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Interplay of crises: Unpacking intraday spillovers in oil and European equities in the shadow of the COVID-19 and the Ukraine-Russia war

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A B S T R A C T

This study investigates the time-varying frequency of spillovers between European stock markets and oil during the COVID-19 pandemic and the Russia-Ukraine war. Using the spillover index by Diebold & Yilmaz, 2012 and Baruník & Křehlík, 2018, we analyze high-frequency data at a 5-min interval to analyze the interplay between crude oil market returns and the Stoxx 600 index returns, including sectors such as auto, basic material, banks, chemicals, food and beverage, health, industrials, insurance, oil and gas, retail, real estate, technology (tech), telecommunication (telecom), and utilities. The sample period is January 3, 2022, to March 25, 2022. Our findings reveal a substantial degree of connectedness within this financial network, with specific sectors—auto, chemicals, food, industrials, insurance, real estate, retail, tech, and telecom—acting as net transmitters of shocks, while other sectors assume the role of net receivers. The Russia-Ukraine war is a significant driver of these interconnected dynamics. Spillovers are most prevalent in the medium-term horizon, with the time dimension affecting the role of sectors and oil. Furthermore, our research highlights the potential benefits of adding oil assets to portfolios, enhancing risk-adjusted performance. However, ongoing risk management remains crucial due to the dynamic hedge ratios. This study offers practical insights for investors and policy makers, aiding risk management and investment strategies in turbulent markets.

1. Introduction

The global financial environment has been marked by unprecedented turbulence, owing to the far-reaching impacts of both the COVID-19 pandemic and the enduring Russia-Ukraine war (Yousaf, Hunjra, Alshater, Bouri, & Li, 2023). These crises have reverberated across the global economy, giving rise to substantial fluctuations in asset prices and heightened volatility. The oil industry, as a cornerstone of the global economic system, has been particularly susceptible to these events, experiencing pronounced price oscillations driven by shifts in supply and demand dynamics (Alshater, Atayah, & Khan, 2021).

Against this backdrop, the concept of "spillover" has gained greater relevance. Spillover refers to the transmission of volatility from one financial market to another on the same trading day, a factor of paramount importance in market dynamics. In this context, understanding intraday spillover is pivotal for unraveling the complex connectedness between oil and stock markets. Changes in oil prices have the potential for profound influence on stock market returns through various channels, including shifts in production costs, consumer spending patterns, increases in the cost of inputs (Filis, 2010), and higher discount rates (Basher & Sadorsky, 2006). Although the existing literature predominantly addresses the relationship between these markets, recent research has turned its focus to intraday spillovers, recognizing their importance in providing investors with a valuable lens for assessing the risks and opportunities due to market fluctuations.

The ongoing Russia-Ukraine war, which broke out in 2014 with

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Table 1
Statistical summary on intraday returns.

	Mean	Variance	Skewness	Kurtosis	Jarque-Bera	ERS	ADF test	KPSS	Q (10)	Corr
Stoxx 600	0.006	0.377	3.137***	92.411***	2186947.530***	−25.090***	−18.924***	0.098	7.762	−0.163
Auto	0.016	2.314	1.833***	47.834***	586706.718***	−15.766***	−17.028***	0.053	11.208**	−0.212
Basic Material	−0.020	1.458	0.100***	49.235***	617952.751***	−31.834***	−17.329***	0.055	4.368	0.255
Banks	0.001	0.095	2.533***	59.430***	906886.741***	−23.736***	−17.320***	0.230	19.246***	−0.165
Chemicals	0.022	3.775	2.313***	61.368***	965475.147***	−34.610***	−17.112***	0.156	10.347*	−0.189
Food & Beverage	0.012	0.968	2.896***	69.211***	1229628.190***	−11.900***	−17.272***	0.116	20.395***	−0.221
Health	0.006	1.518	2.512***	64.650***	1071876.813***	−26.757***	−18.058***	0.370	6.081	−0.137
Industrials	0.017	1.565	2.635***	79.317***	1610818.424***	−24.339***	−16.774***	0.138	7.222	−0.219
Insurance	0.000	0.250	1.839***	85.908***	1884793.123***	−17.111***	−17.952***	0.140	13.755**	−0.207
Oil & Gas	−0.007	0.255	−1.369***	34.790***	310445.131***	−12.587***	−17.627***	0.090	15.306***	0.433
Retail	0.018	0.490	1.286***	51.560***	679357.362***	−21.807***	−17.280***	0.052	17.095***	−0.196
Real Estate	0.003	0.071	1.483***	43.993***	495608.831***	−24.271***	−17.612***	0.102	16.504***	−0.195
Tech	0.022	2.362	1.843***	49.994***	640592.580***	−33.119***	−17.566***	0.192	11.143**	−0.148
Telecom	0.000	0.089	3.250***	93.731***	2250330.511***	−20.267***	−17.809***	0.091	16.277***	−0.216
Utilities	0.005	0.317	1.114***	49.472***	625162.850***	−21.136***	−17.204	0.031	9.532*	−0.155
Oil	−0.007	0.150	−9.605***	370.259***	35041036.545***	−32.340***	−18.924	0.053	13.428**	

Notes: ***, **, * indicate the level of significance at 0.01, 0.05, and 0.1.

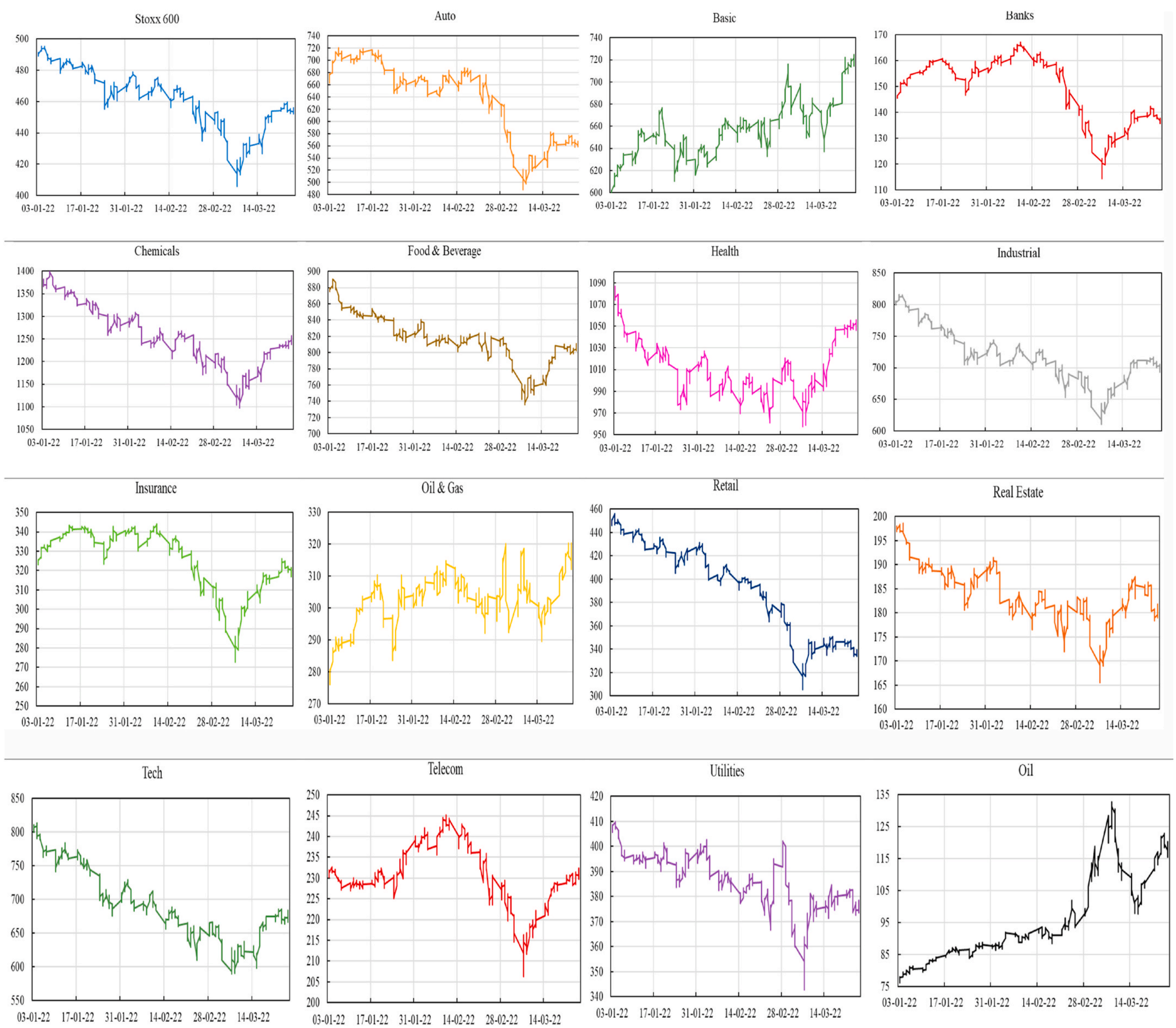


Fig. 1. Intraday prices.

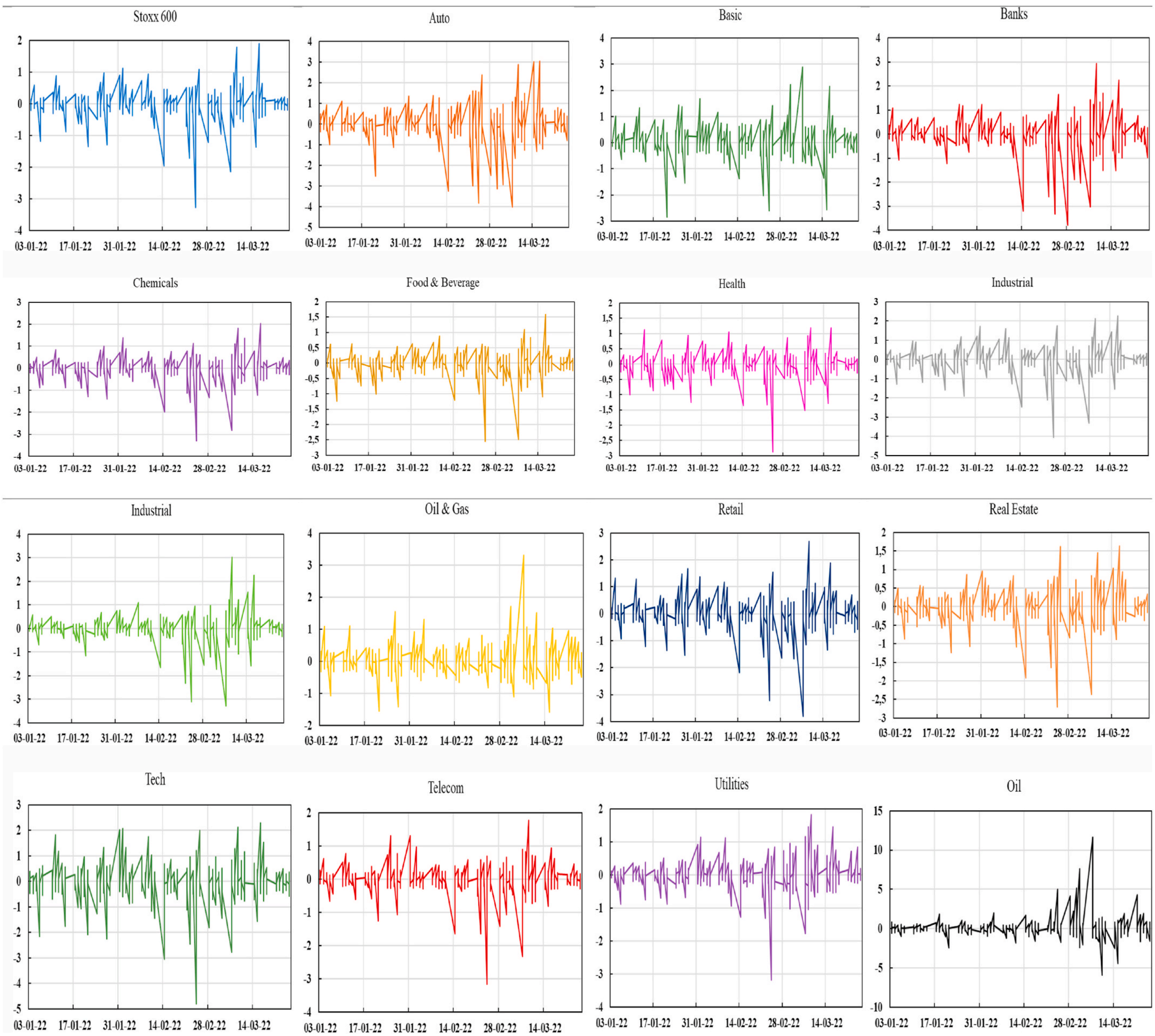


Fig. 2. Intraday returns.

Russia's annexation of Crimea, and persists to this day, has left an indelible mark on the European Union (EU), mainly because of Europe's historical dependence on supplies of Russian oil and gas (Najaf, Joshipura, & Alshater, 2023a; Najaf, Joshipura, & Alshater, 2023b). The disruption in this energy supply chain has had significant economic ramifications for Europe, raising energy costs and reliance on alternative energy sources. Additionally, economic sanctions on Russia imposed by the EU contributed to a decline in trade between them, further exacerbating economic strain. Consequently, this conflict has extensive implications for Europe, with substantial ripple effects due to the region's prior reliance on Russian energy resources. Moreover, the importance of oil as a fundamental economic driver cannot be overstated; its price fluctuations have reverberating effects across diverse sectors, spanning energy, manufacturing, transportation, and beyond.

Examining the interconnectedness between the oil and stock industry sectors is significant because of the diverse impact of oil price fluctuations on different segments of the stock market. This disparity arises from the varying levels of dependence on oil, whether indirect or direct. For example, the energy sector is highly sensitive to oil price shocks, as it directly relies on crude oil as an input, whereas sectors such as retail and health care have minimal or no direct dependence on oil. These discrepancies across sectors motivate our investigation into the interactions between oil and stock sectors over time. This paper offers valuable insights for investors seeking diversification opportunities.

Given that the crisis has affected equity sectors differently, with varying degrees of impact (Haroon & Rizvi, 2020), it is imperative to conduct a sectoral analysis of the correlation between oil and stocks. In light of the foregoing, this study investigates the intricacies of intraday spillovers between oil and European stock markets, particularly in the context of the COVID-19 pandemic and the ongoing Russia-Ukraine war. By harnessing high-frequency data collected at 5-min intervals, we meticulously investigate the spillover and interconnectedness between oil and the Stoxx 600 index, alongside its subsector indices, including auto, basic, banks, chemicals, food and beverage, health, industrials, insurance, oil and gas, retail, real estate, technology (tech), telecommunication (telecom), and utilities. Our dataset comprises 6119 observations, collected from the Datastream database, from January 3, 2022, to March 25, 2022.

Table 2
Average intraday spillover/connectedness.

	Stoxx 600	Auto	Banks	Basic Material	Chemicals	Food & Beverage	Health	Industrial	Insurance	Oil & Gas	Real Estate	Retail	Tech	Telecom	Utilities	Oil	From
Stoxx 600	8.40	5.83	5.26	4.28	7.92	6.86	7.37	8.01	6.41	1.77	7.41	6.35	7.75	7.45	7.18	1.76	91.60
Auto	6.71	9.97	6.84	4.69	7.34	6.06	4.62	7.36	7.66	3.34	7.24	7.31	5.87	6.25	5.12	3.63	90.03
Banks	6.77	8.26	10.10	3.55	7.31	5.75	4.31	6.76	8.24	3.29	6.63	7.83	5.69	6.84	4.93	3.76	89.90
Basic Material	6.59	6.19	3.94	11.81	6.80	6.35	5.39	7.14	5.82	6.06	6.93	6.22	5.89	5.61	4.25	5.02	88.19
Chemicals	7.76	6.18	5.15	4.33	8.42	7.21	6.52	7.85	6.60	2.51	7.36	6.89	6.95	7.08	6.56	2.63	91.58
Food & Beverage	7.30	5.53	4.28	4.26	8.03	8.70	6.36	7.60	6.73	3.43	7.05	7.22	6.26	7.04	6.44	3.79	91.30
Health	8.72	4.78	4.17	4.06	7.86	7.08	9.59	8.22	5.61	1.27	7.26	5.71	8.40	7.92	7.95	1.39	90.41
Industrial	7.85	6.16	4.88	4.48	7.77	6.94	6.84	8.22	6.44	2.41	7.59	6.81	7.37	7.08	6.72	2.43	91.78
Insurance	6.79	7.59	6.19	4.18	7.44	6.79	5.01	7.10	9.08	3.68	6.72	7.83	5.28	6.72	5.73	3.86	90.92
Oil & Gas	4.14	5.73	3.60	8.08	5.97	7.14	2.80	5.68	6.56	15.22	5.35	8.36	3.22	4.36	2.63	11.15	84.78
Real Estate	7.41	6.66	5.25	4.55	7.50	6.81	6.09	7.84	6.80	2.70	8.33	7.11	6.73	7.04	6.24	2.96	91.67
Retail	6.55	6.54	5.40	4.38	7.47	7.16	5.00	7.38	7.54	4.62	7.04	9.00	5.61	6.53	5.24	4.55	91.00
Tech	8.68	557	4.99	4.22	7.78	6.54	7.95	8.36	5.53	1.37	7.57	5.95	9.19	7.52	7.46	1.30	90.81
Telecom	7.72	5.80	5.42	3.79	7.66	6.84	6.87	7.57	6.76	2.16	7.05	6.75	6.98	8.85	7.13	2.64	91.14
Utilities	7.98	5.83	4.62	3.51	7.84	7.20	7.21	7.87	6.45	1.90	7.07	6.31	7.31	7.71	8.89	2.27	91.11
Oil	3.13	5.19	3.45	7.10	5.43	7.54	2.15	4.97	6.22	13.29	5.20	8.00	2.17	4.50	2.10	19.55	80.46
To	104.11	91.83	73.46	69.45	110.12	102.28	84.50	109.71	99.37	53.79	103.46	104.65	91.49	99.67	85.67	53.12	1436.67
Own	112.51	101.80	83.56	81.26	118.54	110.98	94.08	117.94	108.45	69.01	111.79	113.65	100.68	108.53	94.56	72.66	89.79%
Net	12.51	1.80	−16.44	−18.74	18.54	10.98	−5.92	17.94	8.45	−30.99	11.79	13.65	0.68	8.53	−5.44	−27.34	

Notes: This is based on Diebold and Yilmaz (2012) time-domain spillover framework with lag length oder 1 and a 100-step-ahead generalized forecast error variance decomposition. The column (raw) "From" ("To") indicates the directional spillover from all (to all other) markets to (from) a particular market. The row "Net" reveals the negative and positive values which indicate the net receiver and transmitter of spillovers.

Although a considerable body of empirical literature has investigated the correlations between oil and the overall stock market (Mensi, Al-Yahyaee, Vo, & Kang, 2021; Tiwari, Nasreen, Ullah, & Shahbaz, 2021; Zhang & Hamori, 2021), these studies tends to perform a broader, market-level analysis, without exploring the interplay between commodities and stock markets at a more granular sectoral level. Only a handful of studies have probed the relationships between oil and stock indices at the sectoral level (Degiannakis, Filis, & Floros, 2013; Faff & Brailsford, 1999; Huang, An, Huang, & Wang, 2018; Mensi, Beljid, Boubaker, & Managi, 2013, 2022; Mensi, Shafiullah, Vo, & Kang, 2021; Zhu, Tang, Wei, Dai, & Lu, 2021), finding that dynamic interactions between the oil and equity sectors are affected by the type of industry.

Disregarding the variations across sectors in a given country could raise significant issues in terms of portfolio diversification. In simpler terms, investors might assume that any significant event could impact the returns of all sector-specific stock markets uniformly. Consequently, failing to give due attention to underperforming sectors could result in greater losses for investors. This presumption is particularly relevant during the COVID-19 pandemic, whose effects on various sectors varied significantly (Alomari, Al Rababa'a, Rehman, & Power, 2022). This research gap poses essential questions about the potential benefits from delving more deeply into sector-specific analyses. The sensitivity of sector-specific stock performance to commodity prices can be diverse and may vary across time frequencies. Therefore, our analysis has significant value for further studies.

The significance of this study is highlighted by several critical considerations in the contemporary global economic environment. First, the confluence of the COVID-19 pandemic and the ongoing Russia-Ukraine war has introduced unprecedented levels of uncertainty and volatility in financial markets worldwide. This study serves as a timely response to the pressing need for a comprehensive analysis of the intraday spillover dynamics between oil and European stock markets under such challenging circumstances. Understanding how these crises affect market interactions is paramount, as it can inform investment decisions, risk management strategies, and economic policy formulation. Second, the energy industry, particularly oil, is a pivotal driver of the global economy. Oil prices not only influence energy costs but also impact various industries, including transportation, manufacturing, and consumer goods. Any fluctuations in oil prices can have a cascade effect on the broader economy, making it crucial to decipher the intricate relationship between oil and sectoral markets. Third, Europe's dependence on Russian energy resources has long been a cause of concern, from both an economic and geopolitical perspective. The Russia-Ukraine war, along with the subsequent sanctions and supply disruptions, has intensified Europe's vulnerability. This study's focus on European stock markets adds a layer of significance by delving into the intricacies of how these markets respond to oil prices in these challenging times.

This study contributes to the existing studies in several meaningful ways. First, by analyzing high-frequency data, this research offers a granular understanding of intraday spillover dynamics. It delves into the intricacies of how oil price fluctuations are transmitted to European stock markets on a single trading day. This level of detail can provide valuable insights for traders, investors, and financial institutions seeking to navigate volatile market conditions. Second, the study's focus on the interplay between oil and European stock markets during the pandemic and the Russia-Ukraine conflict is especially pertinent. These crises represent some of the most challenging and dynamic events in recent history, and their economic repercussions are profound. By examining market interactions in this specific context, the study addresses real-time concerns and helps stakeholders better prepare for future crises. Third, most existing studies in this field have predominantly centered on global stock markets, such as the S&P 500. This study extends the geographic scope by specifically examining European stock markets. This approach acknowledges the diversity of regional market dynamics and offers valuable insights for market participants interested in the European economic landscape. Given Europe's historical dependence on Russian

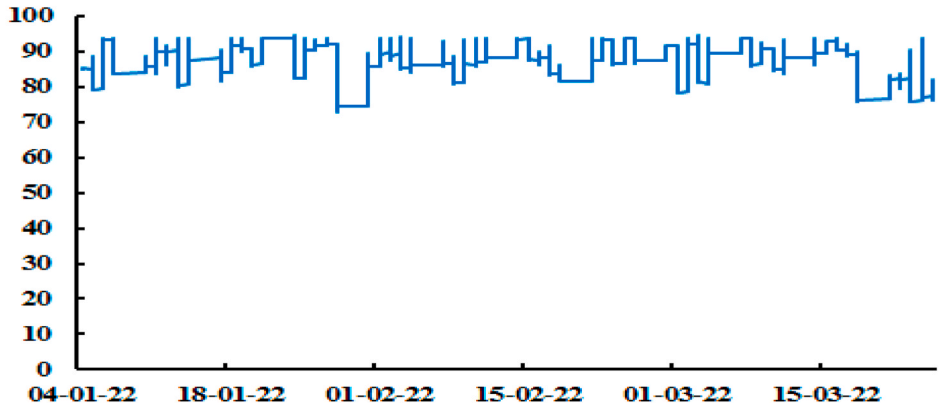


Fig. 3. Dynamic Spillover Index.
Notes: A rolling window size of 200 days and a forecast horizon (H) of 100 days are used to estimate the dynamic spillover index.

energy resources and the disruptions caused by the conflict, this study takes a holistic view of the consequences. It examines how these energy-related challenges reverberate through European stock markets, providing valuable information for policy makers and energy stakeholders in the region. Fourth, considering a sectoral analysis provides a comprehensive perspective, considering the possibility that some investors might prefer to reallocate their funds between sectors in the same country, rather than making global investments. This choice stems from the anticipation that different sectors may respond differently to crude oil prices. Our sectoral analysis equips investors with the tools to craft more efficient investment strategies tailored to diverse equity sectors that interact with oil, as opposed to relying solely on the aggregate stock index. Fifth, this study employs the time-frequency spillover methodology of Baruník and Křehlík (2018; cited as BK 18) and the time-domain spillover index of Diebold and Yilmaz (2012; cited as DY12) to reveal these interconnections. The DY12 spillover index evaluate the transmission of information across sectoral markets. This approach enables us to discern the direction and strength of static spillovers, as well as identify net directional spillovers (whether a net receiver or contributor). However, given that static spillovers may not capture vital information during periods of financial market distress, we employ a rolling-sample approach. This dynamic method helps us capture the evolving nature of the spillover index, particularly in the wake of significant events that may directly impact volatility structures between oil and European sectoral stock markets. Market participants have diverse investment horizons, with speculators and arbitrageurs favoring short-term investment and institutional investors, such as mutual and hedge funds, opting for longer-term positions. The DY12 spillover approach overlooks the time dimension of investment horizons, but the BK18 spillover index addresses this issue. In particular, we disentangle spillovers across different frequencies, enabling us to measure how spillovers propagate across these frequencies. This technique offers market participants a comprehensive overview of how one market spills over into others across different frequencies, thereby facilitating the identification of maximum risk-reducing strategies. Finally, we construct an optimal portfolio, comprising oil and an equity sector, with the goal of minimizing risk while maintaining expected returns. Our approach draws on the work of Kroner and Ng (1998) and Kroner and Sultan (1993) to calculate the weight of the oil and sectors in the portfolio structure, along with the hedge ratio. This analysis helps to identify the most and least cost-effective hedges.

Our research yields several noteworthy findings with significant implications. First, our analysis exposes a high level of interconnectedness among financial assets in Europe, with shocks within this network explaining approximately 90 percent of the total variance of the forecast error. Second, our study highlights the substantial impact of geopolitical events on the dynamic connectedness of financial markets. The total spillover among markets is dynamic and responsive to crises. Third, our research indicates that banks, basic material, health, oil and gas, and utilities sectors are net receivers of shocks, whereas the remaining sectors are net transmitters. By employing the BK18 frequency spillover index method, our analysis demonstrates that medium-term spillovers exceed short- and long-term spillovers throughout the sample period. Oil acts as a net shock transmitter in both the short and medium term but becomes a net shock receiver in the long term. Additionally, the strength of spillovers varies across time dimensions. In terms of portfolio risk analysis, our findings suggest that a diversified portfolio enhances hedging effectiveness, especially through shorting stocks in the food & beverage sector. Investors are advised to consider allocating more to equity shares and reducing exposure to oil in order to minimize risk without compromising expected returns.

Our findings have practical implications for risk management and investment strategies. Investors can use the insights obtained from this research to make more informed decisions and develop effective hedging strategies. Corporations operating in sectors that are sensitive to oil price fluctuations can better assess and mitigate risks, whereas policy makers can use the research to inform economic policies designed to enhance financial stability.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the empirical methods, presents the data, and offers some initial statistics. Empirical results are elaborated in Section 4. Section 5 is the conclusion, summarizing our key findings and their implications.

2. Literature review

Scholarly exploration of the connection between oil prices and stock market returns has a deep-rooted history, encompassing a wide range of econometric methodologies and diverse datasets. The research has covered a spectrum from aggregate to sector-specific stock market indices and individual firm-level data, incorporating models such as vector autoregressive (VAR) and generalized autoregressive conditional heteroskedasticity (GARCH) models to elucidate this complex relationship. Numerous studies have investigated the asymmetric effects of oil prices, revealing divergent impacts on economies based on their status as oil exporters or importers, thereby offering multifaceted insights into the dynamics.

Additionally, scholars have recognized that the connection between oil prices and stock markets is far from static. It evolves due to shifts in economic landscapes and significant geopolitical events. Noteworthy contributions have also shed light on the role of gold as a diversification asset and oil as a hedge, especially during times of crisis. The direction and strength of these relationships appear to be contingent on factors such as the specific time frame, geographic region, and sector under

Table 3
Intraday frequency spillover/connectedness.

	Stoxx 600	Auto	Banks	Basic Material	Chemicals	Food & Beverage	Health	Industrial	Insurance	Oil & Gas	Real Estate	Retail	Tech	Telecom	Utilities	Oil	From_ABS	From_With
Short: 3.14–0.63 (1–5)																		
Stoxx 600	1.47	0.96	0.91	0.76	1.35	1.17	1.31	1.39	1.09	0.28	1.29	1.08	1.37	1.28	1.25	0.27	0.98	7.91
Auto	0.79	1.20	0.84	0.55	0.84	0.67	0.55	0.85	0.90	0.31	0.84	0.82	0.69	0.72	0.58	0.34	0.64	5.17
Banks	0.63	0.68	1.02	0.28	0.60	0.44	0.41	0.57	0.67	0.14	0.58	0.60	0.55	0.60	0.43	0.18	0.46	3.69
Basic Material	0.99	0.89	0.56	1.93	1.01	0.95	0.82	1.07	0.85	0.93	1.04	0.93	0.88	0.82	0.62	0.75	0.82	6.59
Chemicals	0.97	0.73	0.64	0.55	1.05	0.91	0.83	0.98	0.82	0.31	0.90	0.86	0.87	0.89	0.82	0.32	0.71	5.72
Food & Beverage	0.65	0.45	0.36	0.40	0.70	0.80	0.59	0.68	0.57	0.31	0.63	0.62	0.56	0.61	0.57	0.32	0.50	4.02
Health	1.22	0.62	0.56	0.58	1.08	0.99	1.38	1.15	0.77	0.17	1.00	0.78	1.19	1.09	1.12	0.18	0.78	6.27
Industrial	1.36	1.01	0.83	0.80	1.33	1.21	120	1.43	1.09	0.41	1.32	1.17	1.29	1.21	1.16	0.41	0.99	7.94
Insurance	0.81	0.80	073	0.47	0.84	0.77	0.61	0.82	1.07	0.35	0.79	0.88	0.63	0.78	0.69	0.36	0.65	5.19
Oil & Gas	0.55	0.78	0.46	1.40	0.86	1.12	0.36	0.82	0.97	2.88	0.78	1.34	0.41	0.59	0.33	1.99	0.80	6.41
Real Estate	0.95	0.75	0.64	0.58	0.92	0.85	0.80	1.00	0.78	0.29	1.08	0.84	0.89	0.86	0.79	0.30	0.70	5.65
Retail	0.83	0.77	0.69	0.54	0.91	0.86	0.64	0.92	0.92	0.51	0.88	1.11	0.72	0.80	0.66	0.49	0.70	5.60
Tech	1.50	0.92	0.87	0.74	1.32	1.12	1.40	1.45	0.94	0.24	1.32	1.03	1.62	1.29	1.27	0.22	0.98	7.85
Telecom	1.20	0.81	0.83	0.58	1.15	1.03	1.10	1.15	0.99	0.28	1.08	0.97	1.10	1.36	1.08	0.35	0.86	6.88
Utilities	0.92	0.50	0.45	0.33	0.82	0.74	0.88	0.86	0.67	0.11	0.78	0.61	0.85	0.85	1.10	0.12	0.59	4.77
Oil	0.00	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.04
To_ABS	0.84	0.67	0.59	0.54	0.86	0.80	0.72	0.86	0.75	0.29	0.83	0.78	0.75	0.78	0.71	0.41	11.17	
To_With	6.72	5.37	4.71	4.31	6.89	6.45	5.77	6.88	6.05	2.34	6.64	6.30	6.02	6.23	5.71	3.31		**89.70%**
Net	−0.15	0.02	0.13	−0.28	0.15	0.30	−0.06	−0.13	0.11	−0.51	0.12	0.09	−0.23	−0.08	0.12	0.41		
Medium: 0.63–0.14 (5–22)																		
Stoxx 600	2.98	2.02	1.88	1.50	2.77	2.40	2.63	2.82	2.27	0.59	2.60	2.23	2.75	2.63	2.54	0.57	2.01	7.06
Auto	1.95	2.88	2.01	1.32	2.08	1.68	1.35	2.10	2.21	0.83	2.05	2.05	1.70	1.78	1.46	0.86	1.59	5.57
Banks	1.74	1.99	2.71	0.81	1.77	1.34	1.13	1.66	2.02	0.60	1.64	1.85	1.48	1.73	1.24	0.66	1.35	4.75
Basic Material	2.19	2.00	1.27	4.06	2.24	2.12	1.80	2.37	1.91	2.04	2.29	2.07	1.95	1.85	1.39	1.66	1.82	6.39
Chemicals	2.35	1.80	1.56	1.28	2.53	2.17	2.00	2.35	1.98	0.72	2.18	2.06	2.10	2.14	1.99	0.72	1.71	6.00
Food & Beverage	1.84	1.33	1.08	1.05	1.99	2.19	1.64	1.90	1.67	0.80	1.75	1.77	1.59	1.76	1.63	0.85	1.42	4.97
Health	2.80	1.48	1.32	1.30	2.49	2.26	3.11	2.62	1.79	0.39	2.29	1.80	2.70	2.52	2.55	0.41	1.80	6.30
Industrial	2.80	2.14	1.74	1.59	2.75	2.46	2.45	2.92	2.29	0.83	2.68	2.41	2.63	2.51	2.39	0.82	2.03	7.12
Insurance	1.95	2.08	1.80	1.14	2.07	1.88	1.45	1.99	2.64	0.93	1.88	2.19	1.50	1.91	1.65	0.93	1.58	5.55
Oil & Gas	1.28	1.76	1.09	2.73	1.88	2.31	0.86	1.79	2.10	5.32	1.68	2.75	0.98	1.35	0.79	3.73	1.69	5.94
Real Estate	2.18	1.82	1.51	1.30	2.15	1.95	1.80	2.27	1.91	0.69	2.44	1.99	1.99	2.02	1.82	0.73	1.63	5.73
Retail	2.00	1.93	1.67	1.29	2.23	2.11	1.53	2.22	2.27	1.30	2.11	2.70	1.72	1.97	1.59	1.32	1.70	5.95
Tech	3.17	2.01	1.85	1.55	2.82	2.38	2.91	3.05	2.04	0.51	2.76	2.19	3.36	2.75	2.70	0.47	2.07	7.26
Telecom	2.57	1.83	1.80	1.23	2.50	2.22	2.32	2.48	2.21	0.63	2.31	2.16	2.33	2.95	2.36	0.77	1.86	6.51
Utilities	2.09	1.34	1.13	0.79	1.94	1.74	1.97	1.99	1.60	0.30	1.77	1.48	1.93	1.98	2.44	0.33	1.40	4.91
Oil	0.02	0.02	0.02	0.02	0.02	0.03	0.01	0.02	0.02	0.03	0.02	0.03	0.01	0.02	0.01	0.04	0.02	0.06
To_ABS	1.93	1.60	1.36	1.18	1.98	1.82	1.62	1.98	1.77	0.70	1.88	1.81	0.71	1.81	1.63	0.92	25.69	
To_With	6.77	5.60	4.76	4.14	6.95	6.37	5.67	6.93	6.20	2.45	6.58	6.36	5.99	6.34	5.73	3.23		**90.08%**
Net	−0.08	0.01	0.00	−0.64	0.27	0.40	−0.18	−0.05	0.19	−0.99	0.24	0.12	−0.36	−0.05	0.23	0.90		
Long: 0.14–0.00 (22 to infinity)																		
Stoxx 600	3.95	2.85	2.47	2.02	3.80	3.29	3.43	3.80	3.04	0.90	3.52	3.05	3.63	3.54	3.39	0.92	2.73	4.62
Auto	3.97	5.88	4.00	2.82	4.43	3.71	2.72	4.41	4.55	2.20	4.35	4.44	3.48	3.75	3.07	2.43	3.39	5.75
Banks	4.40	5.58	6.37	2.45	4.94	3.97	2.77	4.53	5.55	2.55	4.40	5.38	3.66	4.51	3.26	2.91	3.81	6.45
Basic Material	3.41	3.30	2.10	5.82	3.55	3.28	2.77	3.71	3.05	3.09	3.59	3.21	3.06	2.94	2.24	2.61	2.87	4.86
Chemicals	4.44	3.64	2.96	2.49	4.84	4.13	3.69	4.52	3.79	1.48	4.29	3.98	3.98	4.05	3.75	1.59	3.30	5.59
Food & Beverage	4.80	3.74	2.84	2.81	5.35	5.72	4.14	5.03	4.49	2.32	4.66	4.83	4.11	4.67	4.25	2.61	3.79	6.42

(*continued on next page*)

Table 3 (*continued*)

	Stoxx 600	Auto	Banks	Basic Material	Chemicals	Food & Beverage	Health	Industrial	Insurance	Oil & Gas	Real Estate	Retail	Tech	Telecom	Utilities	Oil	From_ABS	From_With
Health	4.70	2.69	2.30	2.18	4.29	3.83	5.09	4.45	3.06	0.71	3.96	3.13	4.52	4.30	4.28	0.80	3.07	521
Industrial	3.69	3.00	2.31	2.09	3.69	3.28	3.18	3.87	3.06	1.16	3.59	3.23	3.45	3.36	3.17	1.20	2.72	4.60
Insurance	4.03	4.71	3.66	2.57	4.53	4.14	2.96	4.29	5.37	2.40	4.05	4.76	3.15	4.03	3.39	2.57	3.45	5.85
Oil & Gas	2.31	3.19	2.05	3.96	3.23	3.71	1.59	3.07	3.48	7.02	2.88	4.27	1.83	2.42	1.52	5.44	2.81	4.76
Real Estate	4.28	4.08	3.10	2.66	4.43	4.01	3.49	4.57	4.10	1.72	4.81	4.27	3.85	4.16	3.62	1.92	3.39	5.75
Retail	3.73	3.84	3.04	2.55	432	4.18	2.83	4.24	4.35	2.81	4.05	5.19	3.18	3.76	2.98	2.83	3.29	5.58
Tech	4.01	2.64	2.27	1.93	3.63	3.04	3.64	3.87	2.56	0.63	3.50	2.73	4.21	3.48	3.49	0.61	2.63	4.45
Telecom	3.96	3.16	2.80	1.98	4.02	3.59	3.46	3.94	3.56	1.25	3.66	3.61	3.55	4.55	3.68	1.52	2.98	5.05
Utilities	4.97	3.99	3.04	2.38	5.07	4.73	4.35	5.02	4.18	1.50	4.53	4.22	4.53	4.88	5.36	1.82	3.70	6.27
Oil	3.11	5.16	3.43	7.07	5.40	7.51	2.14	4.95	6.19	13.25	5.18	7.97	2.16	4.48	2.08	19.49	5.00	4.48
To_ABS	3.74	3.47	2.65	2.62	4.04	3.77	2.95	4.02	3.69	2.37	3.76	3.94	3.26	3.65	3.01	1.99	52.94	
To_With	6.33	5.88	4.48	4.44	6.85	6.39	4.99	6.82	6.25	4.02	6.37	6.68	5.52	6.18	5.10	3.37		**89.67%**
Net	1.01	0.08	−1.16	−0.25	0.74	−0.02	−0.13	1.31	0.24	−0.44	0.37	0.65	0.63	0.66	−0.69	−3.02		

Notes: This is based on Baruník and Křehlík (2018) frequency domain spillover framework with lag length oder 1 and a 100 – step-ahead generalized forecast error variance decomposition. The results are based on across three frequency bands: short – term (1–5 days), medium – term (5–22 days), and long – term (22 to infinity days). 'With' signifies within, 'ABS' denotes the absolute. "From" refers to the spillover received from other variables, and "To" denotes the spillover sent to other variables. The row "Net" indicates the negative and positive values which indicate the net receiver and transmitter of spillovers.

scrutiny.

Furthermore, emphasis on high-frequency data analysis has grown, which has revealed a deeper understanding of intraday dynamics. This shift in focus has shown nuanced interdependencies and spillover effects among diverse financial markets, insights that were not as discernible in lower-frequency data.

The complex interplay between oil prices and stock market returns has undergone extensive scrutiny, employing diverse datasets and econometric methodologies. Researchers have delved into this dynamic relationship, shedding light on systemic shock transmission, spillover effects, and the evolving nature of these connections. Using a dynamic conditional correlation GARCH model, Abuzayed and Al-Fayoumi (2021) report a heightened impact of oil shocks on Gulf Cooperation Council (GCC) stock market returns during the pandemic compared to tranquil periods, emphasizing the heightened sensitivity of the GCC markets to oil price fluctuations during economic crises. Ali, Mensi, Anik, Rahman, and Kang (2022) investigate the comovement between oil futures markets and stock markets in major countries (China, Canada, Russia, the US, and Venezuela). The results reveal greater comovement during the pandemic, highlighting the global impact of the crisis on the interconnectedness of financial markets. Bouri, Lei, Jalkh, Xu, and Zhang (2021) analyze high-frequency data, using a time-varying parameter vector autoregression (TVP-VAR) model to study spillovers between the S&P 500, gold, and oil markets. They find that realized volatility spillovers were particularly strong, with the US stock index acting as a net transmitter, highlighting the relevance of volatility transmission in financial markets. Costola and Lorusso (2022) take a broader perspective, investigating the influence of Russian geopolitical uncertainty on spillovers, with a focus on oil and gas. They identified oil and gas as major transmitters of spillovers during such periods, demonstrating the importance of geopolitical events on financial markets.

Using the methodologies proposed by BK18 and DY12, Balli, Balli, and Nguyen (2023) scrutinize the frequency connectedness between oil price changes and stock returns in the oil and gas sector. Their study reveals substantial spillover between the oil market and the oil and gas industry sector, particularly in the short term (one to five days) compared to the medium and long term. Additionally, they note that oil price changes have less influence on sectoral returns with higher profitability ratios. More recently, Nekhili, Mensi, Vo, and Kang (2024) investigate connectedness in realized volatility, jumps, skewness, and kurtosis among European stock sectoral indices. Their results demonstrate significant high-order moment connectedness among European sectoral returns before and during the pandemic. Moreover, their study identifies the European energy and chemicals (insurance and industrial) sectors as the largest sources of systemic risk in terms of volatility and jumps (kurtosis and skewness).

Cui, Goh, Li, and Zou (2021) explore the risk connectedness between oil and stock markets in both oil-exporting and oil-importing countries over an extended period. Their findings reveal an intensification of risk connectedness during both the global financial crisis (GFC) and the COVID-19 pandemic, with mixed lead-lag relationships. Dai, Zhu, and Zhang (2022) explore the role of gold and oil as receivers of systemic shocks and Chinese sectors as transmitters, offering insights into asset dynamics in periods of turbulence. Hung and Vo (2021) investigate multifrequency volatility spillovers between crude oil, the S&P 500, and gold markets, using the DY12 spillover index and the wavelet coherence approach. Their study reveals significant dependent patterns in information spillovers among these assets during this period. Lin, Zhou, Jiang, and Ou (2021) employ a Markov regime-switching VAR model to reveal linear risk spillovers from US stock markets to the oil market in the short term, emphasizing the importance of considering market regimes in understanding risk transmission. Mensi, Rehman, Maitra, Al-Yahyaee, and Vo (2021) explore comovements between oil prices and BRICS stock markets over the long term, revealing comovements at lower scales or in the long term, indicating enduring connections

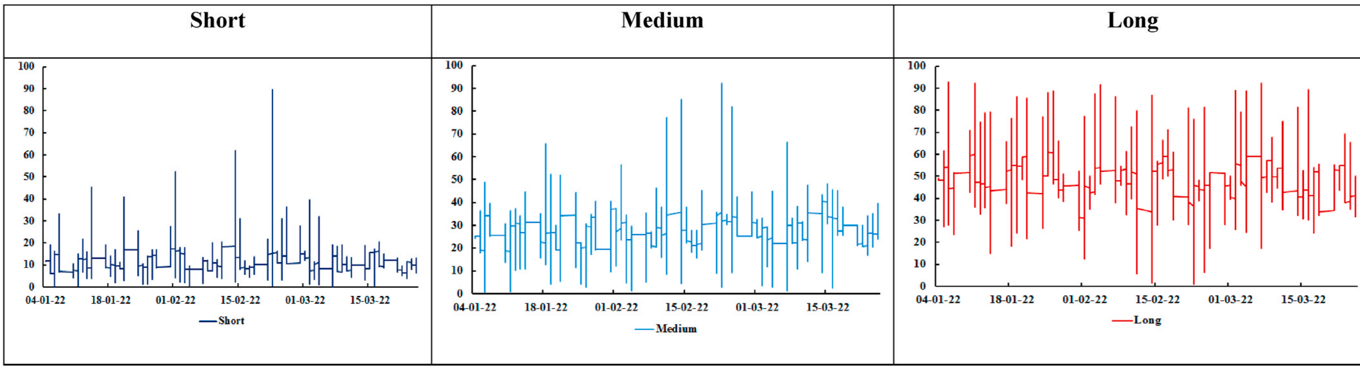


Fig. 4. Intraday total frequency spillover index.

between oil and stock markets. Mensi, Al-Yahyaee, et al. (2021) scrutinize the frequency of spillovers between crude oil futures and MENA stock markets over a broad timeframe. Their findings indicate varying levels of spillovers and mixed lead-lag relationships, emphasizing the dynamic nature of these interactions. Mensi, Al Rababa'a, Vo, and Kang (2021) concentrate on ten Chinese sector stocks, WTI oil, and gold, revealing that bad return spillovers dominate good return spillovers. Furthermore, major events such as the COVID-19 pandemic, the oil crisis, and financial crises intensify asymmetric spillovers, highlighting the significance of hedging strategies. Mensi, Yousaf, Vo, and Kang (2022) investigate 22 sub indices of the Stoxx 600 index, gold, and Brent oil futures. Their research corroborates the findings by Dai et al. (2022), emphasizing the consistency of results about the role of assets during systemic shocks. Wen, Liu, Dai, He, and Liu (2022) focus on Chinese markets, employing Maximum overlapping discrete wavelet transform (MODWT) and a vine–quantile regression model. Their study highlights that volatility spillovers in the Chinese market are more pronounced than spillovers from oil to the Chinese domestic market, showing the importance of domestic factors. Zhang and Hamori (2021) analyze the oil–stock nexus in the context of Germany, Japan, and the US. They find both short-term return spillovers and long-term volatility spillovers between oil and stock markets, which were more pronounced during the GFC. Zhu, Tang, Wei, and Lu (2021) investigate significant risk spillovers from stock markets to oil markets and vice versa, emphasizing the importance of considering risk spillovers from second-board markets to oil markets.

Collectively, these studies demonstrate the intricate and evolving nature of the relationship between oil prices and stock market returns, emphasizing the importance of considering factors such as systemic shocks, geopolitical events, and high-frequency dynamics in understanding this complex interplay, in addition to financial crises, and even global pandemics, making this a timely and pertinent area for further exploration.

Despite these extensive inquiries, a research gap exists in understanding these dynamics within the specific confluence of a global pandemic and a regional war. Most of the available literature examines the impact of oil prices on stock market returns either in isolation or in conjunction with other variables but rarely in the context of two crises, in particular when one of them is a war. The recent escalation of the Russia-Ukraine war provides a unique backdrop for studying these interconnections, as it represents one of the most severe geopolitical tensions in recent history, as it has occurred at the same time as a global pandemic.

Furthermore, most studies have focused on larger, global stock markets, such as the S&P 500, while overlooking the potential impact of oil prices on European stock markets, especially at a sectoral level. The existing literature offers substantial evidence of spillover effects from oil prices to stock markets and vice versa. However, few studies employ high-frequency data to investigate these spillover effects on European stock markets during a geopolitical conflict, particularly one that affects a major energy-producing region.

This study fills these gaps by exploring the intraday spillovers between oil prices and European stock markets during the simultaneous unfolding of the COVID-19 pandemic and the ongoing Russia-Ukraine war. It analyzes the spillover effects between oil and the Stoxx 600 index and its subsector indices using high-frequency data. By doing so, we provide a more granular understanding of the intricate interplay between oil prices and European stock markets at a time of significant global and regional upheaval. Ultimately, this investigation contributes to the existing literature on the impact of the COVID-19 pandemic and geopolitical conflicts on the transmission of spillovers in oil and stock markets, offering valuable insights into effective hedging strategies for assessing financial risk in these uncertain times.

3. Methodology

3.1. Data and statistical summary

We use 5-min data to explore the spillover and connectedness between oil and the Stoxx 600 index as an aggregate market index, including its subsectoral indices for auto, basic (basic material), banks, chemicals, food and beverage, health, industrials, insurance, oil and gas, retail, real estate, tech, telecom, and utilities. The sample data were obtained from the Datastream database for the period January 3, 2022, to March 25, 2022, consisting of 6119 observations. Although daily or weekly data are commonly used to investigate spillovers, we opted for high-frequency data because of its ability to provide good approximations of volatility and a better understanding of the transmission mechanism (Baruník, Kočenda, & Vácha, 2016). We select 5-min high-frequency price data, as it provides a good balance between minimizing microstructure noise and achieving accurate estimations (as noted by Andersen & Teräsvirta, 2009; Degiannakis, 2018; Luo & Ji, 2018).

We calculate intraday continuously compounded returns by taking the difference in logarithmic percentage of two consecutive prices or the logarithm of the ratio of the price at time t to the price at time t-1, estimated as $r_t = \ln(P_t) - \ln(P_{t-1})x100 = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$.

Table 1 presents a statistical summary of the fifteen European indices, representing the fourteen different subsectors in addition to the aggregate index and oil prices. The results show that tech and chemicals sectors had the highest mean return (0.022) during the sample period, followed by retail (0.018) and industrials (0.017). Two subsectors, basic (basic material) and oil and gas, have a negative mean return, as did oil prices. The highest return dispersion is in the chemicals sector, which has the highest returns. The real estate subsector has the lowest volatility of all financial markets.

Our skewness analysis reveals positive tails for all indices, except for oil and gas sector and oil commodity. The kurtosis values surpassed

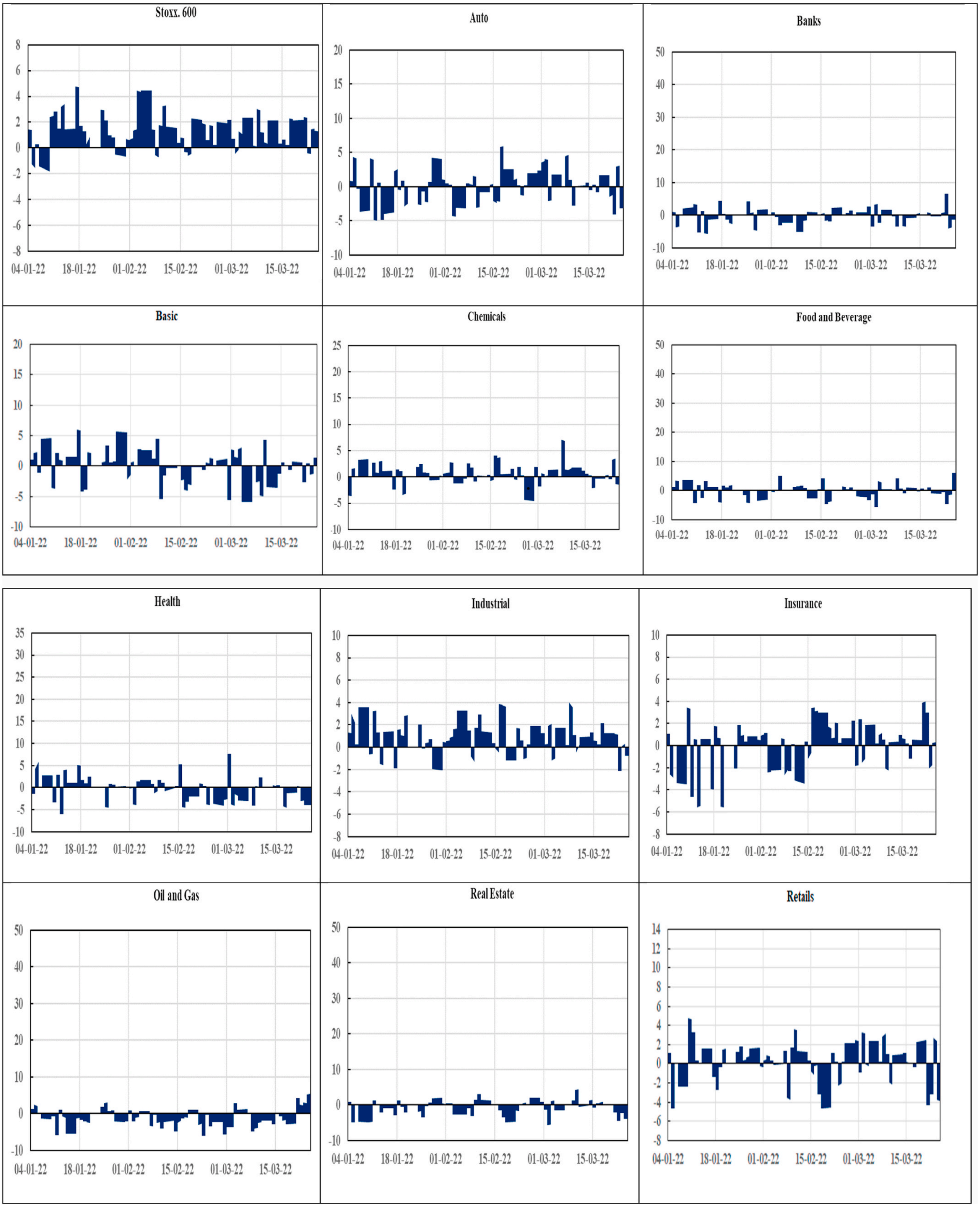


Fig. 5. Net dynamic spillover.

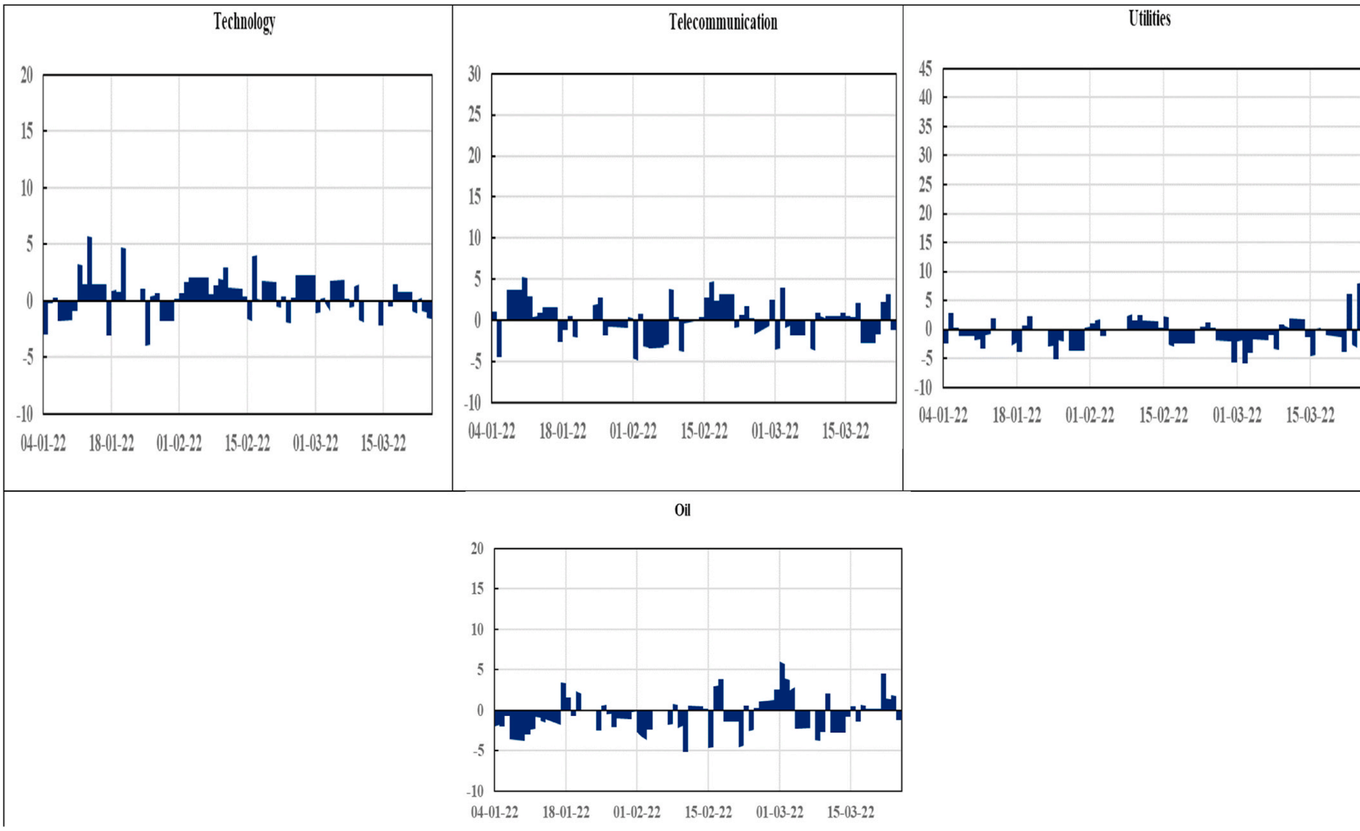


Fig. 5. (*continued*).

those of a normal distribution, signifying fat tails and an elevated likelihood of extreme outliers. The Jarque-Bera test robustly rejects the null hypothesis of normal distributions. All return series exhibited stationarity according to both the augmented Dickey-Fuller (ADF) unit-root test, ERS (Elliott, Rothenberg, & Stock, 1996), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test. The results of the Ljung–Box test demonstrate evidence of serial correlation in standard residuals.

Lastly, our correlation analysis reveals negative correlations between European sectors and oil, except for the basic material and oil and gas sectors. These correlations range from −0.137 (health) to −0.221 (food and beverage), indicating diversification benefits between oil and European sectors. Moreover, we observe a strong positive correlation between the oil and gas sector and oil commodities, whereas health sector has the least correlation with oil (−0.137).

Fig. 1 depicts the intraday price fluctuations of European sectors and oil throughout the sample period. During this period, most sectors have a downward trend, with the notable exceptions of the sector and the oil and gas sector. Oil commodities have an upward trend in line with Costola and Lorusso (2022). Fig. 2 displays the 5-min price return series and shows clustering in volatility and fat tails in the data distribution.

3.2. *Econometric approach*

3.2.1. *Time-domain spillover index*

To examine spillovers and connectedness between the oil market and the European stock section in the time domain, we adopt the DY12 approach. In a structural $VAR(p)$ model, the n-variate process $x_t = (x_{t,1}, x_{t,2}, \dots, x_{t,n})$ at $t = 1, 2, \dots, T$ can be expressed as:

$$\varnothing(L)x_t = \varepsilon_t, \tag{1}$$

where $\varnothing(L) = \sum_h \varnothing_h L^h$ denotes an n x n lag polynomial of order p, and ε_t denotes white noise. The VAR model can be expressed as a moving average:

$$x_t = \Psi(L)\varepsilon_t, \tag{2}$$

where $\Psi(L)$ is an n x n infinite lag polynomial matrix of coefficients. The generalized forecast error variance decompositions (FEVD) are defined as:

$$(\Theta_H)_{j,k} = \frac{\sigma_{k,k}^{-1} \sum_{h=0}^{H} \left((\Psi_h \Sigma)_{j,k} \right)^2}{\sum_{h=0}^{H} (\Psi_h \Sigma \Psi_h')_{j,j}}, \tag{3}$$

where $\sigma_{k,k}^{-1}$ stands for the standard deviation of the error terms in the j^{th} variable. Ψ_h denotes an n x n matrix of coefficients corresponding to lag h. The H-step-ahead error variance in forecasting x_i for $H = 1, 2 \dots n$. The variable $(\Theta_H)_{j,k}$ estimates the contribution of market k to the forecast error variance of market j. Equation (3) can be normalized as:

$$(\widetilde{\Theta}_H)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N} (\Theta_H)_{j,k}}, \tag{4}$$

where $\sum_{k=1}^{N} (\widetilde{\Theta}_H)_{j,k} = 1$ and $\sum_{j,k=1}^{N} (\widetilde{\Theta}_H)_{j,k} = N$. The connectedness measure C_H is calculated as a percentage of the sum of the off-diagonal elements to the sum of the entire matrix:

$$C_H = \left(\frac{\sum_{j \neq k} (\widetilde{\Theta}_H)_{j,k}}{\sum (\widetilde{\Theta}_H)_{j,k}} \right) \times 100 = \left(1 - \frac{\mathrm{T_r}\{\widetilde{\Theta}_H\}}{\sum (\widetilde{\Theta}_H)_{j,k}} \right) \times 100, \tag{5}$$

where T_r denotes the trace operator, and C_H is the total connectedness measure.

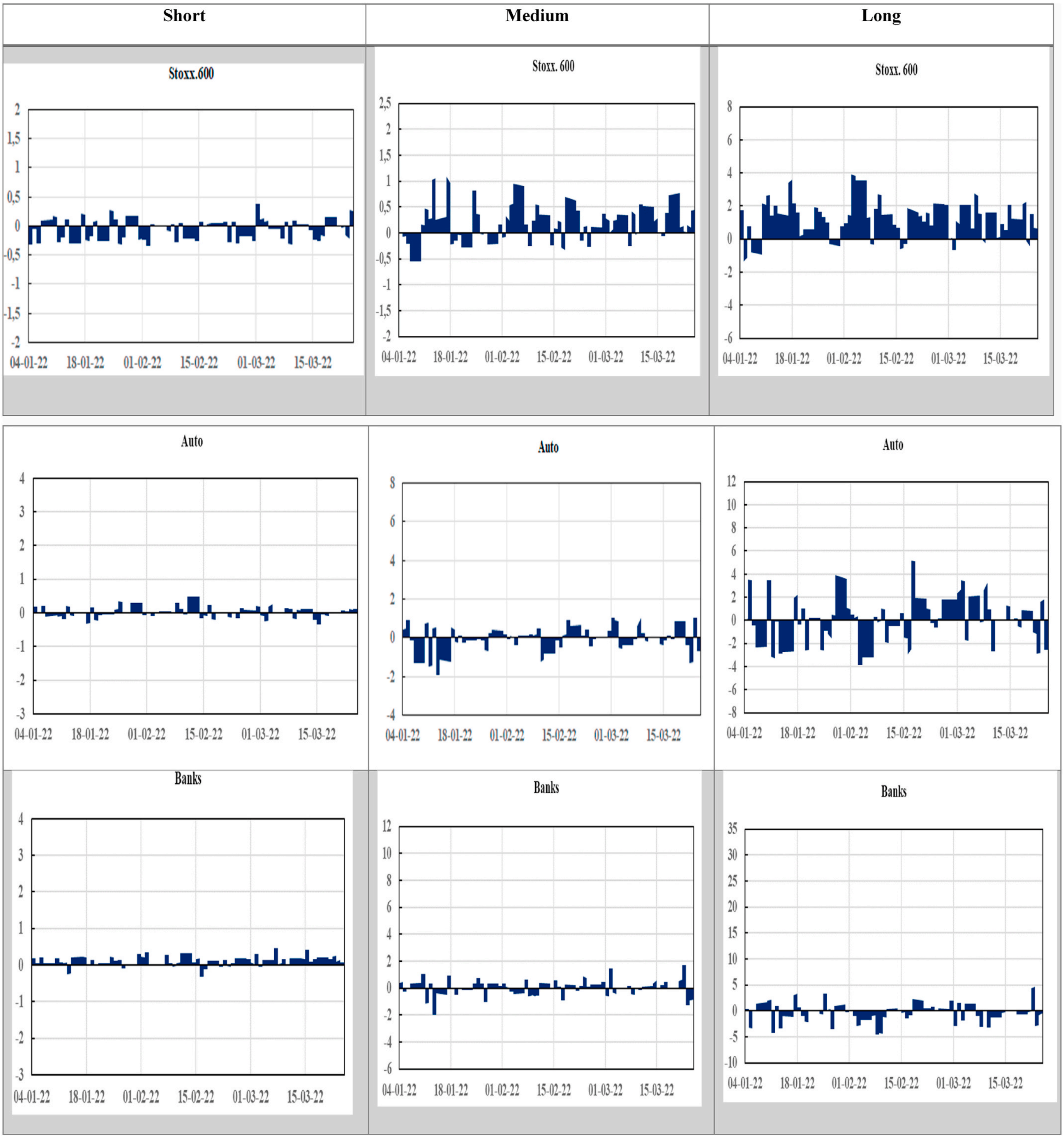


Fig. 6. Intraday Frequency Net Spillover Index.
Notes: This plot shows the short-, medium-, and long-term net connectedness between European sector stocks and oil using Baruník and Křehlík's (2018) technique. We identify a net transmitter and receiver of spillovers in which the values of connectedness are positive and negative.

3.2.2. Frequency connectedness index

We adopt the BK18 approach to measure connectedness between the oil market and the European stock sectors in the frequency domain. The BK frequency connectedness approach is the extension of the DY12 method. The spectral representation of the coefficient matrix Ψ_h is given by the Fourier transform as $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h}\Psi_h$ with $i = \sqrt{-1}$. Using the Fourier transform, the generalized FEVD over frequencies can be written as:

$$f(\widetilde{\Theta}_\omega)_{jk} = \frac{\sigma_{kk}^{-1}\left|(\Psi(\mathrm{e}^{-\mathrm{i}\omega})\Sigma)_{i,k}\right|^2}{(\Psi(\mathrm{e}^{-\mathrm{i}\omega})\Sigma\Psi^{'}(\mathrm{e}^{+\mathrm{i}\omega}))_{jj}}, \tag{6}$$

where $f(\widetilde{\Theta}_\omega)_{jk}$ calculates the portion of the FEVD of market j due to

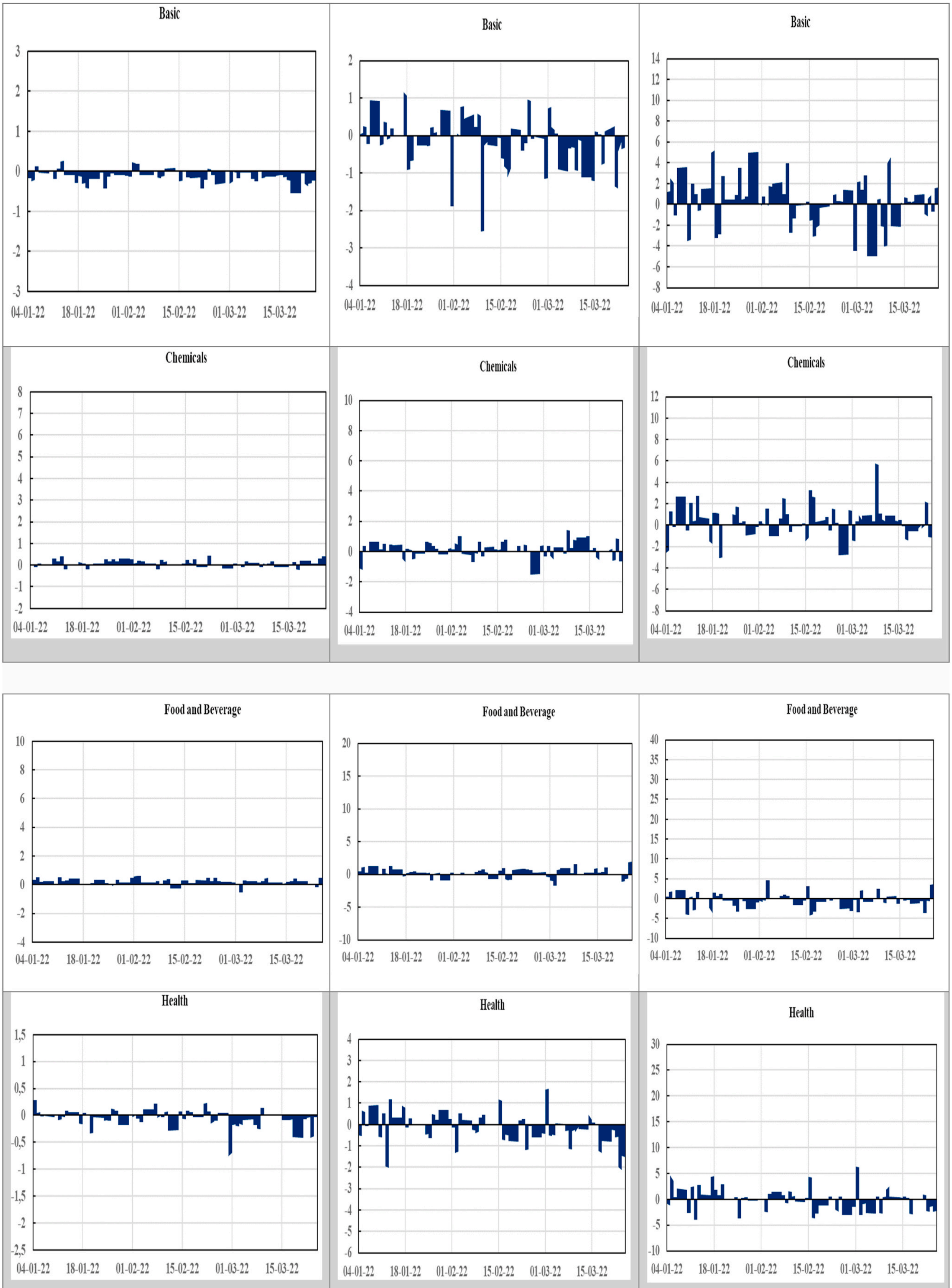


Fig. 6. (*continued*).

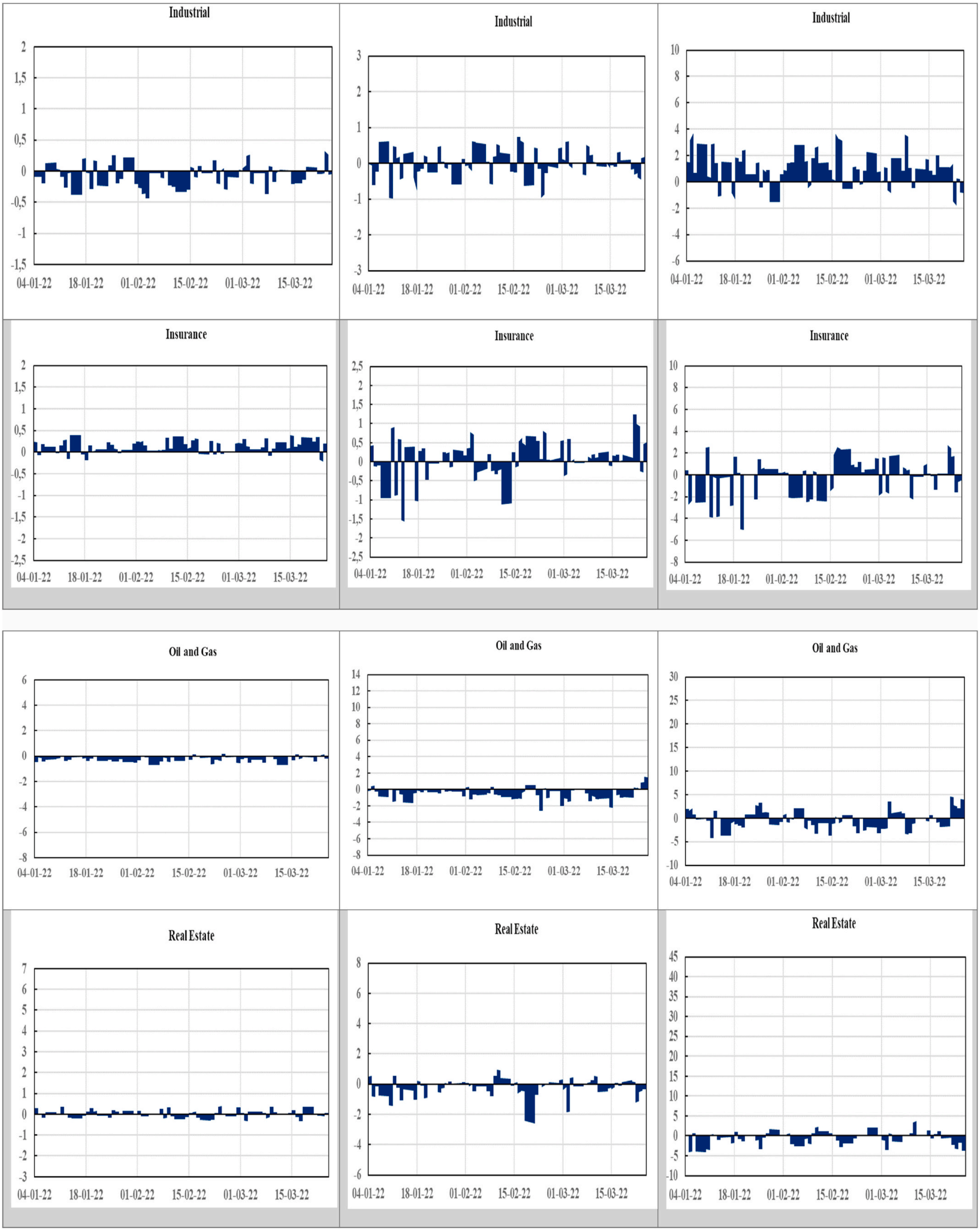
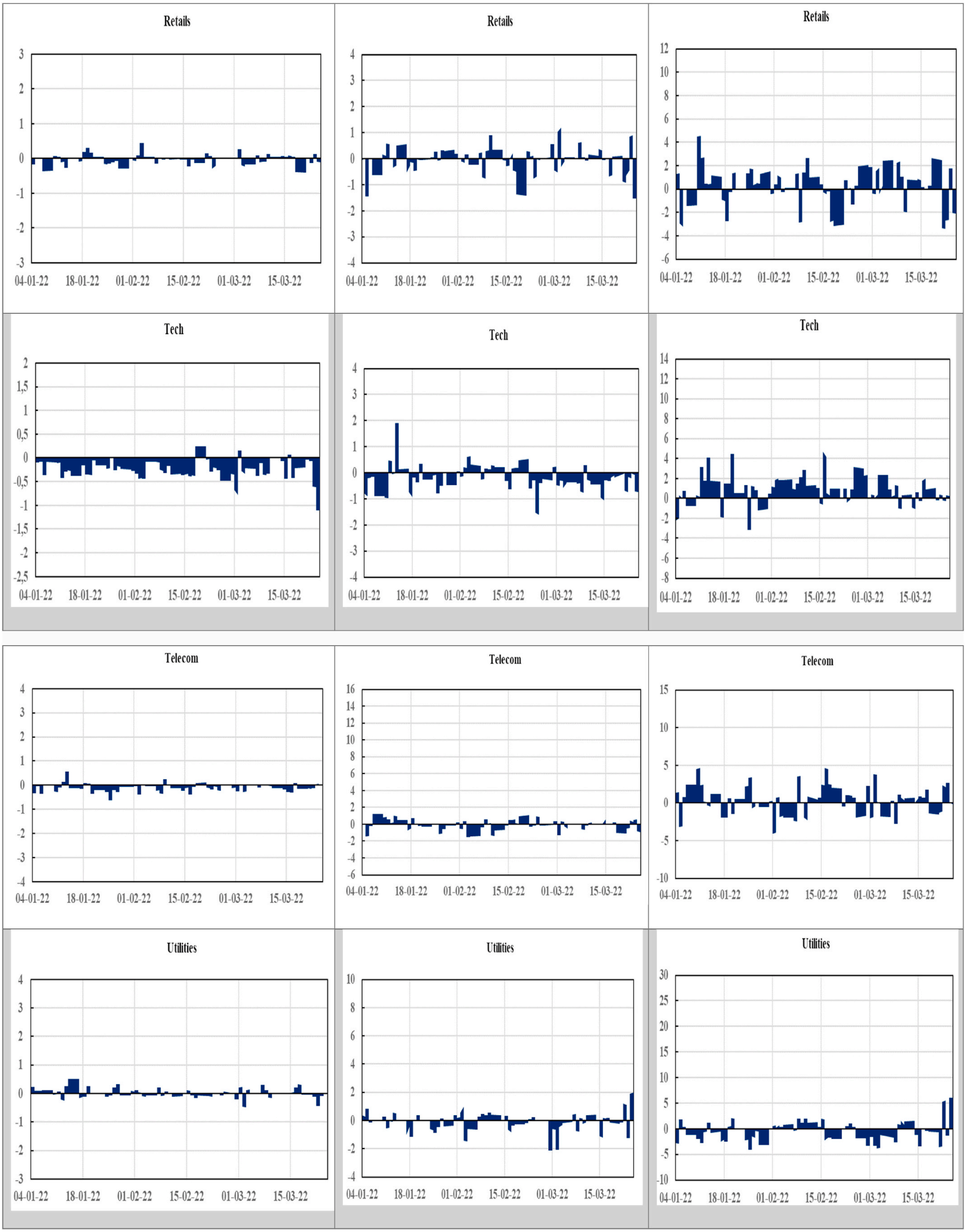


Fig. 6. (*continued*).



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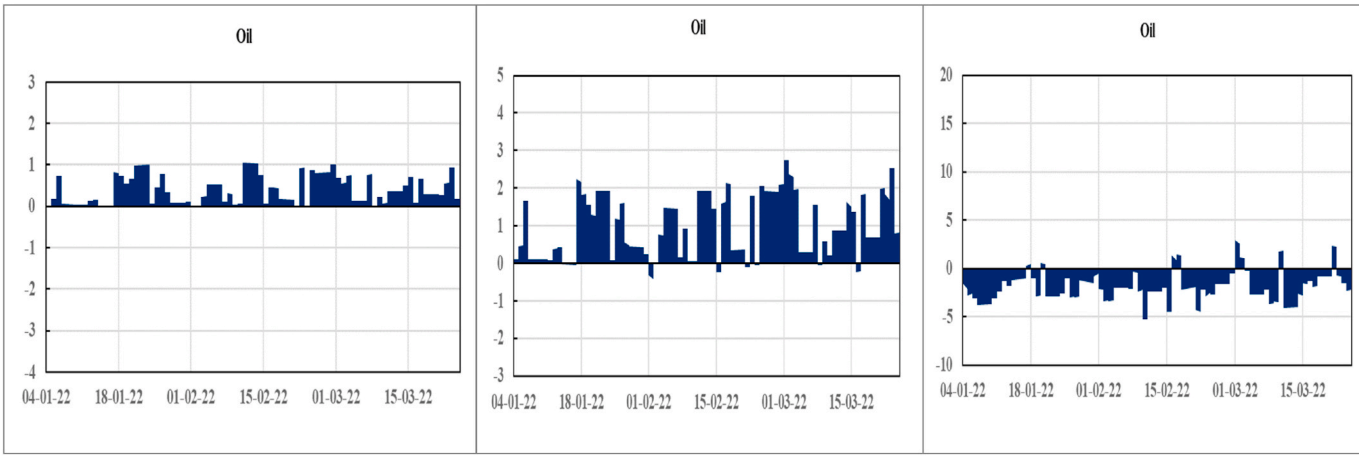


Fig. 6. (*continued*).

shocks explained by market k at frequency ω. Equation (6) can be standardized as:

$$f(\widetilde{\Theta}_{\omega})_{jk} = \frac{(\Theta_d)_{jk}}{\sum_{j=1}^{n}(\Theta_d)_{jk}}, \tag{7}$$

The generalized FEVD on the frequency band $d = (a, b), a, b \in (-\pi, \pi)$ is expressed as:

$$(\widetilde{\Theta}_d)_{j,k} = \int_a^b (\widetilde{\Theta}_{\omega})_{jk} d\omega. \tag{8}$$

Based on this variance decomposition, the total connectedness on frequency band d is measured as:

$$C^d = \frac{\sum_{j=1,j\neq k}(\widetilde{\Theta}_d)_{jk}}{\sum_{ik}(\widetilde{\Theta}_d)_{jk}} = 1 - \frac{\sum_{j=1}(\widetilde{\Theta}_d)_{jk}}{\sum_{ik}(\widetilde{\Theta}_d)_{jk}}. \tag{9}$$

3.2.3. *Directional connectedness*

Then, we measure the directional connectedness to check whether a given market is a receiver or transmitter of shock in a system. So, the contribution (*within from*) of the directional connectedness from all other markets to market j is calculated as:

$$C_{j\to *}(H) = \frac{\sum_{k=1(j\neq k)}^{N}\widetilde{\Theta}_{j,k}(H)}{\sum_{j,k=1}^{N}\widetilde{\Theta}_{j,k}(H)} \times 100 = \frac{\sum_{k=1(j\neq k)}^{N}\widetilde{\Theta}_{j,k}(H)}{N} \times 100 \tag{10}$$

In contrast, the contribution of the directional connectedness (*within to*) from market j to all other markets k is given as:

$$C_{j\to *}(H) = \frac{\sum_{k=1(j\neq k)}^{N}\widetilde{\Theta}_{k,j}(H)}{\sum_{j,k=1}^{N}\widetilde{\Theta}_{k,j}(H)} \times 100 = \frac{\sum_{k=1(j\neq k)}^{N}\widetilde{\Theta}_{k,j}(H)}{N} \times 100 \tag{11}$$

Finally, the *net* directional connectedness is calculated as:

$$Net\ C_j(H) = C_{j\to *}(H) - C_{j\to *}(H) \tag{12}$$

The positive (negative) values of net directional connectedness signify whether a market is a transmitter (receiver) of connectedness.

4. Results

4.1. *Time connectedness analysis*

The first step in this analysis involves evaluating the total connectedness among various assets using the DY12 spillover index approach. The results are reported in Table 2, in which the diagonal values are the "own" shocks both to and from the respective asset, whereas the off-diagonal values in the columns show the spillover from one variable to another (labeled as TO). The off-diagonal values in the rows depict the contribution received by a variable from others (labeled as From). The bottom row labeled Net displays the net spillovers, calculated by subtracting "contributions from others" from "contributions to others" and reveals whether an asset receives (or transmits) more shocks than it transmits (or receives) from other assets. A positive value indicates a net transmitter, meaning that the asset in question spills more shocks to other assets than it receives, whereas a negative value suggests a net receiver, meaning that the asset is driven by other assets. The Total Connectedness Index (TCI) shows the total spillovers transmitted among the assets considered, calculated as the sum of contributions from others (or the sum of contributions to others) as a percentage of the sum of contributions, including "own."

The results in Table 2 demonstrate the average connectedness among the European sectors and oil commodities and the extent to which each sector is a net transmitter or a net receiver. The analysis yields several noteworthy findings. First, cross-index returns explain the highest share of forecast error variance. Second, the TCI is 89.79 percent, which suggests a high degree of connectedness, with around 90 percent of the total variance of the forecast error during the sample period explained by shocks within the network. Third, the net spillovers reveal that auto, chemicals, food, industrials, insurance, real estate, retail, tech, and telecom sectors are net transmitters of shocks, and chemicals and industrials sectors are the highest at 18.54 percent and 17.94 percent, respectively. Meanwhile, banks, basic material, health, oil and gas, and utilities sectors are net shock receivers, with oil and gas sector being the highest (−30.99%). These findings suggest that shocks to any of these indices will significantly influence at least one of the other European sectors, which might indicate the inability of one sector to hedge against another. During this crisis, oil commodities are net receivers, whereas the majority of capital markets are net contributors, as they are significantly influenced by the crisis, in line with Alam, Tabash, Billah, Kumar, and Anagreh (2022) and Mohammed, Tedeschi, Mallek, Tarczyńska-Łuniewska, and Zhang (2023).

Because financial assets continuously interact with and influence one another, the level of connectedness among them can vary over time, influenced by a range of factors. Understanding and managing this dynamic connectedness is crucial for investors and financial institutions, enabling them to navigate the ever-changing financial landscape more effectively and make well-informed investment decisions. Using the methodology in Diebold and Yilmaz (2014), Fig. 3 illustrates the time-varying connectedness, calculated using a 200-day rolling-window size and a 100-day forecast horizon. The results depicted in the figure show that the TCI fluctuates between 75 percent and 95 percent on a single day. This fluctuation indicates that the Russia-Ukraine war significantly impacted connectedness among these markets, potentially

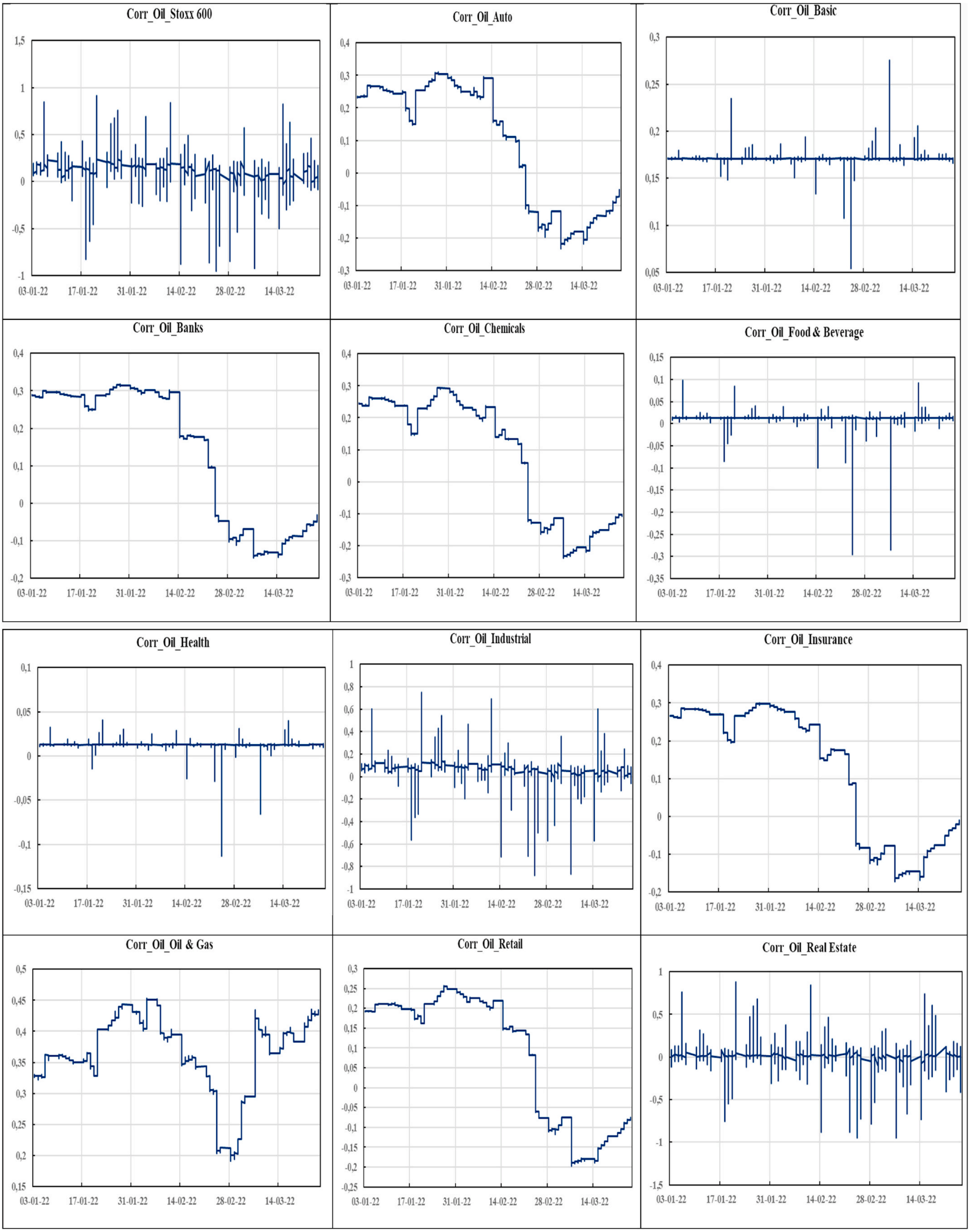


Fig. 7. Dynamic conditional correlations (DCCs) behavior over time.

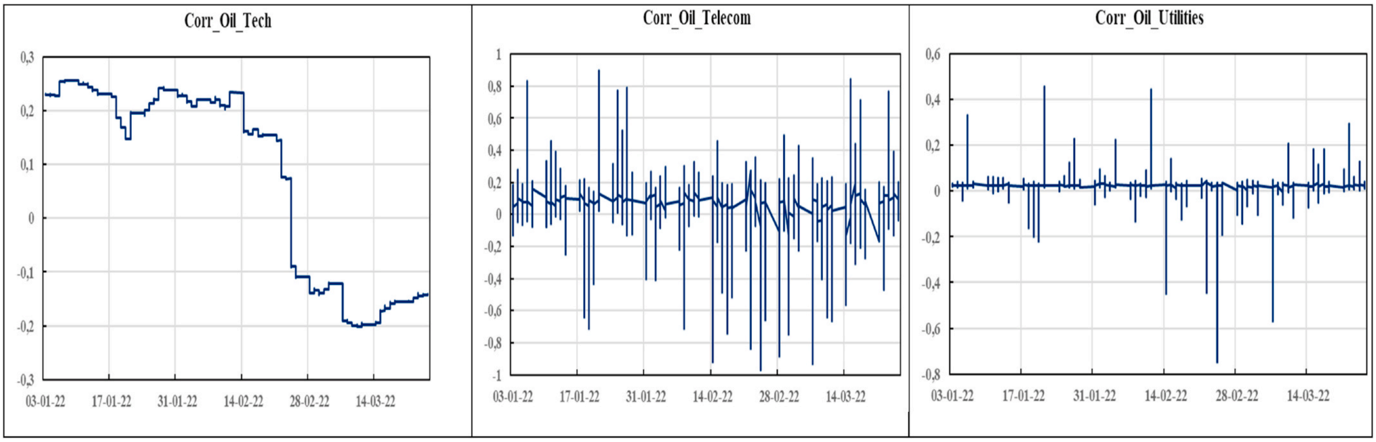


Fig. 7. (*continued*).

driven by market sentiment characterized by fear. Overall, the findings suggest that the Russia-Ukraine war had a significant impact on the dynamic connectedness of financial markets, in line with several studies (Adekoya, Oliyide, Yaya, & Al-Faryan, 2022; Boungou & Yatié, 2022; Mohammed et al., 2023; Umar, Polat, Choi, & Teplova, 2022), which find that spillovers collectively surge across all commodities and markets in times of war. These uncertain events significantly constrain diversification possibilities, as a result of the pronounced interconnectedness of all markets and commodities (Jiang, Tian, & Mo, 2020; Naeem, Pham, Senthilkumar, & Karim, 2022).

4.2. Frequency connectedness analysis

We use the BK18 frequency spillover index to evaluate the risk interconnectedness between oil and stock markets across different periods and frequency bands. To initiate our analysis, we examine the static risk spillover effects at three distinct frequency bands: short term (1–5 days), medium term (5–22 days), and long term (22 days or more). Categorizing connectedness into short-, medium-, and long-term categories proves advantageous because different events or factors may influence connectedness at varying time scales. For instance, short-term connectedness may be more susceptible to market noise or extraordinary events, whereas long-term connectedness may be influenced more by macroeconomic conditions or policy changes. By investigating connectedness at different time scales, we gain a deeper understanding of the diverse factors that affect connectedness and their evolution. This analysis of different frequency bands allows us to probe the mechanisms of risk transmission in the short, medium, and long term between oil and the selected stock markets.

Table 3 illustrates the total risk connectedness between oil and stock markets at different frequency bands. Most risk spillovers between these markets occur in the medium term, accounting for 90.08 percent. This highlights the substantial influence of medium-term market factors on risk spillovers between oil and stock markets. The analysis reveals that industrials, tech sectors, and the aggregate index market are the primary recipients of risk from the oil–stock system in the short and medium term (i.e., d1 or 1–5 days and d2 or 5–22 days). An examination of the contributing TO sectors shows that chemicals and industrials sectors make the most significant contributions in frequency bands d1 and d2, whereas banks and utilities sectors play a larger role over a longer time horizon (i.e., more than 22 days).

Additionally, we evaluate the net connectedness (i.e., net transmitter and net recipient) of each market in the oil–stock system based on the frequency domain. Insurance, real estate, and retail sectors (health and oil and gas sectors) act as net transmitters (receivers) across all frequency bands. Banks, food, utilities sectors, and oil (tech, telecom, and industrials sectors) function as net transmitters during periods of 1–5 days and 5–22 days but shift to net recipients at higher frequency bands (i.e., more than 22 days). Chemicals and autos serve as net transmitters at both lower and higher frequency bands but transition to net receivers in the intermediate band. These results indicate that the insurance, real estate, and retail sectors pose greater risk to other sectors and the market as a whole. In contrast, the banking, food and beverage, utilities, and oil sectors are more susceptible to short-term market noise or exceptional events, resulting in the transmission of greater risk to other sectors in the short term. As market conditions evolve over time, the transmission of risk between various sectors may fluctuate.

Fig. 4 illustrates the intraday spillover index in different time frames. In the short term, the index displays minor fluctuations, with the index surpassing 50 percent on two occasions. In the medium term, fluctuations are more pronounced, and the index exceeds 50 percent more than seven times. This suggests a higher degree of spillover during this period than in the short term. The index has the most substantial fluctuation in the long term, exceeding 50 percent several times and even surpassing 70 percent on more than 20 occasions. This implies a significant level of spillover between trading days over the long term. Therefore, although significant adjustments in trading strategies may not be necessary, traders and investors should exercise greater caution and adapt their strategies accordingly, particularly in the medium and long term. The heightened fluctuations in connectedness in the medium and long term could elevate market risk, emphasizing the importance of vigilance and the implementation of appropriate risk management strategies by investors and traders.

4.3. Net directional connectedness analysis

The identification of the dynamic net transmitters and net recipients of spillovers is crucial for understanding the interdependence between different stock market indices. Investors and traders stand to gain invaluable insights from discerning which indices serve as sources and recipients of spillovers, knowledge that can profoundly shape their investment decisions and risk management strategies. In this context, positive and negative values play a crucial role, signifying whether a particular index acts as a source or recipient of spillovers from other stock market indices. Fig. 5 presents the dynamic landscape of net directional connectedness. It reveals a compelling pattern in which the analyzed indices oscillate between transmitting and receiving spillovers, indicating bidirectional and asymmetric connectedness across the entire spectrum of indices. This finding highlights a fundamental reality: stock market and oil market indices both play dual roles as both sources and recipients of spillovers. This duality shows the ever-evolving nature of their interdependence. Notably, market shocks can emanate from any of the analyzed indices and, subsequently, ripple across different sectors, rendering it imperative for investors and traders to maintain a vigilance

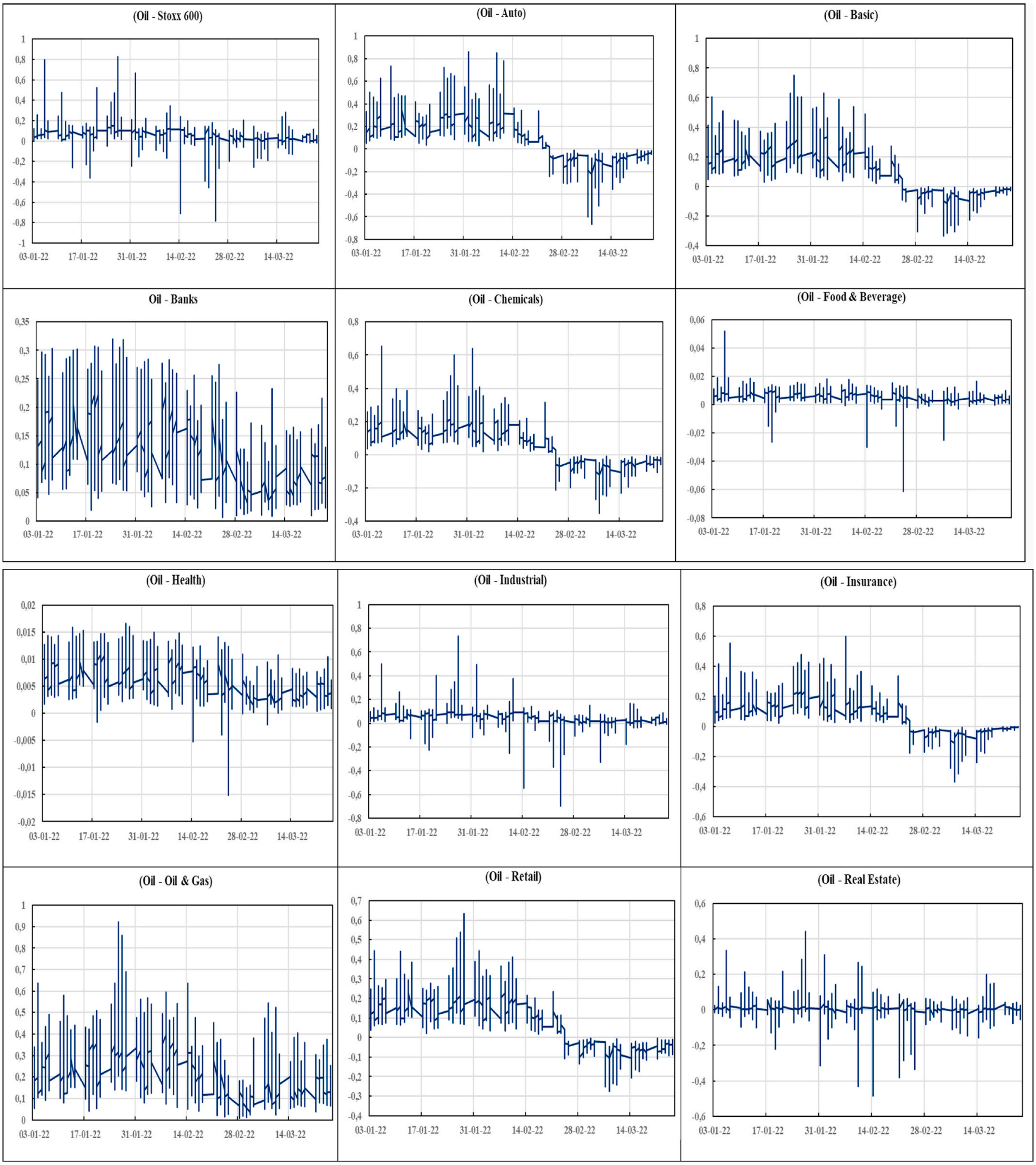


Fig. 8. Dynamic optimal hedge ratios.

over the spillover effects across all indices. This vigilance is key for comprehending market dynamics and making well-informed decisions.

Several findings emerge based on the frequency domain net connectedness results in different horizons shown in Fig. 6. First, the transmission of shocks or disturbances from one market to another has more pronounced fluctuations in the long term than in the short term. This suggests that, although market participants may swiftly respond to spillover effects in the short term by adjusting their positions, potentially mitigating the impact of these spillovers, they might become complacent in the long term. This complacency can stem from an assumption that spillover effects will remain stable or predictable, only to be jolted by larger fluctuations after unexpected shocks. Moreover, it hints at the

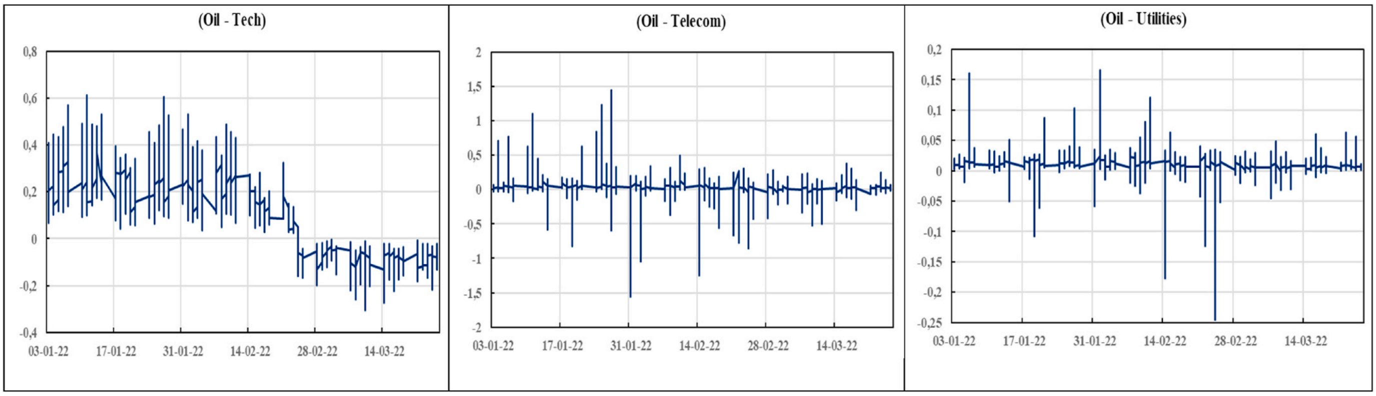


Fig. 8. (*continued*).

Table 4
Results of optimal portfolio weights, hedge ratios, and hedging effectiveness.

	Weights				Hedge Ratios				
	Mean	Min	Max	Standard Deviation	Mean	Min	Max	Standard Deviation	Hedging Effectiveness
Stoxx 600	0.21	−0.39	0.93	0.16	0.06	−0.78	0.83	0.10	88.32
Auto	0.43	−0.02	0.99	0.21	0.10	−0.66	0.86	0.20	74.10
Banks	0.37	−0.02	0.95	0.21	0.12	−0.33	0.75	0.17	76.26
Basic Material	0.34	−0.01	0.82	0.22	0.13	0.01	0.32	0.06	77.50
Chemicals	0.27	−0.02	0.94	0.17	0.08	−0.35	0.65	0.13	86.05
Food & Beverage	0.20	0.00	0.67	0.13	0.01	−0.06	0.05	0.00	90.39
Health	0.22	0.00	0.64	0.15	0.01	−0.02	0.02	0.00	90.19
Industrial	0.33	−0.20	0.94	0.19	0.04	−0.69	0.73	0.08	82.87
Insurance	0.23	−0.02	0.92	0.18	0.08	−0.37	0.60	0.12	85.45
Oil and Gas	0.22	−0.06	0.98	0.21	0.24	0.01	0.92	0.12	79.03
Retails	0.34	−0.01	0.94	0.19	0.09	−0.27	0.63	0.13	80.83
Real Estate	0.25	−0.27	0.82	0.16	0.01	−0.48	0.44	0.02	87.53
Tech	0.46	−0.01	0.94	0.22	0.12	−0.30	0.61	0.18	77.01
Telecom	0.20	−0.59	1.31	0.16	0.04	−1.55	1.45	0.07	89.69
Utilities	0.23	−0.06	0.82	0.15	0.01	−0.24	0.17	0.01	87.06

Notes: This table summarizes the results of the optimal portfolio weights, hedge ratios, and hedging effectiveness between oil- European sector stocks. The conditional variance and covariances extracted from the DCC-GARCH model (Engle, 2002) are used to quantify the optimal portfolio weights, hedging effectiveness, and hedge ratios.

diminishing effectiveness of policy tools in the long term, highlighting the complexity of managing spillover effects over longer timeframes.

Second, our findings align with previous research, affirming that oil functions as a net transmitter in the short term but becomes a net receiver in the long term. This dichotomy implies that, in the short term, oil prices are more susceptible to influence from external factors, such as shifts in other commodities, and can transmit these shocks to other markets. In contrast, in the long term, oil prices tend to exhibit greater stability and are primarily influenced by factors such as supply and demand. The sentiments of investors also enter into the equation, as pessimism in the market can lead to pronounced sentiment spillover effects in oil prices.

Third, specific sectors, such as oil and gas, telecom, tech, basic material and industries assume roles as net recipients over shorter time horizons (1–5 days) but become net transmitters in the long term. This shift shows the dominance of fundamental factors such as business cycles, investment horizons, and sector-specific trends in the long-term dynamics. For instance, oil and gas companies often require substantial capital investment for exploration and production activities, while tech companies may rely on significant investment in R&D to maintain competitiveness. However, sectors such as banks, chemicals, food and beverage, and insurance tend to act as net transmitters in the short term but evolve into net recipients in the long term. This transition can be attributed to their complex connections with other industries in the broader economy. For example, the food and beverage industry heavily rely on agriculture for its raw materials and consumer demand for its sales. Any shock to the agricultural sector or a shift in consumer demand can lead to losses in this industry. Insurance plays a role as a net recipient of shocks in the long term because it is designed to absorb risks. This interplay among different sectors highlights their varying degrees of cyclicality, which influence the direction of capital flows over longer timeframes. Consequently, the dynamic connectedness of sectors is subject to many short-term factors, but over the long term, fundamental forces tend to have greater influence, leading to shifts in the direction and magnitude of capital flows.

4.4. Dynamic conditional correlations

We have taken a critical step forward in comprehensively analyzing the dynamic conditional correlations (DCC) and estimating the ever-changing relationships between oil and each of the European sectors. The DCC model, a powerful analytical tool, enables us to investigate the complex correlations between these variables at each moment in time. Unlike conventional approaches that assume correlations to be constant over time, our model acknowledges the dynamic nature of these relationships, offering valuable insights into their evolution. Fig. 7, which illustrates our findings, reveals the correlation dynamics across the fifteen pairs considered in our study. We observe positive correlations between oil and basic (basic material), as well as oil and oil and gas. In practical terms, this implies that when the price of oil experiences an upswing, the basic (basic material) sector and the oil and gas sector tend to follow suit, reflecting a positive association in their performance. However, what makes our findings particularly intriguing is what occurred at the end of February 2022. At that time, oil and six

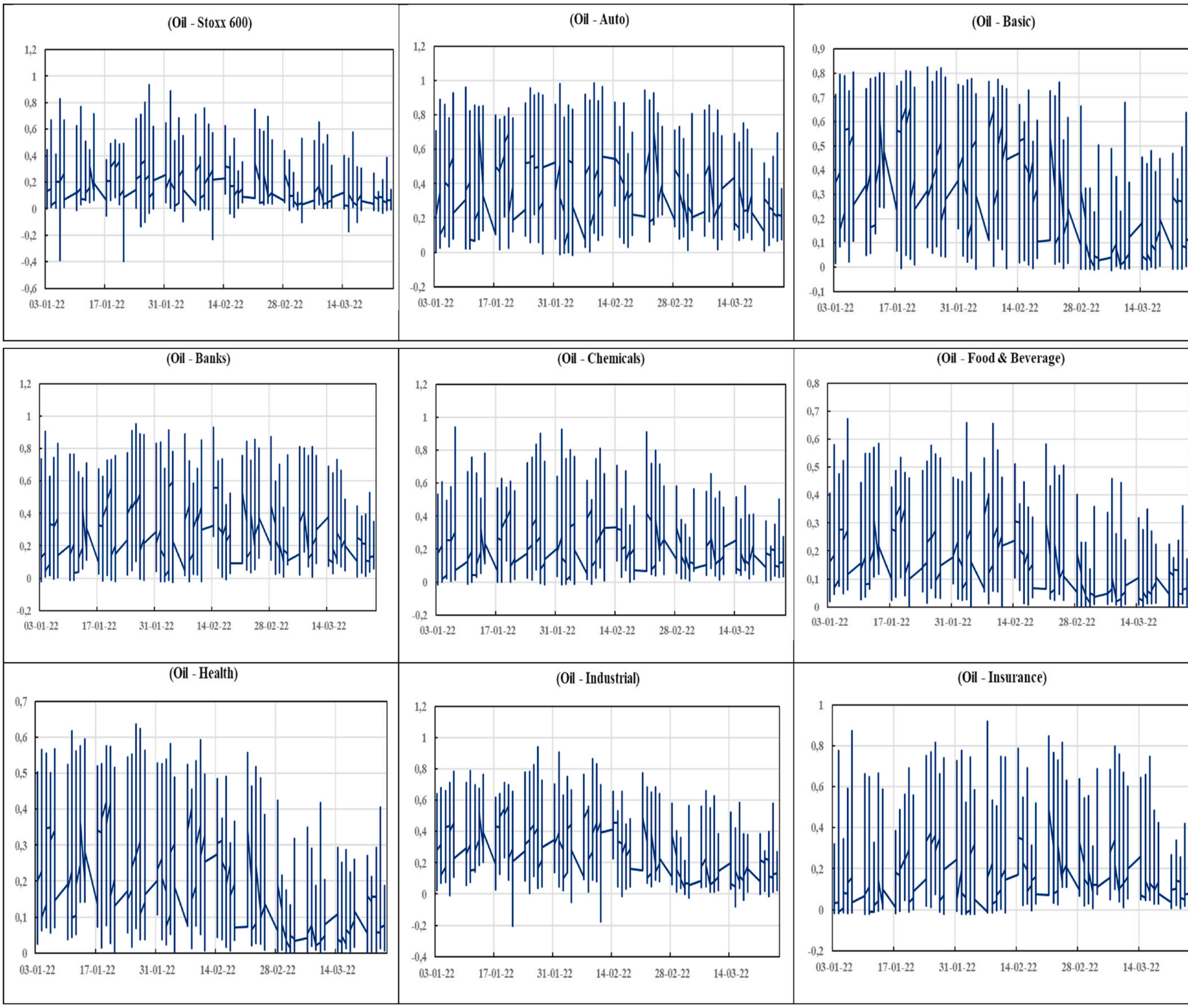


Fig. 9. Dynamic optimal portfolio weights.

sectors—namely auto, banks, chemicals, insurance, retail, and tech sectors, which had previously exhibited positive correlations—underwent a sudden transformation. Their correlations with oil shifted from positive to negative, with profound implications for investors and traders alike, as this change could significantly impact the risk and return characteristics of portfolio investments and trading strategies (see Fig. 8).

This change in correlation dynamics can enhance the diversification benefits of including both oil and these sectors in a portfolio. By holding assets that are negatively correlated with one another, investors could reduce the overall risk of their portfolios while optimizing returns. However, for the remaining pairs—oil/Stoxx, oil/food and beverage, oil/health, oil/industrials, oil/real estate, oil/telecom, and oil/utilities—the correlations are dynamic, fluctuating from positive to negative on multiple occasions.

This dynamic nature of correlations highlights the importance of vigilance by investors and traders. They need to be acutely aware of these changing relationships and be prepared to modify their investment decisions and trading strategies accordingly. For instance, traders who employ a pairs trading strategy might capitalize on these shifting correlations by identifying pairs with negative correlations and exploiting their price differentials. Alternatively, traders who follow a momentum strategy can make real-time adjustments in their positions based on these changing correlations to harness the price momentum of the assets effectively. In summary, our exploration of DCC shows the complex dance between oil and various sectors, emphasizing the need for investors and traders to remain attuned to these fluctuations in order to make informed and strategically sound decisions in the ever-evolving financial landscape.

4.5. Portfolio analysis

Our empirical results stress a critical point: the impact of oil price shocks on various asset prices is far from uniform and, instead, has significant variability. This variability has far-reaching implications, influencing the decisions made by a wide range of economic actors, including investors, corporations, and policy makers. The concept of spillovers takes center stage in this context, as it has profound significance for optimizing portfolios and efficiently allocating assets, both fundamental aspects of investment strategies for individuals and

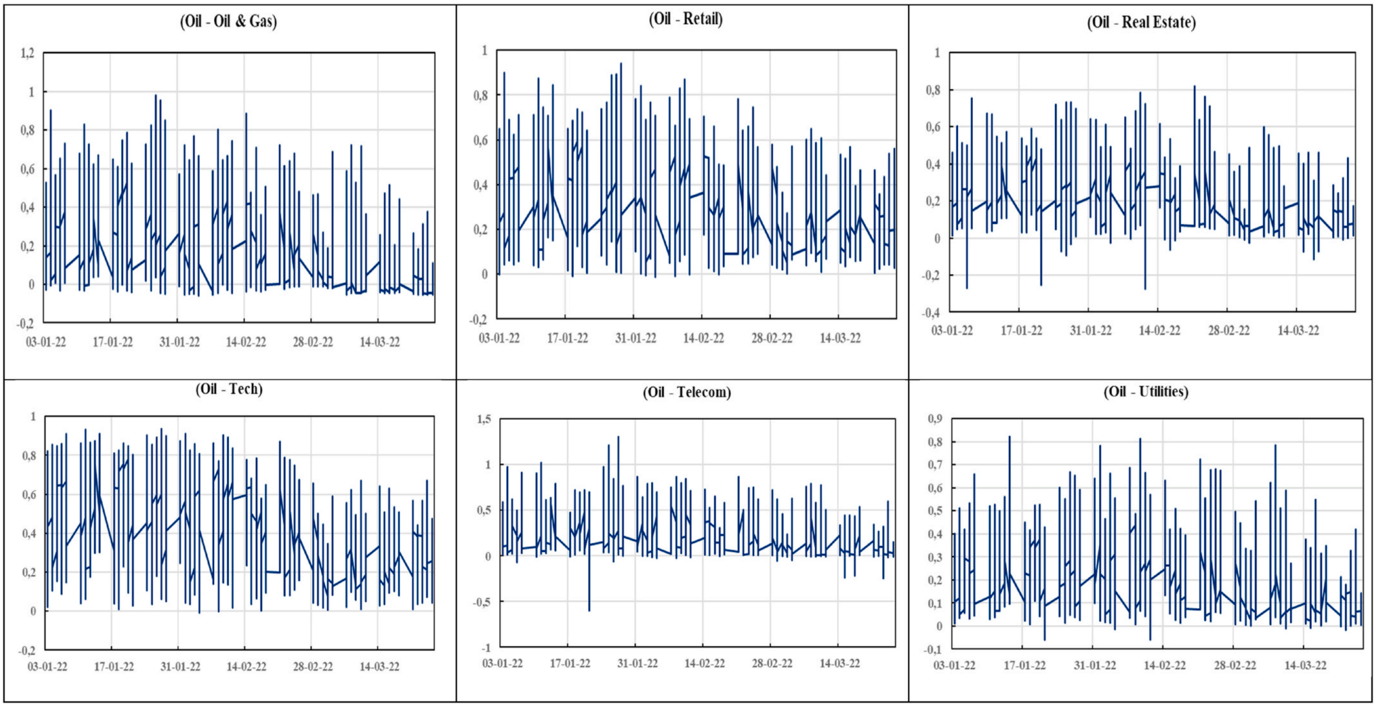


Fig. 9. (*continued*).

investment fund managers alike. To evaluate the effectiveness of hedging strategies and their role in managing financial portfolio risk, Table 4 presents essential metrics, including hedge ratios, optimal portfolio weights, and hedging effectiveness, derived from long-short positions in the assets under examination. This information is valuable for assessing the practicality and efficiency of hedging strategies when confronting financial portfolio risk. One prominent takeaway from our analysis is the variability in optimal portfolio weights across different sectors.

These weights provide crucial guidance to investors seeking to strike a balance between risk and return in their portfolios. For instance, our findings reveal that optimal portfolio weights range from 0.20 for sectors such as food and beverage and telecom to 0.46 for the tech sector. To illustrate, for a $1 portfolio, the optimal allocation would involve investing $0.46 in oil and $0.54 in tech. Although we refrain from delving into specific interpretations of all optimal weights for the sake of conciseness, investors would be wise to allocate more resources to equity shares and reduce their exposure to oil assets. This strategic adjustment can be instrumental in minimizing risk without compromising expected returns, ultimately helping to maximize the risk-adjusted performance of an oil–stock portfolio.

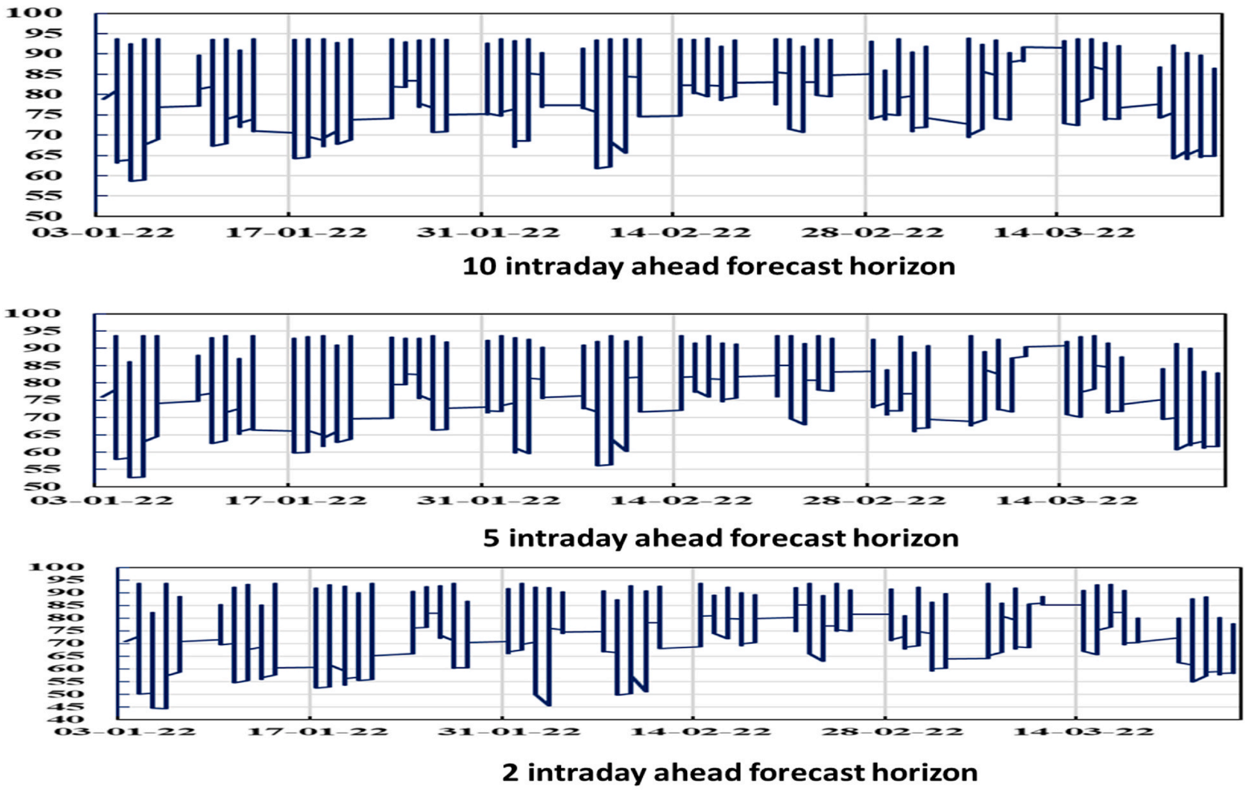
Optimal hedge ratios are generally low, indicating the effectiveness of hedging in the stock sectors analyzed. To illustrate, we consider the oil/European-wide stock market portfolio. For instance, a hedge ratio of 0.06 reveals that approximately 6 cents of the Stoxx 60 index should be shorted for every dollar invested in oil commodities. Hedge ratios across different stock sectors have a range, from as little as 0.01 (e.g., for the food and beverage, health, real estate, and utilities sectors) to as much as 0.24 (for oil and gas). This shows that for every dollar invested in oil commodities, a short position of 1 cent and 24 cents in food and beverage and oil and gas stocks, respectively, should be employed for hedging purposes. Our findings indicate that the food and beverage sector is the most effective choice for hedging against the risk associated with exposure to oil.

Overall, our research demonstrates the advantages of incorporating oil assets into a diversified stock portfolio, potentially improving its risk-adjusted performance. However, the value of hedge ratios is not static; rather, it fluctuates over time. Understanding and analyzing these dynamics are essential for investors making informed investment choices. Therefore, we offer valuable insights into the dynamic nature of hedge ratios and optimal weights in Figs. 7 and 9. These figures illustrate the inherent fluctuations in hedge ratios, especially during turbulent periods, aligning with assertions by Elsayed, Nasreen, and Tiwari (2020) that hedge ratios are volatile over time, especially in during a crisis.

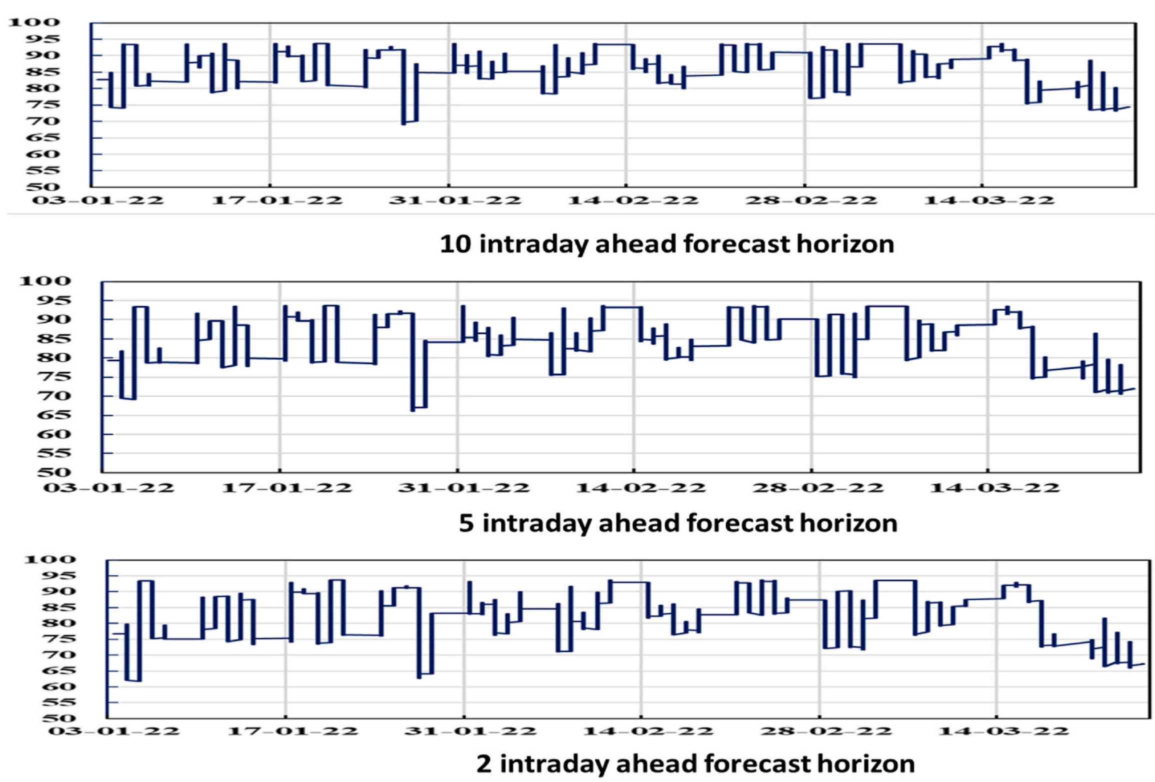
In essence, our research emphasizes the critical importance of ongoing analysis and adaptation when it comes to hedge ratios and the broader realm of risk management strategies. By closely monitoring and adjusting these factors, investors can make more informed investment decisions, ultimately safeguarding and optimizing their financial portfolios in an ever-evolving financial landscape.

4.6. Robustness check

We employ the DY technique to conduct a series of robustness tests, assessing the total spillover across various combinations of VAR forecasting horizons and rolling windows. Fig. 10 illustrates the results, offering insights into the behavior of total spillovers under different conditions. It shows that the trajectories of total spillovers are strikingly similar when we use both 100 and 200 intraday rolling windows, across three distinct intraday-ahead forecast horizons: 10, 5, and 2 (Panels A and B). This consistency in the total spillover plot is insensitive to the specific window selection and forecast horizon used in our analysis. This compelling evidence robustly confirms the reliability of the spillover index technique in estimating the total spillover index in our study. It demonstrates the consistency and stability of our findings across various model specifications and underlying assumptions. These results, which show the robustness of our analysis, bolster our confidence in the accuracy and credibility of our findings. In essence, these robustness tests serve as a testament to the rigor and integrity of our analytical approach, confirming the reliability of our results in different scenarios using methodological variations, ultimately enhancing the credibility of our research within the broader academic and financial community.



Panel A: 100-day rolling windows



Panel B: 200-day rolling windows

Fig. 10. Robustness tests of total spillover index.

5. Conclusion and implications

The Russian invasion of Ukraine in 2022 is a stark reminder that access to affordable oil is a critical factor that cannot be taken for granted. This essential commodity has a significant influence on the performance of various economic sectors. In this comprehensive study, we employ dynamic frequency spillovers (DY12 and BK18) and high-frequency data at a 5-min interval. Our main goal is to identify the main sources of spillovers, distinguishing between net transmitters and net receivers among these assets. Additionally, we calculate optimal weights and hedge ratios, offering valuable insights for investors seeking to diversify across the oil and European sectors. The implications of our findings extend not only to investors but also to policy makers and financial supervisors.

Our research yields several noteworthy findings with significant implications. First, our analysis reveals high interconnectedness among financial assets in Europe. Approximately 90 percent of the total variance of the forecast error is explained by shocks within this interconnected network, highlighting great potential for systemic risk. Investors and financial institutions should be acutely aware of this interconnectedness, as it implies that a shock in one sector can quickly propagate throughout the network, affecting other sectors. For instance, a shock in the oil and gas sector can spread to sectors such as banks, basic (basic material), health, and utilities sectors, which are net receivers of these shocks. Therefore, effective risk management strategies should not only address individual asset risk but also consider the broader systemic implications of interconnectedness. Diversification across sectors and asset classes is essential for mitigating these risks effectively.

Second, our study highlights the substantial impact of geopolitical events on the ever-changing interconnectedness of financial markets. We observe that the Russia-Ukraine war has a significant impact on the transmission of spillovers among European financial markets. This shows the importance of closely monitoring and managing risks associated with geopolitical events to mitigate their impact on investment portfolios. It further emphasizes the importance for investors and financial institutions of diversifying their investment across various sectors and geographic regions to effectively handle the potential repercussions of shocks and market turbulence.

Third, midterm market trends and factors that influence risk connectedness should be closely monitored by investors and policy makers. As macroeconomic conditions, policies, and geopolitical events evolve, they can affect both oil prices and stock market performance. Therefore, midterm investment strategies should be flexible and adaptive, with periodic reassessment to ensure alignment with changing market dynamics. Additionally, our results suggest that ongoing volatility may create arbitrage opportunities, challenging the efficient market hypothesis.

Fourth, our research pinpoints that the industrials, tech, and aggregate index markets are the most vulnerable to risk spillovers from the oil–stock system. Consequently, investors with positions in these sectors may face higher risks from the oil–stock system. They should actively monitor risk connectedness and contemplate diversifying their portfolios to mitigate these risks effectively.

Fifth, our findings demonstrate that sectors such as insurance, real estate, and retail pose higher risk to other sectors or the market as a whole. Policy makers and investors must be aware of this interdependence and take proactive measures to manage associated risks, which may involve increased regulation and oversight to mitigate systemic risk.

Sixth, our research emphasizes the dynamic nature of risk transmission among sectors, which can evolve depending on market conditions. As such, investors and policy makers must continually monitor sectoral relationships and adjust their strategies and policies to manage risks effectively. This may involve implementing hedging strategies, diversifying portfolios, and adopting measures to mitigate sector-specific risks.

Seventh, our analysis of net directional connectedness highlights that market shocks can originate in any of the index analyzed and propagate across different indices. This bidirectional and asymmetric connectedness shows the necessity for investors and traders to closely monitor spillover effects across all indices to gain a comprehensive understanding of market dynamics and make well-informed decisions. Sectors with the capacity to transmit risk should be approached with caution, especially during times of greater market turbulence.

Eighth, our analysis of DCC indicates that correlations between oil and various sectors are not static. They can change over time, significantly impacting the risk and return characteristics of portfolios. Investors should be aware of these shifts, adjusting their strategies accordingly to optimize portfolio performance. Strategies such as pairs trading and momentum trading can be particularly effective when changing correlations are considered.

Finally, the analysis of optimal weights and hedge ratios offers practical advice for investors who aim to navigate risk in their portfolios. Significantly, our results indicate that investors would be prudent to allocate a larger portion of their investment to equity shares and reduce exposure to oil in order to mitigate risk without compromising anticipated returns. The effectiveness of hedging is evident, with low hedge ratios indicating strong hedging potential, in particular shorting stocks in the food and beverage sector. Hedge ratios are dynamic and change over time, illustrating the importance of continuous portfolio monitoring and adjustment. The dynamic nature of these ratios shows the importance of maintaining a proactive approach to portfolio management. Regular rebalancing and asset allocation adjustments are essential for ensuring that portfolios align with desired risk and return profiles.

In conclusion, the implications of our study go beyond the realm of financial markets to broader risk management practices and policy considerations. By heeding these implications, investors and policy makers can enhance their ability to navigate an increasingly interconnected and dynamic financial landscape, ultimately promoting financial stability and informed decision-making.

Declaration of competing interest

I declare that there is no financial conflicts of interests among authors that could have appeared to influence the work reported in this paper.

Acknowledgement

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Appendix A

Authors	Data period	Sample	Methodology	Main conclusion
Abuzayed and Al-Fayoumi (2021)	Daily data from January 2020 to May 2020.	Oil prices and GCC stock price indices	VaR and DCC-GARCH	In the second phase of COVID-19, all GCC stock markets experienced increased systemic risk related to oil.

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Authors	Data period	Sample	Methodology	Main conclusion
Ali et al. (2022)	Daily data from January 2019 to March 2021	Brent and WTI crude oil. Stock markets of the Canada, China, Russia, US, and Venezuela	Wavelet-based Granger causality method	There was a pronounced correlation between oil and stock markets during the pandemic.
Bouri et al. (2021)	5-min data from April 2006 to April 2019	S&P 500 index, gold, and oil	TVP-VAR model and high moment spillover index	Substantial realized volatility spillovers were observed. The primary net contributor of realized volatility and a net receiver of realized skewness and jump spillovers is the US stock market.
Costola and Lorusso (2022)	Weekly data from January 2005 to December 2020	MSCI stock indices of the US, China, and Europe. Russian sector stocks, natural gas, gold, and Brent oil	Time-domain spillover index	Oil and Gas played a prominent role as shock contributors during periods of Russian geopolitical uncertainty.
Cui et al. (2021)	Daily data from January 2004 to October 2020	Oil market and stock markets in oil-importing and oil-exporting countries	Wavelet coherence and time-frequency spillover index	The magnitude of connectedness between oil and stock markets increased during both the global financial crisis (GFC) and the pandemic, with mixed lead-lag relationships.
Dai et al. (2022)	Daily data from December 2014 to May 2021	5 Chinese stock sectoral indices, WTI oil, and gold	Granger causality test and the spillover method	Oil and gold markets (all sectors) acted as net receivers (transmitters) of systemic shocks.
Hung and Vo (2021)	Daily data from January 2018 to April 2020	S&P 500 index, crude oil, and gold	Wavelet coherence and the time-domain spillover index	Amid the pandemic crisis, robust return transmissions are more pronounced, revealing significant dependent patterns in the information spillovers among crude oil, the S&P 500, and gold markets.
Lin et al. (2021)	Weekly data from January 2002, to October 2019	International stock index, WTI, Brent, and Dubai oil.	Markov regime-switching VAR model	Significant linear risk spillovers originate from the US stock markets to the WTI oil market in the short term.
Mensi, al-Yahyaee, et al. (2021a)	Daily closing prices from January 2003 to October 2020.	Daily closing prices of Brent oil futures and 12 MENA stock markets.	Wavelet coherence and the spillover index of DY12 and BK18	The frequency of spillovers between crude oil futures and stock markets exhibits mixed and time-varying lead-lag relationships.
Mensi, Rehman, et al. (2021)	Daily closing spot prices from January 1999 to February 2018	crude oil, natural gas, and the BRICS stock markets	Partial and multiple wavelet coherencies	Comovements between oil prices and stock market returns are noticeable at the lower scale.
Mensi, Al Rababa'a, et al. (2021)	Daily data from January 2005 to May 2020	10 Chinese sector stocks of the CSI 300, WTI oil, and gold	Spillover method of Diebold and Yilmaz	A substantial portion of total spillovers stems from adverse return spillovers. Major events amplify the asymmetric spillovers and influence portfolio design.
Mensi et al. (2022)	Daily data from September 2010 to December 2020	22 sub-indices of the STOXX 600 index, Brent oil, and gold futures	Spillover method of Diebold and Yilmaz	Similar findings with Dai et al. (2022)
Wen et al. (2022)	Daily data from January 2002 to October2020	WTI oil prices, Shanghai Composite Index, and CCFI index	MODWT and vine-quantile regression model	Volatility spillovers within the Chinese market surpass those from oil to the Chinese domestic market.
Zhu, Tang, Wei, & Lu (2021a)	Daily data from December 2019 to February 2021	The US and Chinese stock markets	GARCHSK-Mixed Copula-CoVaR-Network method	Oil markets experience high-risk spillovers from second board markets.

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