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VOLATILITY SPILLOVERS OF CRUDE PALM OIL, CRUDE OIL, COAL, EXCHANGE RATES AND INDONESIAN STOCK MARKET 2013-2023

Savitri Agung Setiahutami[1], Dony Abdul Chalid[2]
[1,2] Department of Management, Faculty of Economics and Business, University of Indonesia, Depok, Indonesia
Email: savitri.agung@ui.ac.id, donny.abdul@ui.ac.id

ABSTRACT

This research is meant to analyze the Volatility spillover between the energy commodity market future (Crude Oil, Coal, and Palm Oil) with the Indonesian JKSE stock market and IDR-USD exchange rate. The data used is daily data taken from May 2013 until September 2023 by BEKK Diagonal Model. This research found that there were different patterns in asset pairs in relation to pre-pandemic and pandemic. Crude oil and palm oil had a positive relationship before pandemic and during the pandemic coal and the exchange rate had a positive relationship. Meanwhile, after the COVID-19 pandemic, no covolatility spillover was found. An increase in covolatility spillover from exchange rate asset pairs was found during the pandemic. This research also shows the potential for portfolio diversification for each asset pair through optimal portfolio weights. Understanding volatility movements and interdependencies in commodity futures, stock markets, and exchange rates is important for proper investment management, and this research can help investors make appropriate decisions.

KEYWORDS *Crude Oil, Exchange Rate, Coal, Palm Oil, Diagonal BEKK model.*

INTRODUCTION

Research by Ftiti et al. (2021) and Louhichi et al. (2021) examined the financial impact of the COVID-19 pandemic on the global economy and found a decline in economic activity as the number of COVID-19 cases increased. During the ongoing pandemic, many countries in the world are experiencing disruptions in important commodities due to lockdowns in commodity supply chains, and the demand-supply imbalance in global commodity markets is a crucial thing that has

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a negative impact on the international financial system that has a negative effect on the global financial system. Major impact on global commodity futures markets (Chendurpandian and Pandey 2022).

The volatility spillover effect is the delayed effect of a yield shock on one physical or financial asset on subsequent volatility or covolatility on another physical or financial asset. Investigating the impact of volatility within and across energy and financial markets is an important aspect of building optimal dynamic hedging strategies (Chang, Liu, and McAleer 2019).

Spillover effects entail the Exchange of information among financial markets, representing a transfer of risk across these markets. The accelerated pace of globalization and advancements in trading technology has led to heightened interconnectedness among markets, facilitating swift transmission of information across diverse financial arenas. While investments may be diversified across various countries and financial markets, the close interlinkages can rapidly disseminate risks, potentially triggering a cascading financial crisis across nations. Hence, exploring spillover effects among markets is essential for gaining insights into the dynamics of financial market fluctuations and understanding how the volatility of each market influences its impact on portfolio returns.

Volatility spillover not only focuses on stock market instruments between countries but also other instruments such as commodity futures markets. Papapetrou, (2001) studied the dynamic relationship between oil prices, real stock prices, interest rates, real economic activity and employment through a multivariate VAR approach. There is a conclusion that changes in oil prices affect real economic activity and employment, while stock returns do not cause changes in real activity or employment. Mensi et al., (2023) examined the relationship between returns and the impact of volatility between the S&P 500 and the commodity price index using the VAR-GARCH model. Wei et al. (2019) applied dynamic conditional correlation (DCC), constant conditional correlation (CCC) and BEKK models to investigate the impact of volatility between G7 country stock prices and WTI crude oil prices. Badamvaanchig et al., (2021) investigated the impact of volatility between stock and bond markets in the G7 and BRICS countries using a newly developed causality-in-variance test.

So far, many investors have considered commodities in their portfolio plans as income diversification due to the development of the commodity market in recent years. So, understanding the effects of Volatility spillover between assets is very important for effective risk management and portfolio diversification (Cao and Wen, 2019).

Among the many portfolio strategies, it is worth examining how to combine commodities and stocks to achieve diversified returns. Theoretically, because the factors that drive commodity prices (such as world demand, productivity growth rates, weather conditions, geopolitical and physical discoveries, and supply constraints) are different from the factors that determine stock values, the correlation and dependency between commodity and stock returns low, which can provide portfolio diversification returns (Daskalaki, Skiadopoulos, and Topaloglou 2017). Hedging is one strategy to keep export-import activities maintained and under control.

Derivative transactions can be used by investment management, financial institution companies, investors, to manage their positions regarding risks from stock and commodity movements, interest rates, foreign exchange rates without affecting the physical position of the product that is the reference.

Futures contracts are a derivative instrument used as a hedging strategy for owned assets. Commodity futures trading has two main objectives. First, it provides an efficient price discovery mechanism. Second, it offers hedging facilities for market participants against the vagaries of price fluctuations. Prices of agricultural products have proven to be highly volatile and susceptible to fluctuations, which exposes producers and traders to increased risks when handling these products. The futures market provides more effective information transmission than the underlying market, the price-volume interactions occurring within the market have become the basic framework for determining the demand and supply of a commodity.

Previous research regarding the profitability and risk diversification capabilities of commodity futures has provided inconsistent conclusions. Some experts believe that commodity futures can diversify portfolio risks and increase profits (Jensen et al., 2000; Gorton and Rouwenhorst, 2006; Conover et al., 2010; Cheung and Miu, 2010; Daskalaki et al., 2017). The prevailing belief is that there exists a negative or limited correlation between returns from commodity futures and those from traditional asset classes, positioning commodity futures as an alternative asset class. Nonetheless, some argue that the advantages derived from commodity futures are not as significant as commonly perceived. (Daskalaki and Skiadopoulos, 2011; Belousova and Dorfleitner, 2012; Bessler and Wolff, 2015; Yan and Garcia, 2017).

Energy futures commodities have their own characteristics. Previous research shows that there is volatility spillover between the energy market and the energy equity market, and with the growing financialization of commodities, the relationship between the energy market and the equity market (Creti et al., 2013; Lee et al., 2014; Adams and Gluck, 2015 ; Kang et al., 2015; Khalfaoui et al., 2015; Basher and Sadorsky, 2016; Maghyereh et al., 2017; Zhang et al., 2017; Shahzad et al., 2018; Demirer et al., 2020; Hu et al., 2020; Ma et al., 2021).

There is still not much research related to palm oil and coal futures, and Indonesia is the first exporter of palm oil and third coal in the world. However, trading on the Indonesian crude palm oil (CPO) futures exchange was only launched on October 13 2023 and is effective on October 23 2023. The data for coal futures on the Indonesian stock exchange market is incomplete. In fact, if local prices become a global reference, it can facilitate marketing and provide added value for producers. Since the reference prices for commodity futures are still in other countries, understanding the spillover volatility between world commodity futures for crude oil, coal and palm oil, the Indonesian stock market and exchange rates is interesting because it can be useful for additional knowledge on portfolio diversification and hedging—value, especially with the research period from 2013-Sept 2023 before, during and after the Covid-19 pandemic.

The main objective of the research is to find out whether there are differences in volatility spillover patterns between crude oil, coal, palm oil, exchange rates and the Indonesian stock market in the period before, during and after the Covid pandemic, whether there is an increase in volatility spillover between crude oil and stone commodities. coal, palm oil, exchange rates and the Indonesian stock market compared to the period before the Covid 19 pandemic and the implications for portfolio diversification and hedge ratios by dividing the research period into different sub-periods: pre-Covid-19 Pandemic, COVID-19 pandemic and post-Covid-19 Pandemic.

All the above arguments show that potential relationships between different markets/assets are possible, using appropriate econometric models. In carrying out empirical analysis, researchers used the NYMEX Light Sweet Crude Oil (WTI) Electronic Energy Future Continuation crude oil futures commodity, which is a futures contract traded on the CME Group exchange. NYMEX WTI is the most liquid oil contract in the world and represents the price of light sweet crude oil in the United States. Coal futures assets use ICE Europe Newcastle Coal Futures Monthly Electronic Energy Future and Palm Oil futures use Bursa Malaysia Crude Palm Oil Commodity Future Continuation, exchange rates with IDR/USD and the Indonesian Stock Market uses IHSG (JKSE) for the time interval from May 20 2013 -September 14 2023 with the following sub periods:

1. Pre Pandemic Covid 19 is May 20 2013-March 10 2020,
2. Pandemic from March 11 2020- May 11 2023.
3. Post Pandemic from May 12 2023 to September 14 2023

This research uses the Baba, Engle, Kraft, and Kroner (BEKK) Diagonal model to study the dynamics of combining variables in pairs (bivariate). Many econometric methods can be used to test price transmission, such as the VAR model and the Granger causality test are the most widely used. The available models include the CCC, VARMA, Diagonal BEKK, Full BEKK, and DCC models to estimate the effect of static and dynamic volatility transmission. However, only the Quasi Maximum Likelihood Estimators (QMLE) of the BEKK Diagonal model has been proven by McAleer et.al. (2008) is consistent and asymptotically normal, with known regularity conditions and asymptotic properties, the results of empirical work are statistically meaningful. They can be based on valid statistical tests.

This research contributes to the literature by examining hedging properties in the periods before the pandemic, during the pandemic and after the pandemic. The calculation of the optimal investment portfolio between different assets and the optimal hedging ratio in this research is based on the BEKK Diagonal model.

Literature Review

Understanding volatility spillover can be useful for seeing and understanding the impact of each market's volatility on portfolio returns. Batten et al.(2017) studied the relationship between oil, gas and coal, and two Asian markets. They found integration of Asian markets with energy portfolios, while de Boyrie and Pavlova (2018) used the DCC GARCH model to fit conditional volatility dynamics and compare co-movements between emerging markets and developed countries with commodities. The research results show that emerging markets, especially in Asia, show less co-movement with commodities than developed markets. Vardar et al. (2018) examines the impact of shocks and volatility between commodity markets and stock markets in developed and developing countries. The results show the average impact of shocks and two-way volatility between commodity markets and stock markets. However, the impact of shocks that occurred in the stock market was stronger than the impact that occurred in the commodity market. Lin et al. (2019) explore risk contagion between the Brent crude oil market, the London gold market, and the Chinese and European stock markets

Portfolio management analysis reveals that mixed portfolios (commodity and stock markets) provide a higher level of hedging effectiveness for both emerging and developed markets. Moreover, the effectiveness of hedging in BRICS markets is more pronounced than in developed markets, regardless of frequency. Hedging effectiveness is also higher when using gold compared to oil and in the short term compared to the medium and long term (Mensi et al., 2021).

This research was conducted before the Covid 19 pandemic, so this study can add to the literature related to volatility spillover during the Covid 19 pandemic. Literature studies related to the relationship between variables are as follows.

Energy Commodity Futures

Coal plays a major role in the electricity sector as an intermediary channel that creates partial movement between coal and petroleum. Coal and crude oil have an interesting relationship. Crude oil is a partial substitute for coal, and rising crude oil prices increase coal use; conversely, when coal prices rise, crude oil use increases (Wang, Yang, and Li 2022).

Previous research by Wang and Zhou (2022) due to disruptions in energy supply and demand due to this epidemic, market efficiency in the first quarter of 2020 has decreased drastically. However, market efficiency is not in line with the development of the epidemic in the second half of 2020. Especially after the announcement of the quantitative easing policy, market efficiency has increased significantly. However, under excessive monetary policy, market efficiency decreased in the first half of 2021. This shows that the policy has had a certain impact in reducing the impact of the epidemic on the energy market. However, these improvements are not sustainable in the long term. When prices rise, inflation continues. In the future, the volatility and risks of the energy futures market will increase. Therefore, in the long term, excessive monetary policy stimulus to the economy will gradually weaken. It will even cause commodity prices to rise and inflation. In the future, the volatility and risk of energy futures markets will increase.

Wang, Yang, and Li (2022) find that the co-movement of Chinese coal prices and crude oil prices largely depends on the shares of oil and coal in China's energy mix, while the co-movement of international coal prices depends on the scale of coal trade. Interfuel substitution dominates China's coal market interactions with other types of energy, but the importance of intermarket transmission is increasing.

Zolfaghari et al. (2020), there is a positive and real link between coal, other energy sources, and the US dollar, especially between energy and US equity markets. In previous research related to palm oil, Jeong et al., (2023), examined the efficiency of the crude palm oil (CPO) futures market by conducting a variance ratio test and comparing it with the West Texas Intermediate (WTI) futures market, finding that the weak form efficient market hypothesis applies to the market. CPO and WTI futures even though there are significant differences in their liquidity. It was found that CPO futures trading with significant profit expectations does not involve a high level of risk like WTI futures trading.

Energy commodity futures with the stock market

The more recent and rapid growth of index investing in commodity markets may be contributing to the integration of these markets with equity and bond markets (Tang and Xiong, 2012). In commodity markets, interactions between crude oil and other commodities are increasingly attracting the attention of financial analysts. Commodity traders (especially oil traders) currently pay close attention to commodity and stock market movements to determine direction in optimizing their investment portfolios (Choi and Hammoudeh, 2010).

The share performance of coal issuers influences the current performance of the JKSE through several factors. The performance of coal issuer shares is influenced by the performance of companies that manage coal mining, which is also influenced by coal prices. Weakening coal prices can affect the performance of shares of coal issuers because these issuers depend on their coal sales. Global demand from India and China, which are the largest coal consumers in the world, influences the performance of shares of coal issuers. External factors, such as government policy and global uncertainty also influence the stock performance of coal issuers. Overall, the share performance of coal issuers influences the current performance of the JKSE through company performance, coal prices, global demand, market conditions and external factors.

CPO prices still refer to the Malaysian Exchange. The implementation of the Indonesian CPO exchange aims to have an impact on shares in the plantation sector, including CPO, so that the level of liquidity increases. Currently research on CPO commodity futures with the Indonesian stock market is still limited.

Commodity futures with exchange rates

Countries are more dependent on commodity prices and/or exchange rate fluctuations. Periods of crisis, both when commodity prices rise or fall and high appreciation or depreciation of the domestic currency, affect a country's growth as well as inflation rates and react differently through its monetary and fiscal policies Manner, Rodríguez, and Stöckler (2024)) and Uddin et al. (2020) examine the interdependence between the US stock market and precious metals and find systematic co-movement, Bouri et al. (2021) find increased spillovers during periods of crisis between the US stock market and the crude oil and gold markets, and Mensi et al. (2017) examine the dependency structure between crude oil prices and major stock markets, finding tail dependencies for both the short and long runs.

This exchange rate responds to palm oil prices at extreme quantiles of the exchange rate in the long term (Chandrarin et al. 2022). so that it can directly and indirectly influence the JKSE rate of return.

The level of significance of the exchange rate spillover effect on crude palm oil prices is shown at the lower exchange rate quantiles and the median at the higher crude palm oil price quantiles. There is a positive and statistically significant impact of the price of crude palm oil on the exchange rate and vice versa. The direction of the impact of the price of crude palm oil on the exchange rate and the reverse direction is similar in the four lags (1, 5, 20, 60). However, the direct impact of crude palm oil prices on the exchange rate decreases slightly over longer periods. Meanwhile, the direct impact of the exchange rate on crude palm oil prices increases slightly over a longer period. However, the exchange rate response to crude palm oil has a different pattern compared to coal prices. The Rupiah exchange rate (IDR) depreciates at palm oil prices in lower quantiles and exchange rates in higher quantiles from the short to medium term. Interestingly, at higher palm oil price quantiles, the Rupiah (IDR) appreciated. (Chandrarin, et al. 2022)

Exchange rate with the Indonesian Stock Market

Since COVID hit and commodity prices have weakened, contractionary US monetary policy and rising commodity prices have had a negative impact on the Indonesian economy. Still, coal, iron and steel companies have done well. In addition, sectors that have benefited from the pandemic, such as pharmaceuticals and healthcare continue to perform better. Telecom equipment stocks surged as people working from home upgraded information and communications technology (ICT) equipment. Banks and the financial sector previously performed poorly when the pandemic hit. Indonesia is included in this category and is exposed to the aggregate Indonesian stock market. However, independent exposure to other variables, such as exchange rates and world demand is relatively small. This is what is expected from an economy whose growth is driven by domestic demand and not net exports (Thorbecke, 2023)

The GARCH model successfully describes the characteristics of fluctuations and the impact of volatility between financial time series. By clearly identifying financial speculation, Wen et al., (2021) supports the view that commodity prices are dominated by actual demand in the long term and influenced by speculation in the short term. Various previous studies have focused on whether there are spillover effects between commodity markets and financial markets, as well as their direction and intensity.

RESEARCH METHOD

Univariate Conditional Volatility

Consider the conditional mean of financial returns:

yt$Y_t = E(y_t|I_{t-1}) + \varepsilon_t$ (1)

where y_t is the difference between (price at t- price at t-1)/price at t-1). It is the information set available at time t − 1, and ϵ_t is a conditionally heteroskedastic error term. In order to derive conditional volatility specifications, it is necessary to specify the stochastic processes underlying the returns shocks, ϵt. To make the discussion more concrete, we briefly introduce the standard GARCH model.

Now, consider the random coefficient autoregressive process of order one underlying the return shocks, ϵt.

$$\varepsilon_t = \phi_t \varepsilon_{t-1} + \eta_t \quad (2)$$

Here
$\phi_t \sim i, id(0, \alpha), \alpha \geq 0$, dan
$\eta_t \sim iid(0, \omega,), \omega \geq 0,$
$\eta_t \sim iid(0, \omega,), \omega \geq 0,$
$\eta_t = \varepsilon_t / \sqrt{h}_t$

Is the standardized residual, with ht defined below. Tsay (1987) derives the ARCH(1) model from Eq. (2) as

It is well-known that both ω and α need to be positive because they are considered as the unconditional variances of a random coefficient autoregressive process. This is a critical regulatory condition that will be referred to later.5 Moreover, when the returns deviate from the normality assumption, one needs to use Maximum Likelihood (ML) methods to estimate the model. In particular, the Quasi Maximum Likelihood Estimators (QMLE) method has been shown to be consistent and asymptotically normal. $\alpha + \beta < 1$ is asufficient condition for the QMLE of-GARCH(1,1) to be consistent and asymptotically normal. In general, the asymptotic properties of GARCH follow from the fact that the model can be derived from a random coefficient autoregressive process.

BEKK Diagonal

The diagonal BEKK model can be derived from a vector random are no regularity conditions (except by assumption) for checking the coefficient autoregressive process of order one, which is the multi-internal consistency of the alternative models, and consequently no variate extension of the univariate process given in Eq (1)
where

$$\varepsilon_t = \phi_t \varepsilon_{t-1} + \eta_t \quad (3)$$

ε_t *and* η_t are vector m x 1
ϕ_t is m x m matrix random coefficients
$\phi_t \sim iid(0, A), A \text{ is positive definite}$
$\eta_t \sim iid(0, C), C \text{ is an } m \text{ x } m \text{ matrix},$

Vectorization of a full matrix A to vec A can have dimension as high as m^2 x m^2, whereas vectorization of a symmetric matrix A to vech A can have a smaller dimension of

$$m(m+1)/2 \times m(m+1)/2$$

In a case where A is a diagonal matrix, with $a_{ii} > 0$ for all i = 1,…,m and $|b_{jj}|<1$ for all j = 1,…,m, so that A has dimension m m × , McAleer et al (2008) showed that the multivariate extension of GARCH(1,1) from Eq.(10) is given as the diagonal BEKK model, namely:

$$Q_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + \beta Q_{t-1}Q' \quad (4)$$

Where A and B are both diagonal matrices, though the last term in eq (4) need not come from an underlying stochastic process. The diagonality of the positive definite matrix A is essential for matrix multiplication as $\varepsilon_{t-1}\varepsilon'_{t-1}$ is matrix mxm. Otherwise, Eq (4) could not be derived from vector random coefficient autoregressive process in Eq (3).

McAleer, (2008) showed that the QMLE of the parameters of the diagonal BEKK model were consistent and asymptotically normal, so that standard statistical inference on testing hypotheses is valid. Moreover, as Qt in (4) can be estimated consistently, Γt can also be estimated consistently.

The ARCH coefficient of matrix A2 represents the grouping of spillovers caused by volatility (ii), which shows that news/surprises occur in an asset, while the GARCH coefficient of matrix B2 represents the impact of volatility persistence (ii). (Zeng et al., 2022)

It is important to emphasize that the spillover effect of covolatility from market i to j is different from the spillover effect from market j to i. The difference between the two impacts depends on the residuals arising from markets i and j. The conditional average of shocks, is useful in understanding the spillover effects of average covolatility (Mai et al., 2022).

The method currently used is bivariate. Considering previous research (Zolfaghari et al., 2020), adding variables will increase the number of iterations for convergence, which can speed up the default option too easily. Therefore, consider a smaller weighting matrix A, and focus on more specific combinations.

For comparison purposes, the bivariate forms of the two models are presented below. The unrestrictedBEKK model in bivariate form can be written as follows:

$$\begin{pmatrix} h_{11} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} = CC' + \begin{pmatrix} a_{11} & a_{12,t} \\ a_{21,t} & a_{22,t} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{1\,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2\,t-1} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12,t} \\ a_{21,t} & a_{22,t} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12,t} \\ b_{21,t} & b_{22,t} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12,t} \\ b_{21,t} & b_{22,t} \end{pmatrix}$$

Hence, we have that

$$h_{11,t} = C^2_{11} + a^2_{11}\varepsilon^2_{1\,t-1} + 2a_{11}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{21}\varepsilon^2_{2\,t-1} + b^2_{11}h_{11,t-1} + 2b_{11}b_{21,t}h_{12,t-1} + b^2_{21}h_{22,,t-1} \quad (5)$$

$$h_{22,t} = C^2_{12} + C^2_{22} + a^2_{11}\varepsilon^2_{1\,t-1} + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a^2_{22}\varepsilon^2_{2\,t-1} + b^2_{11}h_{11,t-1} + 2b_{12}b_{22,t}h_{12,t-1} + b^2_{22}h_{22,,t-1} (6)$$

$$h_{12,t} = h_{2,1,t} = C_{12}C_{11,} + a_{11}a_{12}\varepsilon^2_{1\,t-1} + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{11}a_{12}\varepsilon^2_{2\,t-1} + b_{11}b_{12}h_{11,t-1+} + (b_{12}a_{21} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,,t-1} \quad (7)$$

Nevertheless, as none of the above single equations solely possess their own parameters, interpretation of the parameters could be misleading even in the case of only two time series (Terrell and Fomby, 2006). On the other hand, the bivariate form of the Diagonal BEKK model is given by

$$h_{11,t} = C_{11}^2 + a_{11}^2 \varepsilon_{1\,t-1}^2 + b_{11}^2 h_{11,t-1} \quad (8)$$

$$h_{22,t} = C_{11}^2 + C_{22}^2 + a_{22}^2 \varepsilon_{2\,t-1}^2 + b_{22}^2 h_{22,,t-1} \quad (9)$$

$$h_{12,t} = h_{2,1,t} = C_{12}C_{22,} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{11}a_{12}\varepsilon_{2\,t-1}^2 + b_{11}b_{12}h_{12,t-1}$$
(10)

It can be easily noticed that in the case of the Diagonal BEKK model, the number of parameters to be estimated is very significantly reduced. So the BEKK Diagonal model is used to investigate the dynamics of volatility between commodity futures, stock market and exchange rate asset pairs. Model parameters were estimated with a maximum likelihood approach based on normal and multivariate Student's t error distributions using the BFGS algorithm.

Testing covolatility spillover effects

a) *Definitions*

Before reporting the results, we (re)introduce the notations and conventions that we use for reporting the results.

i) *Matrix A*

The matrix A is a crucial output of the model (aka the weight matrix) and shows the effect of realized shocks on the conditional covariances. (Chang, 2019)

ii) *Diagonal versus scalar*

We compare the general patterns of the spillovers rather than the actual numbers of mean partial covolatility spillovers. The term "diagonal" suggests that the (diagonal) elements of the weight matrix A are different using the diagonal BEKK model. On the other hand, "scalar" means the cells in the weight matrix A are similar for the two assets (i.e., A(i, i) for two assets are similar.) A comparison of the multiplier may be more reasonable than a comparison of the magnitude of the spillover effects.

iii) Symmetry and Asymmetry

The terms "symmetry" and "asymmetry" are also used to refer to sign patterns between two time series. If the sign of both series is the same, we use the term "symmetry"; however, if the sign of one asset is positive and the other negative (or the other way), we refer to it as the "asymmetric" case. The signs of the spillover effects are determined by the return shock in the previous period; thus, the spillover signs can vary considerably. A broad overall pattern between the assets can be shown by calculating the mean spillover effects (Chang et al., 2019)

iv) Partial *covolatility spillover*

Partial covolatility spillover measures the impact of a lagged shock to asset i on the covolatility between asset i and other assets at the current period t. It can be obtained by differentiating the matrix A with respect to the return shocks. The formal definition is:

$$\frac{\partial Q_{ij,t}}{\partial \epsilon_{i,t-1}} = A_{ii}A_{jj}\ \epsilon_{j,t} \ (11)$$

where Q is the conditional covariance matrix, A is the weight matrix, and ε is the residual. According to Mai, Te-Ke (2022), the spillover effect from market i to j is different from the spillover effect from market j to i. The difference between the two securities depends on the residuals arising from markets i and j. The mean residual value of each pair produces a different direction depending on the pair. As highlighted by Chang et al. (2018a) and Chang et al. (2019), the BEKK diagonal model can only be used to test the impact of partial covolatility. A complete BEKK model is needed to report the other two spillover notions, namely full volatility and covolatility spillovers. The partial BEKK model was chosen because of its statistical accuracy, so the impact of partial covolatility will be reported.

Optimal Portfolio Weight

Optimal portfolio weights are also constructed, with no shorting constraints, following Kroner and Ng (1998). The optimal weight of commodity futures assets in a one-dollar portfolio consisting of only A and B is

$$W_{ij} = \frac{h_{jj} - h_{ij,t}}{h_{ii,t} - 2h_{i,j,t} + h_{jj,t}} \quad (12)$$

$$if\ 0 \leq W_{ij} \leq 1$$

Finally, following Dey and Sampath (2018), the dynamic long/short hedge ratio between asset pairs is constructed as

$$\beta_{i,j,t} = \frac{h_{ij,t}}{hjj,t} \quad (13)$$

Data and variables

The data research uses quantitative data in the form of daily time series data as follows

Tabel 3. 1 Variable List

No	Variable	Description	Unit	Sumber
1	Crude oil	Crude oil futures prices NYMEX Light Sweet Crude Oil (WTI) Electronic Energy Future Continuation (CLc1)	USD per metric tonne	Thomson reutes Refinitif eikon www.refinitiv.com
2	Coal	Coal futures price ICE Europe Newcastle Coal Futures Monthly Electronic Energy Future (NCFMc1)	USD per metric tonne	Thomson reutes Refinitif eikon www.refinitiv.com
3	Crude Palm Oil	Palm Oil futures prices Bursa Malaysia Crude Palm Oil Commodity Future Continuation 3 (FCPOc3)	USD per metric tonne	Thomson reutes Refinitif eikon www.refinitiv.com
4	Indonesian stock market	Jakarta Composite Index	IDR	Thomson reutes Refinitif eikon

				www.refinitiv.com
5	Exchange rate	IDR /USD	IDR per USD	Bank Indonesia.

Volatility spillover testing is divided into 3 groups

1) before the pandemic occurred, May 20 2013-March 10 2020 (pre-pandemic), with 1628 observations
2) during the Pandemic from March 11 2020- May 11 2023 (Pandemic) with 749 observations
3) after the Pandemic from May 12 2023 to September 14 2023 (post pandemic), with 80 observations

RESULT AND DISCUSSION

The following is a descriptive statistical table using return data from oil futures commodities (CLc1/ ROIL), coal (NCFMc1/ RCOAL), Palm Oil (FCPOc3/ RPMOIL), Jakarta composite stock price index (RJKSE), and the IDR/USD exchange rate (RCURS). The return value is obtained by calculating the percentage change in the return value in one period compared to the previous period.

Table 4. 1 Data description Pre Pandemic Covid-19

Pre pandemic	RJKSE	RKURS	RCOAL	ROIL	RPMOIL
Mean	-0,0002	-0,0003	-0,0002	-0,0006	-0,0002
Median	0,0000	-0,0003	0,0000	0,0003	-0,0006
Maximum	0,0635	0,0225	0,1449	0,1162	0,0574
Minimum	-0,0765	-0,0233	-0,1298	-0,2822	-0,1104
Std. Dev.	0,0115	0,0043	0,0132	0,0233	0,0139
Skewness	-0,3672	0,2350	0,4596	-1,1716	-0,3473
Kurtosis	7,5708	7,3396	41,5439	18,5366	6,2630
Jarque-Bera	1.454	1.292	100.833	16.747	755
Probability	0,000%	0,000%	0,000%	0,000%	0,000%
Sum	-0,3068	-0,4255	-0,2806	-1,0277	-0,3338
Sum Sq. Dev.	0,2170	0,0305	0,2846	0,8838	0,3126
Observations	1628	1628	1628	1628	1628

Table 4. 2 Data description Pandemic Covid-19

Pandemi	RJKSE	RKURS	RCOAL	ROIL	RPMOIL
Mean	0,000345	3,59E-05	0,001226	-0,004006	0,00054
Median	1,48E-05	-0,000284	0,000825	0,003352	0,001686
Maximum	0,113755	0,025316	0,340572	0,319634	0,096436
Minimum	-0,093748	-0,034474	-0,432454	-3,059661	-0,12311
Std. Dev.	0,013505	0,004558	0,035674	0,127314	0,02697
Skewness	-0,17084	-0,511659	-2,263206	-19,77139	-0,33817

Kurtosis	17,45996	13,42412	54,17577	457,3328	4,382677
Jarque-Bera	6529,003	3423,852	82372,77	6490768	73,93983
Probability	0,0000%	0,0000%	0,0000%	0,0000%	0,0000%
Sum	0,258225	0,026899	0,918482	-3,000241	0,404645
Sum Sq. Dev.	0,136425	0,015539	0,951922	12,12416	0,544092
Observations	749	749	749	749	749

Table 4. 3 Data description *Post Pandemic Covid-19*

pandemi	RJKSE	RKURS	RCOAL	ROIL	RPMOIL
Mean	-0,00026	-0,000466	-0,000507	0,002648	-0,00043
Median	0	-6,65E-05	0	0,005116	-0,00248
Maximum	0,013458	0,007077	0,145129	0,046904	0,063958
Minimum	-0,011961	-0,006396	-0,169159	-0,045178	-0,06445
Std. Dev.	0,00519	0,002492	0,030544	0,01943	0,022654
Skewness	0,097963	0,218319	-0,708627	-0,30715	0,028477
Kurtosis	2,554794	3,213174	18,70023	2,676027	3,180068
Jarque-Bera	0,808367	0,806659	849,0618	1,647939	0,121867
Probability	66,75%	66,81%	0,00%	43,87%	94,09%
Sum	-0,021307	-0,038239	-0,041583	0,217172	-0,03491
Sum Sq. Dev.	0,002182	0,000503	0,075566	0,030581	0,041571
Observations	82	82	82	82	82

Table 4.1-Table 4.3 shows the mean return results for all variables are negative. In contrast, during the Covid-19 pandemic, all mean returns were positive except ROIL, and after pandemic 19 only ROIL produced a positive mean return. The absolute value of mean returns in all markets is close to zero. The standard deviation during the pandemic in almost all markets was higher than before the COVID-19 Pandemic. In contrast, after the Covid 19 pandemic the standard deviation for all assets decreased compared to during the pandemic. Still, the standard deviation during the post pandemic in RCOAL, ROIL and RPMOIL increased compared to the standard deviation during the pre-pandemic Covid 19.

Standard deviation can show that market volatility has increased compared to before the COVID-19 pandemic. This proves that after the crisis, volatility increased. The kurtosis statistic that compares the peak and bottom of a probability distribution with a normally distributed series shows that all levels of the variable are low-topped and thin-tailed (platykurtic). However, all return variables are high-topped and fat-tailed (leptokurtic). This means that the possibility of outliers occurring is higher compared to a normal distribution. The Jarque-Bera statistic (Jarque and Bera, 1980) which measures the normality of distributions using skewness and kurtosis statistics shows that the null hypothesis of normality can be rejected for all sets of levels and returns at specific levels of significance.

The Jarque Bera value indicates that the return data is not normally distributed because the value is far from zero with a kurtosis value far above 3 (normal distribution. However, after the pandemic the kurtosis in JKSE, ROIL, RKURS and RPMOIL is around 3 so it is close to a normal distribution.

From the data above, RCOAL had a maximum return before the Covid 19 pandemic and ROIL had a minimum return. Meanwhile, during the Covid 19 pandemic, RCOAL still provided the highest returns and the lowest ROIL, while after the Covid 19 pandemic, RCOAL still had the highest and lowest maximum values.

Positive values of the skewness statistic indicate less likelihood of large declines in the variable for both the rate series and the return series over the study period. During the pre-pandemic skewness, all variables were negative except KURS and RCOAL. During the pandemic, all were negative and after the pandemic, only RKURS and RJKSE were positive.

Table 4. 4 Tabel Unit Root Test

		pre pandemic			
variable	ADF	critical value 1%	critical value 5%	critical value 10%	prob
RKURS	-34.8541	-3.9640	-3.4127	-3.1283	0.0000
RJKSE	-35.0605	-3.9639	-3.4127	-3.1283	0.0000
RCOAL	-35.0884	-3.9639	-3.4127	-3.1283	0.0000
ROIL	-41.8922	-3.9639	-3.4127	-3.1283	0.0000
RPMOIL	-38.2770	-3.9639	-3.4127	-3.1283	0.0000
		pandemic			
variable	ADF	critical value 1%	critical value 5%	critical value 10%	prob
RKURS	-17.2551	-3.9760	-3.4186	-3.1318	0.0000
RJKSE	-20.8701	-3.9759	-3.4185	-3.1318	0.0000
RCOAL	-22.1861	-3.9759	-3.4185	-3.1318	0.0000
ROIL	-18.2651	-3.9759	-3.4186	-3.1318	0.0000
RPMOIL	-23.4421	-3.9759	-3.4185	-3.1318	0.0000
		Post pandemic			
variable	ADF	critical value 1%	critical value 5%	critical value 10%	prob
RKURS	-16.7578	-3.9827	-3.4219	-3.1337	0.0000
RJKSE	-20.5920	-3.9825	-3.4218	-3.1337	0.0000
RCOAL	-19.2472	-3.9825	-3.4218	-3.1337	0.0000
ROIL	-13.6146	-3.9827	-3.4218	-3.1337	0.0000
RPMOIL	-18.8500	-3.9825	-3.4218	-3.1337	0.0000

The unit root test (ADF test) in table 4.4 shows the rejection of the null hypothesis of the unit root in all return series. The ADF test accommodates serial correlation by explicitly determining the faulty serial correlation structure. The null hypothesis of the ADF test is that the series has a unit root. In Table 3, based on the ADF test results, large negative values in all cases indicate rejection of the unit root null hypothesis at the 1% significance level. Therefore, all series of returns are stationary. The stationary test was carried out on price differentiation, the test results showed that the Exchange Rate, JKSE, RCOAL, ROIL, RPMOIL data were stationary.

Table 4. 5 Stochastik test : ARCH-LM test

The Stochastic tes: ARCHLM test	RJKSE	RKURS	RCOAL	RPMOIL	ROIL
PrePandemic	52.3304*	182.6523*	0.7202	14.9274*	88.7065*
Pandemic	19.7977*	74.6812*	0.0015	6.5943*	0.2850
Post Pandemic	0.7232	7.2304*	17.5179*	11.2834*	2.0091*

* denotes significance level 5%

Before applying the diagonal BEKK model, a preliminary test is performed to ensure that some ARCH effect (i.e. volatility clustering) is present in the data. The results presented in Table 4.5 support the existence of an ARCH effect. All variables show rejection of the null hypothesis except for coal during pre-pandemic, pandemic crude oil during post-pandemic and JKSE during pre-pandemic. However, when analyzed using the ARCH method, there is a significant residual variance with probability <0.05, as well as ROIL and RJKSE. So, the BEKK GARCH diagonal model can be continued.

Correlation Structure

Table 4. 6 *Return Correlation* Pre Pandemic, Pandemic, Post Pandemic Covid 19

Return Correlation Pre Pandemic Covid 19					
	RCOAL	ROIL	RPMOIL	RKURS	RJKSE
RCOAL	1,0000				
ROIL	0,0064	1,0000			
RPMOIL	0,0270	0,1416	1,0000		
RKURS	(0,0161)	(0,0107)	0,0023	1,0000	
RJKSE	0,0550	0,1304	0,1753	0,0521	1,0000
Return Correlation Pandemic Covid 19					
	RCOAL	ROIL	RPMOIL	RKURS	RJKSE
RCOAL	1,0000				
ROIL	0,0622	1,0000			
RPMOIL	0,0245	0,0839	1,0000		
RJKSE	0,0114	0,0620	0,1703	1,0000	
RKURS	0,0102	0,0383	0,0855	0,1673	1,0000
Return Correlation Post Pandemic Covid 19					
	RCOAL	ROIL	RPMOIL	KURS	JKSE
RCOAL	1,0000				
ROIL	0,1090	1,0000			
RPMOIL	0,1145	0,1167	1,0000		
RKURS	(0,2517)	(0,0902)	0,0749	1,0000	
RJKSE	0,1495	0,1905	0,0891	(0,1862)	1,0000

Table 4.6 is the return correlation of 5 variables during pre-pandemic, pandemic and post-pandemic Covid 19. Negative correlation is found in RCOAL with ROIL, ROIL with RKURS. Meanwhile, during the Covid 19 pandemic, all correlations were positive and after the pandemic, the correlation between RCOAL and RKURS and ROIL and RKURS returned to negative. The correlation value for each pair of assets is close to zero, generally between -0.1 to +0.1, so the variables are said to have no linear relationship (or a very weak linear relationship).

Volatility Spillover Effects

To estimate and test the impact of volatility spillover effects, conditional covariance must be calculated using the Diagonal BEK model from matrices A and B. The estimated value of the GARCH coefficient (Bi2) shows the level of volatility persistence. The estimated ARCH coefficient (Aii2) shows that news/shocks in an asset in ROIL, RCOAL, RPMOIL, RKURS and RJKSE in the future, while the importance of the estimated GARCH coefficient shows that the persistence of shocks also influences the future volatility of these two asset prices. Similar results are obtained for the conditional covariance of both assets, which is significantly affected by the news/surprise cross-product and the prior covariance terms.

In table 4.7 are the A and B matrices during the pre-pandemic period using the BEKK Diagonal and models. In table 4.7, all matrix coefficients have significant values, the value of matrix B is higher than matrix A, which shows that unconditional shocks and conditional covariance do not have the same impact. Matrix A in RCOAL and RKURS provides the greatest value compared to other pairs, while in Matrix B the largest is the pair RPMOIL against RKURS. The largest GARCH coefficient comparison during the pre-pandemic period was OIL_COAL, while the smallest was RCOAL_RPMOIL, where RPMOIL had a B matrix value that was greater than RCOAL. In table 4.8 are matrices A and B during the pandemic using the BEKK Diagonal model. From this table, it is found that all coefficients A and B are significant.

Comparison is easier than calculating the value of the spillover impact. If A(I,i) of two assets are similar, this is called a “scalar” effect while Diagonal” states that the elements of the weight matrix A are not congruent, and the weights have also been estimated with the diagonal BEKK model. Diagonal” and “scalar” describe the similarity of multipliers.

Based on (McAleer, 2008) matrix A is a critical model parameter because it provides a symmetric and asymmetric interpretation of the weights for return shocks. The value of A(I,i) cannot be directly interpreted as the magnitude of the impact of volatility spillover because this value has not been multiplied by the return shock and other asset weights. According to Mai, Te-Ke (2022), the spillover effect from market I to j is different from the spillover effect from market j to i. The difference between the two securities depends on the residuals arising from markets I and j. The mean residual value of each pair produces a different direction depending on the pair.

N table 4.9 is a post-pandemic A and B matrix table. From this table, no significant coefficient A was found, and coefficient B was negative, so it was not significant, so no volatility spillover was found after the Covid 19 pandemic. No significant coefficients A and B were found. During the post-pandemic period, this is possible because conditions are stable after the release of the Covid pandemic status in May 2023. During the pandemic, although at first there was turmoil, there were economic stimulus policies from the government and the world so that the financial situation could immediately stabilize.

Table 4. 7 Diagonal BEKK model (Matrix A and B) Pre Pandemic Covid 19

	A1	Std Error	PROB	A2	Std Error	PROB	B1	Std Error	PROB	B2	Std Error	PROB	A1/A2	Sign
ROIL_RCOAL	0,31*	0,04	0,000	0,23*	0,03	0,000	0,98*	0,00	0,000	0,95*	0,01	0,000	1,31	S
ROIL_RJKSE	0,23*	0,02	0,000	0,20*	0,02	0,000	0,97*	0,00	0,000	0,97*	0,00	0,000	1,13	S
ROIL_RKURS	0,20*	0,02	0,000	0,34*	0,02	0,000	0,98*	0,00	0,000	0,94*	0,01	0,000	0,59	S
ROIL_RPMOIL	0,24*	0,02	0,000	0,19*	0,03	0,000	0,97*	0,00	0,000	0,97*	0,01	0,000	1,24	S
RCOAL_RJKSE	0,13*	0,01	0,000	0,26*	0,02	0,000	0,98*	0,00	0,000	0,96*	0,01	0,000	0,49	D
RCOAL_RKURS	0,21*	0,03	0,000	0,54*	0,07	0,000	0,96*	0,01	0,000	0,94*	0,01	0,000	0,40	D
RCOAL_RPMOIL	0,20*	0,02	0,000	0,28*	0,05	0,000	0,95*	0,01	0,000	0,96*	0,01	0,000	0,73	S
RPMOIL_RJKSE	0,19*	0,03	0,000	0,25*	0,02	0,000	0,97*	0,01	0,000	0,96*	0,01	0,000	0,75	S
RPMOIL_RKURS	0,17*	0,02	0,000	0,35*	0,02	0,000	0,98*	0,01	0,000	0,93*	0,01	0,000	0,47	D
RKURS_RJKSE	0,27*	0,02	0,000	0,22*	0,02	0,000	0,96*	0,01	0,000	0,97*	0,01	0,000	1,22	S

* denotes significance level 5% , S(D) denotes scalar (diagonal)multipliers

Table 4. 8 Diagonal BEKK model (Matrix A and B) Pandemic Covid 19

	A1	Std Error	PROB	A2	Std Error	PROB	B1	Std Error	PROB	B2	Std Error	PROB	A1/A2	
ROIL_RCOAL	0,72*	0,22	0,000	0,87*	0,25	0,000	0,84*	0,03	0,000	0,77*	0,03	0,000	0,84	S
ROIL_RJKSE	0,44*	0,07	0,000	0,39*	0,06	0,000	0,80*	0,03	0,000	0,91*	0,02	0,000	1,15	S
ROIL_RKURS	0,48*	0,06	0,000	0,16*	0,03	0,000	0,80*	0,03	0,000	0,98*	0,00	0,000	2,96	D
ROIL_RPMOIL	0,67*	0,07	0,000	0,31*	0,05	0,000	0,93*	0,01	0,000	0,93*	0,02	0,000	2,16	D
RCOAL_RJKSE	0,61*	0,09	0,000	0,27*	0,07	0,000	0,78*	0,03	0,000	0,96*	0,01	0,000	2,28	D
RCOAL_RKURS	0,76*	0,14	0,000	0,22*	0,06	0,000	0,77*	0,03	0,000	0,99*	0,00	0,000	3,42	D
RCOAL_RPMOIL	0,57*	0,08	0,000	0,29*	0,08	0,000	0,77*	0,03	0,000	0,96*	0,02	0,000	1,93	D
RPMOIL_RJKSE	0,32*	0,05	0,000	0,20*	0,03	0,000	0,91*	0,03	0,000	0,95*	0,01	0,000	1,58	D
RPMOIL_RKURS	0,30*	0,05	0,000	0,19*	0,02	0,000	0,92*	0,02	0,000	0,97*	0,00	0,000	1,60	D
RKURS_RJKSE	0,18*	0,02	0,000	0,21	0,04	0,000	0,98*	0,00	0,000	0,95*	0,01	0,000	0,84	S

Table 4. 9 Diagonal BEKK model (Matrix A and B) Post Pandemi Covid 19

	A1	Std Error	PROB	A2	Std Error	PROB	B1	Std Error	PROB	B2	Std Error	PROB	A1/A2
ROIL_COAL	0,13	0,39	0.737	0.18	0.304	0.549	0.86	0,55	0.211	0.873	0.30	0.004*	0,13
ROIL_JKSE	0,24	0,22	0.273	0.30	0.391	0.442	0.91	0,44	0.000	0.544	0.89	0.541	0,24
ROIL_KURS	-0,29	0,23	0.199	0.55	0.207	0.008*	0.91	0,01	0.000*	0.178	0.73	0.809	-0,29
ROIL_PMOIL	0,31	0,41	0.447	0.21	0.208	0.315	0.38	0,31	0.761	0.962	0.08	0.000*	0,31
RCOAL_JKSE	0,29	0,25	0.244	0.60	0.489	0.219	0.78	0,22	0.009	-0.596	0.71	0.404	0,29
RCOAL_KURS	0,18	0,23	0.427	0.53	0.223	0.016	0.88	0,02	0.000	0.356	0.64	0.578	0,18
RCOAL_PMOIL	0,16	0,08	0.049*	-0.15	0.144	0.305	0.93	0,31	0.000	1.057	0.10	0.000*	0,16
RPMOIL_JKSE	-0,39	0,24	0.110	0.46	0.266	0.085	-0.33	0,09	0.765	0.590	0.45	0.186	-0,39
RPMOIL_KURS	-0,37	0,22	0.093	0.65	0.252	0.010	0.43	0,01	0.732	-0.221	0.88	0.802	-0,37
RKURS_JKSE	0,44	0,19	0.022*	-0.23	0.297	0.437	0.52	0,44	0.461	0.786	0.83	0.345	0,44

* denotes significance level 5% , S(D) denotes scalar (diagonal)multipliers

Table 4. 10 Diagonal BEKK mean return shocks for stocks and commodities (2x2)

	R_Oil	R_COAL	R_PMOIL	R_KURS	R_JKSE
pre pandemi	0,2223%	-0,0008%	0,0034%	-0,0028%	-0,0333%
pandemi	-0,5123%	0,0114%	-0,0893%	0,0210%	-0,0227%

post pandemic	-	-	-	-	-

Table 4.10 shows the mean return shock, which shows the direction of the mean covolatility spillover. Mean return shock (ε_t) is used to determine the interpretation of symmetric or asymmetric matrix A as well as matrix multiplication (A1.A2. ε_t). The table shows that the spillover of i on j can be compared with the spillover of j on i. Sym means the covolatility spillover multiplier is the same, and the market is moving in the same direction. Meanwhile, the overflow multiplier Asym has different values and the two assets move in opposite directions.

Table 4. 11 *Covolatility Spillover* PrePandemic and Pandemic

Asset Pairs	***Covolatility* Spill over A1.A2.E**		**Change**	**Directional Patterns of *Covolatility* Spillover**	
	Pre Pan-demi	**Pandemi**	**Pan-demi /pre-pandemi**	**Pre Pan-demi**	**Pandemi**
ROIL_RCOAL	0,0159%	-0,3213%	decrease	Asym	Asym
RCOAL_ROIL	-0,0001%	0,0071%	decrease		
ROIL_RJKSE	0,0102%	-0,0874%	decrease	Asym	Sym
RJKSE_ROIL	-0,0015%	-0,0039%	decrease		
ROIL_RKURS	0,0156%	-0,0397%	decrease	Asym	Asym
RKURS_ROIL	-0,0002%	0,0016%	Increase		
ROIL_RPMOIL	0,0102%	-0,1051%	decrease	Sym	Sym
RPMOIL_ROIL	0,0002%	-0,0183%	decrease		
RCOAL_RJKSE	0,0001%	0,0019%	Increase	Sym	Asym
RJKSE_RCOAL	-0,0011%	-0,0038%	decrease		
RCOAL_RKURS	-0,0001%	0,0019%	Increase	Sym	Sym
RKURS_RCOAL	-0,0003%	0,0035%	Increase		
RCOAL_RPMOIL	0,0000%	0,0019%	Increase	Asym	Asym
RPMOIL_RCOAL	0,0002%	-0,0148%	decrease		
RPMOIL_JKSE	0,0002%	-0,0057%	decrease	Asym	Sym
RJKSE_RPMOIL	-0,0016%	-0,0015%	decrease		
RPMOIL_RKURS	0,0002%	-0,0050%	decrease	Asym	Asym
RKURS_RPMOIL	-0,0020%	0,0012%	Increase		
RKURS_RJKSE	-0,0002%	0,0008%	Increase	Sym	Asym
RJKSE_RKURS	-0,0021%	-0,0009%	decrease		

From table 4.11 shows the covolatility spillover from crude oil to coal, crude oil to palm oil, crude oil to the exchange rate, and crude oil to the Indonesian stock market, coal to palm oil, coal to the exchange rate, coal to stock market, palm oil to exchange rate, palm oil to Indonesian stock market is significant and vice versa during pre-pandemic and pandemic times.

It should be emphasized that the covolatility spillover effects from market i to market j are different from the spillover effects from market j to i. The difference between these two effects depends on the residuals arising from markets i and j. From Table 4.11 you can see the mean residual shocks which can help to understand covolatility spillover effects. The ROIL and RPMOIL variables had a positive mean residual value during the pre-pandemic period but negative during the pandemic. Meanwhile, the mean residual RCOAL and RKURS were positive during the pandemic. The results of the covolatility spillover

calculation are in table 4.11. It can be seen that those with positive spillover covolatility are ROIL pairs, namely ROIL with RCOAL, ROIL and RKURS, ROIL and RPMOIL, ROIL and RJKSE and RPMOIL pairs, RPMOIL with ROIL, RPMOIL with RCOAL, RPMOIL with RKURS and RPMOIL with RJKSE, the rest is covolatility negative value during the pre-pandemic period. Meanwhile, for the pandemic, the RCOAL and RKURS pairs have positive covolatility such as RCOAL with ROIL, RCOAL with RJKSE, RCOAL with RKURS, RCOAL with RPMOIL, and RKURS with ROIL, RKURS with RCOAL, RKURS with RPMOIL and RKURS with RJKSE.

The spillover impact of COVID-19 is enormous compared to before and after COVID-19. For example, the partial covariance effect from RCOAL to RPMOIL during COVID-19 is 0.0019%, which is about 19 times larger than the pre-COVID-19 value of 0.001%. Another example is the partial covariance effect from RCOAL to ROIL, which was close to zero before COVID-19 but was −0.0001% during COVID-19. Table 4.23 shows that there was an increase in covolatility spillover during the pandemic in the asset pairs RKURS_ROIL, RCOAL_RJKSE, RKURS_RCOAL, RCOAL_RKURS, RCOAL_RPMOIL, RKURS_PMOIL, RJKSE_RKURS while the rest experienced a decrease. The increase in covolatility indicates that, during the COVID-19 period, commodity futures markets experienced significant uncertainty and shocks, which caused a much larger partial volatility spillover impact.

In the post-pandemic period, no covolatility spillover was found due to the fact that significant A and B coefficients were not found during the post-pandemic period. This is possible because conditions were stable after the release of the Covid pandemic status in May 2023.

Table 4. 12 Skalar dan Diagonal Bekk dan return shock saat Pre Pandemi (pasan-gan 2x2)

Prepandemi	**ROIL**	**RCOAL**	**RPMOIL**	**RKURS**	**RJKSE**
ROIL					
RCOAL	S,Asym				
RPMOIL	S,Sym	S,Asym			
RKURS	S,Asym	D,Sym	D,Asym		
RJKSE	S,Asym	D,Sym	S,Asym	S,Sym	

Table 4. 13 Skalar dan Diagonal Bekk dan Tanda Return Shocks (pasangan 2x2) Pandemi

Pandemi	**ROIL**	**RCOAL**	**RPMOIL**	**RKURS**	**RJKSE**

ROIL				
RCOAL	S,Asym			
RPMOIL	D,Sym	S,Asym		
RKURS	D,Asym	D,Sym	D,Asym	
RJKSE	S,Sym	D,Asym	D,Sym	S,Asym

Source: processed researcher (2023)

Table 4.12 is obtained from a combination of table 4.7 with table 4.11 when there is a return shock from asset i in table 4.10. The results of the partial covolatility spillover pair are scalar, where matrix A1 and Matrix A2 have almost the same value, giving a mean covolatility spillover effect with comparable values. The meaning of sym is symmetry and Asym is the asymmetry of the sign pattern between two time series. Sign asymmetry shows that two assets have different signs. Therefore, on average, the two spillovers between i and j have different effects in different directions. Asymmetry shows signs that these two markets can be used as portfolio hedging as a spillover effect that moves in different directions.

During the pre-pandemic period, the values that showed asymmetry were ROIL_RCOAL, ROIL_RKURS, ROIL_RJKSE, R_COAL_RPMOIL, R_PMOIL_RKURS, and RPMOIL_RJKSE from this pair of variables, showing that these assets can function as hedging because the covolatility spillover moves in the opposite direction.

In table 4.13, during the pandemic, the pairs ROIL_RCOAL, ROIL_RKURS, RCOAL_RPMOIL, RCOAL_RJKSE, RPMOIL_RKURS and RJKSE_RKURS have direction asymmetry. The total number of asymmetrical couples before and during the pandemic was 6 pairs. 4 pairs have asymmetry from before the pandemic to the pandemic, namely ROIL_RCOAL, ROIL_RKURS, RCOAL_RPMOIL, RPMOIL_RKURS, which shows that these assets both before the pandemic and during the pandemic are useful as hedging.

CONCLUSION

Based on the research results and discussion, it can be concluded that: 1. The covolatility spillover effect pattern that has asymmetric pairs both before and during the Pandemic is ROIL_RCOAL, ROIL_RKURS, RCOAL_RPMOIL, RPMOIL_RKURS. The sign of asymmetry indicates that the two markets as a hedge portfolio, due to their spillover effects, move in different directions. These results support previous findings that coal has a positive and real connection between coal, other energy sources, and the US dollar, especially between energy and the US equity market (Zolfaghari et al., 2020) so that it can be useful for hedging, but in research, This also found a positive relationship between the IDR/USD exchange rate and the Indonesian commodity market and stock market during the Covid 19 pandemic. Meanwhile, Crude Oil and CPO had a positive relationship before the COVID-19 pandemic. After the COVID-19 pandemic, no volatility spillover was found. This is possible because the condition is stable. 2. Increased covolatility spillover between crude oil, coal, palm oil futures, exchange rates and the Indonesian stock market compared to the period before the Covid 19 pandemic can be found in the assets RKURS_OIL, RCOAL_JKSE, RKURS_RCOAL, RCOAL_KURS, RCOAL_PMOIL, RKURS_PMOIL, RJKSE_KURS. This reinforces that the exchange rate increases spillover volatility in commodity futures and stock markets. 3. Through optimal portfolio weights and hedge ratios, coal and palm oil futures commodities can overcome risk exposure from volatility spillovers between the crude oil, coal, palm oil as futures commodity markets, exchange rates and the Indonesian stock market, which have higher volatility especially during the Covid 19 pandemic. Pairs that can be a good hedge are RCOAL_RPMOIL, RPMOIL_RKURS, ROIL_KURS.

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