

Impact of the Russia–Ukraine Conflict on Commodity-Driven Stock Price Volatility in the Indonesian Market

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Abstract

This study analyzes the impact of the Russia–Ukraine conflict on the volatility of commodity-based stocks in Indonesia, especially the oil, gas, coal, gold, and wheat sectors. Using the BEKK-GARCH and Vector Autoregression (VAR) models, this study compares the periods before and during the conflict. The results show a significant increase in the spillover effect, especially in the coal and gold sectors. During the conflict, oil prices had a negative impact on ENRG, while coal prices that previously had a positive impact on ADRO turned negative. Gold volatility increased on PSAB, while its impact on ANTM weakened. Meanwhile, the effect of wheat prices on INDF became insignificant, but MYOR and ROTI experienced a change in the direction of spillover. These findings indicate the need for risk mitigation strategies and more adaptive policies in dealing with market volatility due to geopolitical instability.

Keywords: volatility spillover, Russia–Ukraine conflict, BEKK-GARCH, vector autoregression, Indonesian stock market.

1. Introduction

The Russia–Ukraine conflict began on 24 February 2022, following political instability, with Russia being concerned about NATO dominance and Ukraine’s growing Western alliances. The conflict has led to geopolitical and economic risks, affecting global financial markets and the economy due to sanctions imposed by the US and EU. The role of Russia as a leading energy exporter sets it apart from other nations. The conflict has led to volatility in commodity prices and stock markets globally, particularly in Indonesia. Therefore, studying the conflict’s impact on commodity prices and the Indonesian Stock Exchange can help policymakers and investors understand the correlation between the conflict and commodity prices and navigate these difficult circumstances.

The ongoing conflict has significantly influenced the global economy, particularly regarding commodity stability. In terms of the energy and agricultural sectors, Russia is a significant supplier of crude oil, natural gas, and petroleum products, dominating the global energy market (Qian et al., 2023). The conflict has caused a significant decrease in Russian energy exports, particularly in Europe, where energy storage capacity has reached its maximum limit. As a result, crude oil prices reached a maximum of \$123.8 per barrel in March 2022 (Zeynalov & Tiron, 2022). The surge in prices has profoundly affected the global economy, leading to a rise in transportation expenses and exacerbating inflationary forces as elevated energy costs influence other sectors (Thoti & Sudheer, 2023).

The protracted conflict significantly affects countries heavily reliant on coal as a primary energy source. It shows the fundamental weaknesses in the energy composition of the European Union, as nations like Bulgaria, Estonia, Hungary, and Poland substantially depend on coal for electricity production (Kravchenko et al., 2023). The conflict also caused disruptions in the production and trading of important agricultural commodities, including wheat, corn, and vegetable oils. Russia and Ukraine are prominent producers and exporters of various agricultural goods. Therefore, any interruptions in supply could result in worldwide shortages of these products and substantial price hikes. For instance, the price of wheat rose by about 112% in the previous 12 months, while the prices of corn, soybeans, and vegetable oils experienced an increase of approximately 80% (Wang, 2022). This has a profound effect on countries heavily relying on imports of essential goods, particularly in developing nations where food poverty is a significant issue. The long-term implications of the conflict remain indeterminate, and the global economy could face significant consequences due to disruptions in supply networks and uncertainties around the sustainability of the current trading system (Chen et al., 2022).

The conflict between Ukraine and Russia has significantly impacted commodity prices and stock markets, but investigations on its impact on Indonesian Stock Exchange issuers are limited. This study aimed to address this gap by analyzing spillover volatility in oil, gas, coal, gold, and wheat commodity prices before and after the Russia–Ukraine conflict, focusing on producers of Indonesian oil and natural gas, coal, gold mining, and wheat-based food processing.

2. Literature review

2.1 Geopolitical Tension Implications

Geographical proximity to the Russia–Ukraine conflict has a significant negative impact on European markets due to the large dependency on commodity trade but has no impact on non-European markets (Silva et al., 2023). Moreover, geopolitical risk has a greater effect on volatility in developing countries, nations exporting crude oil, and those remaining neutral. This study enhanced the current body of knowledge on the relationship between geopolitical risk and financial market volatility by offering a more comprehensive and integrated viewpoint (Zhang et al., 2023). On the other hand, trade conflict had a broader impact on most agricultural commodities compared to other exogenous shocks, including the global financial crisis and the COVID-19 pandemic. This has important implications for investors and portfolio managers, as well as commodity exporting and importing countries, because changes in commodity price volatility can have a significant impact on export revenues, import expenditure, and, consequently, on global supply chains (Cheng et al., 2023).

Tee et al. (2023) found a relationship between global stock market reactions and the financial sanctions imposed on Russia during the initial phase of the Russia–Ukraine conflict. The study also showed companies registered in countries imposing sanctions against Russia experienced higher Cumulative Abnormal Returns (CAR) compared to countries that did not impose sanctions.

2.2 Spillover Volatility in Commodity and Financial Instruments

Volatility spillovers have been extensively analyzed in emerging markets to understand how global shocks transmit through financial systems. Using a VAR-BEKK GARCH model, Darinda and Permana (2019) identified that oil prices, exchange rates, and global indices significantly drive volatility in ASEAN-5 stock markets, with different spillover patterns under high and low oil price regimes. Zeng

et al. (2022) found dynamic and bidirectional spillovers between China's stock, oil, and exchange rate markets, particularly around structural break periods. Asymmetric and regime-dependent spillovers between oil prices and US–China equity markets were also documented through a vine copula and BEKK-GARCH approach by Yu et al. (2020). Pan et al. (2024), using wavelet-based trivariate VAR-BEKK-GARCH, revealed multi-scale transmission among INE, WTI, and Brent crude futures. Meanwhile, Sarwar et al. (2020) demonstrated that volatility spillovers from oil to stock markets in South Asia intensified after the global financial crisis. In a macroeconomic context, Jui et al. (2024) found that remittances, FDI, and inflation affect GDP in Bangladesh, Pakistan, and Sri Lanka with time-varying volatility, better captured by BEKK-GARCH than traditional VAR models. These findings collectively reinforce the robustness of BEKK-GARCH in modeling both immediate shocks and persistent volatility across financial and macroeconomic variables.

Dahl et al. (2020) found that after 2006, the crude oil market became a net receiver and showed greater influence than the agricultural commodity market. A significant decline in crude oil prices, such as in 2008 and 2014, caused an increase in volatility spillover from crude oil markets to agricultural commodities. Factors such as biofuel production, energy, agricultural intensity, weather conditions, and the financialization of commodity markets significantly increased the transmission of interdependence and volatility between the agricultural and petroleum commodity markets in the post-2006 period.

The current study used daily commodity data from Russia and Ukraine, two major producers of commodities such as oil, gas, coal, mineral metals, and wheat. It specifically aimed to examine the relationship between the prices of these commodities and the performance of selected issuers from the Indonesian Stock Exchange, who were dependent on and affected by the commodity prices. The study comprised the following commodity categories and issuers, as shown in Table 1.

Table 1. Data and variables

No	Commodity Futures	Company Sector and Name	JKSE Stock Code
1.	WTI Crude Oil index	Oil and Gas producing company	
		a. Medco Energy International	MEDC
		b. Energi Mega Persada	ENRG
		c. Perusahaan Gas Negara	PGAS
2.	Newcastle Coal index	Coal producing company	
		a. Adaro Energi	ADRO
		b. Bumi Resource	BUMI
		c. Bayan Resource	BYAN
3.	Gold Price (COMEX)	Gold producing company	
		a. Aneka Tambang	ANTM
		b. Merdeka Copper Gold	MDKA
		c. J Resource	PSAB
4.	KC HRW Wheat Futures	Food manufacturing company (Wheat Importers)	
		a. Indofood Sukses Makmur	INDF
		b. Mayora Indah Terbuka	MYOR
		c. Nippon Indosari Corpindo Tbk	ROTI

Notes: This table presents the commodities and the corresponding companies listed on the Indonesia Stock Exchange (IDX) that are included in the analysis. Each company is categorized by the commodity they are primarily associated with, and their stock codes are provided for reference.

3. Methodology, Data, and Analysis

The secondary data used in this study are from Yahoo Finance and Investing.com, including daily closing data for share prices of Indonesian Stock Exchange issuers and futures indices for commodity prices. Furthermore, observations were carried out for two years, starting from 1 February 2021 to 28 February 2023. The data sampling was divided into two groups of frame periods, namely one year before the conflict (pre-conflict) from 1 February 2021 to 21 February 2022 and one year after (during-conflict) from 22 February 2022 to 28

February 2023. This study was carried out to examine the differences in correlation between the two periods, as evidenced by Biswas et al. (2024).

The current study specifically used the GARCH modeling method to test the dynamics of the impact of volatility between the commodity market and the stock market. The analysis started by examining the volatility of energy, metal, and food commodity prices due to the Russia–Ukraine conflict and subsequently investigating the spillover impact on stock issuers on the Indonesian Stock Exchange. In general, GARCH (p, q) can be formulated as follows:

$$\begin{aligned}\sigma_t^2 &= \alpha_0 + \alpha_1 e_{t-1}^2 + \cdots + \alpha_p e_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \\ &= \alpha_0 + \sum_{i=1}^p \alpha_i e_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2\end{aligned}\quad (1)$$

The conditional likelihood function for μ from GARCH (1,1) is

$$L(\mu) = \prod_{i=1}^n \left(2\pi\hat{\phi}_i(\mu) \right)^{-\frac{1}{2}} \exp\left(-\frac{1}{2} \frac{(x_i - \mu)^2}{\hat{\phi}_i(\mu)} \right) \quad (2)$$

Quantitative analysis of time series data that includes many variables, namely multivariate time series, necessitates a method capable of modeling data with significant volatility and heteroskedasticity effects. This issue can be addressed using Multivariate Generalized Autoregressive Conditional Heteroskedasticity (M-GARCH), a multivariate version of GARCH. M-GARCH enables the modeling of time-varying volatility and correlation across numerous assets or financial markets concurrently. It also facilitates prior modeling of the conditional covariance matrix of the independent variables. M-GARCH comprises various models, including Baba-Engle-Kraft-Kroner (BEKK), Constant Conditional Correlation (CCC), and Dynamic Conditional Correlation (DCC).

A multivariate BEKK model, representing the conditional covariance model proposed by Engle and Kroner (1995), was selected to examine the relationship between commodity prices and stock issuers in terms of volatility. The BEKK-

GARCH model was chosen for its ability to analyze volatility dynamics across multiple markets or assets, making it well-suited to test the impact of volatility between these variables. This model can explain how the volatility of one asset variable affects the volatility of other assets. The BEKK-GARCH equation (Bauwens et al., 2006) is formulated as follows:

$$H_t = CC' + A'u_{t-1}u'_{t-1}A + B'H_{t-1}B \quad (3)$$

where H_t is the conditional covariance matrix and C represents the 2×2 upper triangular matrices. A_{ij} of the 2×2 matrix A denotes the impact of the volatility of variable i on variable j and embodies the volatility ARCH effect. B_{ij} of the 2×2 matrix B indicates the continuity of volatility transmission between market i and market j , and represents the GARCH impact of volatility. The cumulative estimated parameters of the bivariate BEKK-GARCH (1,1) model can be expressed as:

$$H_t = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}^T \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}^T \begin{bmatrix} \varepsilon_{11,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{22,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}^T \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \quad (4)$$

where $h_{11,t}$ is the variance element of the conditional variance-covariance matrix H_t . It represents the variance of the first component of the residual vector $(\varepsilon_{1,t})$. The variance shows how big the spread or volatility of the value of the first variable is over time t . A detailed explanation of the equation is as follows:

- c_{11}^2 is a constant variable.
- $\alpha_{11}^2 \varepsilon_{1,t-1}^2$ and $\alpha_{21}^2 \varepsilon_{2,t-1}^2$ measure the effect of past squared errors $\varepsilon_{1,t-1}$ and $\varepsilon_{2,t-1}$ against current variance.
- $2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ measures the interaction effect between two past errors on the current variance.
- $\beta_{11}^2 h_{11,t-1}$, $2\beta_{11}\beta_{21}h_{12,t-1}$ and $\beta_{21}^2 h_{22,t-1}$ measure the effect of past conditional variance $h_{11,t-1}$, $h_{12,t-1}$, $h_{22,t-1}$ against current variance.

Additional analysis was performed using inferred forecast error variance decompositions which are part of a generalized vector autoregression (VAR) framework. This research assesses the relation of commodities and share price, based on the findings of Diebold and Yilmaz (2014). The technique eliminates order dependency in its results and is based on prior research. A covariance stationary dataset with several variables undergoes variance error decomposition using the VAR model, as proposed by Koop et al. (1996). The dataset may be characterized using the following VAR(p) model specifications:

$$x_t = \sum_{i=1}^p \phi_i x_{t-i} + \epsilon_t \quad \text{where } \epsilon \sim (0, \sigma) \quad (5)$$

The variance decomposition of the residual VAR model is then conducted. The generalized forecast error variance decompositions (FEVD) for KPPS H-step-ahead are computed as follows:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma \Theta_h' e_i)} \quad (6)$$

Θ_h is the coefficient matrix and relates to the “lagged shock” variable, and $\theta_{ij}^g(H)$ is the prediction error variance decomposition variable that signifies another essential component. The selection vector is represented by e_i' , while the covariance matrix of the shock vector is shown by σ_{jj}^{-1} . The total volatility spillover index (TVI) is articulated as follows:

$$(H) = \frac{\sum_{i,j=1}^N \tilde{\theta}^g(H)}{\sum_{i,i=1}^N \tilde{\theta}^g(H)} \cdot 100 = \frac{\sum_{i,j=1}^N \tilde{\theta}^g(H)}{N} \cdot 100 \quad (7)$$

The TVI assesses the impact of volatility shocks that permeate all markets on the total prediction error variance. The directional volatility spillovers received by market i from all other markets j , together with those transmitted by market i to all other markets j , may be articulated as:

$$S_{i \leftarrow j}^g(H) = \frac{\sum_{i,j=1}^N i j \tilde{\theta}^g(H)}{\sum_{i,i=1}^N i j \tilde{\theta}^g(H)} \cdot 100 = \frac{\sum_{i,j=1}^N i j \tilde{\theta}^g(H)}{N} \cdot 100 \quad (8)$$

$$S_{i \rightarrow j}^g(H) = \frac{\sum_{i,j=1}^N \tilde{\theta}^g(H)}{\sum_{i=1}^N \tilde{\theta}^g(H)} \cdot 100 = \frac{\sum_{i,j=1}^N \tilde{\theta}^g(H)}{N} \cdot 100 \quad (9)$$

Net volatility spillover refers to the disparity between shocks sent to and received from other markets. The determination of whether a market is the source or receiver of spillover is achieved via the analysis of net volatility spillover. The following definition pertains to the net spillover from asset i to all other assets j :

$$S_i^g(H) = S_{i \rightarrow j}^g(H) - S_{i \leftarrow j}^g(H) \quad (10)$$

4. Result

4.1 Stationary Test

Based on Table 2, the ADF and Phillips-Perron tests show that only the INDF and ROTI time series had p-values below 0.05. While these two time series were stationary at the data level, other variables were not steady due to p-values being greater than 0.05. Based on ADF and PP results, it was necessary to separate practically all time series component data before the onset of the conflict in order to achieve stationarity. However, there were a few indicators already stationary at the starting level.

Table 2. Stationary test results at the first-difference level of each commodity and stock variable

Variable	t-Statistic PreWar				t-Statistic During War***			
	ADF	Signif	PP	Signif	ADF	Signif	PP	Signif
OIL	-15.7827	***	-15.8155	***	-12.2268	***	-15.2059	***
MEDC	-17.3312	***	-17.3312	***	-14.3006	***	-14.3056	***
ENRG	-17.7934	***	-17.6109	***	-14.3951	***	-14.379	***
PGAS	-15.1014	***	-15.1014	***	-16.615	***	-16.6002	***
COAL	-14.4861	***	-14.4605	***	-14.2204	***	-14.2171	***
ADRO	-16.8892	***	-16.9254	***	-16.2547	***	-16.2166	***
BUMI	-15.0872	***	-15.0865	***	-14.0335	***	-14.0746	***
BYAN	-11.3222	***	-11.647	***	-10.526	***	-10.6198	***
GOLD	-11.9622	***	-15.0036	***	-16.001	***	-15.9899	***
ANTM	-14.6734	***	-14.6861	***	-16.2769	***	-16.1425	***
MDKA	-17.8392	***	-17.8656	***	-16.3816	***	-16.4113	***

PSAB	-18.2213	***	-18.3246	***	-16.2072	***	-16.2753	***
WHEAT	-14.2086	***	-14.2071	***	-12.9414	***	-13.3009	***
INDF	-17.8845	***	-17.9412	***	-17.3515	***	-17.3278	***
MYOR	-14.8303	***	-14.8338	***	-16.2497	***	-16.2967	***
ROTI	-5.3321	***	-17.2276	***	-16.2375	***	-16.2616	***

4.2 Descriptive Statistics

A descriptive analysis was conducted to offer a comprehensive overview and comparison of the characteristics of the data utilized in this study throughout a certain time frame. In addition, the analysis included examining the distribution of data to ensure normality conditions were met and identify any outliers capable of affecting the accuracy of subsequent analysis.

Table 3. Descriptive statistics of Log-Return Commodity Prices and Associated Stock Prices pre-Russia–Ukraine conflict

A. Oil and Gas	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
OIL	-0.000763	-0.001119	0.033886	-0.024982	0.009697	0.595429	4.80514	25.33197
MEDC	0.001192	0.003341	0.031258	-0.037248	0.012312	-0.651126	3.570852	10.95107
ENRG	-0.000277	0.003619	0.030669	-0.049797	0.014701	-0.867121	4.134237	23.25967
PGAS	0.001122	0.001530	0.031498	-0.031906	0.010138	-0.144447	4.26499	9.119815
B. Coal	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
COAL	-0.002356	-0.001161	0.008101	-0.049876	0.006021	-3.962481	31.19744	4646.961
ADRO	-0.000348	0.001703	0.025807	-0.036140	0.009890	-0.800613	4.665696	28.91671
BUMI	0.000659	0.000000	0.030814	-0.051153	0.013201	-0.793057	5.337377	43.22006
BYAN	-0.000135	0.000000	0.031408	-0.048986	0.009834	-0.511427	9.442364	230.4807
C. Gold	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
GOLD	0.000135	-0.000121	0.020492	-0.009955	0.004201	1.076278	6.937377	109.0724
ANTM	0.000281	0.001680	0.031498	-0.047150	0.014394	-0.626533	4.220742	16.57709
MDKA	9.68E-05	0.001586	0.030669	-0.045162	0.013026	-0.423082	3.773234	7.116869
PSAB	0.001021	0.002182	0.030759	-0.046576	0.011878	-0.845039	6.693615	89.37045
D. Wheat	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
WHEAT	-0.000547	-0.00025	0.032232	-0.024594	0.009264	0.204975	3.788283	4.276183
INDF	-5.30E-05	0.00000	0.020934	-0.025604	0.006935	-0.370695	4.921606	22.97874

MYOR	0.000760	0.00000	0.025554	-0.02193	0.007237	0.056827	4.587312	13.71759
ROTI	0.000267	0.00000	0.01639	-0.055125	0.007394	-3.824088	29.38691	4088.303

Notes: This table presents the descriptive statistics for the log-return commodity indices and the associated stock prices of companies listed on the Indonesia Stock Exchange (IDX) pre-Russia–Ukraine Conflict (1 Feb 2021 – 21 Feb 2022), categorized by sector: Oil and Gas, Coal, Gold, and Wheat.

Table 4. Descriptive statistics of Log-Return Commodity Prices and Associated Company Stock Prices during the Russia–Ukraine conflict

A. Oil and Gas	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
OIL	-0.001003	-0.001333	0.060795	-0.022541	0.009818	1.995955	13.70796	712.8356
MEDC	-0.000608	0.000000	0.030566	-0.058595	0.013470	-0.600774	4.90067	27.59876
ENRG	-0.001393	0.000000	0.029963	-0.087476	0.015530	-2.368507	13.06625	675.5713
PGAS	-0.001102	0.001450	0.019505	-0.040466	0.009992	-0.851963	4.409556	26.69242
B. Coal	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
COAL	-0.000992	-0.000871	0.187812	-0.052347	0.020925	5.382816	52.65422	14090.36
ADRO	-0.001612	0.000000	0.031379	-0.061572	0.012303	-0.802639	6.424325	78.0701
BUMI	-0.000800	0.000000	0.030814	-0.091770	0.018369	-1.774149	9.857554	325.4065
BYAN	-0.002822	0.000000	0.031335	-0.075436	0.014140	-2.363245	12.67386	632.7483
C. Gold	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
GOLD	-0.000201	-0.000222	0.010736	-0.008657	0.003597	0.344006	3.794961	6.033231
ANTM	0.000320	0.001813	0.031382	-0.049892	0.010986	-0.644020	6.576161	78.86185
MDKA	-0.001117	0.000000	0.028751	-0.057771	0.011559	-1.649604	9.130111	264.5274
PSAB	0.000641	0.002640	0.030814	-0.044506	0.011086	-0.530094	5.261459	34.05015
D. Wheat	<i>Mean</i>	<i>Median</i>	<i>Max.</i>	<i>Min.</i>	<i>Std. Dev.</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>
WHEAT	-0.000417	0.000000	0.018174	-0.018272	0.007486	-0.129252	2.529567	1.572719
INDF	3.94E-05	0.000000	0.023944	-0.016901	0.006053	0.146209	4.569066	13.90497
MYOR	0.000674	0.000000	0.015394	-0.022725	0.006935	-0.636593	3.726546	11.72925
ROTI	-1.25E-05	0.000000	0.030489	-0.049866	0.006783	-2.929934	29.0858	3901.655

Notes: This table presents the descriptive statistics for the log-return commodity indices and the associated stock prices of companies listed on the Indonesia Stock Exchange (IDX) during the Russia–Ukraine Conflict (22 February 2022 – 28 February 2023), categorized by sector: Oil and Gas, Coal, Gold, and Wheat.

Tables 3 and 4 present descriptive statistics of the log-returns of commodity prices and related stock prices before and during the Russia–Ukraine conflict. Statistics presented include mean, median, maximum, minimum, standard deviation, skewness, kurtosis, and Jarque-Bera values. Before the conflict, oil prices had an

average return of -0.000763, while one of its related stocks, MEDC, recorded a positive return of 0.001192, indicating the resilience of the stocks despite the decline in oil prices. However, during the conflict, the average return for oil fell further to -0.001003, and ENRG experienced a minimum decline to -0.087476, reflecting increased volatility. For coal, the pre-conflict return was negative (-0.002356), but volatility spiked during the conflict, with COAL recording a maximum return of 0.187812 and the standard deviation increasing from 0.006021 to 0.020925. ADRO and BUMI, as the main coal stocks, showed large fluctuations, with BUMI reaching a minimum return of -0.091770.

Gold, known as a safe-haven asset, was relatively stable before and during the conflict, with the average return of GOLD changing from 0.000135 to -0.000201. However, MDKA stocks experienced increased risk, with the minimum return dropping from -0.045162 to -0.057771. For wheat, returns remained stable, but ROTI recorded a minimum return of -0.055125 before the conflict and -0.049866 during the conflict, indicating a more limited impact. Overall, the conflict increased volatility, especially in coal and oil stocks, which impacted market stability and investor sentiment.

4.3 Correlation Analysis

Table 5. Correlation table from Commodity Prices and Associated Company Stock Prices during the Russia–Ukraine conflict

Pre War Correlation					During War Correlation				
	OIL	ENRG	MEDC	PGAS		OIL	ENRG	MEDC	PGAS
OIL		0.04351	0.01031	0.09654	OIL		-0.00431	0.23846	0.24943
ENRG	0.04351		0.29157	0.32567	ENRG	-0.00431		0.18957	0.14423
MEDC	0.01031	0.29157		0.35077	MEDC	0.23846	0.18957		0.34943
PGAS	0.09654	0.32567	0.35077		PGAS	0.24943	0.14423	0.34943	
	COAL	ADRO	BUMI	BYAN		COAL	ADRO	BUMI	BYAN
COAL		0.07340	0.17621	-0.17784	COAL		0.02940	0.11072	0.11852
ADRO	0.07340		0.45863	0.06005	ADRO	0.02940		0.55672	0.20954

BUMI	0.17621	0.45863		-0.03913	BUMI	0.11072	0.55672		0.25940
BYAN	-0.17784	0.06005	-0.03913		BYAN	0.11852	0.20954	0.25940	

	GOLD	ANTM	MDKA	PSAB		GOLD	ANTM	MDKA	PSAB
GOLD		0.25472	0.08736	0.14580	GOLD		-0.05839	0.00434	-0.01261
ANTM	0.25472		0.48282	0.26685	ANTM	-0.05839		0.31844	0.30150
MDKA	0.08736	0.48282		0.49016	MDKA	0.00434	0.31844		0.22737
PSAB	0.14580	0.26685	0.49016		PSAB	-0.01261	0.30150	0.22737	

	WHEAT	INDF	ROTI	MYOR		WHEAT	INDF	ROTI	MYOR
WHEAT		-0.11079	0.09675	0.14769	WHEAT		-0.03408	-0.05926	-0.12297
INDF	-0.11079		-0.00561	0.12735	INDF	-0.03408		-0.16506	0.21305
ROTI	0.09675	-0.00561		0.06410	ROTI	-0.05926	-0.16506		-0.13676
MYOR	0.14769	0.12735	0.06410		MYOR	-0.12297	0.21305	-0.13676	

The correlation table shows the changes in the relationship between commodity prices and related stocks before and during the Russia–Ukraine conflict. Before the war, oil (OIL) had a small positive correlation with its stocks, but during the war, MEDC (0.23846) and PGAS (0.24943) showed stronger correlations, indicating a greater influence of oil prices. The correlation between coal (COAL) and ADRO and BUMI increased from 0.45863 to 0.55672. Meanwhile, gold (GOLD) lost its relationship with its related stocks, with ANTM falling from 0.25472 to -0.05839, reflecting market uncertainty. Moreover, there is a negative correlation between wheat (WHEAT) and INDF before the war (-0.11079). During the war, the wheat price had a negative correlation with all stocks (INDF, ROTI, and MYOR), indicating that there is a distinct movement between wheat and its stocks.

4.4 BEKK-GARCH Analysis

In the initial stage, an analysis was conducted on oil commodities and stocks in the oil and gas industry. Based on Table 6.A (Pre-War Oil Spillover Effect), the shock effect of oil on the energy sector (ENRG) is not significant, with $\alpha_{12} = -0.00766$ ($\rho = 0.96124$). This shows that before the conflict, changes in oil prices did

not have a direct impact on the energy sector. However, in Table 6.B (During War Oil Spillover Effect), the α_{12} value becomes -0.51147 ($\rho < 0.01$), which means that during the conflict, oil price shocks have an impact on the energy sector. In terms of volatility (β_{12}), before the conflict and during the conflict, the volatility of ENRG was $\beta_{12} = 0.30195$ ($\rho = 0.25923$), which was not significant. However, during the conflict, β_{12} increased to 0.34510 ($\rho = 0.07350$), indicating that during the war, the increase in oil price volatility began to have a greater effect on the energy sector. Meanwhile, Oil and Gas price on PGAS and MEDC remain insignificant before and during the conflict (α_{12} pre-war = 0.07611, $\rho = 0.22424$; α_{12} during war = -0.14727, $\rho = 0.34116$).

Table 6. BEKK (1,1) pre- and during conflict commodity spillover effect result

A. Pre-War Oil Spillover Effect						B. During War-Oil Spillover Effect					
Variable	Coeff	Std.Error	T Stat	SignIf	Remarks	Variable	Coeff	Std.Error	T Stat	SignIf	Remarks
Oil → MEDC						Oil → MEDC					
a_{12}	-0.17531	0.13680	-1.28156	0.20000		a_{12}	-0.16832	0.13339	-1.26183	0.20701	
b_{12}	0.25684	0.17696	1.45137	0.14668		b_{12}	0.07235	0.08177	0.88482	0.37625	
Oil → ENRG						Oil → ENRG					
a_{12}	-0.00766	0.15755	-0.04860	0.96124		a_{12}	-0.51147	0.15141	-3.37800	0.00073	***
b_{12}	0.30195	0.26763	1.12822	0.25923		b_{12}	0.34510	0.19283	1.78970	0.07350	*
Oil → PGAS						Oil → PGAS					
a_{12}	0.07611	0.06262	1.21533	0.22424		a_{12}	-0.14727	0.15472	-0.95187	0.34116	
b_{12}	0.02990	0.03367	0.88801	0.37454		b_{12}	0.58387	0.43155	1.35295	0.17607	
C. Pre-War Coal Spillover Effect						D. During War-Coal Spillover Effect					
Variable	Coeff	Std.Error	T Stat	SignIf	Remarks	Variable	Coeff	Std.Error	T Stat	SignIf	Remarks
Coal → ADRO						Coal → ADRO					
a_{12}	0.49652	0.30115	1.64877	0.09920	*	a_{12}	-0.19191	0.08352	-2.29788	0.02157	*
b_{12}	-0.84997	0.17223	-4.93502	0.00000	****	b_{12}	0.35157	0.09081	3.87165	0.00011	****
Coal → BUMI						Coal → BUMI					
a_{12}	0.02151	0.22865	0.09409	0.92503		a_{12}	0.33155	0.08203	4.04162	0.00005	****
b_{12}	1.51850	0.26590	5.71083	0.00000	****	b_{12}	0.40695	0.06079	6.69455	0.00000	****
Coal → BYAN						Coal → BYAN					
a_{12}	0.32597	0.09936	3.28074	0.00104	***	a_{12}	0.23414	0.07254	3.22758	0.00125	***

b_{12} 0.28191 0.12688 2.22187 0.02629 *

b_{12} 0.02642 0.04512 0.58544 0.55825

E. Pre-War Gold Spillover Effect

Variable	Coeff	Std.Error	T Stat	SignIf	Remarks
Gold → ANTM					
a_{12}	-0.99377	0.38923	-2.55318	0.01067	**
b_{12}	1.99003	0.70065	2.84028	0.00451	***
Gold → MDKA					
a_{12}	-1.04764	0.39037	-2.68373	0.00728	**
b_{12}	-0.48838	0.35559	-1.37343	0.16962	
Gold → PSAB					
a_{12}	1.81851	0.51881	3.50513	0.00046	****
b_{12}	-0.57114	0.32517	-1.75645	0.07901	*

G. Pre-War Wheat Spillover Effect

Variable	Coeff	Std.Error	T Stat	SignIf	Remarks
Wheat → INDF					
a_{12}	-0.42870	0.10011	-4.28214	0.00002	****
b_{12}	0.07098	0.27455	0.25852	0.79600	
Wheat → MYOR					
a_{12}	0.44755	0.12043	3.71641	0.00020	****
b_{12}	0.33461	0.20446	1.63652	0.10173	
Wheat → ROTI					
a_{12}	-0.06375	0.06708	-0.95040	0.34191	

F. During War-Gold Spillover Effect

Variable	Coeff	Std.Error	T Stat	SignIf	Remarks
Gold → ANTM					
a_{12}	0.01093	0.27426	0.03987	0.96820	.
b_{12}	0.02949	0.00931	3.16679	0.00154	***
Gold → MDKA					
a_{12}	0.49442	0.29865	1.65554	0.09781	*
b_{12}	1.20748	0.52331	2.30741	0.02103	*
Gold → PSAB					
a_{12}	0.17027	0.29787	0.57163	0.56757	
b_{12}	-1.71519	0.22055	-7.77697	0.00000	****

H. During War Wheat Spillover Effect

Variable	Coeff	Std.Error	T Stat	SignIf	Remarks
Wheat → INDF					
a_{12}	0.04289	0.12955	0.33109	0.74058	
b_{12}	-0.57554	0.29490	-1.95162	0.05098	*
Wheat → MYOR					
a_{12}	-0.35891	0.11362	-3.15880	0.00158	***
b_{12}	-0.36183	0.15184	-2.38295	0.01717	**
Wheat → ROTI					
a_{12}	-0.44738	0.05682	-7.87425	0.00000	****

b_{12}	0.19290	0.06007	3.21137	0.00132	***	b_{12}	-0.26909	0.04306	-6.24928	0.00000	****
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Notes: ****, ***, **, and * denote the significance at the 0.1%, 1%, 5%, and 10% levels, respectively. This table highlights the substantial impact of conflict on commodity spillover effects, with varying implications across different commodities.

In Tables 6.C and 6.D, the shock effect of coal prices on ADRO shares is significant before and during the war, with values of ($\alpha_{12} = 0.49652, \rho < 0.1$) and ($\alpha_{12} = -0.19191, \rho < 0.05$), respectively. This result is consistent with the volatility before and during the conflict. The coal prices transmit their volatility to ADRO, with a significance value of less than 0.1%. This finding shows that during the war, coal price instability has a greater impact on increasing ADRO stock volatility. For BUMI stocks, the shock effect before the conflict was not significant ($\alpha_{12} = 0.02151, \rho = 0.92503$), but during the conflict it became significant ($\alpha_{12} = 0.33155, \rho < 0.001$). This shows that during the war, coal prices transmit their volatility to BUMI. The result remains consistent with the volatility; both before and during the conflict, coal prices are able to transmit their volatility to BUMI with values of ($1.51850, \rho < 0.001$) and ($0.40695, \rho < 0.001$), respectively. However, BYAN is slightly different; the volatility is significant before the conflict and insignificant during the conflict. This means that coal prices do not transmit their volatility to BYAN during the conflict.

Before the conflict (Table 6.E), gold price shocks had a significant value on ANTM shares ($\alpha_{12} = -0.99377, \rho < 0.01$), but during the conflict (Table 6.F), this gold price does not transmit its shock to ANTM ($\alpha_{12} = 0.01093, \rho = 0.96820$). In terms of volatility, before and during the conflict, gold prices are significant even though the significance values are decreased with ($\beta_{12} = 1.99003, \rho < 0.001$) and ($\beta_{12} = 0.02949, \rho < 0.01$), respectively. For PSAB stocks, before the conflict, the shock effect was significant ($\alpha_{12} = 1.81851, \rho < 0.001$), but during the conflict, the impact decreased drastically and became insignificant ($\alpha_{12} = 0.17027, \rho = 0.56757$). However, its volatility underwent a major change, with β_{12} pre-war = -0.57114 ($\rho = 0.07901$) turning into $\beta_{12} = -1.71519$ ($\rho < 0.001$) during the conflict, indicating that during the conflict, gold volatility had a stronger negative impact on PSAB stocks. Moreover, gold prices transmit their shock and volatility to MDKA during the conflict ($\alpha_{12} = 0.49442, \rho = 0.1$) and ($\beta_{12} = 1.20748, \rho < 0.1$), respectively.

From Table 6.G (Pre-War Wheat Spillover Effect), the shock effect of wheat price on INDF stock is significantly negative ($\alpha_{12} = -0.42870, \rho < 0.001$), but during the conflict (Table 6.H), this effect becomes insignificant ($\alpha_{12} = 0.04289, \rho = 0.74058$). Wheat volatility on INDF is not significant ($\beta_{12\text{pre-war}} = 0.07098, \rho = 0.79600$) and becomes significant during the war ($\beta_{12} = -0.57554, \rho < 0.05$), indicating that wheat prices transmit their volatility only during the war. MYOR stock experiences significant changes in shock effects and volatility. Before the conflict, the shock effect is ($\alpha_{12} = 0.44755, \rho < 0.001$), and during the conflict, it turns negative ($\alpha_{12} = -0.35891, \rho < 0.01$). Volatility has a similar trend, $\beta_{12\text{pre-war}} = 0.33461, \rho = 0.10173$ to $\beta_{12\text{during war}} = -0.36183, \rho < 0.05$. Meanwhile, the shock effect on ROTI before the conflict was not significant ($\alpha_{12} = -0.06375, \rho = 0.34191$), but during the conflict, the impact became significant ($\alpha_{12} = -0.44738, \rho < 0.001$). The volatility value of ROTI is significant before and during the war $\beta_{12} = 0.19290, \rho < 0.001$ and $\beta_{12} = -0.26909, \rho < 0.001$, respectively, indicating that wheat prices consistently transmit their volatility to ROTI.

To rigorously establish that spillover changes are driven by the Russia–Ukraine conflict, we perform Wald tests for joint significance of BEKK-GARCH spillover parameters.

Table 7. Wald test results pre- and during conflict

Pre-War			During-War		
Spillover Direction	Wald p-value	Remarks	Spillover Direction	Wald p-value	Remarks
Oil → MEDC	0.247	No significant spillover	Oil → MEDC	0.412	No significant spillover
Oil → ENRG	0.532	No significant spillover	Oil → ENRG	0.002	Significant spillover
Oil → PGAS	0.378	No significant spillover	Oil → PGAS	0.291	No significant spillover
Coal → ADRO	0.000	Significant spillover	Coal → ADRO	0.000	Significant spillover
Coal → BUMI	0.000	Significant spillover	Coal → BUMI	0.000	Significant spillover
Coal → BYAN	0.001	Significant spillover	Coal → BYAN	0.058	Significant spillover

Gold → ANTM	0.003	Significant spillover	Gold → ANTM	0.002	Significant spillover
Gold → MDKA	0.008	Significant spillover	Gold → MDKA	0.023	Significant spillover
Gold → PSAB	0.000	Significant spillover	Gold → PSAB	0.000	Significant spillover
Wheat → INDF	0.000	Significant spillover	Wheat → INDF	0.082	No significant spillover
Wheat → MYOR	0.000	Significant spillover	Wheat → MYOR	0.001	Significant spillover
Wheat → ROTI	0.001	Significant spillover	Wheat → ROTI	0.000	Significant spillover

Notes: This table presents the results of Wald tests for the joint significance of spillover parameters (α_{12} , β_{12}) derived from the BEKK-GARCH model, across pre-war and during-war periods.

The Wald test results show that the Russia–Ukraine conflict significantly amplified the volatility spillover between commodities and related sector stocks. Before the war, significant spillovers mainly occurred in coal, gold, and wheat-related stocks, while oil sector stocks had not shown any significant effects. However, during the conflict, a significant shift occurred: the oil sector, especially the Oil → ENRG pair, began to show statistically significant spillovers ($p = 0.002$), while some previously significant spillovers, such as Wheat → INDF, disappeared. This finding reflects the structural disruption of global energy and commodity markets due to geopolitical shocks. Overall, this comparison reveals a pattern of the emergence, persistence, and disappearance of spillover channels in response to armed conflict.

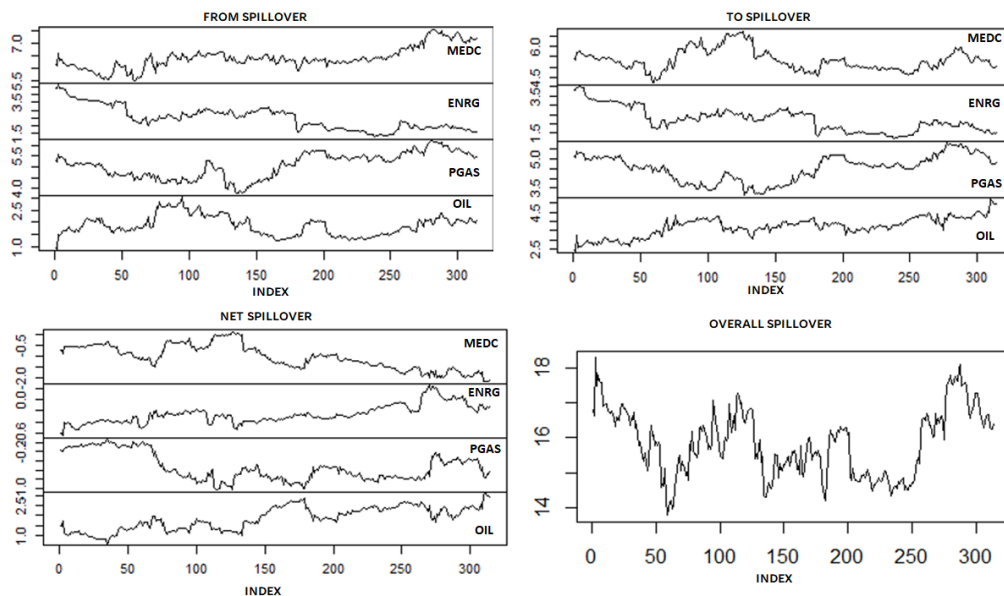
4.5 Vector Autoregression Analysis

Further investigation is implemented to strengthen the BEKK analysis by using the VAR method (Diebold & Yilmaz, 2009, 2014). This model examines the net transmitter and net receiver of an asset. The total spillover index (TSI) is computed as the sum of cross-variable forecast error variance shares relative to the system-wide total. Directional spillovers are calculated in two ways: spillover received by an asset (FROM others) and spillover transmitted to others (TO others). The net spillover is defined as the difference between these two measures and reflects whether the asset is a net transmitter or receiver of volatility.

Table 8. Return and volatility VAR spillover Oil commodity

	Return					Volatility			
	MEDC	ENRG	PGAS	Oil		MEDC	ENERG	PGAS	Oil
MEDC	76.08	2.77	11.64	9.5	MEDC	81.2	6.66	8.47	3.67
ENRG	3.32	91.26	4.21	1.21	ENERG	4.17	95.33	0.27	0.23
PGAS	12.37	3.64	81.22	2.78	PGAS	7.13	2.04	90.09	0.74
Oil	2.74	0.95	2.08	94.23	Oil	2.14	2.07	0.12	95.67
TO	4.61	1.84	4.48	3.37	TO	3.36	2.69	2.22	1.16
FROM	5.98	2.19	4.7	1.44	FROM	4.7	1.17	2.48	1.08
Net Spillover	-1.37	-0.35	-0.22	1.93	Net Spillover	-1.34	1.52	-0.26	0.08
Total Spillover	14.3				Total Spillover	9.43			

Figure 2. Directional volatility spillover of Oil to/from stock price



Note: The x-axis denotes each variable in the system (e.g., MEDC, ENRG, PGAS, OIL), while the y-axis indicates the proportion of forecast error variance (%) transmitted to other variables.

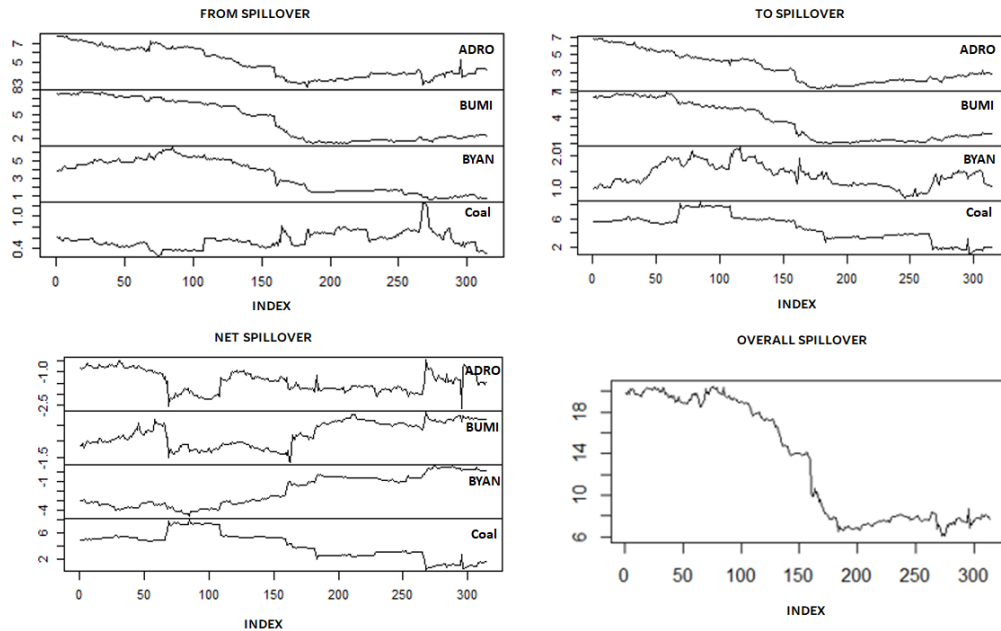
Based on Table 8 results, Oil (1.93%) acts as a net transmitter, meaning that changes in crude oil prices have a significant impact on other energy stocks. On the other hand, MEDC (-1.37%), ENRG (-0.35%), and PGAS (-0.22%) act as net receivers, indicating that their returns are more influenced by external factors than by having an impact on other assets. Meanwhile, in terms of volatility spillover, the total spillover was recorded at 9.43%, lower than the return, indicating that volatility

between assets in the energy sector is more stable. ENRG (1.52%) is the only significant net transmitter, while MEDC (-1.34%) and PGAS (-0.26%) receive more impact from the volatility movements of this sector.

Table 9. Return and volatility VAR spillover Coal commodity

	Return					Volatility			
	ADRO	BUMI	BYAN	Coal		ADRO	BUMI	BYAN	Coal
ADRO	81.39	10.35	0.71	7.54	ADRO	80.69	3.34	0.09	15.87
BUMI	10.78	85.33	0.86	3.03	BUMI	16.19	81.2	0.68	1.93
BYAN	2.33	0.76	93.45	3.46	BYAN	0.15	0.36	98.73	0.76
Coal	0.28	0.14	0.32	99.26	Coal	2.38	0.98	0.06	96.58
TO	3.35	2.81	0.47	3.51	TO	4.68	1.17	0.21	4.64
FROM	4.65	3.67	1.64	0.18	FROM	4.83	4.7	0.32	0.85
Net Spillover	-1.3	-0.86	-1.17	3.33	Net Spillover	-0.15	-3.53	-0.11	3.79
Total Spillover	10.14				Total Spillover	10.7			

Figure 3. Directional volatility spillover of Coal Price to/from stock price



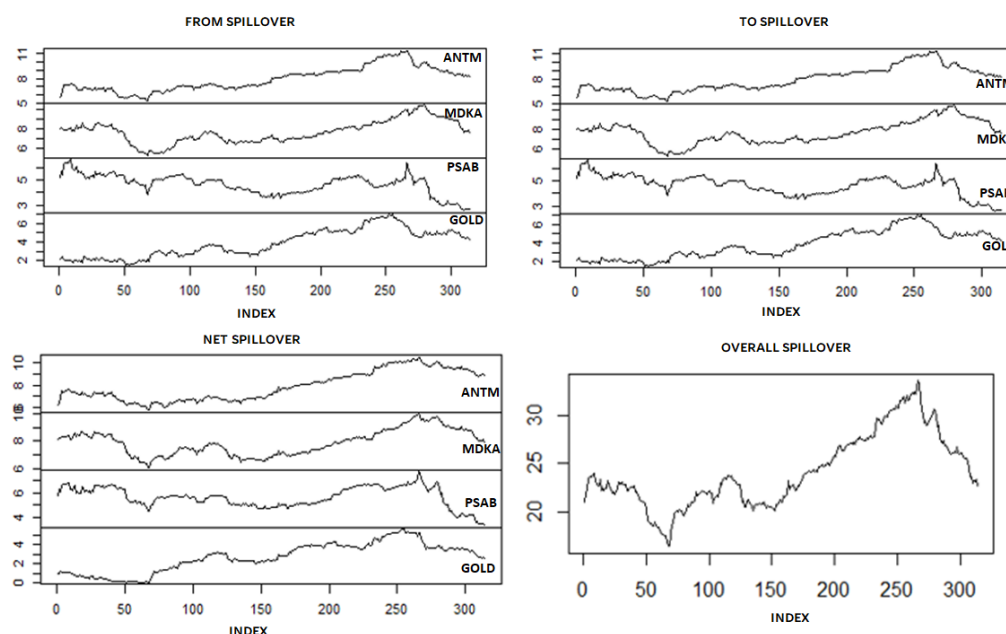
Note: The x-axis denotes each variable in the system (e.g., ADRO, BUMI, BYAN, Coal), while the y-axis indicates the proportion of forecast error variance (%) transmitted to other variables.

Table 9 shows that coal has a dominant role as a net transmitter, both in returns (3.33%) and volatility (3.79%), which means that changes in coal prices have a significant impact on stocks in this sector. In contrast, ADRO (-1.3%), BUMI (-0.86%), and BYAN (-1.17%) stocks act more as net receivers in returns, indicating that their price movements are more influenced by external factors than having an impact on other assets. A similar pattern is also seen in volatility, where BUMI experienced the largest negative net spillover (-3.53%), reflecting its sensitivity to overall sector volatility. With a total spillover of 10.14% in return and 10.7% in volatility, these results indicate that coal price dynamics are quite closely related to the movement of stocks in this sector, especially in terms of volatility.

Table 10. Return and volatility VAR spillover Gold commodity

	Return					Volatility			
	ANTM	MDKA	PSAB	Gold		ANTM	MDKA	PSAB	Gold
ANTM	71.99	17.16	5.3	5.55	ANTM	85.26	7.45	3.58	3.71
MDKA	16.96	70.12	7.96	4.96	MDKA	8.15	75.11	2.94	13.8
PSAB	6.57	8.72	81.14	3.57	PSAB	0.42	12.35	85.44	1.79
Gold	4.26	2.82	1.49	91.43	Gold	8.44	6.55	1.48	83.53
TO	6.95	7.18	3.69	3.52	TO	4.25	6.59	2	4.82
FROM	7	7.47	4.71	2.14	FROM	3.69	6.22	3.64	4.12
Net Spillover	-0.05	-0.29	-1.02	1.38	Net Spillover	0.56	0.37	-1.64	0.7
Total Spillover	21.33				Total Spillover	17.67			

Figure 4. Directional volatility spillover of Gold to/from stock price



Note: The x-axis denotes each variable in the system (e.g., ANT, M, PS, GOLD), while the y-axis indicates the proportion of forecast error variance (%) transmitted to other variables.

Gold acts as the main net transmitter (1.38%), as shown in Table 10, indicating that gold price movements have a significant impact on gold stock returns, while PSAB (-1.02%), MDKA (-0.29%), and ANT (-0.05%) stocks receive more impact than they influence other assets. Meanwhile, in volatility spillover, the total spillover was recorded at 17.67%, indicating a lower level of volatility association compared to returns. ANT (0.56%), MDKA (0.37%), and Gold (0.7%) act as net transmitters, while PSAB (-1.64%) receives more volatility effects from other assets.

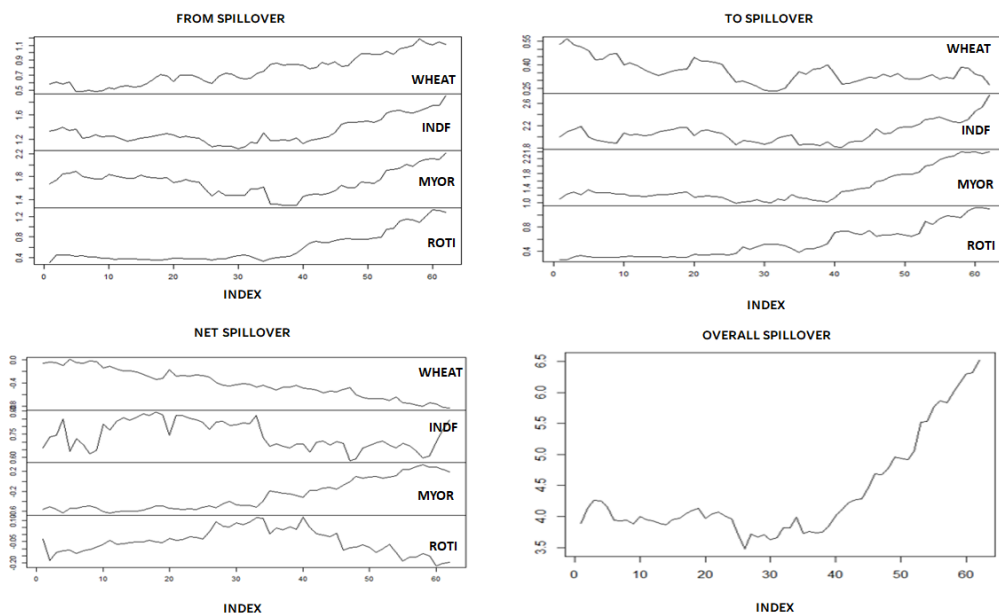
Table 11. Return and volatility VAR spillover Wheat commodity

	Return					Volatility			
	INDF	MYOR	ROTI	Wheat		INDF	MYOR	ROTI	Wheat
INDF	96.66	2.91	0.12	0.31	INDF	98.91	0.21	0.23	0.65
MYOR	3.36	93.1	0.46	3.08	MYOR	0.13	99.13	0.12	0.62
ROTI	0.19	0.33	99.39	0.09	ROTI	0.24	0.09	99.41	0.26
Wheat	0.25	2.33	0.3	97.12	Wheat	1.53	2.09	0.25	96.13
TO	0.95	1.39	0.22	0.87	TO	0.48	0.6	0.15	0.38
FROM	0.84	1.72	0.15	0.72	FROM	0.27	0.22	0.15	0.97
Net Spillover	0.11	-0.33	0.07	0.15	Net Spillover	0.21	0.38	0	-0.59

Total Spillover 3.43

Total Spillover 1.61

Figure 5. Directional volatility spillover of Wheat to/from stock price



Note: The x-axis denotes each variable in the system (e.g., INDF, MYOR, ROTI, WHEAT), while the y-axis indicates the proportion of forecast error variance (%) transmitted to other variables.

The wheat commodity exhibits the least spillover effect compared to other commodities. Before the war, wheat price is a net receiver with a value of -0.2. INDF is the highest net transmitter, and Wheat, MYOR, and ROTI are the net receivers. However, during the war, wheat price, MYOR, and ROTI are the net transmitters, and only INDF is the net receiver. This result indicates that during the war, wheat prices are transmitting their volatility by 0.38 to other related stocks, even though the value is much lower than MYOR, which is 1.24.

5. Discussion

This study aimed to investigate the influence of the Russia–Ukraine conflict on the stock prices of Indonesian companies involved in oil, gas, coal, gold, and wheat commodities by analyzing the volatility of their prices. The application of BEKK GARCH to assess the spillover impact and comprehend a geopolitical event, such as the conflict, might generate volatility in particular sectors of the Indonesian

Stock Exchange. Further investigation was also implemented by using the VAR method (Diebold & Yilmaz, 2009, 2014) to examine the net transmitter and net receiver of an asset.

The study provided empirical evidence of the Russia–Ukraine conflict spillover effects on the Indonesian Stock Exchange, affecting commodity prices and related companies' stock prices. It also analyzed specific sectors within the Indonesian Stock Exchange, focusing on those directly influenced by oil, gas, coal, gold, and wheat prices. The study was relevant to emerging markets, as it provided insights into the vulnerability of these markets to global geopolitical shocks and commodity price fluctuations. Moreover, the results had implications for policymakers and investors seeking to manage risk in commodity-sensitive sectors.

The results from Table 6 show that before the conflict, oil price shocks had minimal impact on the energy sector, but during the war, their influence became significantly negative, increasing market uncertainty. Coal price shocks initially had a positive effect on ADRO but reversed during the conflict, reflecting growing risk perceptions. Gold, typically considered a safe haven, showed mixed results, with its spillover effects diminishing for ANTM but increasing in volatility for PSAB. Wheat price volatility, which had negatively impacted INDF pre-war, became insignificant during the war, while MYOR experienced a reversal in spillover direction, highlighting instability in consumer goods sectors. These findings indicate that geopolitical tensions significantly alter commodity price transmission across industries, reinforcing the need for robust risk management strategies.

The VAR analysis indicates that the commodities of coal and gold exhibit the highest percentages of being net transmitters to the related stocks, with volatilities of 0.33 for coal and 1.38 for gold. Nonetheless, oil and wheat continue to function as net transmitters, ranking second highest after ENRG and second highest after MYOR for wheat. This conclusion aligns with the BEKK-GARCH findings,

which indicate the strongest volatility transmission from coal and gold to the related stocks.

The current study emphasized the importance of risk management in commodity-related stocks on the Indonesian Stock Exchange, particularly those related to oil, gas, coal, and gold, due to geopolitical events like the Russia–Ukraine conflict. Diversification strategies should consider these sensitivities. Sector-specific strategies are also necessary, as the impact of different commodities varies. Geopolitical developments should be closely monitored to assess the potential impact on commodity markets and stocks. Emerging market economies, such as Indonesia, are vulnerable to global shocks, necessitating managers to consider hedging strategies to mitigate potential risks. This proactive approach can help anticipate market movements and make informed investment decisions.

The study was limited in scope, as it focused solely on the Indonesian Stock Exchange. Therefore, the results might not be applicable to other emerging markets or developed economies due to variations in responses to geopolitical events and fluctuations in commodity prices. In addition, the data only included a short period of time, starting with the beginning of the Russia–Ukraine conflict. The conclusions drawn from these data might not be valid in the long run because of changing geopolitical circumstances and other variables. There might be concurrent influences from various factors on both commodity prices and the Indonesian Stock Exchange, including worldwide economic conditions, alterations in monetary policy, or even more geopolitical occurrences. Neglecting to consider these factors could result in imprecise assessments of the actual impact of the conflict.

6. Conclusion

The Russia–Ukraine conflict significantly impacted global markets, particularly in terms of commodity stability. The results show a significant increase

in the spillover effect, especially in the coal and gold sectors. During the conflict, oil prices had a negative impact on ENRG and increased the volatility of PGAS. Coal prices that previously had a positive impact on ADRO turned negative. Gold volatility increased on PSAB, while its impact on ANTM weakened. Meanwhile, the effect of wheat prices on INDF became insignificant, but MYOR and ROTI experienced a change in the direction of spillover. These findings indicate the need for risk mitigation strategies and more adaptive policies in dealing with market volatility due to geopolitical instability.

The conflict caused a decrease in Russian energy exports, leading to crude oil prices reaching a high of \$123.8 per barrel in March 2022. This led to a rise in transportation expenses and exacerbated inflationary forces. The conflict affected countries heavily reliant on coal, showing the weaknesses in the energy composition of the European Union. It also disrupted the production and trading of important agricultural commodities, such as wheat, corn, and vegetable oils. The long-term implications of the conflict remained indeterminate, with disruptions in global supply networks and uncertainties around the sustainability of the current trading system. Therefore, this study was specifically important for policymakers and investors to understand and effectively navigate the repercussions of geopolitical events on financial markets.

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