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SYSTEMIC RISK AND CONTAGION IN THE COMMODITY MARKET: IDENTIFYING VOLATILITY TRANSMISSION DURING CRISIS PERIODS

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Abstract. The commodity market is a key element of the global economy. It is influenced by the political and economic situation of the major participants on the supply and demand side, as exemplified by the geopolitical and economic situation related to the conflict in Ukraine. Another aspect of this influence is the close relationship between commodity markets and financial markets. Both factors contribute to the possibility of the commodity market becoming subject to contagion, resulting in the transfer of supply and demand shocks and volatility. The aim of this article is to identify the commodities that are the source of contagion (volatility) during the transmission of shocks and the increase of systematic risk in selected periods. Combining traditional network theory with vector autoregression (VAR) model, we aim to estimate systemic linkages as a measure of systemic risk and the contagion process underlying it. We used time series of commodity returns from the Refinitiv Eikon database to observe the relationships between commodities during crisis periods, starting from 2006. The results suggest that the commodities with the largest increase in volatility transmission compared to the pre-crisis period acted as a transmission gate for market shocks.

Keywords: contagion, volatility transmission, commodity market, systemic risk.

JEL Classification: Q02, G01, O13.

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1. Introduction

Researchers have been studying the characteristics of relationships in financial markets in the context of the stock market for many years. However, little attention has been paid so far to the study of connections in global commodity markets. Meanwhile, in recent years, interesting phenomena have occurred in international commodity markets. For example, in 2020, there was a dramatic drop in oil prices, coupled with changes in precious metals prices. This was peculiar in that, on the one hand, precious metals became cheaper due to the drop in oil prices. On the other hand, their price was rising due to “flight to gold” in the face of deepening global economic uncertainty and slowing global growth.

One of the key factors determining the stability of economic systems is the specific or systemic nature of the risks they face. As long as the risk is specific, it poses a threat to individual entities but does not threaten the stability of the entire system, market, or economy. However, once the risk becomes systemic, it affects a larger group of entities to the same extent, becoming a source of threat that cannot be neutralized through diversification of activities, formally referred to as diversification.

The traditional source of systemic risk is mainly adverse changes in economic parameters that are exogenous to the entire economic system. The crisis experiences of recent years have intensified the lively discussion on another source of systemic risk, which has become a phenomenon of "contagion" for the economy. As a result, a unitary economic shock, like an infectious disease, spreads to other entities, transforming into systemic risk. The channels that enable the propagation of problems from a single institution to the entire system are inter-organizational, functional, legal, or political economic connections. In this context, the phenomenon of "financial contagion" deserves particular attention as a specific case of a broader process resulting from the growing importance of the financial sector.

In recent times, the political factor shaping the contagion process based on commodities, especially energy resources, has become particularly important. This expands the potential scope of negative impact on the real economy through contagion that utilizes network connections between key commodities. The aim of this article is to attempt to identify commodities that are a source of contagion (variability) during the transmission of shocks and the increase of systematic risk in selected periods.

This research paper provides additional insights into the sources of contagion and shock transmission in the commodity market, which is an important step in identifying sources of systemic risk in times of crisis, based on the study of market relationships.

In our research, we use the Diebold and Yilmaz (2009) approach, which involves estimating systemic linkages as a measure of systemic risk and the contagion process underlying it. This approach allows us to assess how much systemic risk in the financial system is associated with responses to the impact of uncertainty in the price formation of specific assets. In other words, whether volatility in a particular class of commodities leads to volatility points that spread to the rest of the commodity markets.

2. Literature review

The term "contagion" was first introduced in June 1997, when the currency crisis in Thailand rapidly spread to other countries in central Asia, and then to Russia and Brazil. Since then, economists have treated this process as a subject of separate research (Peetz & Genreith, 2011). For the purposes of this study, the contagion phenomenon can be treated as a process of transferring negative phenomena occurring within one market, economy, or country to subsequent entities, in the absence of identifiable, fundamental premises for such a process (Pritsker, 2001). Temporarily bringing the infection problem to the securities markets (which, in a model approach, can be treated as a simplified form of the functioning of more complex economic organisms), the formulated definition of the contagion mechanism can be directly verified based on Equation (1):

$$r_i = \alpha_i + \beta_i f + u_i, \tag{1}$$

where: r_i – return rate; f – macroeconomic factors; u_i – specific component.

According to the Equation (1), the realized rate of return on the local market depends on many macroeconomic factors f and on the specific component u (Jajuga & Jajuga, 2011). We have a contagion between different markets when the specific components occurring in the equations describing them are in mutual correlation. This means the occurrence of a consistency of price changes in individual markets, which is not justified by fundamental premises (Ahnert & Bertsch, 2022).

The formulated model interpretation of the contagion phenomenon is criticized due to two fundamental weaknesses. The first of them is related to doubts about the possibility of isolating a complete set of significant fundamental factors. In a situation where one of them was omitted, there is a concern that it would be to it that the causality of market rate of return changes should be attributed.

The second doubt is related to the possibility of the occurrence of a phenomenon called cross-market hedging. Seeking to hedge against the risk that has arisen as a result, they can make rebalancing (hedging) transactions on other markets, transferring to them the non-specific fluctuations from the domestic market (Junttila et al., 2018).

Therefore, instead of modeling the phenomenon, a more useful approach may be the identification and characterization of the main channels of variability transmission, which will hereafter be referred to as "infection channels".

The economy of each country is a complex system, traditionally consisting of the real sector and the financial sector. For the purposes of simplified analysis of contagion processes, the economic system can be considered as consisting of several essential elements: the real sector, financial markets, banks, and non-bank participants in financial markets (Ahnert & Bertsch, 2022; Fotiou et al., 2022; Maneejuk & Yamaka, 2021; Agénor & Aizenman, 1998; Park & Shin, 2017).

Against the background of the formal considerations of the contagion mechanism, it is important to highlight selected aspects of this phenomenon, mainly in the context of recent years due to numerous and intensifying crisis phenomena. The key issue, as commonly recognized, is the intensification of financialization of the economy (Gimet et al., 2019). This means that the internal financial links of contagion chains are becoming longer and more complex. Moreover, instead of serving the real sphere as before, finance has become increasingly autonomous. This means that the motives for making more and more significant financial decisions are less and less justified by the needs arising from the real sphere. Thus, the phenomenon previously referred to as contagion is increasingly identified with financial contagion (Foster et al., 2021).

The growing importance of the financial sector is largely associated with the expansion of financial markets. It is on these markets that numerous escalating phenomena have focused on both generating and propagating instability. This is primarily due to the enormous increase in transaction volume in recent years, as well as their speculative nature. In turn, the real economy has become only a small percentage of all financial activity (Alami, 2021). For financial intermediaries, this situation is a source of income. The possibility of making fortunes on financial transactions on financial markets has led to a huge stratification of societies, which increasingly leads to social unrest. This process seems to herald new social channels for transmitting economic shocks.

The accumulation of derivative instruments and lack of accessible data make it very difficult to determine their actual value and associated risks (Aalbers, 2019). These phenomena increase the volatility and suddenness of impulses, which spread freely through electronic links. A significant portion of new derivative instruments has emerged as a result of securitization (Lazonick, 2011).

By generating huge volumes of transactions, they contribute to the creation of obligations that far exceed the value of the real market. As a result, in recent years, abnormal price fluctuations have occurred in various primary markets. Speculative activities in food markets seem particularly unethical (Staugaitis & Vaznonis, 2022). Inspired by the financial sector, they spread not only to other financial entities but also act destructively on the real economy.

Especially in recent times, a clear risk factor has emerged in the form of political risk, which manifests itself through the monopolization of energy sources and their use to manipulate the prices of key commodities. The systemic impact of this contagion process is strengthened by the network effects, i.e., the influence of price shocks of one commodity on others. The effects of network interactions are currently particularly severe in the ongoing inflationary scenario, which is caused by the cost impact of energy carriers on other commodities. Armed conflicts are an obvious amplification of contagion processes, as they can create a specific accumulation and negative direction of influence on the most important commodities through polarization of economic dependencies. Therefore, the question arises as to how to quantitatively determine the systematic risk associated with this linkage?

Another important component of research is the development of new models for understanding and predicting changes in commodity markets. For example, factor models are widely used to identify commodity price co-movements, as well as to understand the determinants affecting price volatility. One such factor is rapid changes in the price of energy carriers (Ji & Fan, 2016; López Cabrera & Schulz, 2016; Wang et al., 2014). They can also include exchange rate volatility (Bodart et al., 2012; Zhang et al., 2016), macroeconomic variables (Hammoudeh et al., 2015; Śmiech et al., 2015) and financial/derivative markets (Berger & Uddin, 2016; Mellios et al., 2016). Byrne et al. (2013) conducted a study in which they apply vector autoregression with factors (FAVAR) to discover evidence of a determinant causing similar changes in commodity prices. Wang et al. (2023) attempt to determine the impact of oil prices and economic policy uncertainty on the green bond index.

West and Wong (2014) use monthly prices of energy, metals, and agricultural commodities in a factor model and find evidence of price reverting to the factor. Beckmann et al. (2014) studied the relationship between monetary policy and commodity market developments. They also found that the impact of global liquidity has a significant impact on commodity markets and exhibits time-varying characteristics. Yin and Han (2015) studied commodity returns. They identified three components that shape their level in global, sectoral and individual dimensions. They observed an increase in the importance of the global component.

Some studies have also applied various other time series approaches. For example, dynamic conditional correlation (DCC) models (Berger & Uddin, 2016; López Cabrera & Schulz, 2016; Mensi et al., 2014; Ohashi & Okimoto, 2016) have been used to account for heteroskedasticity in underlying price movements and time-varying correlations. Many researchers use the VAR model approach to determine the relationship between energy prices and major macroeconomic quantities (industrial and agricultural production) (Wang & McPhail, 2014) or to study the volatility of industrial metal prices and their cycles (Issler et al., 2014). In addition, the use of machine learning-based approaches appears to have significant potential for this type of research (Gao et al., 2024; Chen et al., 2024).

Referring to the methodology that we adopted in our study, the concept of dynamic spillover, first introduced in the groundbreaking article by Diebold and Yilmaz (2009), has been extensively investigated. The method, described in detail below, has proven to be a powerful tool for studying the relationships between markets. Its key advantage is that it has greater descriptive power in capturing the interconnections among systemic variables, and thus systemic risk concepts, while retaining all the benefits that VAR models have. For example, Zhang (2017) uses this method to investigate the role of oil price shocks on international equity markets and finds that oil prices have become more financially integrated since the 2008 global financial crisis. Yip et al. (2017) use the VAR model to examine the interaction between commodities and commodity currencies with higher frequency data, such as daily or intra-day. This method has also been used in some recent studies, such as Yang and Zhou (2016), Zhang et al. (2018).

3. Research methodology

In this study, we adopt the approach of Diebold and Yilmaz (2009), using system connectedness estimation as a measure of systemic risk. This methodology allows us to examine the extent to which systemic risk spreads when there is price uncertainty originating from a specific location in the system. For example, it allows us to analyze whether price fluctuations in a particular commodity (or class of commodities) cause significant volatility that spreads to the broader commodity market in a meaningful way.

The concept of network interconnectedness, developed by Diebold and Yilmaz (2009), combines the traditional network approach with dynamic econometric methods such as the vector autoregression model (VAR). The approach presents new opportunities to study system behavior by reorganizing the results of the VAR model's variance decomposition, revealing the relative importance of various factors. It has the potential to be applied to study a wide range of policy topics.

In a macroeconomic system, all variables are interdependent and interact with each other continuously, making it challenging to develop an accurate theoretical model that can be structurally estimated. To tackle this issue, Sims (1980) proposed the VAR model, which allows for a simpler framework that can still provide useful insights and accurate descriptions of economic system dynamics. The VAR model is particularly useful in the presence of complex endogeneity, where a more precise theoretical model may be impractical. Since its introduction, the VAR model has become a widely used method in mainstream macroeconomics.

The VAR model is often too complex to be interpreted by examining the coefficient values alone. To overcome this issue, there are two common methods used to interpret the model: the impulse response function (IRF) and the forecast error variance decomposition (FEVD).

Both of these tools are forward-looking, with the IRF showing how a shock to one variable affects the response of other components in the system, and the FEVD defining that part of the future variation of a system variable that is affected by other variables. When modeling interconnectivity within the system, the FEVD is preferred over the IRF as it is easier to aggregate.

Diebold and Yilmaz (2009) introduced an innovative approach to interpreting VAR models which involves repackaging FEVD results to produce a network connectedness snapshot. This approach is relatively simple yet highly effective. The process involves aggregating standard FEVDs into a "connectedness matrix", with off-diagonal elements. These elements define the portion of future prices that are affected by interactions between endogenous variables in the system, such as spillover effects from other components of the system. This connectedness matrix provides a tool for presenting systemic risk. The diagonal elements represent how changes in a variable affect its future values. A more comprehensive explanation will follow after a formal description of a typical VAR model.

The standard VAR(p) model for N-variables is represented as:

$$Y_t = C_0 + \sum_{i=1}^{p} C_i Y_{t-i} + \varepsilon_t, \tag{2}$$

where: Y – the vector containing the N variables in the system that are assumed to be endogenously related to each other; C_0 – the N × 1 vector of constants; C_1 – the N × N matrix of coefficients for each lag; $\varepsilon \sim (0, \Sigma)$ – the vector of i.i.d error terms.

Equation (2) represents the VAR model for p lags. This means that the explanatory variables differ from the explained variables by the number of lags. The VAR model generates a large number of parameters to be estimated, which makes interpretation difficult. For this reason, the IRF and FEVD approaches make it possible to exploit the analytical potential of the model. The least squares method (OLS) can be used to estimate the model parameters.

Once the VAR model is estimated, the next step is to apply the FEVD approach for analysis. This involves decomposing the H-period-ahead forecast error, which gives the contribution of one variable to another, represented by $\tilde{\theta}_{ij}^{H}$. However, it is crucial to select the appropriate VAR lag-length using various information criterion. The FEVD values can then be used to create a connectedness matrix, as proposed by Diebold and Yilmaz (2009), although this method has a limitation due to the sensitivity of FEVD results to the variable ordering in a VAR model. To address this issue, Diebold and Yilmaz (2012) suggest the use of the generalized FEVD method by Koop et al. (1996) to ensure the robustness of the results. This modification has enabled the spillover framework to be applied widely in the analysis of systemic risk and sectoral spillovers, as demonstrated in studies by Antonakakis et al. (2014), Zhang (2017), and Zhang et al. (2018).

Diebold and Yilmaz (2012) focus on three ways to measure network connectedness and spillovers. These measures include: the spillovers originating from variable *i* and affecting all other variables in the system 'From' (represented by *F*); the spillovers directed towards variable *i* from all other variables in the system 'To' (represented by *T*); and the net directional connectedness, or balance of connectedness, between variable *i* and the rest of the system '*NDC*'. These measures can be expressed as:

$$F_i = \sum_{j=1}^{N} \tilde{\theta}_{ij}^{H}, \text{ for } j \neq i; \tag{3}$$

$$T_i = \sum_{j=1}^{N} \tilde{\theta}_{ji}^{H}, \text{ for } i \neq j; \tag{4}$$

$$NDC_i = \sum_{j=1}^{N} \tilde{\theta}_{ji}^{H} - \sum_{j=1}^{N} \tilde{\theta}_{ij}^{H}, \text{ for } i \neq j, \tag{5}$$

where: $\tilde{\theta}_{ji}^{H}$ denotes pairwise contributions defined in combination with a generalized FEVD.

Finally, the strength of systemic risk is obtained using the relationship:

$$SYS = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}_{ij}^{H}, \text{ for } i \neq j. \tag{6}$$

This provides a simple and clear measure of systemic risk, ranging from 0 to 1, where 0 indicates no systemic risk and 1 indicates that all risk is driven by system interactions/dynamics. In addition, Diebold and Yilmaz (2014) examine the concept of connectedness using network theory and propose the use of network diagrams to visually depict the system's interactions. For all pairs of variables in the system, it is possible to show their relative contribution (pairwise net contribution) by constructing the value $PNC_{ij} = \tilde{\theta}_{ij}^{H} - \tilde{\theta}_{ji}^{H}$. If the value of PNC_{ij} is positive, it means that variable j contributes more to the system than it receives from variable *i*, or it is a net contributor. In this scenario, an arrow can be drawn from variable *j* to variable *i*. By connecting all pairs in the system, a network diagram can be created that demonstrates how the system operates. This network diagram provides a concise overview of the location and direction of risk within the system.

Using the BIC and AIC information criteria, the values of the maximum lag of the variables, denoted as p, were determined. Both criteria indicated $p = 2$ lags were included in the adopted VAR model.

A diagnostic of the elements of the characteristic polynomial was carried out to test the stability condition of the VAR model. The stability condition of VAR states that the modulus of every eigenvalue must be less than 1.

4. Results

The study utilized daily time series of logarithmic returns for selected commodities. The time range of the time series was from January 1st, 2006 to April 1st, 2022. Daily price quotes were obtained from Refinitiv Eikon database (2022). The data used for the study, including daily return time series for each commodity, exhibited descriptive statistics typical of such random variables (Table 1). The distributions of logarithmic returns for the selected commodities, except for Orange Juice, were not similar to a normal distribution. The distributions for energy and metal commodities exhibited fat tails (increased kurtosis). Most soft commodities had distributions with kurtosis similar to a normal distribution. It is noteworthy that, except for crude oil, natural gas, and wheat, negative skewness was observed.

Table 1. Descriptive statistic of returns

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Crude oil	0.00027	0.02713	0.13709	20.0986	49672,78
Natural gas	–0.00013	0.03356	0.63965	9.49132	7561.066
Cocoa	0.00016	0.016	–0.2511	5.8406	1213.909
Soybean oil	0.00027	0.149	–0.1015	2.4712	21.581
Wheat	0.00024	0.021	0.235	3.602	222.730
Orange juice	0.00005	0,021	–0.0099	2.785	1.081
Aluminium	0.00004	0.0095	–0.6521	6.314	1376.826
Copper	0.0001	0.0176	–0.0814	3.813	57.098
Gold	0.00027	0.0116	–0.3415	5.527	851.324
Platinum	–0.00013	0.0155	–0.3999	5.014	370.507

Note: *1% level of significance.

The study utilized two approaches to data analysis: for the full sample and a moving window approach. Based on the analysis of the full sample, it can be concluded that the total linkage level amounted to 27.61%. This means that in this part of the sample, the variability of the return rates of its components is explained by the linkages between them. In the remaining part, this variability is due to the contribution of each component (commodity) included in the sample.

Table 2 shows the percentage influence of each sample component on the variability of the remaining components (denoted as F). In addition, the percentage influence of all sample components on the variability of a given component is also presented (denoted as T). The difference between T and F determines the net relationship of a given component in relation to the entire sample. If Net > 0, the given element is a factor creating variability in the return rates of the analyzed group of commodities. If Net < 0 for a given element, it means that it is a "receiver of variability" in the analyzed group, i.e., other components shape the variability of its return rate. The strength of this influence is determined as a percentage.

Table 2. Connectedness for full sample

	T	F	Net
Crude oil	29.52%	20.24%	9.28%
Natural gas	23.65%	18.05%	5.60%
Cocoa	26.13%	27.24%	–1.11%
Soybean oil	29.87%	31.54%	–1.67%
Wheat	27.33%	30.27%	–2.94%
Orange juice	25.32%	27.48%	–2.16%
Aluminium	31.25%	33.62%	–2.37%
Copper	35.47%	37.56%	–2.09%
Gold	23.19%	24.64%	–1.45%
Platinum	24.33%	25.42%	–1.09%

Taking into account the full sample, the commodities with the highest influence on variability (F indicator) were Copper (F = 37.56%), Aluminium (F = 33.62%), and Soybean oil (F = 31.54%). The highest influence of the entire sample on the variability of individual components (T indicator) was also found for these same commodities (Copper T = 35.47%, Aluminum T = 31.25%, Soybean oil T = 29.87%).

Regarding which commodity had the greatest net impact on return variability, Wheat (net = –2.94%), Aluminum (net = –2.37%), and Orange juice (net = –2.16%) were the top three. The only net receivers of variability of the remaining sample components were Crude oil (net = 9.28%) and natural gas (net = 5.06%).

These quantities determine the strength of the transmission of variability between commodities. However, most of the variability comes internally from the factors shaping the situation in the market for a given commodity. In this example, we can observe the flow of variability, i.e., whether commodities are integrated in this regard.

Using the rolling window estimation, we can observe more regularities, especially in the changes caused by crisis conditions. In the first examined crisis period, the sample was divided on September 1, 2008. September was a period when Lehman Brothers declared bankruptcy, which caused the escalation of the crisis and variability in the markets. The size of the windows was determined by the number of observations included over a period of two years.

In the period after September 2008, there was a significant increase in the concentration of explaining variability within the examined basket of commodities. In cases such as Copper, the percentage influence of this commodity on the variability of returns of other commodities increased from 27% before the crisis to 86% after the crisis. Similarly, the degree of influence of other commodities on the variability of Copper returns increased from 21% to 74%. Similar increases applied to other commodities (see Table 3). It is also characteristic that the level of T and F indicators increased the most within soft commodities and industrial metals. Energy commodities and precious metals showed a lower increase in the integration of the influence on variability within the analyzed portfolio.

Table 3. Differences of connectedness before and after of the crisis of 2008

	Before the crisis of 2008			After the crisis of 2008		
	T	F	Net	T	F	Net
Crude oil	16.47%	12.78%	3.69%	48.63%	31.24%	17.39%
Natural gas	14.38%	11.26%	3.12%	52.43%	41.13%	11.30%
Cocoa	15.78%	15.62%	0.16%	52.26%	57.81%	–5.55%
Soybean oil	27.33%	28.16%	–0.83%	72.57%	75.46%	–2.89%
Wheat	26.84%	24.28%	2.56%	77.62%	78.69%	–1.07%
Orange juice	22.43%	15.23%	7.20%	75.96%	73.28%	2.68%
Aluminium	18.23%	26.43%	–8.20%	61.92%	74.38%	–12.46%
Copper	21.73%	27.15%	–5.42%	74.23%	86.79%	–12.56%
Gold	20.15%	21.03%	–0.88%	43.57%	42.89%	0.68%
Platinum	19.48%	20.88%	–1.40%	56.24%	53.76%	2.48%

Note: sample division is the first day of September/2008.

Referring to the difference between the Net for T and F indicators, it can be stated that some components of the examined commodity portfolio have become greater recipients of the influence of other portfolio elements. This applied especially to energy commodities (for crude oil Net before the crisis = 3.69%; Net after the crisis = 17.39%) and precious metals (for Platinum Net before the crisis = –1.40%; Net after the crisis = 2.48%). Other components increased their influence on the variability of other commodities (for Cocoa Net before the crisis = 0.16%; Net after the crisis = –5.55%; for Copper Net before the crisis = –5.42%; Net after the crisis = –12.56%). These included soft commodities (cocoa, wheat, soybean oil) and industrial metals (copper, aluminum).

Differences between commodity groups reflect both their importance as investment assets and as sources of transmitted volatility in response to market shocks. Among commodities, energy and precious metals have the greatest investment importance, which translates into a less pronounced increase in the T and F indices that reflect their significance in transmitting volatility during crisis shocks. These commodities are more closely linked to financial markets, and therefore the volatility of other commodities does not have a relatively large impact on them. These portfolio components did not become the main focus of investors' reactions to the crisis in 2008. Conversely, elements such as wheat, soybean oil, cocoa, and industrial metals, which traditionally have lower investment importance, became the main transmission element of volatility to other commodities during the market shock. In other words, the valuation of energy commodities better reflected the crisis situation than the valuation of soft commodities.

In Figure 1, the order of placement determines whether a commodity is a net volatility provider or a volatility absorber. The higher in the Figure 1, the commodity whose variance explains more of the variance of the others. Before the 2008 crisis, these were industrial and precious metals, while soft commodities gained in importance as a result of the crisis. The main volatility absorbers were energy commodities. Countries with increased exposure to import/export commodities from initial positions are more exposed to the effects of price shocks in these markets.

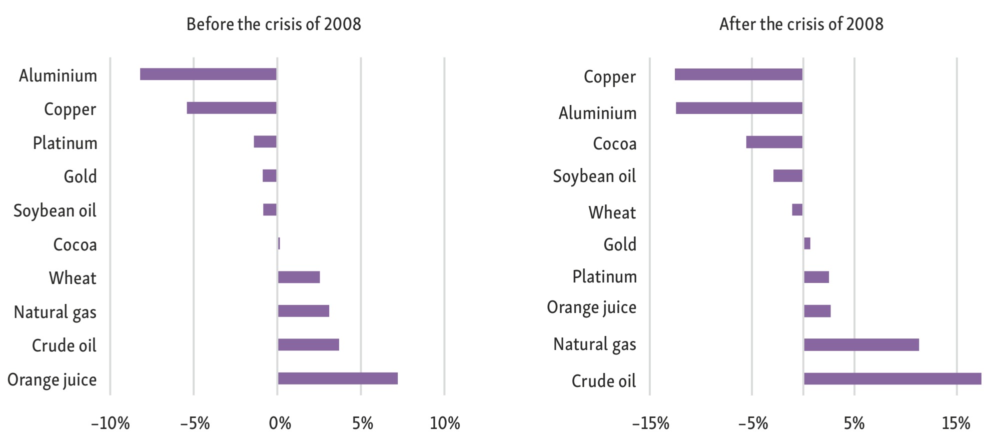

Figure 1. Order of commodities by the Net value before and after the 2008 crisis

Table 4. Differences of connectedness before and after of the crisis of 2020

	Before the crisis of 2020			After the crisis of 2020		
	T	F	Net	T	F	Net
Crude oil	25.82%	23.24%	2.58%	54.38%	58.21%	–3.83%
Natural gas	21.78%	17.43%	4.35%	43.12%	48.47%	–5.35%
Cocoa	25.39%	28.26%	–2.87%	78.22%	80.68%	–2.46%
Soybean oil	28.32%	33.04%	–4.72%	72.48%	69.27%	3.21%
Wheat	26.91%	32.22%	–5.31%	61.84%	58.73%	3.11%
Orange juice	20.57%	15.49%	5.08%	87.42%	78.28%	9.14%
Aluminium	30.67%	41.64%	–10.97%	74.67%	79.87%	–5.20%
Copper	32.35%	44.37%	–12.02%	74.93%	83.71%	–8.78%
Gold	42.08%	25.19%	16.89%	61.49%	58.48%	3.01%
Platinum	34.54%	27.55%	6.99%	58.90%	51.75%	7.15%

Note: sample division is the first day of March 2020.

A significant increase in the degree of influence of these commodities on the volatility of other commodities within the studied group was also observed during the COVID-19 pandemic-induced crisis shock (Table 4).

However, there are certain differences in comparison to the 2008 crisis. First of all, energy commodities were no longer just recipients of volatility. During the COVID-19 crisis, they became a factor affecting the volatility of other examined commodities. Among the possible reasons for this phenomenon, one can point to a change in the nature of their interaction (Table 4). The COVID-19 crisis was a crisis related to the real economy. We were dealing with supply shocks, and energy commodities, as basic production factors, gained importance in these circumstances and expanded the area of their volatility impact. It can be said that commodities exist in two spheres: financial (as investment assets, portfolio assets) and real (as cost carriers). The conclusion that can be drawn in this case is that if a crisis shock affects both the financial and real spheres, commodities are expected to become a source of volatility for other commodities.

The situation is more dramatic for soft commodities (cocoa, wheat, orange juice, and soybean oil), which have less significance in the financial sphere (as financial assets) compared to energy commodities. Their value mainly arises from their use in the real sphere as production factors. In this way, their volatility can trigger and react to supply shocks. This periodic use as investment assets for stabilizing portfolio returns increases their impact on the volatility of other commodities. The nature of the crisis determines whether they act as a source of volatility or absorb the volatility of other commodities (net minus or plus). If the crisis shock mainly revolves around supply chains related to a particular commodity, it can be presumed that it will become a source of volatility for other commodities. The same applies to industrial metals (copper and aluminum).

As a result of the COVID-19 crisis (Figure 2), industrial metals and energy commodities became the providers of volatility. The crisis affected the real sphere and was accompanied by a commodity war, which contributed to the rise in crude oil and natural gas. Absorbers were soft commodities which was all the more risky because there are limited opportunities in hedging this risk.

Confirmation of these assumptions can be found in the evaluation of the crisis situation caused by the war in Ukraine (Table 5).

The crisis in Ukraine translates into the destabilization of energy and food markets. In other words, the source of variability is the real sphere concerning energy commodities, soft commodities, and industrial metals.

Representatives of each group of commodities in our study, with regard to the current crisis, have a negative net value, meaning that their net variability affects the increased variability of other commodities in the studied group. Only precious metals, whose variability depended on other commodities, had positive net values. The demand for precious metals in this period had a secondary character as a reaction to rising inflation.

Table 5. Differences of connectedness before after of the crisis of 2022

	Before the crisis of 2022			After the crisis of 2022		
	T	F	Net	T	F	Net
Crude oil	27.53%	24.44%	3.09%	57.15%	63.37%	–6.22%
Natural gas	22.89%	17.52%	5.37%	65.22%	69.26%	–4.04%
Cocoa	25.87%	30.19%	–4.32%	69.37%	54.62%	14.75%
Soybean oil	29.01%	35.47%	–6.46%	62.73%	71.69%	–8.96%
Wheat	27.21%	33.89%	–6.68%	43.78%	65.19%	–21.41%
Orange juice	23.16%	24.63%	–1.47%	40.59%	42.17%	–1.58%
Aluminium	30.45%	42.89%	–12.44%	45.22%	48.63%	–3.41%
Copper	34.78%	46.15%	–11.37%	66.18%	76.23%	–10.05%
Gold	43.11%	28.49%	14.62%	76.77%	50.72%	26.05%
Platinum	47.44%	27.78%	19.66%	55.13%	40.26%	14.87%

Note: sample division is the first day of February 2022.

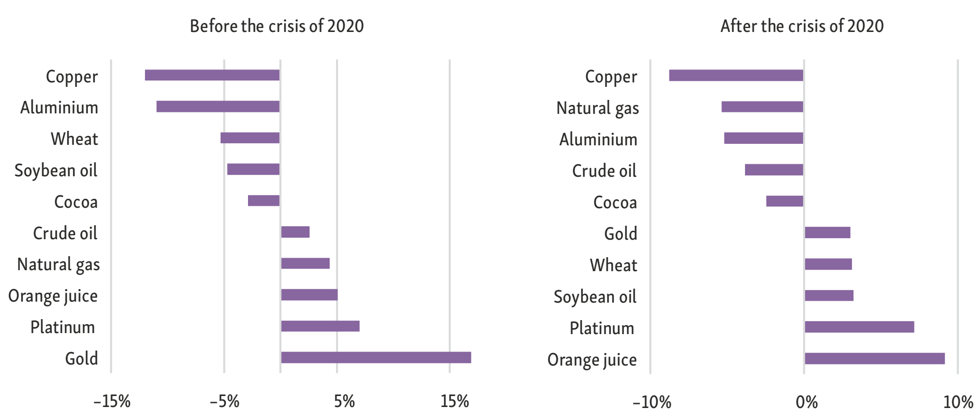

Figure 2. Order of commodities by the Net value before and after the 2020 crisis

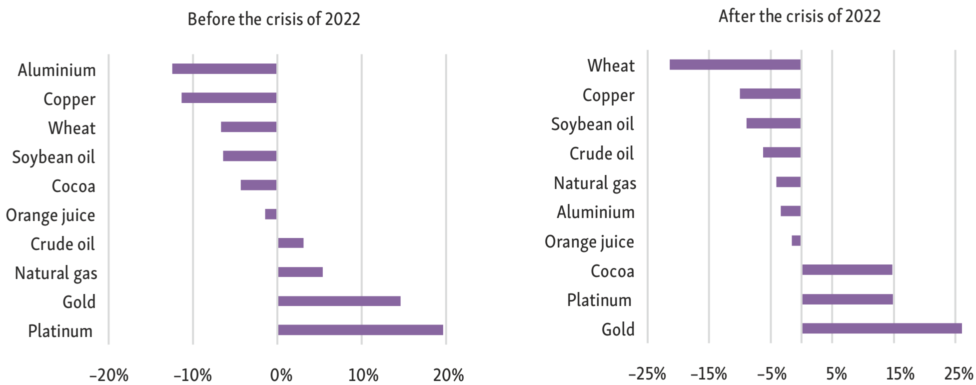

Figure 3. Order of commodities by the Net value before and after the 2022 crisis

As shown in Figure 3, as a result of the war crisis, most commodities have become providers of volatility. This is a dangerous situation because of the possibility that commodities markets can be easily destabilized, especially in an unstable environment (trade wars).

5. Discussion

In this study, we looked at the interactions and dynamic linkages between commodities, taking into account the temporal location during periods of crises. Thus, the purpose of the article which was to try to identify commodities that are a source of contagion (volatility) during the transmission of shocks and the increase in systematic risk in selected periods was achieved using the VAR linkage study method of Diebold and Yilmaz (2009). The evaluation of time-varying commodities linkages, determining the dynamics of sources of volatility during the crises of recent years, is an original contribution of the study to previous work. It confirmed for commodities the observations of other studies that market variables operate in a non-isolated system (Osei & Adam, 2020; Asafo-Adjei et al., 2022).

The results obtained from this study were threefold. First, it was found that the maximum value of the connectedness measure in the full sample was 37.56% for copper, and the lowest value was 18.5% for natural gas. This indicated the existing differentiation between commodities. Second, based on averaged dynamic measures of connectedness, energy commodities were net recipients of shocks among other commodities. Conversely, soft commodities, industrial and precious metals were net sources of shocks. The reasons for this phenomenon with regard to crue oil are reflected in studies noting that it is subject to significant financialization (Cheng & Xiong, 2014; Ji & Zhang, 2019; Zhang, 2017). It should be stated that the opinion of researchers on the relationship with financialization is not clear. However, the existence of discussion suggests that the topic is open and requires research. It also shows that there is a problem of risks that can be spread by commodity markets.

Third, the net directional linkage technique revealed that a fixed number of commodities were consistent net senders through the 2008 crisis and 2020 crisis periods. While during the 2022 crisis period, most commodities became a net source of volatility. We opine that spillover linkages are influenced by economic events with a few shock recipients acting as safe havens or hedging against excessive shocks. Considering the situation in commodities markets over the past decade, it is fair to say that this has caused unprecedented volatility, as confirmed by Arezki et al. (2014) and Fernández et al. (2018). Record levels of food commodity prices have also caused clear concern and uncertainty around the world (Tadasse et al., 2016).

The survey results suggest that through commodities networks, risk minimization rather than massive integration is possible. Investors are most likely increasingly convinced of this. This results in an increase in the impact of the financialization process, which has been a known cause of the contagion process for years. The issue of whether commodity prices are subject to increasing financialization has been the subject of many studies (Arezki et al., 2014). Some studies confirm the existence of this phenomenon in the energy market (Zhang, 2017) while others for commodity markets as a whole (Cheng & Xiong, 2014). After recognizing that commodities now have one of the primary asset classes used by financial investors, our understanding of how commodity markets work begins to diverge significantly.

In addition, in the context of financialization, our results confirm that during crisis periods commodities that have a close relationship with the financial market are less affected by the volatility of other commodities. This is especially true for precious metals. The reasons may be due to the use of these commodities as a hedging element of financial portfolios. This corresponds with the results of a study by Öztek and Öcal (2017), which addressed the relationship between the prices of stocks, agricultural commodities and precious metals. The conclusions of the study suggested the existence of higher returns on portfolio investments that included the above commodity groups during moments of growth in the stock markets. On the other hand, however, Aït-Youcef's (2018) research does not confirm such a broad relationship between commodity markets and stock markets, with the exception of agricultural commodities, during periods of crises. Similar results for oil were obtained by Zhang (2017).

6. Conclusions

The process of contagion in the economy, with financial contagion being a particular form, is neither a new phenomenon nor does it have a homogeneous nature that allows for a clear description. It is rather identified symptomatically, often referring to the transmission of negative effects from one economic area to another.

In assessing the course of this process within commodity markets, the channels of volatility transmission in the contagion process are of importance. The transmission of volatility is networked, taking the form of interactions between the volatility parameters of the commodity portfolio components. The transfer of volatility is strengthened by various factors, including the nature of transactions (speculation), the influence of IT technology on the speed and quantity of transactions, the financialization of markets, and the complexity of financial instruments. The impact of these elements leads to an increase in the systematic risk.

The above general observations align with the conclusions of research conducted using a chosen research method, which allowed for the observation of networked volatility transmission within the portfolio of commodities listed on the global commodity market.

Taking into account the full sample of observations of time series of selected commodity returns, it was found that net volatility providers were mainly industrial metals (copper and aluminum) and soybean oil. Meanwhile, net volatility absorbers in the examined group were energy commodities (crude oil, natural gas). It should also be noted that the main portion of volatility is generated by fundamental factors related to a given commodity or raw material (related to, among other things, the significance of a given raw material for the real economy sector). However, volatility arising from networked interactions within the commodity portfolio also occurs. This interaction is related to the phenomenon of financialization and the functioning of commodities as investment assets in financial markets (significant for the financial sector). The observation made constitutes an average for the entire time range. More detailed results were obtained by comparing the effect of volatility transmission before and after the outbreak of a certain crisis phenomenon.

Generally, evidence has been obtained that the crisis phenomena of 2008, 2020–2021, and 2022 led to an increase in the scale of contagion variability in the studied group of commodities. Differences mainly related to the role played by energy commodities, metals, and soft commodities during the individual crises.

Commodities that characterized the largest increase in transmission of variability compared to the pre-crisis period constituted a sort of gate for transmitting market shocks. In 2008, these were mainly industrial metals such as copper and aluminum. In the years 2020–2021, in addition to industrial metals, energy commodities were also included in this group. In 2022, after the conflict in Ukraine, wheat and soft commodities also became elements that increased variability in the studied group of commodities.

Taking into account the context of events in the market environment, it can be argued that the increase in the number of commodities that were a source of variability was caused by the scope of the given crisis situation. The greater the scope of the crisis (first affecting the financial sphere and later also the real economy), the greater the increase in transmission of shocks (contagion) in the system (increase in systemic risk).

The value of F and T indicates the percentage of volatility associated with other commodities. The higher this value, the greater the potential for systemic risk contagion. The net value determines the direction of contagion. If it is negative, the asset is a source of volatility transmission (the more negative, the stronger the effect on other commodities). If the net value of an asset is positive, it is an absorber of volatility from other commodities (taking on systemic risk).

On the basis of market analysis in the context of crisis events in commodities markets, it is possible to create a general characteristic of changes:

If F and T are low and Net is positive, such a commodity is a volatility absorber. The volatility of its price is mainly generated by fundamental factors, e.g., the volume of world production and stocks, production capacity, trade restrictions. It does not pose a significant threat to the economic stability of a region because its volatility is largely predictable.

If F and T are high and Net is positive, then such a commodity is vulnerable to the volatility of other asset classes (i.e., contagion from others) and absorbs the volatility of others. It can potentially be used indirectly as part of a speculative game by investors from other markets. At the same time, if it has a high weight in the economy (e.g., oil), it can cause inflationary effects and be used in economic warfare (e.g., creating high volatility in its price by manipulating the prices of other assets).

When F and T are low and Net is negative, the commodity is a source of volatility (it affects the volatility of other commodities, i.e., it infects other assets with volatility). At the same time, its volatility is largely the result of fundamental factors (production volume, stocks). If its production is monopolized and it has a high importance in the economies of other countries, such a commodity can be used as an element of economic warfare by triggering supply shocks (e.g., energy sources, raw materials for electric cells) by certain countries.

If the value of F and T is high and the net is negative, the commodity is a source of volatility (affects the volatility of other commodities). It can be a source of volatility contagion to other commodities, with its volatility being the result of a largely diffuse game of speculation (it is subject to financialization). It can be subject to speculative attacks, triggering price shocks in other assets.

Attempting to systematize the description undoubtedly serves its understanding and prevention. Unfortunately, any attempts at formalization seem to be inadequate to very dynamic processes in a short time. The dominance of the financial sector over the real economy means that the contagion problem is almost automatically reduced to financial contagion. This is another proof of the uneven structure of modern economies that favors the spread of economic shocks, the source of which lies in financial decisions. The presented aspects of the phenomenon seem to clearly indicate the lack of the possibility of complete elimination. Therefore, in order to limit its destructive effects, special care for transparency and simplicity of economic relations at the interface of different economic entities is required. This would first of all be facilitated by a gradual "de-financialization" of economies, which would limit the excessive participation of the financial contagion mechanism in creating systemic instability of economies.

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