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Dynamic connectedness analysis between crude oil price changes and Polish stock market sectors

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Abstract: The price of oil has registered important fluctuations over time. The crisis caused by the emergence of the COVID-19 virus caused a significant drop in the price of oil. Therefore, this article presents the research results of the spillovers of oil price changes in the sectors of stocks traded on the Polish stock market. Rolling window-based Quantile VAR (QVAR) is used, based on which the spillover indices proposed by Diebold and Yilmaz are calculated. The reference period for the daily oil prices and sector indices used is March 10, 2011 - September 9, 2022. The sectors considered are energy, oil and gas, banks, developers, chemicals, construction, basic materials, IT, media, and food. The methodology allowed obtaining results confirming a more important spillover in the right and left quantiles of the conditional distributions than in the mean and median. This situation confirms a significant spillover from oil price changes to the equity sectors traded in extreme market conditions. It was also identified that connectedness in the right tail is higher than in the left, though only for the stock market's energy and oil and gas sectors. The results highlight the importance of diversified portfolios based on sector-specific responses to oil price fluctuations and different market conditions.

Keywords: stock market, sectors, spillovers, QVAR

Introduction

Crude oil price represents an important input factor for almost all economic sectors. The economic literature (Fang & Egan, 2018; Shahzad et al., 2023) demonstrated that the effects of crude oil price fluctuation are not stabilized at the national level but at the international market level, including stock markets from all over the world, affecting both earnings and stock prices. Additionally, crude oil prices are taken as a benchmark by Central Banks' policies in their sustained work on inflation targeting, considering the great weight of crude oil prices in influencing the price of other commodity production processes (which creates scope for a monetary policy response).

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There is an ongoing debate in the literature concerning the measures of contagion or co-movement within markets (Tessler & Venezia, 2022). According to some authors (Forbes & Rigobon, 2002), the contagion is defined as a "significant increase in cross-market linkages after a shock" and, by using a structural vector autoregression methodology, Ding et al. (2017) confirmed a negative contagion effect of crude oil price on the Chinese stock market investor sentiment. However, the impact of oil price shocks on the stock market is more elaborate. according to some studies (Asadi et al., 2022; Jiang & Yoon, 2020; Khraief et al., 2021; Reboredo & Rivera-Castro, 2014; Schüler, 2021), it should also be observed in the business structure and level of cash flow, discounted cash flow (adjusted by interest rates or inflation), and cross-border discounted cash flow (also influenced by exchange rate) and must be assessed at different time scale.

Emphasizing its importance in asset pricing and risk analyses, the volatility of the oil market was studied by Dutta et al. (2021). According to Mensi et al. (2021), in their study about asymmetric spillover and network connectedness, the high volatility of the oil market induces fluctuations in market share prices by growing the cost of production, which affects the level of cash flows. Summarizing the literature, Mensi et al. (2021) present three research directions regarding the relationship between oil and stock market returns, the time-varying multiscale relationship, the returns and volatility spillovers, and upper and lower tail dependence analysis with mixed results. The volatility spillover has also been studied in the literature, considering stock markets (Chirilă & Chirilă, 2020), exchange-traded funds (Rizvi et al., 2022) or currencies (Rizvi et al., 2022).

This evidence is complemented by Iwanicz-Drozdowska et al., (2021) in their study about the contagion effect on stock markets due to the impact of economic and non-economic events on 16 emerging countries during 2000-2020, who found that the COVID-19 pandemic, which began in March 11, 2020, was in the proximity of the oil war between Saudi Arabia and Russia (March 8, 2020) affected the widest variety of sectors and countries in the analyzed period.

The pandemic caused by the emergence of the COVID-19 virus has led to a sharp drop in the stock and energy markets (Chirilă & Chirilă, 2022; Nuta et al., 2024). The oil price has reached the lowest level of the last decade, and uncertainty has increased in both the stock and energy markets. Jebabli et al. (2022) identify a volatility spillover between the two markets during the pandemic, which is more important than the volatility spillover of 2008, the global financial and economic crisis. This is why analyzing the volatility spillover between oil prices and stock markets became a research topic for an increasing number of studies (Antonakakis et al., 2020; Fiszeder et al., 2023; Nygaard & Sørensen, 2024). Volatility spillovers between stock markets and the oil market are the subject of research in many recent studies, such as Awartani and Maghyereh (2013), Du and He (2015), Sarwar et al. (2020).

Fewer studies are conducted on the volatility spillover between stock market sectors and the oil market. Zhu et al. (2021) study the correlation between oil and stock market sectors in China. Their results confirm the correlation between oil prices and stocks in the industrial, utilities, and consumer discretionary sectors. Their results also confirm no direct connection between oil and the financial, pharmaceutical, telecommunications, and consumer goods sectors.

Liao et al. (2021) studied the return and volatility spillover between stock markets, oil, and gold in several periods characterized by health emergencies. The authors confirm that the highest return and volatility spillover occurs during the COVID-19 pandemic, with the oil market becoming a source of risk. The study by Mensi et al. (2021) on the Chinese stock market confirms that negative returns in this market can lead to higher oil market volatility. They also conclude that portfolio diversification can benefit to the extent that the stock market sector is less affected by volatility spillover. Mensi et al. (2022) study the link between the oil market, the gold market, and the European Union (EU) stock market sectors. Their results confirm that the spillover effect was higher between the oil market and the stock market during the crisis caused by COVID-19, suggesting that investors should consider the gold market during the crisis.

The relationship between oil and stock market movements continues to produce conflicting results in the literature. However, there is an increasing focus on the impact of information transmission on stock markets, particularly in the digital age. Arcuri et al. (2023) found a short-term effect of fake news on stock returns in both Europe and the United States. Additionally, as observed by Hong et al. (2023) in their study, fake news plays a significant role in developing countries.

The overarching goal of studying the dynamic connectedness between crude oil price changes and Polish stock market sectors is to understand how fluctuations in the oil market impact the performance of various sectors within the market. This understanding is crucial for investors, policymakers, and businesses operating in Poland. The following specific objectives were sought to be achieved in this research:

- to identify the degree of connectedness, which means determining the strength and direction of relationships between crude oil price changes and specific Polish stock market sectors. This involves quantifying the extent to which sector returns are affected by fluctuations in oil prices;
- to analyze the dynamic nature of connectedness that will allow the investigation of how the relationships between oil prices and stock sectors change over time. This involves identifying periods of strong and weak connectedness, as well as potential structural breaks or shifts in relationships;
- to assess the heterogeneity across sectors because different sectors may respond differently to oil price shocks due to their varying exposures to energy costs;
- to compare these findings with other markets to benchmark them with other Central and Eastern European countries or other emerging or developed markets to see if the relationships observed in Poland are unique or part of a broader regional or global pattern.

The quantile VAR methodology proposed by Ando et al. (2022) is used in research to achieve the proposed objectives. The methodology allows the study of information spillovers in different quantiles representing different market situations: normal and extreme conditions.

This research has some novelties regarding the markets considered, the methodology used for estimation, and the comparability of the results. In this paper, particular importance is given to the Polish capital market because, on the one hand, it is the most developed stock market in Central and Eastern Europe and, on the other hand, it is the only market in the Central and Eastern Europe for which we have sectoral stock market indices.

Regarding the methodology, Quantile VAR has not been used to assess the impact of crude oil price changes on the Polish stock market. This allows the study of information spillovers in different quantiles representing different market situations: normal and extreme conditions. It has the great advantage of estimating spillovers in both directions: the received and the transmitted spillovers for each sector or market. And the results obtained can be compared with those of developed markets as long as studies for other Central European markets are not carried out.

Our results confirm that the oil market is a net receiver of information, and that there is a time-varying return spillover; in extreme market conditions, information spillover is significantly higher than in normal market conditions and is a more intense connectedness of oil price changes with the banks, basic materials sectors and overall market conditions.

This paper continues with a literature review and research questions followed by section 2 of the Polish stock market, the sections methodology and data, and results, and conclusions.

1. Literature review and research questions

The empirical studies covering the relationship between the oil price evolution and the stock markets were analysed from several perspectives, most of which refer to the aggregate level, not the sectoral one. The sectoral perspective considers the miscellaneous response of different stock market sectors to crude oil price alteration.

In this sense, empirical analyses have highlighted, on the one hand, tail dependence between oil prices and stock indices for Mexico, using TGARCH methodology, with increased volatility on the right but more stability on the left (Lorenzo Valdés et al., 2016) and, on the other hand, some differences in the interactions and an asymmetric response of the stock market index to oil price shocks, using a Nonlinear Autoregressive Distributed Lag (NARDL) model on four South Asian countries (Alamgir & Amin, 2021).

A significant part of the literature approached China's interaction between crude oil and stock markets. Thus, some papers find positive dependence between stock market returns and the global crude oil market (Hashmi et al., 2022) using the VAR-

DCC-GARCH model. Other authors (Wen et al., 2012) also find weaker contagion effects between energy and stock markets during financial crises, in China, rather than in the USA. Thus, the first research question of this study focuses on the direction and intensity of information spillover between the stock and oil markets in Poland.

Moreover, as highlighted in the literature, an important aspect in analysing the oil price shock impact on the stock market is to consider whether the change in oil prices is driven by supply or demand shocks (Kilian & Park, 2009). In a study evaluating both demand and supply oil shocks on the relationship between crude oil prices and S&P 500 and S&P 500 ex-energy indices, using a DCC-GARCH from 2006 to 2016, Nadal et al. (2017) found that demand shocks positively affected the correlations between crude oil prices and stock market returns in the period of maximum volatility of financial markets and, related to the exogenous supply shocks, they generally found little impact on firms' cash flow, except for 2006 to 2008 and from 2014 to 2016, when shocks in oil price significantly affected businesses' cash flows.

Also, negative oil prices influence stock returns more visibly in contrast to the positive crude oil prices impact, as the literature (Narayan & Gupta, 2015; Pan, 2014; Wang et al., 2020) suggests.

Furthermore, Ahmed and Huo (2021), studying the Chinese stock market during 2012-2017, observed a significant unidirectional return spillover effect from the oil market to the stock market, using a tri-variate VAR-BEKK-GARCH model. However, no return spillovers were found from the stock market to the Chinese oil market.

In a study evaluating the volatility connectedness across crude oil, natural gas, coal, stock, and currency markets in the US and China, Asadi et al. (2022) found a lower level of connectedness among energy, stock, and currency markets.

Pan et al. (2015) find strong evidence of contagion between crude oil and stock markets, using a model-free test using the spot price data of WTI and Brent crude oil, and S&P 500 index (US), FTSE 100 (UK) and the DAX index (Germany).

The evidence is complemented by Lin et al. (2019) who analyzed the risk contagion among the Brent crude oil market, the London gold market, and stock markets in China and Europe and found that a single direction of risk can be observed in the case of rare events, which can also induce contagion from European stock market to crude oil. Also, bidirectional risk contagion was found in extreme events between the crude oil market, London gold market, and stock markets. Furthermore, the authors also pointed out that only unidirectional risk contagion exists under extreme events running from stock markets to the Brent crude oil market.

Other findings (Reboredo & Rivera-Castro, 2014) indicate no effect of oil price changes on the aggregate and sectoral stock market returns levels and no evidence of lead and lag effects in the pre-crisis period in Europe and the USA in the pre-crisis period. The relationship between oil and the stock market was different during the financial crisis, where contagion and positive interdependence were reported at both levels.

Exploring co-movement between crude oil and the stock market, Wu et al. (2020) found crude oil as the main driver in the medium and long term, also considering the interdependence between oil-importing and oil-exporting countries.

In parallel, Bhatia and Basu (2021), investigating the demand and supply-driven crude oil shocks on sectoral stock indices, have found a heterogeneous impact across shocks, across bullish[5], bearish[6], and regular market conditions and across sectors, using a non-parametric causality-in-quantiles approach. Moreover, Wang et al. (2020) acknowledge that the effect of oil price changes on the stock markets is more substantial and asymmetric under extreme circumstances than under normal circumstances, using an extreme Granger causality analysis model for BRICS countries. In this sense, the second research question aims to determine whether the intensity of information spillover differs under normal, bear, and bullish market conditions.

Finally, since the sectoral approach has been less explored, the third research question seeks to identify which sectors of the Polish stock market are most strongly influenced by changes in the oil market.

2. Polish stock market

The Warsaw Stock Exchange (WSE-GPW) is the largest stock market in the Middle Eastern Europe area (Kusy 2022), based on the statistics published by the Federation of European Securities Exchanges (FESE) (FESE, 2023) for December 2022 regarding the total capitalization (EUR 137,837.35) and the number of listed companies (799). Thus, concerning the market value of the Warsaw Stock Exchange, it occupies one of the higher positions of the ranking. Even if the place held by the WSE indicates the critical size of the capital volume, the Warsaw market was subjected to the last period of substantial fluctuations, both from the perspective of the COVID-19 pandemic, the depreciation of the Polish currency (PLN) and the crisis induced by the outbreak of the Russia-Ukraine war and its impact on the energy market.

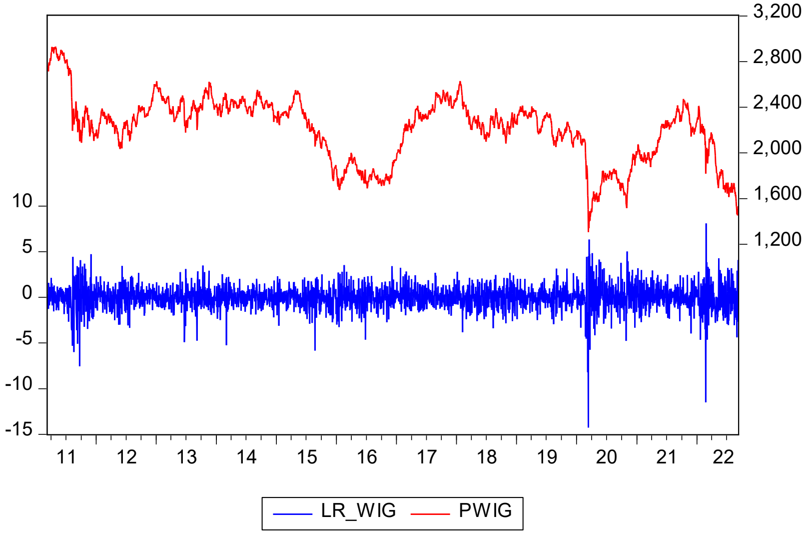
According to the GPW 2021 integrated report (GPW, 2021), the Warsaw Stock Exchange is the biggest in Central and Eastern Europe (PLN 174 billion) from the stock market capitalization point of view. Also, according to the same report, regarding the value of equity turnover, the European leader in 2021 was the Euronext Group (EUR 2.49 trillion), followed by Deutsche Boerse (EUR 1.69 trillion). GPW was EUR 70.0 billion in 2021, remaining the CEE leader ahead of Vienna, Budapest, Prague, and Bucharest. The data for 2022 show a similar position to WSE, with over EUR 137.88 billion in market capitalization.

[5] A bull market represents a market on the rise.
[6] A bear market represents a market in decline.

WSE represents 9.93% of the total stock exchange of the Federation of European Securities Exchanges, considering the number of companies listed in December 2022. The number of domestic companies is increasing, considering that in 2021, the GWP group (GPW, 2021) reported 787 domestic companies.

Thus, the Warsaw Stock Exchange Index, WIG 20, which includes the performance of the twenty largest companies listed on the WSE (Figure 1), shows the fluctuations in the market and the volatility of the Polish stock market in the last problematic years. Nevertheless, this image did not affect the fact that the Polish stock market is one of the largest in the region, including a diverse portfolio of foreign and local investors.

Figure 1. The evolution of The Warsaw Stock Exchange Index (March 11, 2011-September 9, 2022)



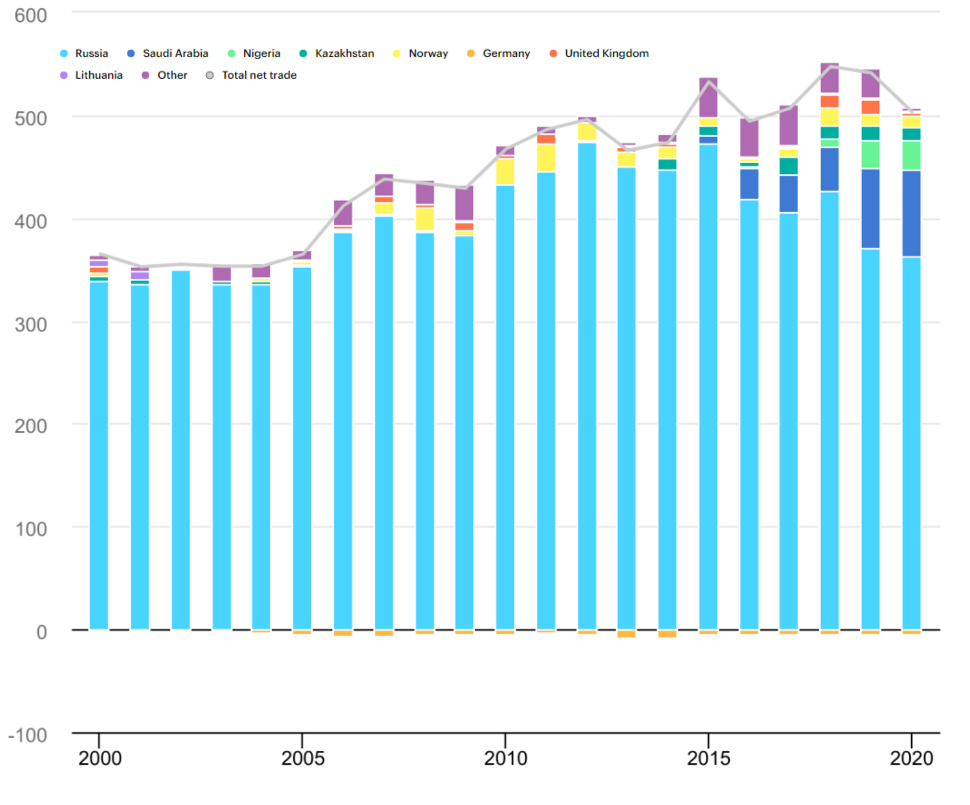
Note: PWIG, LR_WIG - WIG 20 index values and Polish stock market returns
Source: authors' representation

The Warsaw capital market has played an important role (Dietl & Zarzecki, 2022) in the economy of Poland in the last 30 years (starting from its rehabilitation in 1991), its presence being a catalyst for the transformation of savings into investments within the Polish economy with great potential for economic growth (World Bank, 2019), assuring the necessary funding for both short and long term. Also, WSE is strongly connected with Ukraine, a significant capital source for Ukrainian companies. In addition, according to the Polish Economic Institute (Dębkowska et al., 2022), in the first nine months of 2022, more than 13 800 new businesses were registered in Poland in the context of the wave of refugees. Also, the number of companies with Ukrainian capital registered in Poland in the same period was 12.5% higher than last year.

According to International Energy Agency data, Poland is one of the EU countries representing a major Russian oil importer (among other countries such as Germany, Slovakia, Lithuania, and Finland). Until recently, Poland bought more than three-quarters of its oil from Russia, but its representatives stated that since the country has the infrastructure, Poland will be the leading supplier for Central and Eastern Europe.

According to the IEA data illustrated in Figure 2, Crude oil net imports in 2020 mostly came from Russia. The geopolitical context changed this picture, considering that the EU banned Russian crude oil imports starting in December 2022. Also, in 2021, Poland imported 24 Mt of crude oil and, according to Enerdata (Enerdata, 2023), 69% of oil products are used in transport and 14% in industry.

Figure 2. Crude oil net imports in Poland between 2000-2020



Source: IEA, Crude oil net imports in Poland, 2000-2020, IEA, Paris https://www.iea.org/data-and-statistics/charts/crude-oil-net-imports-in-poland-2000-2020, IEA. License: CC BY 4.0

Poland's economy is diversified, and the banking, basic materials, chemicals, construction, developers, energy, food, IT, and media sectors contribute differently to the country's GDP: the banking sector is well-developed and plays an important role in Poland's economy, making a significant contribution to the services sector, the basic materials and chemical sectors are part of the industrial sector, which accounts for approximately 30% of Poland's GDP, the IT and media sectors are part of the services sector, which accounts for over 57% of Poland's GDP, and they are rapidly growing due to digitalization.

3. Methodology and data

A newly introduced research methodology for studying spillovers between financial asset markets, considered in a system, is advanced by Ando et al. (2022). The methodology allows the study of information spillover in different quantiles representing different market situations: normal conditions and extreme conditions. For this purpose, we use the quantile connectedness approach to analyze the spillover between changes in crude oil prices and the sectors of the Polish stock market.

The methodology is based on quantile vector autoregression QVAR(p). GFEVD (generalized forecast error variance decomposition) was advanced by (Diebold & Yilmaz, 2012; 2014) to determine spillover metrics. According to them, we first define an infinite order vector moving average (MA) representation for VAR(p). In the case of QVAR, the required MA can be written as follows:

$$y_t = \mu(q) + \sum_j^p \Phi_j(q) y_{t-j} + u_t(q) = \mu(q) + \sum_{i=1}^{\infty} \Omega_i(\tau q) u_{t-i} \quad (1)$$

For a forecast horizon h, GFEVD is defined as follows:

$$\Theta_{ij}^g(H) = \frac{\Sigma(q)_{ij}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(q) \Sigma(q) e_j\right)^2}{\sum_{h=0}^{H-1} e_i' \Omega_h(q) \Sigma(\tau) \Omega_h(q)' e_i} \quad (2)$$

in which: e_i - zero vector that has value 1 at the *i* position

$$\tilde{\Theta}_{ij}^g(H) = \frac{\Theta_{ij}^g(H)}{\sum_{j=1}^k \Theta_{ij}^g(H)}, \text{ where } \sum_{j=1}^k \tilde{\Theta}_{ij}^g(H) = 1 \text{ and } \sum_{i,j=1}^k \tilde{\Theta}_{ij}^g(H) = 1 \quad (3)$$

The total spillovers index at the quantile (q) is calculated in compliance with the relation (4) as follows:

$$TCI_t(q) = \frac{\sum_{i,j=1, i\neq j}^k \tilde{\Theta}_{ij}^g(H)}{k-1} \quad (4)$$

Equation 5 presents the possibility of calculating the entire connectedness from variables j to all other variables i at quantile (q):

$$TO_{j,t}(q) = \sum_{i=1, i\neq j}^k \tilde{\Theta}_{ij,t}^g(H) \quad (5)$$

Moreover, the possibility of calculation of the entire connectedness from variables i to all other variables j at quantile (q) is presented in equation 6:

$$FROM_{j,t}(q) = \sum_{i=1, i\neq j}^k \tilde{\Theta}_{ij,t}^g(H) \quad (6)$$

The total net spillovers index at quantile (q) is obtained as a difference as follows:

$$NET_{j,t}(q) = TO_{j,t}(q) - FROM_{j,t}(q) \quad (7)$$

If $NET_{j,t}(q)$ has a positive value, then we identify a market or a sector of the stock market that is a net spillover, and if it has a negative value, then we can conclude that the market is a net receiver from other markets.

$$NPDC_{i,j,t}(q) = \tilde{\Theta}_{ij}^{g} - \tilde{\Theta}_{ji}^{g} \quad (8)$$

For the estimation of dynamic connectedness at quantile, we adopt a 200-day rolling window.

In estimating the quantile vector autoregression QVAR(p), several steps are followed:

- the variables that make up the system are chosen: these are represented by the changes in the oil price, the changes in the values of the sectoral indices and the changes in the Polish market index (WIG) according to the relation (9);
- the stationarity of the series of variables considered is evaluated because it is a necessary condition in estimating the VAR system: two stationarity tests ADF - Augmented Dickey-Fuller unit root test (Dickey & Fuller, 1979), and ERS - Elliott et al. (1996) are taken into account;
- since the stationarity condition is fulfilled, the VAR model is estimated. The appropriate lag order of the VAR model is selected according to the information criteria Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values and then, the selected model is validated (by testing the compliance of the hypotheses regarding the residuals);
- the conditional quantile functions for each variable in the system are estimated, conditional on its own lags and the lags of the other variables, and thus we obtain the estimate of QVAR;
- based on the previously estimated QVAR, spillovers indices are calculated according to relations (4) – (8).

To study the connectedness between crude oil price changes and Polish stock market sectors, the indices calculated for the following sectors are considered: banks (BK), basic materials (BM), chemicals (CHE), construction (CO), developers (DE), energy (EN), food (FOD), IT (IT), media (ME), oil & gas (OG) and the WIG 20 index (WIG) which show the overall trend of this stock market. Brent Oil Futures Prices (OIL) were considered for the oil market. The daily data was taken from the website www.investing.com and covers the period from March 10, 2011, to September 9, 2022. Thus, 3001 observations are recorded for each index. The returns of equity sectors and crude oil price changes are determined according to the relation:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \cdot 100$$

where P_t, P_{t-1} represents the values of the indices on day t and the previous day, t-1, respectively.

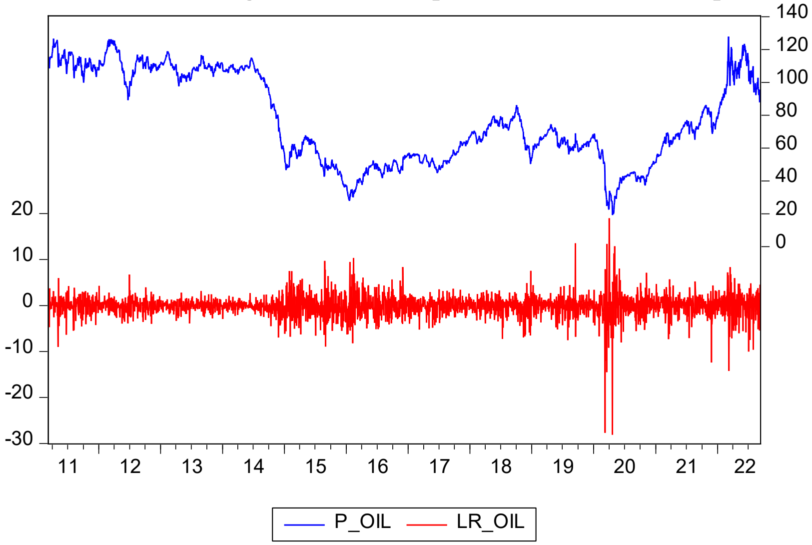
Based on the values recorded for each index, 3000 daily returns were calculated, covering the period from March 11, 2011, to September 9, 2022.

The estimation of connectedness within the system determined by the activity sectors of the stock market and the oil market is carried out based on the methodology advanced by Ando et al. (2022), a method that is based on the calculation of indices connectedness originally advanced by Diebold and Yilmaz (2009) but estimated for different quantiles. The methodology advanced by Ando et al. (2022) thus allows the study of connectedness under different market conditions by analyzing the extreme and median quantiles.

4. Results

The analysed period considers the maximum data availability period: it starts on March 10, 2011, when values for sectoral indices of the Polish stock market are available and ends on September 9, 2022. The index values' evolution and the sectors' returns are presented in Appendix A, Figure A1. As shown in Figure 3 and Table A1, oil price and sector indices exhibit empirical characteristics specific to financial series: volatility is higher when the market is falling, and volatility is lower when the market is rising, suggesting volatility asymmetry. This feature is amplified during the COVID-19 pandemic, when a significant decline in the oil market causes extreme volatility.

Figure 3. Evolution and changes in oil market price (March 11, 2011-September 9, 2022)



Note: P_OIL and LR_OIL – price and changes in oil market
Source: authors' representation

The analysis of the descriptive statistical indicators, presented in Table A1, reveals leptokurtic distributions for all distributions of returns calculated and their lack of normality. Estimating the VAR model underlying the estimation of the return spillover requires testing the stationarity of returns. The unit root tests, ADF - Augmented Dickey-Fuller unit root test (Dickey & Fuller, 1979), and ERS - Elliott et al. (1996) unit root test demonstrates the stationarity of returns.

4.1. Static spillovers

Table A2, Table A3, and Table A4 show the results obtained from the quantile VAR estimation for the quantiles q=0.05, q=0.50, and q=0.95. The methodology used in estimating connectedness indices advanced by Ando et al. (2022) allows studying the return spillover between the oil market and economic sectors of companies listed on the Polish stock market in three different situations of the financial market, bear, normal and bullish market.

The lower outlier quantile, q=0.05, allows the study of the financial market when faced with the emergence of unexpected new bad/negative information. In contrast, the upper outlier quantile, q=0.95, allows the study of the market when faced with the emergence of unexpected, good, positive information. The median quantile, q=0.50, allows studying the market in a normal situation.

According to Table A2, the spillover of oil price changes differs in intensity to the sectors of shares listed on the Polish market. The highest spillover is towards the basic materials sector (7.48%), followed by construction (7.31%) and developers (7.22%). Also, changes in the oil price are highly influenced by its previous values (13.46%). The same situation emerges in all sectors, with the information from their own sector having a higher impact. Changes in the oil price also receive information from the stock market sectors. Most information is received from the basic materials sector (8.59%), followed by the construction sector (8.14%), and the macroeconomic situation reflected by changes in the stock market index (8.03%).

Overall, oil price changes are a net receiver, with less information spillovers towards the equity market sectors than information spillovers received from the equity market sectors. The reported result confirms the vulnerability of crude oil changes in the studied system. It is worth mentioning that when the stock market faces unexpected new negative information, the total connectedness index in this system is very high, reaching 87.41%.

In the median quantile (q=0.50), as per Table A3, the total spillover in the system changes significantly, being only 59.05%, much lower than in the previous situation. The spillovers from oil price changes towards the Polish stock market sectors are much lower than in the low quantile (q=0.05). The highest spillovers of information are still registered towards the basic materials sector (2.62%), followed by developers (1.87%), construction (1.80%), and oil and gas (1.78%). Oil price changes are mainly influenced by information from the basic materials sector

(5.09%), the economic situation reflected by the market index (4.15%), and the oil & gas sector (3.29%).

Under normal financial market conditions, oil price changes are overwhelmingly influenced by their own information (68.97%). The same situation is observed for the other sectors, but their own spillovers have lower values ranging from 28.72% to 50.52%, with the highest values registered for the food and IT sectors. Oil price changes are a net receiver of external shocks, like in the case of lower quantiles (q=0.05) but to a much larger extent -13.15%.

When the stock market faces unexpected positive news, the sectors' own information and the oil market's information influence to a lesser extent than when the market faces unexpected negative news (as shown in Table A4). Thus, there are registered values of 13.46% compared to 13.37% for oil market changes, 12.01% compared to 11.66% for the basic materials sector, and 12.20% compared to 11.88% for the developers' sector.

The largest spillovers from oil price changes to the stock market sectors are towards the basic materials (7.25%), chemicals (7.16%), and construction (7.05%) sectors. Oil price changes receive information from the basic materials (8.26%), banks (8.18%), and energy (8.15%) sectors. Overall, the oil market is still a net receiver of external shocks.

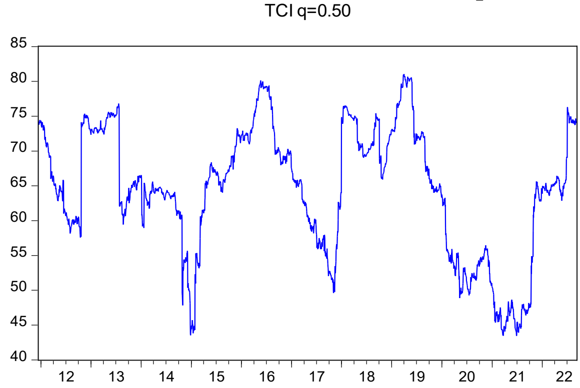
The total connectedness in the system is 87.60%, a value compared to the spillover achieved in a low quantile of 87.41%.

4.2. Dynamic spillovers

The graphical representations illustrated in Figure 4 and Figure 5 show that, throughout the study period, the total connectedness index (TCI) has significantly higher values in the extreme quantiles when the market is confronted with unexpected new negative and positive information. In this situation, most TCI values are higher than 95.5% while in normal market conditions, TCI values sometimes barely reach 75%.

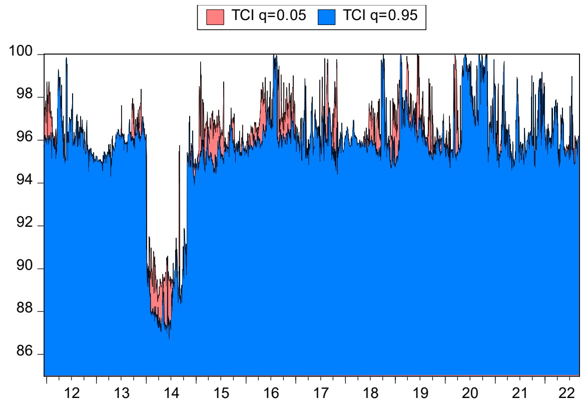
Also, the same graphical representations highlight that the TCI index has relatively constant values throughout most of the period studied in the bear and bullish markets. The situation is different in normal market periods when the total connectedness index (TCI) shows cyclical developments that are influenced by the European Debt Crisis (January 4, 2010 – December 31, 2012), Oil Crisis, and the Brexit referendum (August 21, 2015 – September 29, 2019) and COVID-19 pandemic (January 2, 2020 - November 9, 2020) fact also confirmed by Mensi et al. (2024) on the Vietnam stock market. Thus, the situation of some strong information spillovers under extreme market conditions and cyclical spillovers under normal market conditions is emphasized.

Figure 4. Evolution of the total connectedness index at the quantile VAR (q=0.5)



Source: authors' representation

Figure 5. Evolution of the total connectedness index at the quantile VAR (extreme lower quantile q=0.05, extreme upper quantile q=0.95)



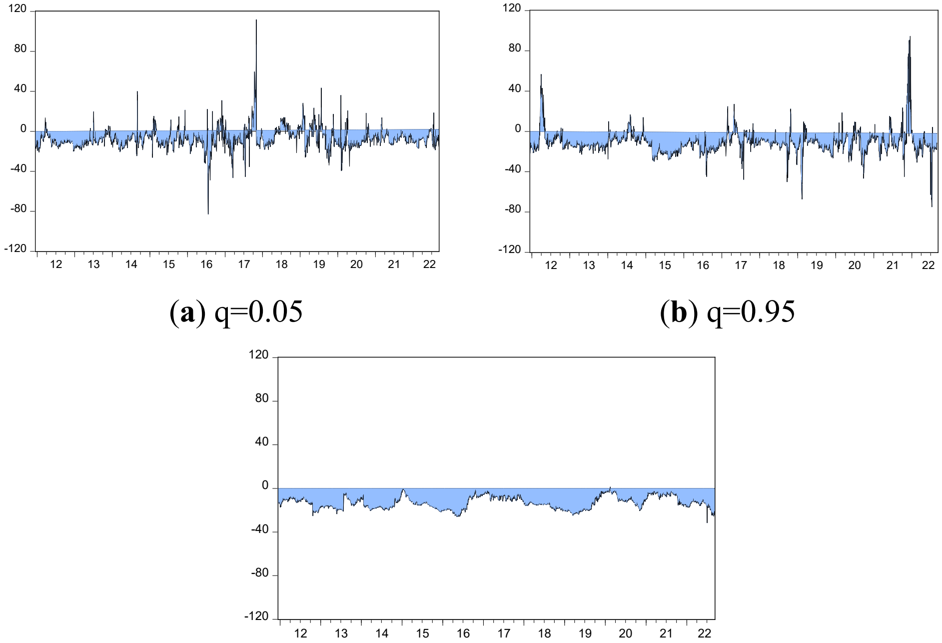
Source: authors' representation

The TCI values quantifying the information spillover from (FROM) the crude oil market to each sector of the Polish stock market at the quantile level are shown in Figure A.2, a-k. The TCI values are much higher for extreme, lower, or upper quantiles compared to the value at the median quantile, where TCI records lower values. This again confirms a high level of connectedness under extreme market conditions. The symmetry of the graphical representations suggests the lack of an important difference in information spillover between the bear and the bullish market.

Figure A.2 shows the evolution of the TCI index, at the quantile level, for information spillovers from each stock market sector to the crude oil market. The features are similar to those identified in the previous graphic representation: a higher level of connectedness under extreme market conditions than under normal conditions and symmetry of connectedness during periods of extreme conditions.

It was determined that oil price changes are a net receiver, with less information spillovers to the stock market sectors than information spillovers received from the stock market sectors. The evolution of these spillovers over time is shown in the figure below:

Figure 6. Evolution of the net connectedness index at the quantile VAR (extreme lower quantile q=0.05, extreme upper quantile q=0.95, and median quantile q=0.50)



(**a**) q=0.05 (**b**) q=0.95

(**c**) q=0.50

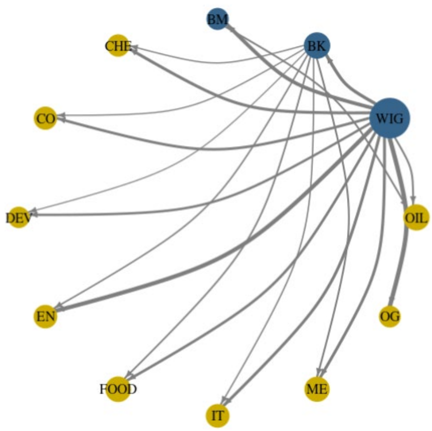
Source: authors' representation

While under normal market conditions, oil market changes receive information spillovers from stock market sectors with different intensities (cyclical evolution) throughout the period, under extreme market conditions, there are also frequent but very brief moments when oil market changes spillover information to equity market sectors. Hence, the oil market is also an information spillover.

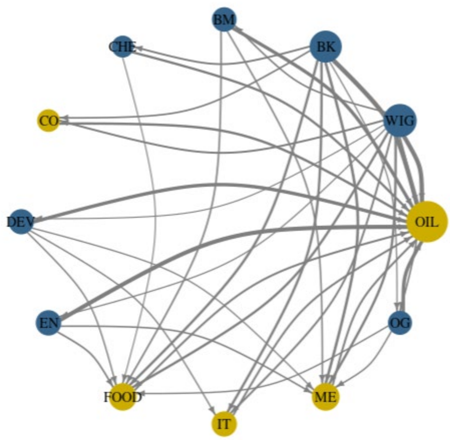
4.3. Pairwise spillovers

Figure 7 shows net pairwise directional network spillovers between Polish stock market sectors and crude oil price changes during normal (median quantile, q=0.50), bull (lower extreme quantile, q=0.05), and bear (upper extreme quantile, q=0.05) market conditions.

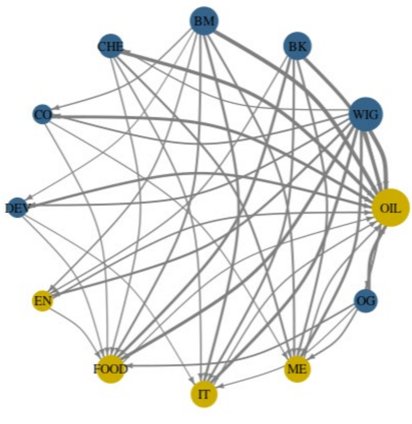
Figure 7. Net pairwise directional connectedness network at the median and extreme quantile



(a) q=0.05



(b) q=0.95



(c) q=0.50

Source: authors' representation

In the above situations, crude oil is a net receiver of returns. The situation of the sectors is different. Under normal market conditions, the energy, food, IT, media, and crude oil sectors are significant net receivers of returns from the other sectors that are part of the system under analysis. The thickness of the lines in Figure 7, connecting the elements of the system, represents the proportion/intensity of the spillovers. Crude oil is connected with all the system elements. However, the largest information spillovers are from the banks, basic materials, chemicals, construction developers, oil and gas sectors, and the overall economic situation quantified by the WIG index.

Also, when the market is facing unexpected positive new information (q=0.95), crude oil is a receiver of information from all sectors. The sectors it receives the most from are the following: energy, developers, banks, oil and gas, and the stock market overall. Along with crude oil, the construction, food, IT, and media sectors are net spillover receivers.

When the stock market faces unexpected negative information (q=0.05), crude oil is also a receiver of returns. In this case, significant spillovers are recorded from the basic materials sectors and the stock market overall, reflecting the country's economic situation.

Conclusions

Information spillover in financial markets has become evident over the past few years. If, for a long time, the information, returns, and volatilities spillover have been studied mainly during financial and economic crises, the quantitative methods developed have allowed us to identify and carry out such a quantitative analysis in other periods. Quantile VAR and the spillover indices developed have enabled the study of markets based on high-frequency data under normal and extreme market conditions.

Also, while research has been carried out to analyse the information spillover between financial markets of different countries, the need to study the spillovers in the systems determined by different financial markets and sectors of economic activity within one country has been identified. This is also the case in this research which analysed the information spillover between the oil market and the Polish stock market sectors.

The first research question concerns the direction of information spillover between the stock market and oil market sectors. The results confirm that the oil market is a net receiver. Similar situations were also obtained in the research conducted by (Mensi et al., 2024) for Vietnam, (Mensi et al., 2021) for China, and (Zhu et al., 2021) for the US market. Besides this finding, an additional focus on the origins of the oil price change (Kilian & Park, 2009) can also be considered in further studies. The research has also highlighted that the results differ depending on the market situation, also studied by An et al. (2018). Under normal market conditions, net information spillover occurs only from stock market sectors to the oil market, but the spillover intensity evolves cyclically, contradicting the Katsampoxakis et al. (2022) who found no interdependence between oil and stock prices in their results for European countries in balanced periods. In extreme market conditions, there are also very short but frequent periods of net information spillover from the oil market to the stock market sectors. Thus, it has been identified as a spillover from the stock market sectors to the oil market and vice versa, also in line with Katsampoxakis et al. (2022) findings for high volatility periods.

The intensity of information spillover shows a clear "U" shape; in extreme market conditions, information spillover is significantly higher than in normal market conditions. This also answers the second research question. The obtained result also confirms an asymmetry of information spillover and confirms previous research by Mensi et al. (2022), Rahmanto et al. (2016) for the Indonesian market and Kelikume and Muritala (2019) for Africa.

In order to answer the third research question, a more intense connectedness of oil price changes with the banks, basic materials sectors and overall market conditions was identified, a result that confirms previous research by Chirilă and Chirilă (2022), and Mensi et al. (2022). Raw materials and financial industries are more affected by the oil price fluctuations considering the demand-side induced effects, as previously found in Indonesia (Rahmanto et al., 2016) and G-7 countries (Lee et al., 2012).

Considering market conditions enhances the study's value by examining the evolution of variables within different macroeconomic frameworks. The research also highlights the role of oil prices in directly influencing the Polish stock market as a whole, while also analysing movements across various sectors.

The results obtained are important for ensuring portfolio diversification but also for policymakers who must make decisions to maintain or create financial stability. Therefore, traders' decisions should be grounded in a solid understanding of how oil prices change and the potential impact on various sectors. Moreover, adapting to macroeconomic conditions and managing the increased volatility during certain periods can lead to better asset portfolio management. Tackling these kinds of influences is also useful for decision-makers, allowing them to adjust the tools within the macroeconomic framework to foster market recovery. Further research can be directed towards studying the connectedness of individual companies listed on the stock market to obtain more detailed information for portfolio diversification.

Our study also has some limitations stemming from the elements included in the system considered. In our analysis, we have focused on the overall Polish market by using the WIG20 index (along with sector indices and oil prices), representing the systematic information available in that market. However, the system could be further enriched by incorporating elements related to uncertainty in the studied market, investor sentiment, or the attractiveness of stock market investments to both potential and current investors.

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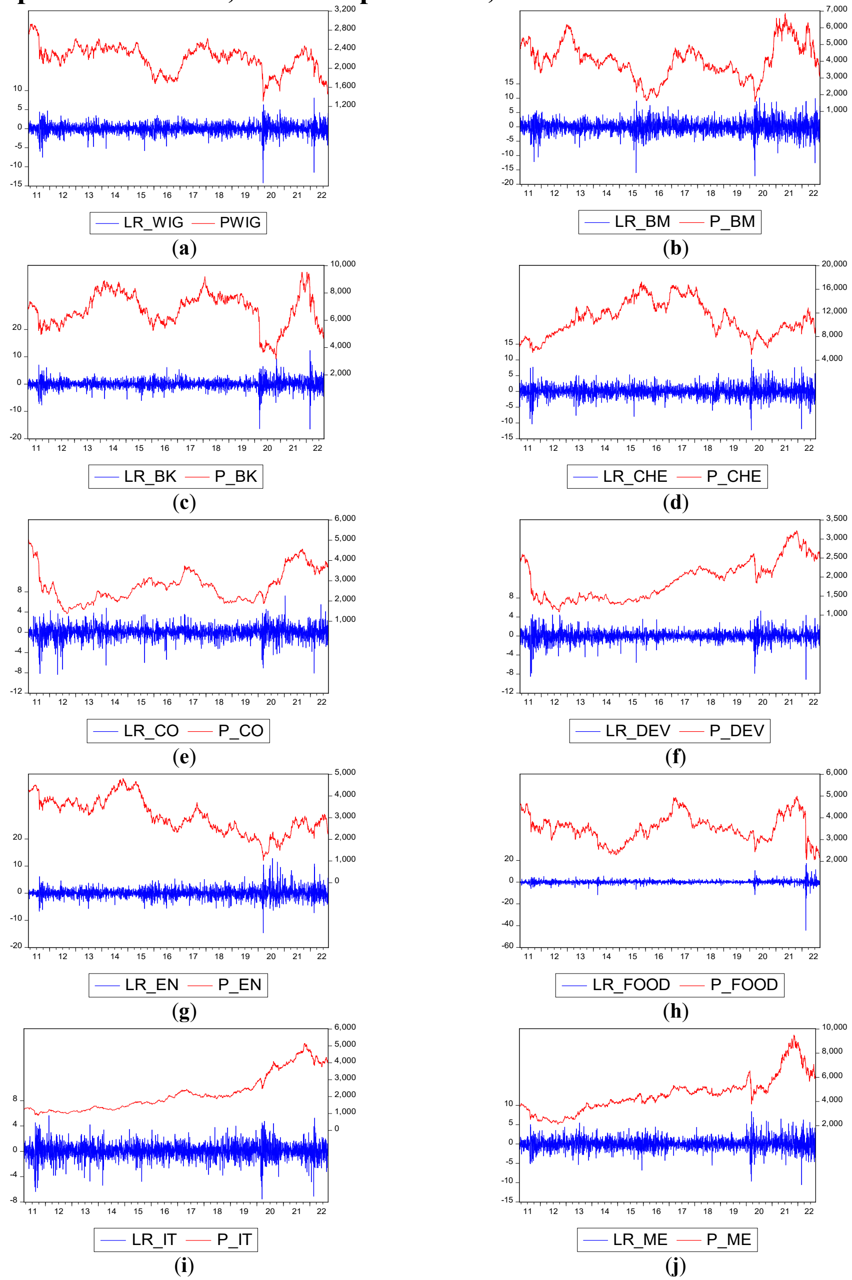
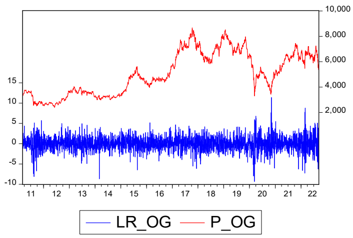
Appendix A

Figure A1. Evolution of index values and returns of Polish stock market sectors in the period March 11, 2011 – September 9, 2022

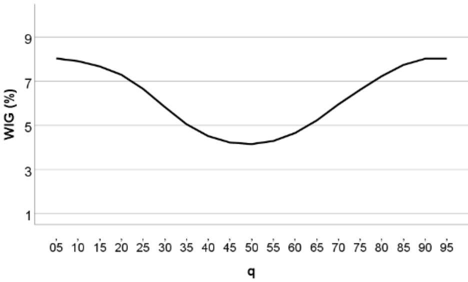




(k)

Figure A2. Directional total spillovers from each sector on the Polish stock market to crude oil market (TO) from March 11, 2011 – September 9, 2022.

(a)



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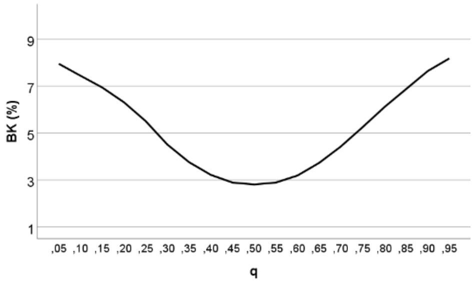

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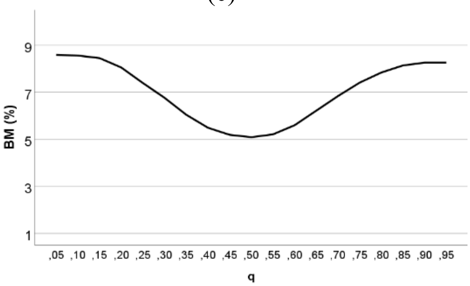

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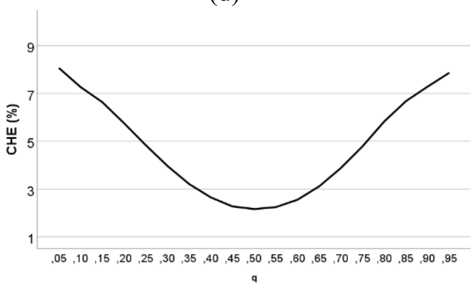

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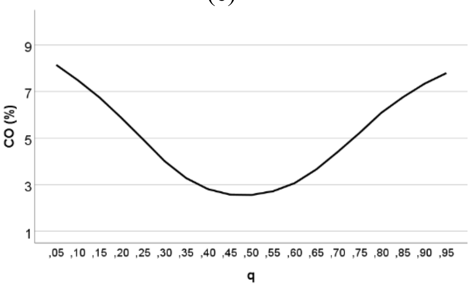
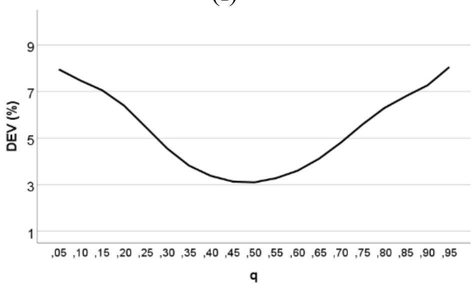
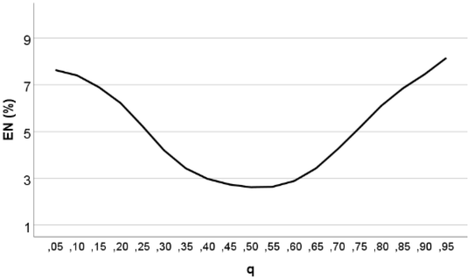


(f)



(g)



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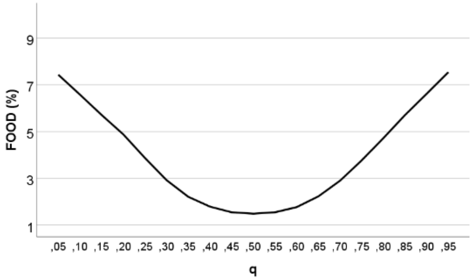
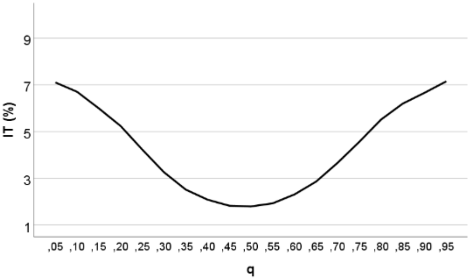
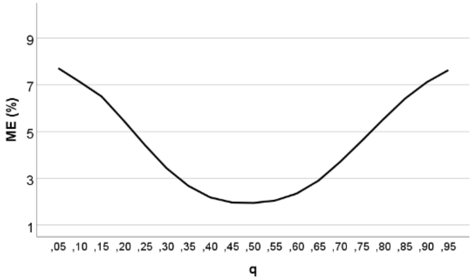
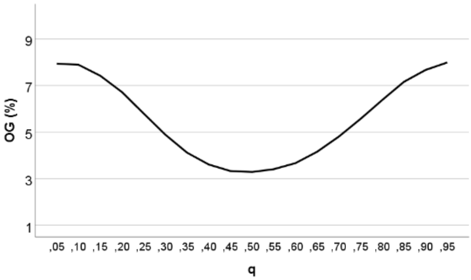


(i)



(j)





(k)

Note: WIG, BK, BM, CHE, CO, DEV, EN, FOOD, IT, ME, and OG represent the Polish stock market index, banks, basic materials, chemicals, construction, developers, energy, food, IT, media and respectively oil and gas sectors; results obtained by the authors.

Table A1. Indicators of descriptive statistics of returns for the period March 10, 2011 - September 9, 2022

	OIL	WIG	BK	BM	CHE	CO	DEV	EN	FOOD	IT	ME	OG
Mean	-0.007	-0.019	-0.010	-0.012	0.009	-0.011	0.001	-0.018	-0.025	0.039	0.016	0.016
Median	0.076	0.000	0.00	0.000	0.000	0.000	0.000	-0.0002	0.000	0.000	0.000	0.000
Maximum	19.077	8.099	12.385	10.173	10.202	7.211	5.329	12.810	17.181	105.078	8.421	11.422
Minimum	-27.976	-14.245	-16.531	-17.168	-12.292	-8.379	-9.161	-14.794	-44.665	-102.763	-10.589	-9.358
Std. Dev.	2.341	1.290	1.633	2.234	1.764	1.240	1.088	1.767	1.819	2.921	1.480	1.717
Skewness	-0.995	-0.837	-0.631	-0.354	-0.211	-0.682	-0.805	0.426	-4.865	0.945	-0.234	-0.089
Kurtosis	21.401	12.797	13.946	7.238	7.144	8.030	10.729	9.273	133.890	1068.89	7.299	5.801
Jarque-Bera	42837*	12353*	15182*	2309*	2169*	3397*	7795*	5011*	2154083*	142063256*	2339*	984*
ADF	-54.320*	-54.159*	-54.144*	-52.098*	-50.714*	-50.86*	-50.877*	-51.343*	-22.439*	-27.020*	-52.615*	-54.667*
ERS	-15,321*	-5,599*	-7,560*	-9,296*	-20,533*	-16,97*	-7,178*	-22,397*	-6,068*	-33,368*	-11,603*	-3,790*

* Note: OIL-crude oil price changes, WIG, BK, BM, CHE, CO, DEV, EN, FOOD, IT, ME, OG - returns for the Polish market, banks, basic materials, chemicals, construction, developers, energy, food, IT, media and respectively oil and gas sectors. ADF - Augmented Dickey-Fuller unit root test (Dickey & Fuller, 1979); ERS - Elliott et al. unit root test Elliott et al. (1996) *, ***, *** Significant at 1%, 5%, respectively 10% Results obtained by the authors.

Table A2. Return spillovers estimated on the quantile VAR (q=0.05)

	OIL	WIG	BK	BM	CHE	CO	DEV	EN	FOOD	IT	ME	OG	FROM
From OIL to	13.46	8.03	7.95	8.59	8.07	8.14	7.95	7.63	7.43	7.1	7.71	7.94	86.54
From WIG to	6.88	10.82	9.8	9	8.18	7.81	7.91	8.4	7.4	7.25	7.62	8.91	89.18
From BK to	6.95	10.03	11.51	8.46	8.18	7.92	7.99	8.09	7.63	7.14	7.74	8.35	88.49
From BM to	7.48	9.13	8.43	12.01	8.24	7.94	8.14	7.96	7.48	7.13	7.7	8.36	87.99
From CHE to	7.09	8.55	8.34	8.37	12.3	8.11	8.07	8.05	7.69	7.33	7.72	8.38	87.7
From CO to	7.31	8.32	8.14	8.34	8.33	12.13	8.52	7.66	7.82	7.44	7.95	8.04	87.87
From DEV to	7.22	8.45	8.27	8.45	8.15	8.41	12.2	7.72	7.81	7.39	7.94	7.99	87.8
From EN to	7.15	9.05	8.48	8.39	8.25	7.73	7.73	12.36	7.47	7.29	7.57	8.53	87.64
From FOOD to	7.09	8.3	8.39	8.07	8.1	8.2	8.17	7.82	12.88	7.38	7.65	7.96	87.12
From IT to	6.7	8.09	7.76	7.83	7.77	7.67	7.69	7.58	7.26	16.91	7.28	7.46	83.09
From ME to	7.27	8.39	8.36	8.27	8.32	8.29	8.2	7.74	7.63	7.21	12.39	7.94	87.61
From OG to	7.03	9.48	8.54	8.43	8.35	7.89	7.85	8.3	7.45	7.13	7.46	12.09	87.91
TO	78.17	95.82	92.46	92.2	89.94	88.11	88.22	86.94	83.09	79.78	84.35	89.86	1048.94
Incl, Own	91.63	106.64	103.97	104.21	102.24	100.24	100.42	99.3	95.98	96.69	96.74	101.95	
Net	-8.37	6.64	3.97	4.21	2.24	0.24	0.42	-0.7	-4.02	-3.31	-3.26	1.95	
								TCI=87.41					

Note: *OIL - crude oil price changes, WIG, BK, BM, CHE, CO, DEV, EN, FOOD, IT, ME, OG - returns for the Polish market, banks, basic materials, chemicals, construction, developers, energy, food, IT, media and respectively oil and gas sectors. Results obtained by the authors.

** From OIL to - represents the information transmitted from crude oil price changes to its own variation and then to the other elements in the system according to the relation (6).

*** FROM represents all the information transmitted to the other elements in the system and TO represents the total information received from the other elements in the system according to the relation (5) and Incl, Own represents the total information received from the other elements in the system to which its own information is added. Net represents the difference between TO and FROM

**** TCI - total spillovers index according to the relation (4).

Table A3. Return spillovers estimated on the quantile VAR (q=0.50)

	OIL	WIG	BK	BM	CHE	CO	DEV	EN	FOOD	IT	ME	OG	FROM
From OIL to	68.97	4.15	2.81	5.09	2.16	2.56	3.1	2.62	1.49	1.8	1.95	3.29	31.03
From WIG to	1.6	22.54	16.34	10.62	6.25	5.02	5.56	8.01	3.7	5.1	4.26	11.02	77.46
From BK to	1.42	20.79	28.72	7.29	5.79	4.94	5.61	5.85	3.9	4.55	4.41	6.74	71.28
From BM to	2.62	15.7	8.47	33.84	5.71	4.93	5.53	5.41	3.09	3.97	3.84	6.88	66.16
From CHE to	1.33	10.38	7.59	6.61	38.52	5.58	5.51	5.68	3.44	4.35	4.43	6.58	61.48
From CO to	1.80	8.73	6.68	6.02	5.86	39.76	7.70	4.08	4.67	5.49	4.72	4.49	60.24
From DEV to	1.87	8.92	7.18	6.16	5.7	7.19	39.11	4.3	4.69	4.85	5.1	4.95	60.89
From EN to	1.59	13.74	7.96	6.37	5.74	3.86	4.44	39.35	2.8	4.34	3.28	6.54	60.65
From FOOD to	1.16	7.39	6.21	4.34	4.24	5.39	5.75	3.36	50.52	3.94	3.92	3.77	49.48
From IT to	1.24	9.17	6.47	4.92	4.67	5.54	5.24	4.61	3.46	47.4	3.27	4.02	52.6
From ME to	1.48	8.28	6.94	4.88	5.08	5.16	6.09	3.9	3.76	3.63	47.19	3.62	52.81
From OG to	1.78	17.15	8.17	7.25	6.14	4.11	4.68	5.97	2.86	3.42	2.94	35.51	64.49
TO	17.88	124.41	84.82	69.55	57.35	54.27	59.21	53.79	37.85	45.42	42.11	61.9	708.57
Incl, Own	86.85	146.95	113.54	103.4	95.87	94.03	98.32	93.14	88.37	92.82	89.3	97.41	
Net	-13.15	46.95	13.54	3.4	-4.13	-5.97	-1.68	-6.86	-11.63	-7.18	-10.7	-2.59	
								TCI=59.05					

Note: *OIL-crude oil price changes, WIG, BK, BM, CHE, CO, DEV, EN, FOOD, IT, ME, OG - returns for the Polish market, banks, basic materials, chemicals, construction, developers, energy, food, IT, media and respectively oil and gas sectors. Results obtained by the authors.
** From OIL to - represents the information transmitted from crude oil price changes to its own variation and then to the other elements in the system according to the relation (6).
*** FROM represents all the information transmitted to the other elements in the system and TO represents the total information received from the other elements in the system according to the relation (5) and Incl, Own represents the total information received from the other elements in the system to which its own information is added. Net represents the difference between TO and FROM
**** TCI - total spillovers index according to the relation (4).

Table A4. Return spillovers estimated on the quantile VAR (q=0.95)

	OIL	**WIG**	**BK**	**BM**	**CHE**	**CO**	**DEV**	**EN**	**FOOD**	**IT**	**ME**	**OG**	**FROM**
From OIL to	13.37	8.02	8.18	8.26	7.87	7.79	8.05	8.15	7.54	7.15	7.63	7.99	86.63
From WIG to	6.73	10.7	9.65	8.81	8.18	7.75	8.11	8.64	7.58	7.31	7.64	8.91	89.3
From BK to	6.83	9.9	11.58	8.33	8.03	7.88	8.13	8.28	7.69	7.2	7.76	8.39	88.42
From BM to	7.25	9.3	8.64	11.66	7.99	7.8	8.12	8.36	7.49	7.35	7.66	8.37	88.34
From CHE to	7.16	8.5	8.59	8.18	11.68	8	8.27	8.29	7.79	7.42	7.75	8.36	88.32
From CO to	7.05	8.33	8.39	8.02	8.18	12.18	8.55	8.09	7.88	7.47	7.91	7.95	87.82
From DEV to	7.02	8.45	8.34	8.17	8.18	8.33	11.88	8.03	8.01	7.55	7.95	8.09	88.12
From EN to	6.9	9.01	8.51	8.27	8.25	7.88	8.05	12.25	7.52	7.39	7.7	8.27	87.75
From FOOD to	6.94	8.29	8.41	7.99	8.13	8.07	8.45	8.02	12.43	7.45	7.81	8.01	87.57
From IT to	6.56	7.89	7.92	7.58	7.65	7.59	7.96	7.6	7.37	17.23	7.16	7.5	82.77
From ME to	7.02	8.36	8.55	8.13	8.05	8.14	8.33	8.17	7.87	7.19	12.18	7.99	87.82
From OG to	6.94	9.4	8.77	8.38	8.26	7.76	8.19	8.31	7.6	7.18	7.56	11.66	88.34
TO	76.41	95.45	93.95	90.12	88.78	87.01	90.21	89.94	84.34	80.66	84.51	89.84	1051.21
Incl, Own	89.78	106.15	105.52	101.78	100.46	99.18	102.09	102.19	96.77	97.89	96.7	101.5	
Net	-10.22	6.15	5.52	1.78	0.46	-0.82	2.09	2.19	-3.23	-2.11	-3.3	1.5	
								TCI=87.60					

Note: *OIL-crude oil price changes, WIG, BK, BM, CHE, CO, DEV, EN, FOOD, IT, ME, OG - returns for the Polish market, banks, basic materials, chemicals, construction, developers, energy, food, IT, media and respectively oil and gas sectors. Results obtained by the authors.

** From OIL to - represents the information transmitted from crude oil price changes to its own variation and then to the other elements in the system according to the relation (6).

*** **FROM** represents all the information transmitted to the other elements in the system and **TO** represents the total information received from the other elements in the system according to the relation (5) and **Incl, Own** represents the total information received from the other elements in the system to which its own information is added. **Net** represents the difference between TO and FROM

**** **TCI** - total spillovers index according to the relation (4).