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Volatility and Return Connectedness Between the Oil Market and Eurozone Sectors During the Financial Crisis: A TVP-VAR Frequency Connectedness Approach

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Abstract: This paper analyzes the returns and volatility connectedness between oil prices and Eurozone sector returns during the global financial crisis. We employ the TVP-VAR frequency connectedness approach with daily data of Brent prices and 18 Eurozone supersector indices from 15 November 2014 to 24 November 2023. Our results show a high average connectedness of the returns and volatilities. Industrial Goods are the largest transmitter contrariwise Media supersector is the largest receiver of shocks on returns. The same finding is for volatility, the result shows that Industrial Goods and Services transmit the highest risk in contrast, the Media has the highest receiver volatility indices. The time-varying connectedness (TCI) of returns and volatilities in both show a drastic increase in March 2020. This increase is a result of COVID-19. Whereas, there has been no rise in connectivity following Russia's invasion of Ukraine. Our result highlighted that Brent was a net receiver of volatility shocks during the Russian invasion of Ukraine.

Keywords: oil market; Eurozone Super sectors; TVP-VAR frequency connectedness; volatility transmission; volatility spillovers.

JEL classification: G15; D53.

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1. INTRODUCTION

For a loan, the macroeconomic effect of commodity price shocks is an important theme that has attracted the attention of several researchers over the past decade. Crude oil prices are considered a leading economic indicator, with Sokhanvara and Bouri (2022), and others suggesting a significantly negative relationship between high oil prices and economic growth. Lorusso and Pieroni (2018) found that the consequences of oil price changes on UK macroeconomic aggregates depend on different oil types shocks. Cai *et al.* (2022) show that OPEC and non-OPEC oil supply shocks decrease industrial production but increase the employment rate in the Euro area. Since the second half of 2021, energy prices have risen sharply in the EU and globally. Fuel prices have risen further following Russia's unprovoked and unprovoked aggression against Ukraine, which has also raised concerns about the security of EU energy supplies. Russia's decision to suspend gas supplies to several EU member states has further aggravated the situation. The Russian-Ukrainian war has negative consequences on global energy and food security, characterized by higher inflation, which affects the United States and the leading European economies. The 2022 annual average OPEC oil price stands show at 104.01 U.S. dollars per to 69.72 U.S. dollars the previous year is explained by and comes in the wake of an energy supply shortage and sanctions on Russia following the Russia-Ukraine war. Le and Luong (2022) found that oil prices and sentiment are net transmitters of shocks in the US. The relationship between oil price, stock market returns, and investor sentiment is time-varying and driven by time-specific developments and events. Yuan *et al.* (2022) found that Stock markets are more affected by negative oil returns, while oil markets are more affected by positive stock returns. Hernandez *et al.* (2022) examined the return spillovers between US stock sectors under low and high volatility regimes. They show evidence that oil volatility has a causal impact on the spillover dynamics of US stock sectors and that the effect is particularly strong in the high volatility regime.

Diebold and Yilmaz (2014) affirm that Connectedness would appear central to modern risk measurement and management, and indeed it is. It features prominently in key aspects of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counter-party and gridlock risk (bilateral and multilateral contractual connectedness), and not least, systemic risk (system-wide connectedness). It is also central to understanding underlying fundamental macroeconomic risks, in particular business cycle risk (intra- and inter-country real activity connectedness). Two objectives are presented in this study. First, we analyze the volatility connectedness between oil prices and the Eurozone supers sector. Second, we investigate the conditional correlation between oil prices and super sector returns.

Even though previous papers showed that the financial crisis induced significant changes in the oil-stock market relationship for some studied markets, no studies investigated the spillover connectedness between oil prices and super sector returns. Furthermore, to my knowledge, no previous study has analyzed the volatility connectedness between the oil market and Eurozone sectors.

This article aims to fill this gap by examining the volatility connectedness between oil prices and Eurozone sector returns. We offer new insights into the returns and volatility spillovers between oil and the super sector, particularly during highly uncertain periods such as COVID-19 and the Russia-Ukraine war. We employ the TVP-VAR frequency connectedness approach with daily data of Brent prices and 18 Eurozone supersector indices covering the period from 15 November 2014 to 24 November 2023.

The rest of the paper is organized as follows. Section 2 presents a literature review. Section 3 adopted the data. Section 4 describes the methodology. Section 5 presents empirical findings Section 6 concludes.

2. LITERATURE REVIEW

2.1 Theoretical Framework

There is no controversial that the Generalized Vector Autoregressive (VAR) method, developed by Koop *et al.* (1996) and then Pesaran and Shin (1998) often referred to as KPPS remains the basis of the various alternative methods often utilized for analyzing spillover in the literature. However, partially due to its relative newness and robustness, the Diebold and Yilmaz (2014) method has been widely accepted as the well-liked measure of the connectedness index. Unlike the conventional VAR, the DY which uses decomposition of forecast error variance from VAR is suitable for evaluating the degree of interdependence among oil markets and Eurozone supersector indices.

2.2 Empirical Literature

The connectedness effect is defined as the information links between financial markets; its essence is the risk transfer between markets: Udeaja (2019) shows that the increasing integration of financial markets across the globe has further exacerbated the vulnerability of economies around the world, to systemic shocks either emanating domestically, from intra-financial markets connectedness or globally, from the perspective of inter financial market connectedness. While acknowledging the potential of such integration to facilitate trade among nations, the risks and uncertainties associated with such connectedness remain a major source of concern. Li *et al.* (2021) investigate the impact of information transmission speed on stock volatility. They found the information transmission speed is slow, and stock volatility decreases with the increase of the information transmission speed. Volatility spillovers may also affect financial contagion. Liu *et al.* (2022) employed the delta Co VAR and Co VAR networks to analyze the risk spillovers from oil markets to the G20 stock system from both otherwise and systemic perspectives. They found, illustrated significant risk spillovers from oil to G20 stocks only during the crisis period. Also, the results show that the G20 stock contagion presents regional characteristics and oil-related characteristics conditional on oil in extreme risk, and verify the significant risk spillovers from the oil market to the global stock system. Huang *et al.* (2023) investigate the dynamic volatility spillover among energy commodities and financial markets in pre- and mid-COVID-19 periods by utilizing a novel TVP-VAR frequency connectedness approach and the QMLE-based realized volatility data. Their findings indicate that the volatility spillover is mainly driven by long-term components and prominently time-varying with a remarkable but short-lived surge during the COVID-19 outbreak. They further spot that WTI and NGS are prevailingly transmitting and being exposed to the system volatility simultaneously, especially during the global pandemic, suggesting the energy commodity market becoming more integrated with, more influential, and meanwhile vulnerable to global financial markets. The consistently growing interconnectedness of drastic volatilities in energy commodities and fluctuations in non-energy commodities and other financial assets attracts much attention from financial investors, policymakers, and academic researchers as Adekoya and Oliyide (2021); Balcilar *et al.* (2021); Shah *et al.* (2021); Farid *et al.* (2022). Farid *et al.* (2022) and Gong and Xu (2022) find that the return and volatility transmission among energy commodities and global financial assets are significantly strengthened and increasingly complex due to globalization, technological development, and the financialization of commodity markets. It is widely acknowledged that global market integration and financialization not only result in increased liquidity and ease of trading in energy commodity markets but also tend to foster speculation and thus increase market volatilities, which may serve as the channel for the time-varying and asymmetric volatility spillovers across energy commodities and non-commodity markets. Umar *et al.* (2022) investigate the impact of geopolitical risks caused by the Russian-Ukrainian conflict on Russia, European financial markets, and the global commodity markets. We measure the dynamic connectedness among them using time- and frequency-based time-varying parameter vector autoregression (TVP-VAR) approaches. The empirical findings indicate that: first their relationship has changed due to the conflict; second European equities and Russian bonds are the net transmitters of shocks; and finally the conflict affects return and volatility connectedness among them in terms of short- and long-term frequencies, respectively. Hernandez *et al.* (2022) investigated the return spillovers between US stock sectors under low and high volatility regimes by implementing a Markov regime-switching vector autoregression. They concluded that energy is the largest transmitter and receiver of spillovers to/from other sectors. Mensi *et al.* (2022) used the asymmetric Baba-Engle-Kraft-Kroner (BEKK)-GARCH model and the frequency spillover methodology by Barunik and Ellington (2020) to examine spillovers and portfolio management between crude oil and US Islamic sector stocks. The authors find significant time-varying spillovers between oil and Islamic sectors. Ahmad *et al.* (2021) examined the spillover role of the implied volatilities of oil, gold, and the stock market with US equity sectors. They concluded that the market's expectation of oil price volatility (OVX) spillovers less strongly on the US sectorial returns than the market's expectation of US stock market volatility (VIX). The authors also found that the US equity sectors' spillovers on the VIX and OVX strengthened because of the coronavirus (COVID-19) outbreak. He *et al.* (2021) used the TVP-FAVAR model to study the spillover effect of international EPU on the energy sector in the Chinese stock market. They argue the that Chinese energy sector's stock volatility is positively related to EPU shocks. Zhang *et al.* (2022) applied the asymmetric ARMA-EGARCH-ARJI model to analyze the dynamic jumps in global oil prices and their impacts on China's industrial sector at the aggregate and subsector levels. The authors that caused the oil price have the impacts on the return and volatility of China's industrial sector. Mensi *et al.* (2022) examined the frequency dynamics of volatility spillovers between Brent crude oil and stock markets in the US (S&P500 index), Europe (STOXX600 index), Asia (Dow Jones Asia index), and stock markets of five vulnerable European Union (EU) countries known as the GIPSI (Greece, Ireland, Portugal, Spain, and Italy). They found that the spillover effect between the oil and the considered stock markets is time-varying, crisis-sensitive, and frequency-dependent. Aslan and Posch (2022) investigate how the volatility of carbon emission allowance (EUA) prices affects European stock market sectors using a network analysis of prices of EUA futures and FTSE stock market sector indices and they found that the EUA is mostly a net receiver of volatility connectedness and significantly receives volatility across most sectors during the recent European energy crisis. Urom *et al.* (2022) used the Time-Varying Parameter (TVP-VAR) model to characterize the level of spillovers among the clean energy sectors and oil market uncertainty under different investment horizons. They found that the level of shock spillovers is weak in the short-term but strengthens towards the intermediate- and long-term. Tiwari *et al.* (2018) used asymmetric quantile regression to investigate the impacts of oil price shock on the Indian stock market sectorial index. Their results found that oil price tail risk affects all sectorial indices than the carbon sector and a contagion effect for negative oil price shocks is found in six sectors. Cevik *et al.* (2020) examined the relationship between crude oil prices and stock market returns in Turkey, considering volatility spillovers that exemplify second-moment moment effects. Their empirical results suggest that crude oil prices significantly affect stock market returns in Turkey.

2.3 Hypotheses

Even though previous papers showed that the financial crisis induced significant changes in the oil–stock market relationship for some studied markets, no studies investigated the spillover connectedness between oil prices and super sector returns. So, our paper tests the hypotheses presented below:

H1: *During the financial crisis, there is a significant relationship between the oil market and the performance of Eurozone sectors*

H2: *The oil market is a transmitter of shock volatility for the Eurozone super sector.*

3. DATA

Our dataset consists of daily returns for Brent crude oil prices and daily supersector per sector indices for the period from 15 November 2014 to 24 November 2023. The analysis sector-wise is focused on the Eurostoxx indices, from which the Eurostoxx 50 is derived. According to the Industry Classification Benchmark (ICB), we use 18 super sectors (automobiles and parts, bank, primary resources, chemicals, construction and materials, financial services, food and beverages, health care, industrial goods and services, retail, insurance, media, oil and gas, real estate, technology, telecommunications, travel and leisure, and utilities). The prices are listed in EURO and the data can be sourced online at Energy Information Administration (EIA) for the Oil prices while the Eurostoxx super sector indices are collected from the STOXX limited database. The daily sector returns $\left(R_{iES,t}\right)$ and the Brent Oil market returns $\left(R_{BO,t}\right)$ is defined as:

$$R_{i,t} = Ln\left(p_{i,t}\right) - Ln\left(p_{i,t-1}\right) \tag{1}$$

where $p_{i,t}$ is the price of (Sector, Brent Oil) $(i = 1,2 \ldots .n)$. Our empirical analysis begins with calculating summary statistics for the Sector and Brent Oil price returns. The Augmented Dikey-Fuller (ADF) and Phillips- Perron (PP) tests are used to examine the existence of unit roots in the price returns. Furthermore, Engle's ARCH –LM test for ARCH effects is used to examine whether volatility modeling is needed for the price returns of each variable. The test results suggest that the closing price sectors of all sectors and Brent Oil are stationary and exhibit ARCH effects and a multivariate GARCH methodology can be used not to investigate only to model the returns (sector, Brent oil) conditional variances but also to analyze the volatility transmission effects between them.

4. METHODOLOGY

This paper investigates volatility transmission effects between Brent Oil prices and the Eurozone supersector returns, which are determined through the conditional covariance matrix. The conditional mean equation is written as:

$$R_{it} = c + \varepsilon_t \tag{2}$$

where $\boldsymbol{R_{it}}$ is a (2×1) vector of the price returns for $sector_i$ (iES) and Brent Oil WTI (BO) at time$t$; c is the vector of the mean of the returns and ε_{it} is the vector of residuals with a conditional covariance matrix H_t given the available information set φ_{t-1}.

The TVP-VAR connectedness

Antonakakis *et al.* (2020) presented a TVP-VAR connectedness methodology based on Diebold and Yilmaz (2014) connectedness approach; Antonakakis *et al.* (2020) achieved this by allowing the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factors, following Koop and Korobilis (2014). The total connectedness index (TCI) is defined as:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{m} \times 100 \tag{3}$$

The total directional connectedness to others, that is, *i* propagating its shock to all other variables *j* is defined as:

$$C_{i\to j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{n} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\phi}_{ij,t}(H)} \times 100 \tag{4}$$

The total directional connectedness from others, that is, *i* receives from all other variables *j* is given as:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{n} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\phi}_{ij,t}(H)} \times 100 \tag{5}$$

Net total directional connectedness:

$$C_{i,t}(H) = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \tag{6}$$

5. EMPIRICAL FINDINGS

5.1 Descriptive statistics

Table no. 1 reports the results of the descriptive statistics for the returns. The mean returns of indices are positive for all sectors except Bank, Basic Resources, Media, Oil and Gas, Retail, Telecom, and Utilities. The highest standard deviation is attributed to the Construction and Material returns. The Oil indices confirm the negative and significant correlation between all sectors except for the Chemicals returns and Telecom are positive and significant. The kurtosis statistics are greater than the acceptable level, another notable statistic of returns observed. In contrast, during this period, the opposite result was true for the price returns of Auto and Parts, Construction and Material, Food and Beverages, and positively skewed Media, indicating that high positive price returns are more common than significant negative returns. The test normality for all price return series is also confirmed by the Jarque-Bera (JB) test results, which reject the null hypothesis of normally distributed returns for all the returns series.

Table no. 1 – Descriptive statistics of stock returns

	Mean10^{-3}	Max	Min	Standard Deviation	Skewness	Kurtosis	J-B	Corrélation
Auto and Parts	0.08	0.049	-0.043	0.012	0.098	38.68	21.02	-0.038
Bank	-0.4	0.066	-0.198	0.020	-1.35	15.81	4591.2	-0.093
Basic Resources	-0. 3	0.083	-0.097	0.021	-0.175	5.71	200.3	-0.027
Chemicals	0.18	0.046	-0.052	0.012	-0.167	3.89	24.56	0.078
Construction and Material	0.09	5.851	-0.131	0.231	25.01	631.2	106265	-0.003
Financial services	0.23	0.050	-0.105	0.014	-1.01	9.95	1404.9	-0.06
Food and Beverages	0.01	0.128	-0.127	0.019	0.299	9.71	1215.7	-0.037
Health Care	0.02	0.149	-0.167	0.032	-0.046	6.41	312.3	-0.088
Industrial Goods and Services	0.2	0.034	-0.069	0.012	-0.516	4.98	134	-0.062
Insurance	0.22	0.043	-0.119	0.014	-1.20	11.92	2284.9	-0.101
Media	-0.03	0.308	-0.029	0.007	0.365	4.332	61.77	-0.061
Oil and Gas	-0.26	0.061	-0.084	0.016	-0.141	4.67	76.75	-0.046
Real Estate	0.12	0.043	-0.101	0.012	-0.865	9.73	1292.9	-0.103
Retail	-0.19	0.023	-0.021	0.004	0.112	6.48	326	-0.063
Technology	0.33	0.053	-0.055	0.013	-0.207	4.19	42.89	-0.045
Telecom	-0.07	0.046	-0.089	0.013	-0.373	6.96	434.4	0.028
Travel and Leisure	0.22	0.049	-0.089	0.013	-1.01	9.46	1230.2	-0.045
Utilities	-0.26	0.062	0.042	0.086	0.012	3.662	7.97	-0.075
Brent	0.01	0.045	-0.090	0.013	-0.540	6.22	308.8	1

Sources: conducted by authors

5.2 Connectedness analysis

Overall, the TVP-VAR frequency connectedness model employed in this paper provides a comprehensive picture of the return and volatility transmission among Brent Oil and the Eurozone supersector returns. The connectedness measures include the estimated spillovers of returns and volatility based on the Forecasted Variance Decomposition methodology developed by Diebold and Yilmaz (2014).

Tables no. 2 and no. 3 report the results of the average connectedness values for the returns and the volatilities among oil prices and the Eurozone supersector during the global financial crisis. We find that the spillover effects are high indicating raised interconnectedness over time, which may indicate an increase in uncertainty and systemic risk. The average connectedness results show that the total spillover connectedness of the returns and volatilities are 70.05% and 65.64%, respectively. The industrial Goods and Services supersector is the largest transmitter of shocks (109.27%) on returns. Retail (95.16%) transmits the second-highest spillovers. By contrast, Brent propagates the lowest shocks to the returns of the other indices (15.92%). However, we note that Media is the most receiver of return shocks (89.2%). Brent; Insurance; Chemicals; Food and Beverages; Media; Oil and Gas, Real Estate, and Health Care are the net receivers of shocks; whereas the remaining return series are the net transmitters.

As per the volatilities, Industrial Goods and Services transmit the highest volatility shocks (101.26%). Retail transmits the second-largest volatility shock (90.97%). In contrast, the Media has the highest receiver volatility indices (85.24%). Industrial Goods and Services; Auto and Parts; Technology; Telecom; Utilities; Travel and Leisure; Oil and Gas; Basic Resources and Retail are the net transmitters of volatility shock; while the rest are the net receivers of shocks volatility.

Figure no. 1 presents the time-varying connectedness (TCI) of returns and volatilities to account for time-varying connectedness dynamics. Both indices notably surged in March 2020 and hit their apexes (70% and 90%, respectively). This increase is a result of the COVID-19 virus spreading quickly. Our findings indicate that the global pandemic significantly intensifies cross-market volatility. This result corroborates the finding of Huang *et al.* (2023). Whereas, there has been no rise in connectivity following Russia’s invasion of Ukraine. We provide the net directional connectivity in Figures no. 2 and no. 3 to categorize the transmitters and recipients of return and volatility over time. Based on Figures no. 2 and no. 3 several conclusions can be drawn. First, Industrial Goods and Services; Auto and Parts; Bank; Basic Resources; Construction and Material; Financial services; Industrial Goods and Services; Retail; Technology; Telecom; Travel and Leisure; Utilities are the net transmitters of the return over most of the study period. Contrary, Insurance and Services and Brent their role is the net receiver of return. Second, our result highlighted that Brent and Real Estate are the net receivers of volatility shocks. By contrast, Industrial Goods, and Services and Technology are the net transmitters during the Russian invasion of Ukraine.

Table no. 2 – Average connectedness values for the returns

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	FROM
Auto and Parts	35.70	11.0	0.66	4.01	9.34	9.28	0.82	6.04	1.37	0.94	1.37	1.13		5.97	1.31	1.28	1.26	1.08	1.61	64.30
Bank	13.3	23.88	0.65	3.78	12.34	13.69	0.89	9.09	0.98	0.82	0.95	0.93	1.13	6.51	0.85	1.03	1.01	0.92	0.92	76.12
Basic Resources	0.99	0.95	67.25	0.82	1.06	0.72	4.35	1.07	2.13	3.25	1.55	2.04	0.93	1.03	2.71	2.76	1.88	3.09	1.01	32.75
Chemicals	5.21	7.88	0.86	39.01	9.20	10.44	1.00	8.21	1.23	1.16	0.90	0.99	2.04	3.92	1.27	1.21	1.13	1.02	1.33	60.99
Construction and Material	11.1	11.92	0.60	5.11	17.74	16.14	0.68	11.18	1.01	0.90	0.89	0.85	0.99	8.14	0.95	0.94	1.03	0.89	0.97	82.26
Financial services	9.51	13.45	0.48	5.16	15.44	20.44	0.60	11.55	0.97	0.85	0.81	0.79	0.85	7.08	0.93	0.83	1.04	0.81	0.97	79.56
Food and Beverages	1.00	0.99	5.07	0.86	1.02	0.81	52.24	1.10	3.82	8.10	3.33	3.48	0.79	1.59	2.83	4.05	3.81	4.15	0.79	47.76
Health Care	4.67	11.23	0.79	4.44	12.58	15.23	0.98	24.56	1.24	1.18	0.97	0.88	3.48	8.45	1.24	0.99	1.19	1.16	1.50	75.44
Industrial Goods and Services	0.45	0.51	3.09	0.51	0.40	0.39	2.02	0.54	19.62	8.55	7.35	12.73	0.88	0.37	13.71	8.64	11.8	8.32	0.49	80.38
Media	0.41	0.47	2.68	0.46	0.32	0.32	2.33	0.42	15.69	10.80	8.73	12.86	12.73	0.38	11.76	10.75	11.0	9.70	0.44	89.20
Insurance	14.49	10.32	0.80	3.80	11.52	11.41	0.92	8.41	1.32	0.99	1.24	1.05	12.86	8.92	1.19	1.19	1.14	1.04	1.12	80.88
Oil and Gas	0.63	0.56	3.86	0.79	0.47	0.46	1.93	0.55	11.71	8.21	28.36	9.20	1.05	0.42	7.23	9.12	7.89	7.61	0.48	71.64
Retail	0.54	0.70	3.34	0.78	0.63	0.54	2.18	0.69	13.40	7.40	6.60	22.26	9.20	0.65	10.17	9.47	11.55	8.15	0.45	77.74
Real Estate	6.97	7.83	0.84	3.49	10.09	8.41	0.98	11.07	1.18	1.06	1.10	1.06	22.26	31.64	1.13	1.04	1.44	1.21	1.48	68.36
Technology	0.41	0.51	2.58	0.59	0.46	0.46	1.97	0.58	16.61	8.04	5.59	11.68	1.06	0.50	22.24	7.90	10.35	8.47	0.60	77.76
Telecom	0.69	0.57	2.22	0.67	0.38	0.41	2.57	0.45	10.47	8.31	7.80	10.98	11.68	0.35	8.03	24.78	9.04	11.28	0.63	75.22
Travel and Leisure	0.42	0.57	3.13	0.65	0.49	0.59	2.23	0.51	13.96	7.18	5.68	13.37	10.98	0.46	10.09	9.20	22.52	8.04	0.52	77.48
Utilities	0.74	0.56	3.06	0.69	0.39	0.45	2.46	0.41	10.36	8.09	6.70	9.38	13.37	0.47	8.73	12.48	8.50	25.28	0.63	74.72
Brent	3.79	2.57	1.72	2.08	2.62	3.02	0.96	2.62	1.82	1.55	1.41	1.75	9.38	2.78	1.66	1.46	2.13	1.50	61.67	38.33
TO	75.44	82.60	36.46	38.67	88.75	92.78	29.87	74.49	109.27	76.58	62.97	95.16	1.75	57.99	85.78	84.35	87.3	78.43	15.9	1330.9
NET	11.14	6.49	3.70	-22.32	6.49	13.22	-17.89	-0.94	28.89	-12.62	-22.81	-8.67	17.42	-10.37	8.02	9.13	9.82	3.71	-22.41	cTCI/TCI= 73.94/70.05

Table no. 3 – Average connectedness values for the volatilities

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	FROM
Auto and Parts	38.39	6.91	2.59	2.90	6.71	5.35	4.43	2.00	1.45	7.38	1.73	3.12	4.93	1.69	1.98	2.26	1.91	2.06	2.06	61.61
Bank	13.55	27.19	2.26	2.21	6.57	6.10	7.25	2.06	1.81	8.86	1.73	2.36	4.77	1.74	2.32	2.82	2.05	2.33	2.33	72.81
Basic Resources	2.69	2.28	57.16	2.64	1.66	1.68	1.64	2.21	2.22	2.48	2.53	2.90	1.73	2.27	2.74	2.12	4.07	1.66	1.66	42.84
Chemicals	2.99	3.23	1.97	52.60	3.64	3.27	2.99	2.30	2.35	2.77	1.93	1.76	2.95	2.17	2.79	2.33	2.49	2.09	2.09	47.40
Construction and Material	9.45	6.45	1.92	2.66	22.16	14.98	10.32	1.79	1.69	7.70	1.43	1.90	6.29	2.01	1.87	1.71	1.57	2.17	2.17	77.84
Financial services	7.76	6.51	1.84	3.08	17.83	25.43	8.17	1.81	1.85	6.48	1.65	1.90	5.14	1.90	1.84	1.66	1.52	2.01	2.01	74.57
Food and Beverages	2.15	2.58	3.82	2.91	1.56	1.71	1.46	3.19	3.79	3.22	2.28	3.20	1.12	2.80	2.78	3.21	2.86	1.60	1.60	46.24
Health Care	4.75	7.74	1.69	2.08	10.13	8.66	29.43	2.09	1.78	7.64	1.95	2.03	6.44	2.47	2.46	2.49	2.05	2.37	2.37	70.57
Industrial Goods and Services	1.17	1.09	2.05	1.11	0.58	0.58	1.46	25.96	7.00	0.80	6.05	11.51	1.18	16.09	7.70	5.48	7.47	0.93	0.93	74.04
Media	0.99	1.05	1.50	1.15	0.64	0.87	1.36	15.80	14.76	1.09	8.69	11.04	1.02	11.73	9.39	6.99	8.46	1.16	1.16	85.24
Insurance	13.36	7.55	2.59	1.93	8.17	6.63	8.43	2.22	1.80	23.05	2.29	2.63	6.62	2.06	2.20	1.86	1.81	2.09	2.09	76.95
Oil and Gas	1.46	0.91	2.55	2.29	1.17	1.59	1.76	7.29	6.87	1.18	36.73	5.93	1.88	4.78	6.85	6.32	7.02	1.61	1.61	63.27
Retail	1.47	1.18	2.94	1.79	0.94	0.84	1.21	11.87	5.03	1.21	4.87	29.85	0.96	9.06	9.10	6.99	7.11	1.01	1.01	70.15
Real Estate	4.82	5.34	2.26	2.04	8.26	5.61	10.02	2.07	2.11	6.98	2.19	1.84	33.97	2.15	2.30	2.15	1.99	2.24	2.24	66.03
Technology	1.22	1.26	2.40	1.30	0.75	0.59	1.66	18.34	6.16	1.07	4.23	10.10	1.09	28.28	6.37	4.60	7.67	0.88	0.88	71.72
Telecom	1.89	1.55	2.93	1.56	0.91	0.84	1.28	7.86	5.63	1.72	8.16	8.21	1.25	6.45	33.01	5.09	8.43	0.99	0.99	66.99
Travel and Leisure	1.59	2.01	1.88	1.71	0.87	1.37	1.44	7.28	5.28	1.51	5.40	9.07	1.34	6.44	7.12	36.63	5.06	1.62	1.62	63.37
Utilities	1.31	1.24	3.28	1.55	0.70	1.09	2.32	8.63	6.94	1.19	4.73	8.65	1.25	8.60	8.70	4.25	31.93	1.14	1.14	68.07
Brent	2.86	2.91	2.60	2.64	3.44	2.95	2.83	2.46	2.01	3.62	1.87	2.81	2.81	2.44	2.07	2.56	2.46	52.59	52.59	47.41
TO	75.47	61.78	43.06	37.55	74.54	64.70	40.32	70.02	101.26	65.78	66.89	63.69	90.97	52.79	86.84	80.59	64.89	76.01	29.98	1247.12
NET	13.86	-11.03	0.23	-9.86	-3.30	-9.87	-5.92	-0.55	27.22	-19.46	-10.06	0.42	20.82	-13.24	15.13	13.60	1.51	7.94	-17.44	cTCI/TCI= 69.28/65.6

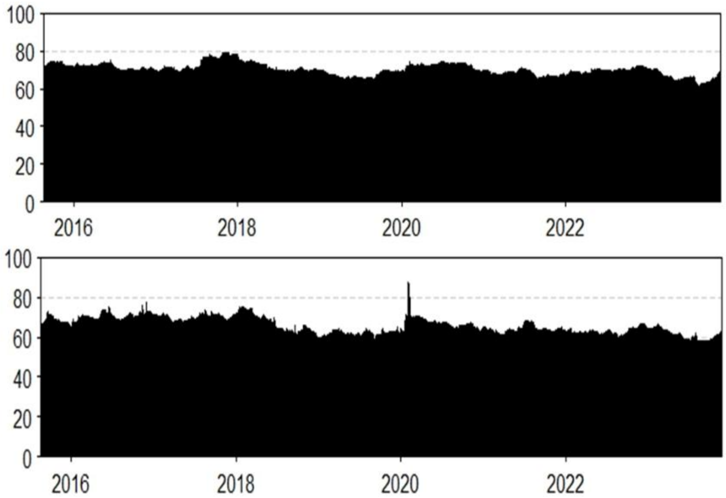
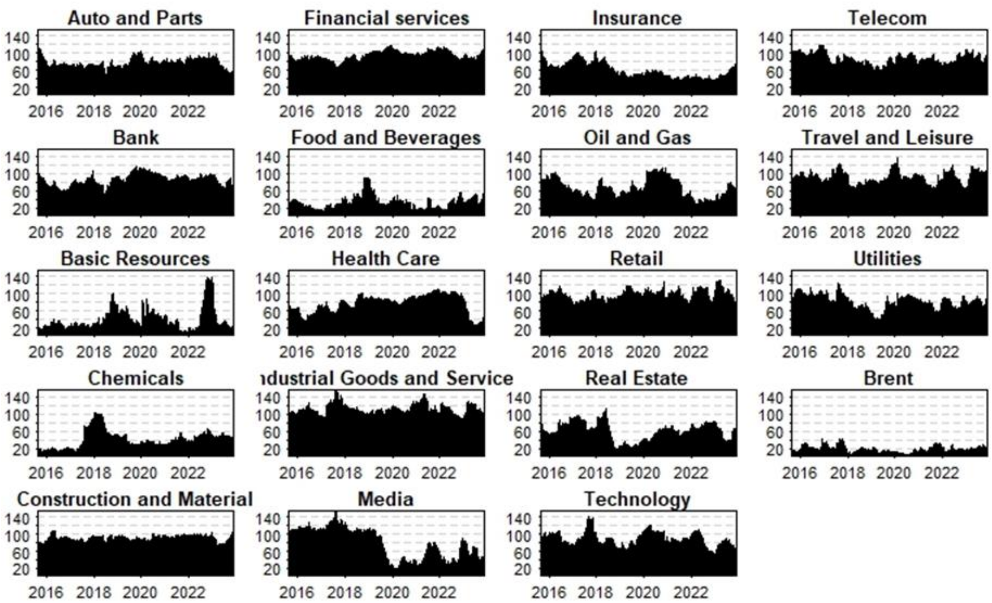
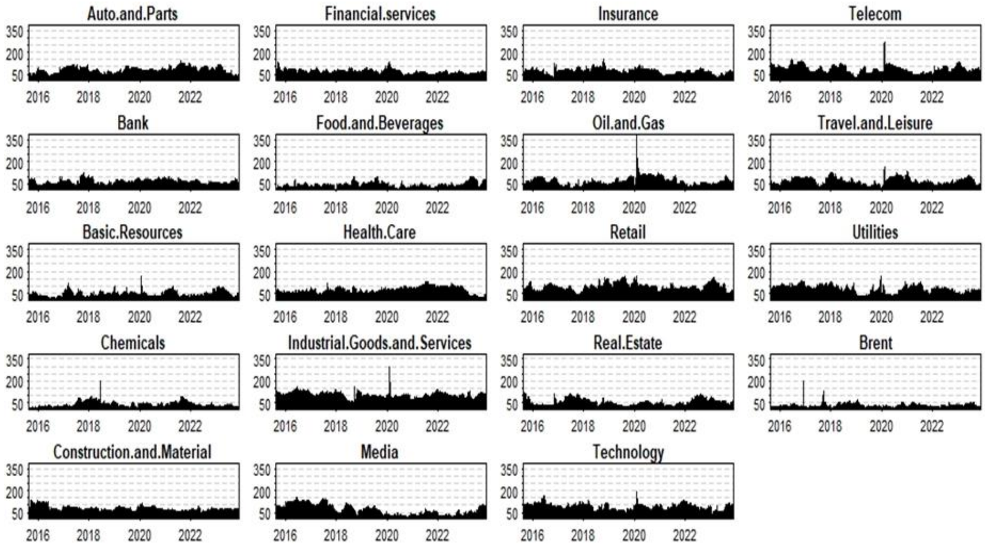


Figure no. 1 – TCIs of the returns and volatilities: This shows the total connectedness indices of the returns and volatilities of the 18 super sectors and oil



Notes: This graph displays the net connectedness of oïl prices and the 18 Eurozone supersector. A positive value indicates a net transmitter, whereas a negative value indicates a net receiver.

Figure no. 2 – Total net time-varying connectedness for the returns



Notes: This graph displays the net connectedness of oil prices and the 18 Eurozone supersector. A positive value indicates a net transmitter, whereas a negative value indicates a net receiver

Figure no. 3 – Total net time-varying connectedness for the volatilities

6. CONCLUSION

This research investigates returns and volatility dynamics, interlinkages, and conditional correlation between Brent Oil prices and the Eurozone supersector returns during the global financial crisis. It analyzes the effects of the Oil crash, COVID-19, and Ukraine-Russian crises on volatility transmissions. We employ the TVP-VAR frequency connectedness approach with daily data of Brent prices and 18 Eurozone supersector indices from 15 November 2014 to 24 November 2023. This approach allows for analyzing various risk transmission mechanisms and hedging characteristics across different asset markets at various time horizons and periods, hence providing investors with time-varying connectedness to better manage their portfolios. Our results show a high average connectedness of the returns and volatilities. Industrial Goods and services is the largest transmitter contrariwise Media supersector is the largest receiver of returns shocks. By contrast, Brent propagates the lowest shocks to the returns of the other indices. Brent; Insurance; Chemicals; Food and Beverages; Media; Oil and Gas, Real Estate, and Health Care are the net receivers of shocks; whereas the remaining return series are the net transmitters. As per the volatilities, Industrial Goods and Services receive the highest volatility shocks. The Retail transmits the second-largest volatility shock. Industrial Goods and Services; Auto and Parts; Technology; Telecom; Utilities; Travel and Leisure; Oil and Gas; Basic Resources and Insurance are the net transmitters of volatility shocks; while the rest are the net receivers of shocks. Furthermore, the time-varying connectedness (TCI) of returns and volatilities indices show there was a drastic increase in TACI in March 2020 when the COVID-19 epidemic spread drastically around the world. The result confirms that the COVID crisis mainly affected the relationship, between Brent Oil prices and the Eurozone supersector, of returns and volatilities. Meanwhile, there has been no change in connectivity patterns due to the Russo-Ukrainian War.

The originality of our analysis is due to the rigor of the results because they allow us to understand the financial impacts of the ongoing conflict so that investors, portfolio managers and policymakers can design effective financial strategies.

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