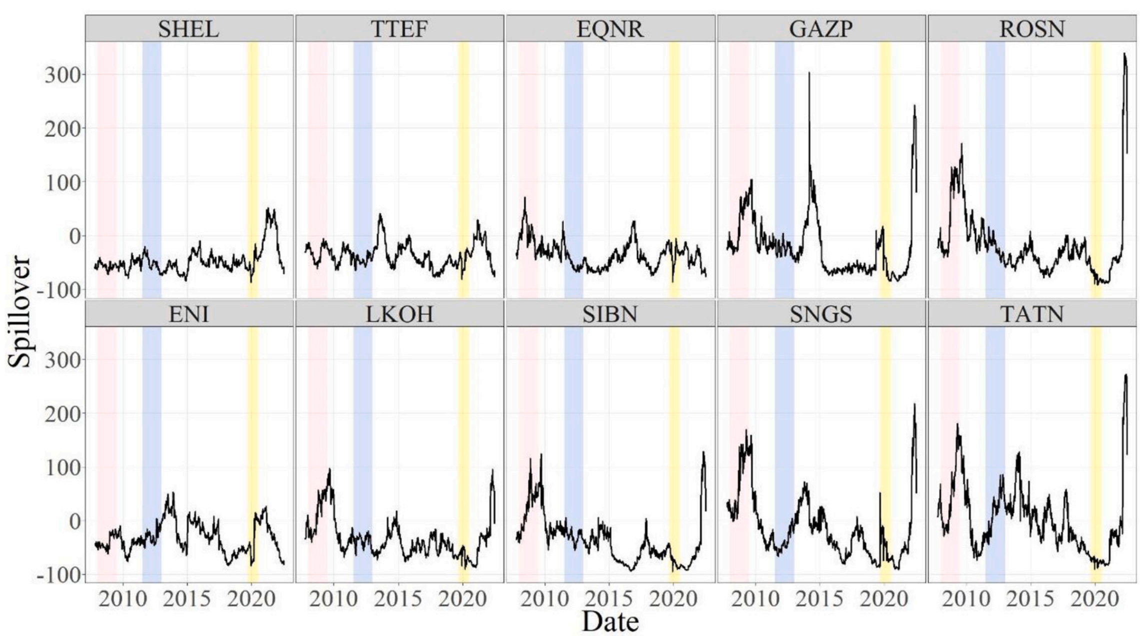


Fig. B.1. Net individual volatility spillover of the European energy companies from the Integrated Oil and Gas segment over the period from October 2006 to June 2022.

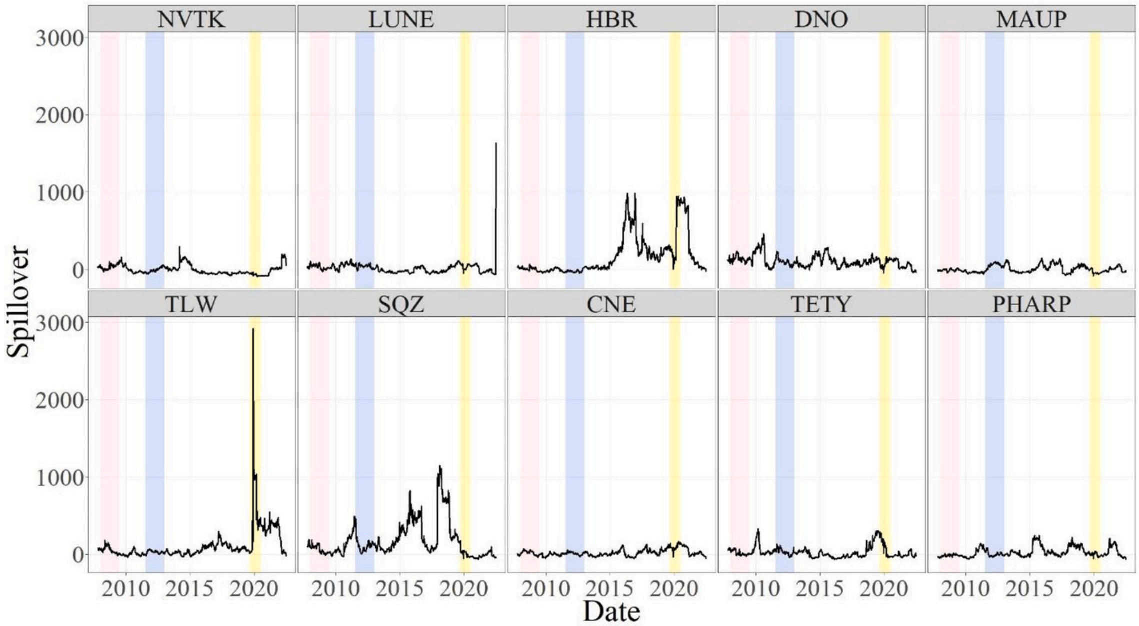


Fig. B.2. Net individual volatility spillover of the European energy companies from the Upstream segment over the period from October 2006 to June 2022.

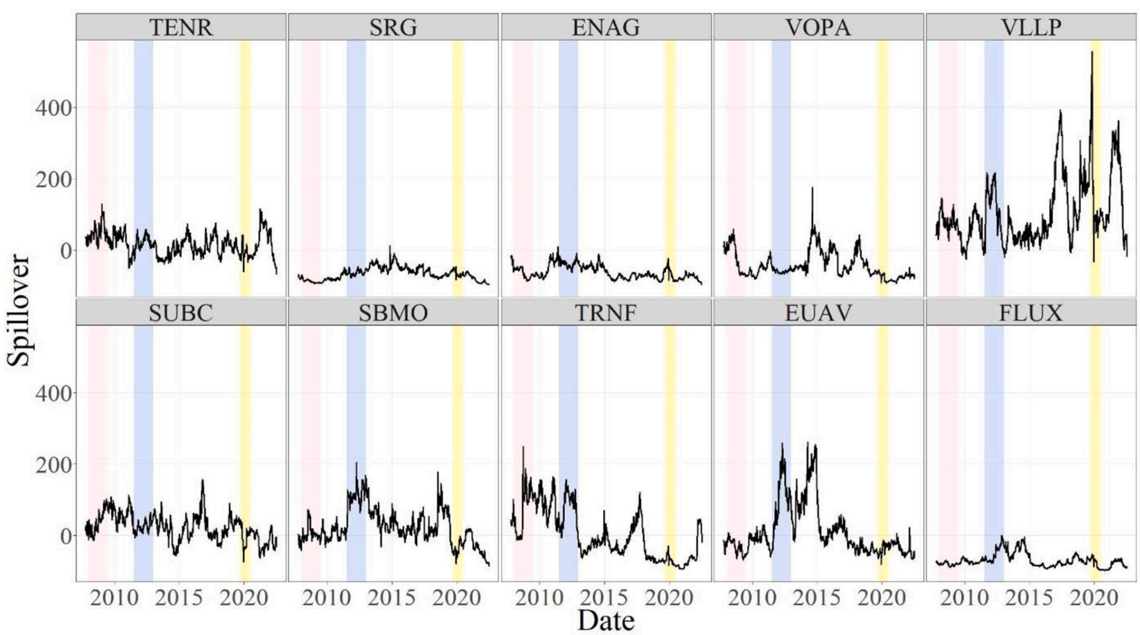


Fig. B.3. Net individual volatility spillover of the European energy companies from the Midstream segment over the period from October 2006 to June 2022.

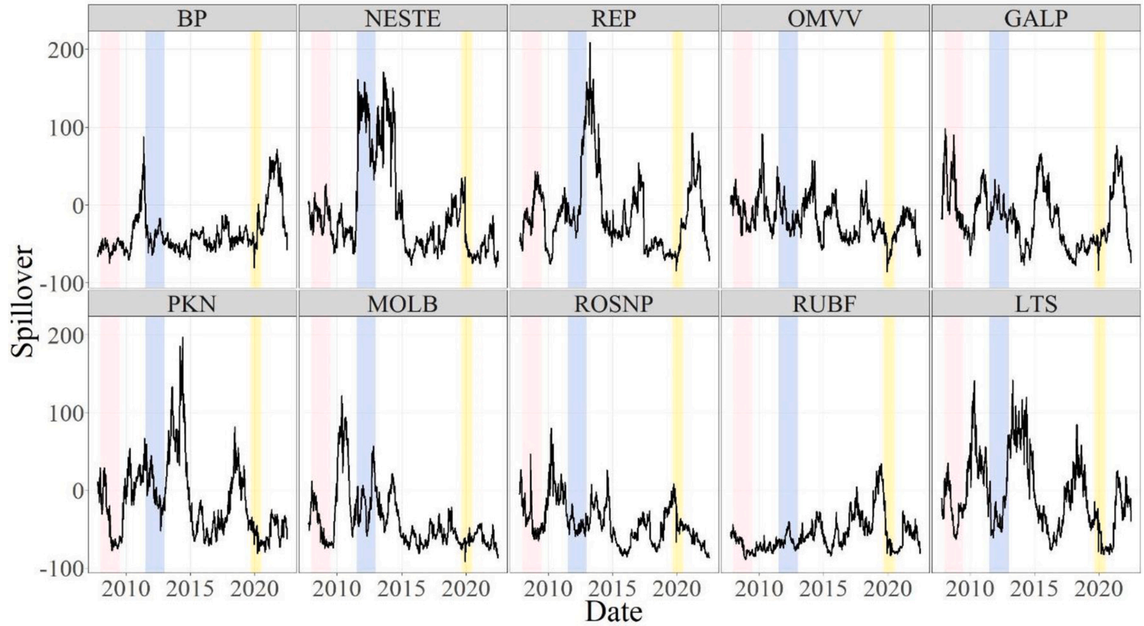


Fig. B.4. Net individual volatility spillover of the European energy companies from the Downstream segment over the period from October 2006 to June 2022.

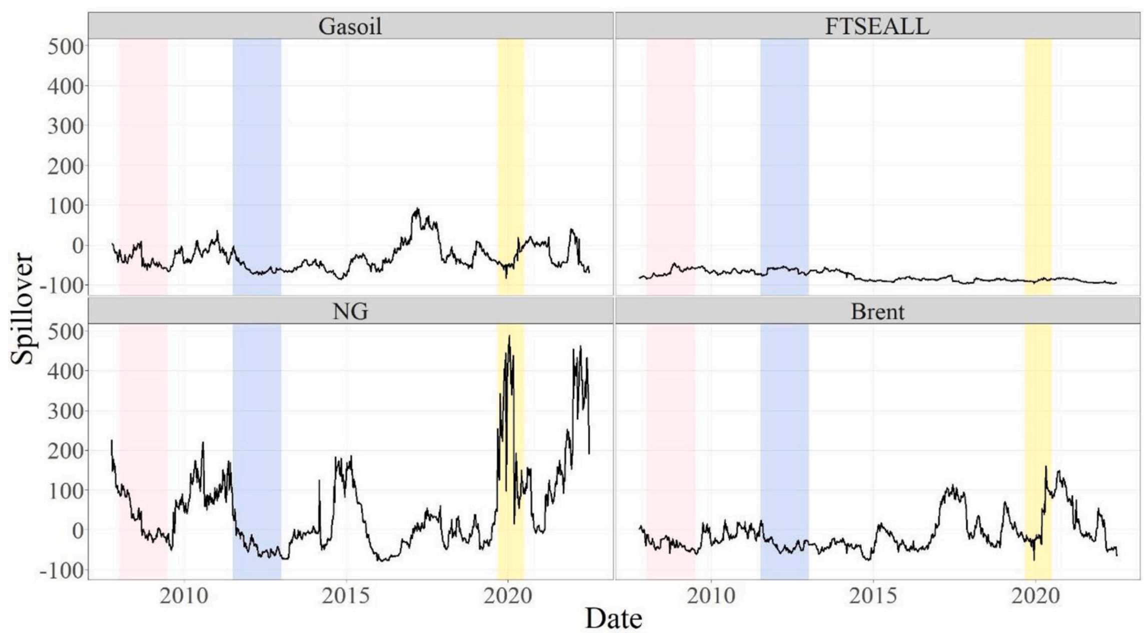


Fig. B.5. Net individual volatility spillover of the ICE Europe Brent Crude Oil 1 M futures, the Dutch TTF Natural Gas 1 M futures, the ICE Europe Low Sulphur Gasoil 1 M futures and the FTSE All World Index over the period from October 2006 to June 2022.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107052.

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