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Asymmetric Volatility Spillover and Risk Contagion During the COVID-19 Outbreak: Empirical Investigation from the Indonesian and Global Stock Markets

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ABSTRACT

This paper shows evidence of a dramatic change in the structure and time-varying patterns of volatility connectedness between Indonesian and global stock market volatility during the COVID-19 outbreak. The Diebold-Yilmaz volatility spillover. The dynamic total connectedness across the stock market was moderate and relatively stable until early 2020. After that, the real connectedness spikes, and the direction of connectedness alters, which concurs with the COVID-19 outbreak. DJIA and EURO indices were the primary transmitters of shocks before the pandemic, whereas JKSE became the primary transmitter of shocks during the COVID-19 pandemic. Even though JKSE was a robust transmitter during the COVID-19 outbreak, the connection with DJIA warrants close and regular observation due to the very high spillover. The COVID-19 episode had immediate and unsettling impacts, which are essential for formulating policies to achieve financial stability. The findings are also very important not only for investors but also for policymakers.

Keywords: Asymmetric spillover, Diebold-Yilmaz, COVID-19, Stock market, Volatility.

1. INTRODUCTION

The unpredictable impact of the COVID-19 pandemic has affected all lines of people's lives, including the financial services sector. The COVID-19 pandemic in financial markets has increased volatility, uncertainty, complexity, and ambiguity (VUCA), thereby increasing investment risk [1]. The COVID-19 pandemic caused an unprecedented volatility phenomenon. The value of the CBOE Volatility Index (VIX) as the proxy of the global market volatility index soared by more than 80 on March 16, 2020, surpassing the global crisis of 2008 [2]. The phenomenon is becoming a public concern, prompting the Indonesian Financial Services Authority (OJK) to take action to maintain the stability of the financial services sector.

The collapse of the international stock market due to the COVID-19 pandemic began on February 20, 2020. From February 24 to 28, 2020, the global stock market experienced its most significant decline in a week since the 2007–2008 financial crisis, and these unstable conditions continued until early March 2020. On March 9, most global markets reported severe contractions caused by the COVID-19 pandemic and the oil price dynamic in Russia and the OPEC countries. On that date, the Dow Jones Industrial Average (DJIA) index declined by 13% daily, the most extensive correction since October 1987. In addition, the S&P 500 and Nasdaq Composite indexes also experienced significant daily declines of 12% and 12.3%, respectively. This condition was later analogous to Black Monday 2020 [3],[4].

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Meanwhile, the shocks that occurred in the global financial market ultimately affected Indonesia's financial market, especially in the stock markets. The downward trend in Indonesian stock prices has occurred since mid-February 2020. On March 9, 2020, the Indonesian composite stock price index (JKSE) decreased by 6.6% in one day. This condition is inseparable from the influence of international stock market shocks that were turbulent due to the COVID-19 pandemic. The impact of COVID-19 varies significantly between countries. This condition depends on the policies of local authorities and investors' expectations of each stock market [5], [6].

There are differences in responses in some stock markets to the impact of COVID-19, implying an asymmetric effect of COVID-19 on stock movements, especially in Indonesia. Therefore, understanding the interconnectedness of the global stock market is crucial for investors to make informed investment decisions [7]. This study will empirically investigate the connectedness of the Indonesian stock market with the stock markets in other countries, especially concerning risk contagion and volatility spillover between these stock indices.

Previous research on risk contagion, volatility spillover, and the connectedness of various stock prices has primarily employed conventional and standard analytical methods. Only a limited number of papers address the problem of asymmetric and non-linear relationships that are intuitively associated with stock price movements. This paper will explore the issue of volatility spillover of the Indonesian and global markets in the COVID-19 period based on Diebold and Yilmaz [8], [9]. The advantage of the Diebold-Yilmaz approach is that it can measure the total volatility of the spillover [10], [11], and its dynamics over time in the direction of the spillover volatility.

The primary objective of this study is to examine the asymmetric impact of the COVID-19 pandemic on Indonesian and global stock markets, as well as to assess the risk spillover and contagion between the Indonesian market and global stock markets, both pre- and post-COVID-19.

This research is arranged into five parts. The following section presents a literature review in the form of relevant theories and previous research. Section 3 describes the data and methods used in the study. Section 4 presents the results of the research and discusses the appropriate arguments. Finally, section 5 summarizes the key elements, provides a framework for policy implications, and concludes the study's results.

2. LITERATURE REVIEW

2.1 Theory

The integration and interdependence of international financial markets are increasing from time to time. Therefore, the transmission of financial market volatility between markets is becoming increasingly important and interesting to observe. Volatility transmission encourages risk transmission mechanisms that can weaken financial market stability.

Volatility information is inseparable from the media's role, such as the liberalization of capital movements worldwide, the diversification of production between countries by multinational companies, deregulation in financial markets and institutions, and the fall in the cost of international economic transactions due to increasing up-to-date information technology [12], [13].

Shocks that occur in one stock market can affect other stock markets. This event is due to several things, including:

a) Dominant economic power: after the onset of World War II, the United States became the most influential country in the economy. This state is caused by the U.S. currency (U.S. dollar) being dominant in international trade. Research conducted by Achsani and Strohe [14] also found that the U.S. stock market has a powerful influence on the stock markets globally, including on the stock markets of the European and Asian regions.

b) Common investor groups: geographically adjacent countries typically have the same investment destination group, so those markets will influence each other.
c) Multiple stock listing: when a stock is traded in several markets, shocks in one market can be transmitted to other markets.

Advances in technology and improvements in information processes worldwide provide convenience and efficiency to international transactions, especially in the financial sector. At the same time, the liberalization of capital and securities movement in the stock market has increased sharply, enabling the national stock market to react quickly to new information from the international market.

Trends in the stock market allow for the transmission of volatility between markets [15]. They were investigating what happened in October 1987. Most stock markets fell simultaneously in that period despite varying economic conditions. The investigation constructed a model that "contagion" between markets results from rational agents' efforts to price changes in other markets. This condition indicates that an "error" in one market can be transmitted to another, also known as *the contagion effect*.

2.2 Empirical study

Liu and Pan [16] conducted research on *mean returns* and the effect of volatility *spillovers* from the United States and Japan on four Asian stock markets, including Hong Kong, Singapore, Taiwan, and Thailand. This study used the GARCH model to test *mean returns* and *volatility spillovers*. The result is that ARMA (1.1)-GARCH (1.1) is a fit model for describing data. In addition, there is a fact about the instability of the *mean international return* and the volatility transmission after the October 1987 stock market crisis. The United States market has become more influential than Japan in transferring returns and volatility to Asian markets. Liu et al. [17] conducted research to test the structure of international transmission on the daily *returns* of six national stock markets, including the United States, Japan, Hong Kong, Singapore, Taiwan, and Thailand. The analysis of the interaction structure among the six stock markets is based on the vector-autoregressive analysis (VAR) introduced by Sims [18]. VAR is used to test the *dynamic structure* of international transmission on the stock market for the six countries. The results showed that the United States market played a dominant role in influencing the Pacific-Basin market; Japan and Singapore also had a persistent, significant effect on the Asian market.

Veiga and McAleer [19] explored the influence of volatility between *mature* stock markets worldwide and investigated the relationship between the stock markets of the United States, the United Kingdom, and Japan. The study results showed that the three markets influence each other's volatility. The United States stock market had the most significant influence in transmitting volatility from these three markets. In addition, Liu et al. [17] found that Japan, Hong Kong, Singapore, and the U.S. influence each other and significantly impact the Asian market.

The research conducted by Miyakoshi [20] used the EGARCH bivariate method to see the influence of the United States and Japanese stock markets on Asian stock markets, including Indonesia. This study showed that the United States stock market has a dominant force on the *stock returns* of several Asian stock markets. Unlike the case of volatility, the Japanese stock market had a dominant influence on stock *returns* in several Asian stock markets. In addition, the study found that Japanese stock markets and Asian markets exhibit mutual volatility.

Spillover volatility of asset *returns* on Asian stock markets has received significant attention in the economic literature since the Asian financial crisis of 1997-1998. investigating the transmission of volatility *returns* in three Asian stock markets, namely Hong Kong, South Korea, and Thailand, using the multivariate models GARCH and VAR [21]. The study's results revealed Hong Kong's essential role in transmitting volatility in a reciprocal direction for other Asian stock markets. In contrast, the volatility transmission from South Korea to Thailand is one-way. Research concerning the spillover effect of volatility on asset returns was conducted according to the spillover volatility effect [22]. The VAR-GARCH model is used in several Asian countries, such as India, Hong Kong, South Korea, Japan, Singapore, and Taiwan. The study results concluded that the spillover effect of volatility between stock markets in the six countries exists significantly.

Diebold and Yilmaz [8] measured the *volatility spillovers* of financial markets using VAR, where the FEVD does not change with the order of variables. *Volatility spillovers* are measured in total and partial pairs against each financial market. In addition, the direction of the *spillover effect* is calculated in both complete and partial forms. The advantage of this approach lies in its dynamic spillover model, which outperforms other static models that fail to account for time variations. The results showed that despite significant volatility fluctuations in all four markets during the sample, *cross-market spillovers* were quite limited until the global financial crisis, which began in 2007. As the crisis intensified, *a spillover from the stock market to other markets occurred following* the collapse of Lehman Brothers in September 2008.

Research conducted by Shahzad et al. [24] and Zhang et al. [25] related to *Asymmetric Risk Spillover* in China. This study employed a vector autoregressive (VAR) model, utilizing financial sector stock price indices and ten sectoral stock indices in China as variables. This research shows that financial sector stocks in China have a complex *spillover effect* in dealing with the impact of financial risks. During the COVID-19 period, *adverse* shocks have a more significant influence than positive *shocks*.

3. MATERIAL AND METHODS

3.1 Data

The data used in this study is daily data from October 2018 to March 2021, with data sources from the Indonesia Stock Exchange (IDX) and Bloomberg. The research variables are the stock price index of Indonesia and other countries. Indonesia is represented by the Jakarta Composite Index (JKSE). Meanwhile, the global stock price index expresses the movement of international stock prices. In this study, the Dow-Jones stock price index (DJIA) was used to describe the United States, the Euro stock price index (EURO) to represent Europe, the Singapore stock price index (MSCI) as a proxy to define the share price of the ASEAN Region, and the Nikkei stock price index (NIKKEI) to represent stock indices in East Asia. In the analysis process, all variables are expressed in the form of daily volatility, allowing the entire discussion in this paper to focus on the daily fluctuations of *spillover* between variables.

3.2 Methodology

Volatility is challenging, so a proxy is needed to measure volatility. If the conditional mean is zero, the squared return gives an unbiased estimator that correctly underlies the volatility process. Therefore, volatility in the stock market is often observed by looking at variations in returns from stock prices. The approach used to measure volatility based on variations in returns from stock prices in this study is fromParkinson's (1980), which states the interpretation of the return based on the highest (P_{it}^{max}) and lowest prices (P_{it}^{min}). Parkinson's volatility ($\hat{\sigma}_{it}^2$) calculated using the following formula:

$$\hat{\sigma}_{it}^2 = 0.361[\ln(P_{it}^{max}) - \ln(P_{it}^{min})]^2 \quad (1)$$

So that the daily volatility ($\hat{\sigma}_{it}$) is

$$\hat{\sigma}_{it} = 100\sqrt{365.\hat{\sigma}_{it}^2} \quad (2)$$

The examination of the interconnectedness between the variables analyzed and measured the spillover that occurs. This study adopts the *spillover* approach developed by Diebold and Yilmaz [8],[9]. The *spillover* approach from Diebold and Yilmaz, according to the original design of the *generalized vector autoregressive* (VAR) model used to calculate *forecast error variance decomposition* (FEVD). This approach has many advantages over other *spillover* techniques developed previously. First, the results are independent of the variable order, as they do not utilize the *Cholesky* factor identification of the VAR model. Secondly, it allows tracking the connectedness at different levels, ranging from pairs to the whole system of equations, coherently and consistently with each other. In addition, this *spillover* model is dynamic compared to other static models that fail to account for variations in time.

The decomposition of the variety associated with an N-variable VAR can explain the spillover between variables. Diebold and Yilmaz [8],[9] focused on total spillover within a simple VAR framework, but by measuring directional spillovers within a general VAR framework, they eliminate the possibility of dependents. Consider the N-stationary variable covariance VAR(p), $x_t = \sum_{i=1}^{p} \emptyset_i\, x_{t-i} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$ is independently distributed and has an identical shock vector. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i\, \varepsilon_{t-i}$ where matrix A_i And coefficients, NxN obey the recourse $A_i = \emptyset_1 A_{i-1} + \emptyset_2 A_{i-2} + \cdots + \emptyset_p A_{i-p}$ A_0 transformed as an identity matrix NxN with $A_i = 0$ for i < 0. The *moving average* coefficient is the key to understanding the dynamic system. Decomposition of the variance allows for parsing the approximate error variance of each variable into parts caused by various shocks to the system.

To calculate the *spillover* between variables, the part of the variable variance itself is defined as a fraction of the error variance in forecasting x_i Which is caused by the shock in x_i, for i = 1, 2,..., N, and cross variance allocation or *spillovers*, as a piece of the H-*step-ahead* variance error in forecasting x_i that was caused by the shock x_j , for i, j = 1, 2, . . . , N, so that i≠j . KPPS *H-step-ahead Forecast error variance decompositions* denote $\theta_{ij}^{g}(H)$, for H = 1, 2, . . . which formulated as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma\, e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma\, A_h' e_i\right)} \quad (3)$$

where Σ is the variance matrix for error vectors e, σ_{jj} is the standard deviation of the *error term* in the j^{th} equation, and e_i It is the chosen vector, with one as the e^{th} element and zeroes otherwise.

As mentioned above, the total composition of each row of the variance decomposition table is not equal to 1: $\sum_{j=i}^{N} \theta_{ij}^{g} \neq 1$. To use the information available in the variance decomposition matrix in the *spillover* index calculation, it must normalize each variance decomposition matrix entry by the number of rows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \quad (4)$$

where, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) = 1$ *and* $\sum_{j=1}^{N} \theta_{ij}^{g}(H) = N$

The volatility contribution of variance decomposition is utilized so that the formula can calculate the total volatility spillover index

$$S^{g}(H) = \frac{\sum_{i,j=1_{i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}.100 = \frac{\sum_{i,j=1_{i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}.100 \qquad (5)$$

The VAR approach enables the study of the direction of spillover volatility across crucial variables, making it possible to examine the direction of directional spillovers between the variables used. *In* the *reactional spillovers* accepted by the variable or in the context of this study, the stock market to *i* of all other markets *j* formulated by:

$$S_{i.}^{g}(H) = \frac{\sum_{j=1_{j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}.100 = \frac{\sum_{j=1_{j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}.100. \qquad (6)$$

In the same way, measuring *intentional spillovers* transmitted by the stock market to *i* of all other markets *j* is formulated by:

$$S_{.i}^{g}(H) = \frac{\sum_{j=1_{j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)}.100 = \frac{\sum_{j=1_{j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N}.100. \qquad (7)$$

Thus, the net volatility (*Net* spillovers) of the market *i* to all other market *j* is the difference between two *directional spillovers*, received and transmitted, or formulated by:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H). \qquad (8)$$

In more detail, net *spillovers* between the two stock markets (*net pairwise volatility spillover*) can be seen by the formula:

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)}\right).100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N}\right).100 \qquad (9)$$

Net pairwise volatility spillover between stock markets i and j is the difference between the gross volatility shock transmitted from stock *i* to stock *i* and the shock transmitted from *j* to *i*.

4. RESULTS AND DISCUSSION

4.1 Total and time-varying volatility spillover (connectedness)

The *spillover* index value for volatility is obtained from the best VAR model, specifically the FEVD. Table 1 shows the magnitude of *spillover* from each stock market in the overall research period from October 2018 to March 2021 (full-sample). The number of *off-diagonal columns* marked with (labeled by contribution to others) and the number of rows (labeled by contribution from others) are *directional spillovers* from one market *to* another and *spillovers* received from one market to another. The difference between accepted and transmitted spillover is *net spillover*. In addition, the total spillover index is shown in the number located in the lower right corner of the *spillover* table, which estimates the total number of *off-diagonal* columns corresponding to the total number of rows, including the diagonal. The comprehensive *spillover* index is depicted through percentages.

Table 1: Total volatility spillover (connectedness).

	DJIA	EURO	MSCI	NIKKEI	JKSE	From Others
DJIA	63.7	12.4	5.6	7.1	11.1	36.3
EURO	14.4	62.1	9.9	6.9	6.8	37.9
MSCI	7.2	12.3	65.5	10.6	4.4	34.5
NIKKEI	9.4	8.8	10.3	64.7	6.9	35.3
JKSE	8.1	5	3.5	2.8	80.6	19.4
Contribution to others	39	38.4	29.3	27.4	29.2	163.4
Contribution including own	102.7	100.5	94.8	92.1	109.8	**32.70**

Spillover transmissions from one stock market to another exhibit less variability in their value. The markets with spark plugs passing through *spillover* transmission to other relatively large markets are the DJIA and the EURO, respectively, at 39 and 38.4 percent. Furthermore, based on the column "directional from others," the *spillover* from other stock markets received by the EURO is relatively large, about 37.9 percent. They are followed by the DJIA, with a percentage of 36.3 percent. *Net volatility spillovers* are evident in the most significant numbers, specifically the differences between DJIA and others (39 – 36.3 = 2.7 percent), as well as between EURO and *others* (38.4 – 37.9 = 0.5 percent). This condition is not a surprising result. The DJIA and the EURO are the stock markets of large and dominant countries worldwide, so their influence is also significant to other markets [26],[27]. Especially in the DJIA or the United States (U.S.) financial markets, shocks that occur in the U.S. can significantly impact the world stock market. Especially if those countries have a higher level of economic openness, trade relations with the U.S., and a vulnerable fiscal position [26].

Meanwhile, JKSE only provided spillover transmission at 29.2 percent and received *spillover* from other markets at 19.4 percent. This occurrence shows that JKSE receives the smallest spillover of any other market. JKSE makes the most significant contribution to the system of equations for itself. In total, JKSE has a contribution value of 109.8 percent of FEVD. The close connectedness of the entire stock market can be proxied by the total value or average spillover of all samples in the study period, which is 32.70 percent. Based on this, the conclusion of Table 1 is that the total *spillovers* are higher than those experienced by the Indonesian stock market. As Mensi et al. [10] mentioned, Indonesia is a robust transmitter.

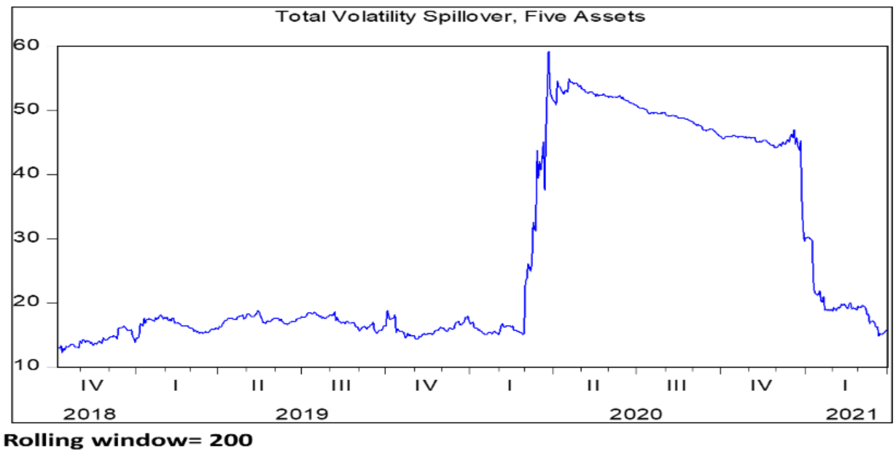

Figure 1: Time-varying total volatility spillover.

The results presented in Table 1 are aggregated results of the overall research period, regardless of changes over time. To see the spillover over time, a dynamic model. In this case, the spillover's volatility is described using a rolling window of 200 samples, moving forward and continuing to the period's end. The degree and nature of the spillover variation over time are illustrated through the time series in the form of a graph, known as time-varying total volatility spillover, in Figure 1. As can be seen from Figure 1, dynamic connectedness fluctuates over time, especially during the COVID-19 pandemic around March 2020. The suggestion is that connectedness in financial markets depends on time and events [28].

From the end of 2018 to the end of 2019, *the total volatility spillover* remained relatively stable, with no significant fluctuations. This case demonstrates that, prior to the COVID-19 pandemic, the spillover index was durable, remaining below 20 percent. During the COVID-19 pandemic, there was a significant increase in the *spillover* index in the first three months of 2020. This case indicates the *spillover* index, which rose sharply to about 59 percent. This increase suggests that the level of connectedness between the stock markets is getting stronger. Changes that occur in one market can be transmitted to another market. This condition will happen until the beginning of 2021.

As economic conditions improved after the COVID-19 pandemic, the connection between the entire stock market weakened. The *spillover* index initially declined to 59 percent, then decreased to around 48 percent by the end of 2020, and subsequently experienced a significant decline to 20 percent at the beginning of 2021, continuing to decline in the subsequent period. This phenomenon shows the *asymmetric effect* of COVID-19, where *volatility spillover* tends to be very different during COVID-19 and outside the Pandemic period. These results are consistent with previous studies that discussed *the asymmetric effect* of COVID-19 and crises. This signals that [28],[29],[30] risk contagion will increase during COVID-19 [31].

4.2 Net volatility spillovers

This section will discuss the *net volatility spillover* between JKSE and the overall global stock market. Net volatility spillovers from JKSE to others are represented by the difference between JKSE and others, using a dynamic model of *time-varying total volatility spillover* (Figure 2). Based on Figure 2, *JKSE's net volatility spillovers* were hostile from the beginning of the study period (October 2018) to June 2019, with a magnitude of around -10 percent. This phase indicates that the other four stocks had an influence on JKSE at that time. Furthermore, since June 2019, *JKSE's net volatility spillovers* have slowly increased, even though they are only between 0 and 5 percent until the end of September 2019.*JKSE's net volatility spillovers* began to grow since the beginning of October 2019. They experienced a dramatic increase at the start of the COVID-19 pandemic, reaching 110 percent. At the moment, *JKSE's net volatility spillovers* are positive, which means that JKSE affects the other four stocks more in this period.

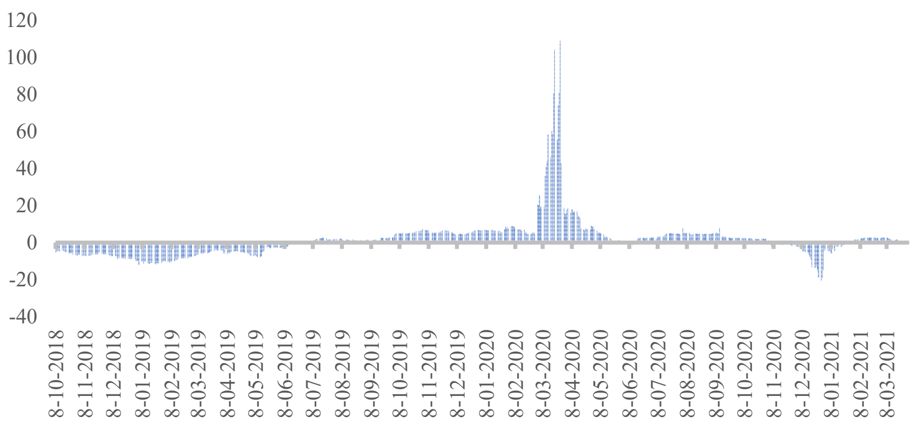

Figure 2: Net Volatility Spillovers JKSE.

The increase in the *net spillover* value of JKSE was short-lived, and by April 2020, JKSE's net spillover had decreased drastically to around 20 percent, coinciding with the onset of the COVID-19 pandemic. This value continued to fluctuate until June 2020, with JKSE's net spillover value at 0 percent, but again increased from the beginning of July 2020 to the end of September 2020. Following the pandemic, which began in October 2020, JKSE's *net spillover* decreased again to -20 percent in January 2021. Again, this decline was short-lived. In February 2021, the net spillover value of JKSE increased again and had a positive value, similar to the period before the COVID-19 pandemic.

The spillover surge during COVID-19 is unusual. At the beginning of 2019, *JKSE's net spillover* tended to be hostile or dominantly influenced by other stock markets. However, entering the pandemic period starting at the end of 2019 [32]*JKSE's net spillover* increased towards positive until its peak in March 2020. Conditions before COVID-19 were in line with the findings of Balli et al. [33], which stated that Indonesia's *spillover* was relatively negative all the time. These new findings have implications for the Indonesian authorities and investors to establish a policy and minimize risks through hedging and other measures [34].

4.3 Net pairwise volatility spillovers

The *total volatility spillovers* approach indeed provides information that is already informative. However, this approach becomes more enjoyable when examining the specific relationship between the two stock markets. The connectedness between the two stock markets is presented through the index *net pairwise volatility spillovers*. This section focuses on JKSE's connectedness to each of the other four markets.

4.3.1. DJIA – JKSE

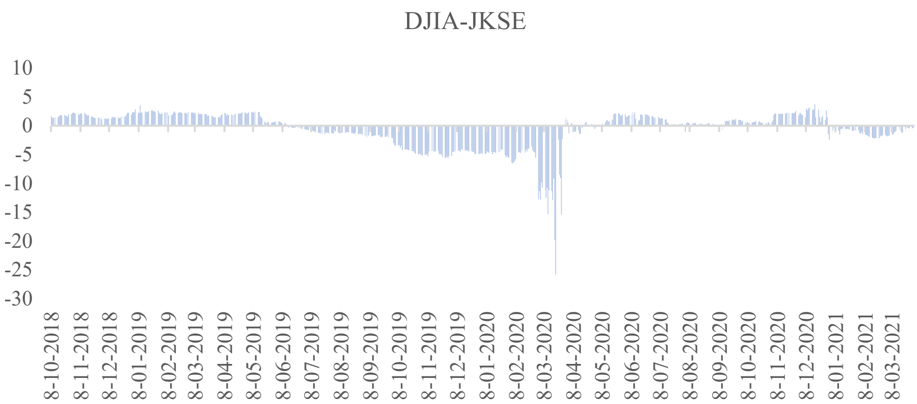

Figure 3: Net Volatility Spillovers DJIA – JKSE.

Net volatility spillovers between DJIA and JKSE refer to the difference between the impact of DJIA on JKSE and the impact of JKSE on DJIA. In Figure 3, the *net volatility spillovers* between DJIA and JKSE have a positive value from the beginning of the research period (October 2018) to the end of June 2019, with values ranging from 0 to 5 percent. Furthermore, from July 2019 to April 2020, the value of *net volatility spillovers* between DJIA and JKSE decreased continuously to a value of -25 percent. From May 2020 to the end of the study period in March 2021, the weight of *net volatility spillovers* between DJIA and JKSE fluctuated between positive and negative values. At a time when *net volatility spillovers* are positive, this indicates that the DJIA had a greater impact on JKSE during that period. When net volatility spillovers are negative, it indicates that JKSE had a greater influence on the DJIA at that time.

4.3.2. EURO – JKSE

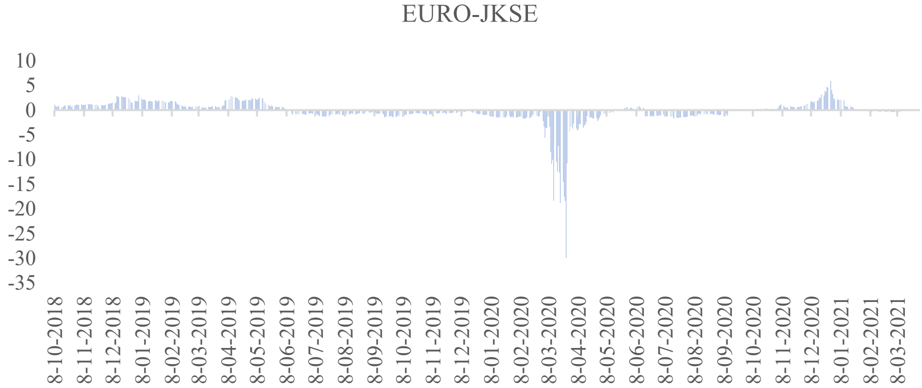

Figure 4: Net Volatility Spillover EURO – JKSE.

4.3.3. MSCI – JKSE

Figure 4 shows that the *net volatility spillovers* between the EURO and JKSE had a positive value from October 2018 to the end of June 2019, with values ranging from 0 to 3 percent. Furthermore, from the beginning of July 2019 to July 2020, the value of *net volatility spillovers* between the EURO and JKSE continuously decreased until it was negative. The most significant decrease occurred in May 2020, with a value of -30 percent. From July 2020 to the end of the research period in March 2021, the value of *net volatility spillovers* between the EURO and JKSE was volatile between positive and negative values. Until January 2021, the *net volatility spillover* value of EURO–JKSE experienced the highest value of 5 percent. At a time when *net volatility spillovers* are positive, this indicates that the EURO had a greater impact on JKSE during that period. Whereas at a time when *net volatility spillovers* are negative, this suggests that the EURO was more concerned by JKSE at that time.

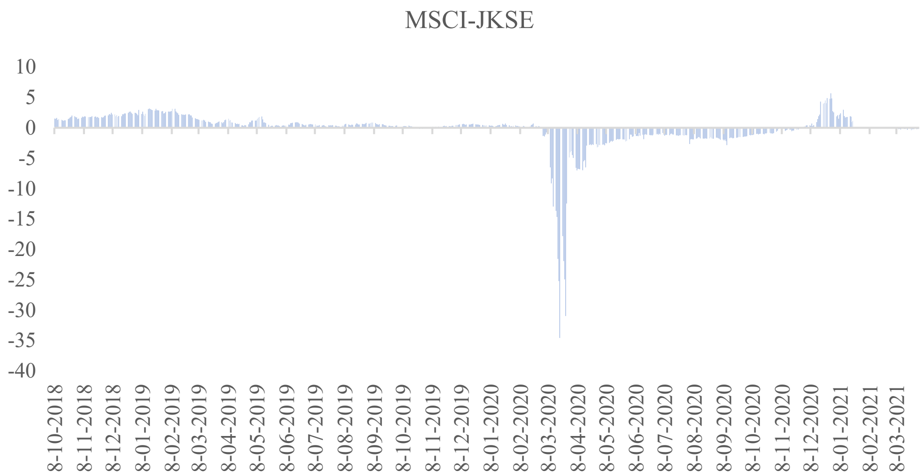

Figure 5: Net Volatility Spillover MSCI – JKSE.

In Figure 5, the *net volatility spillovers* between MSCI and JKSE had a positive value from October 2018 to the time when the COVID-19 pandemic occurred around March 2020, with values ranging from 0 to 3 percent. Furthermore, from the beginning of March 2020 to August 2020, the value of *net volatility spillovers* between MSCI and JKSE decreased drastically to -33 percent in April 2020. The decline in the value of the *net volatility spillover* finally increased again until the end of July 2020, but it was still negative. Since the beginning of August 2020, there has been a resurgence until the end of the research period. The *net volatility spillover* value of MSCI - JKSE reached the highest value of 5 percent. At a time when *net volatility spillovers* are positive, this indicates that MSCI had a greater influence on JKSE during that period. Whereas at a time when *net volatility spillovers* are negative, this indicates that MSCI was more affected by JKSE at that time.

4.3.4. NIKKEI – JKSE

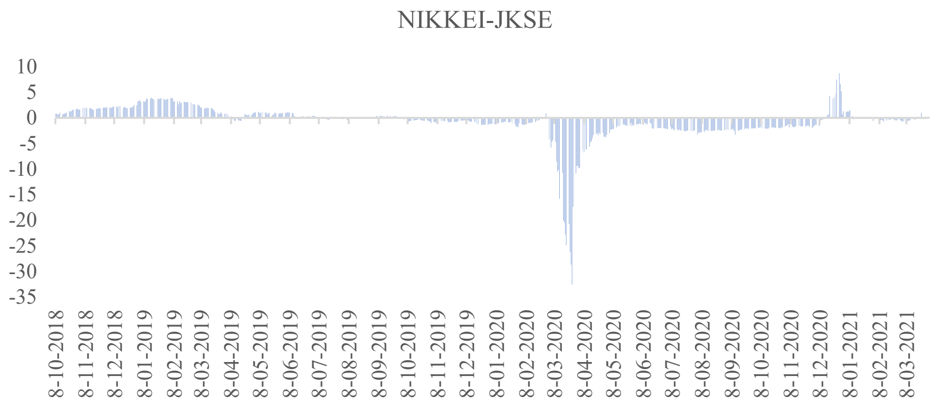

Figure 6: Net Volatility Spillover NIKKEI – JKSE.

Figure 6 shows that *the net volatility spillovers* between NIKKEI and JKSE had a positive value from October 2018 to June 2019, ranging from 0 to 5 percent. Furthermore, from August 2019 to the end of August 2020, the value of *net volatility spillovers* between NIKKEI and JKSE decreased. During the COVID-19 pandemic, which began in April 2020, there was a significant decrease of 30 percent, which continued until December 2020. This decrease in the value of *net volatility spillover* finally increased again at the beginning of January 2021 to be worth 10 percent. At a time when *net volatility spillovers* are positive, this indicates that NIKKEI has a greater impact on JKSE during such periods. When *net volatility spillovers* are negative, it indicates that NIKKEI was more affected by JKSE at that time.

Based on JKSE's connectedness pattern with the other four stock markets, the changes *in volatility spillovers* from or by JKSE over time tend to be the same. There is an *asymmetric effect* of COVID-19 because the changes in the COVID-19 period are pretty significant. Then, JKSE exhibits strong volatility spillovers with DJIA, as evidenced by the high value of spillovers over time, both from DJIA to JKSE and vice versa. The connectedness of these two stock markets has a long history of events, but it is still interesting to study. These findings give JKSE both good and bad signals. The good news is that during the COVID-19 pandemic, JKSE was a reasonably strong stock market, largely unaffected by domestic turmoil, and even provided a shock transmission to other stock markets. The bad news is that under normal conditions, JKSE must be wary of *risk contagion* from the DJIA [36],[37]. Investors in the JKSE should pay attention to the movements of the DJIA to protect their assets.

5. CONCLUSION

The COVID-19 pandemic has affected all lines of people's lives, including the financial services sector. The pandemic increases *volatility*, *uncertainty*, *complexity*, and *ambiguity* (VUCA), thereby increasing investment risk. Therefore, this study explores the connectedness of the stock market in Indonesia with the global stock market, especially considering how *risk contagion* and *volatility spillover* between these stock indices. More specifically, this study examines how COVID-19 has increased market volatility and interconnectedness with other markets. The Diebold-Yilmaz volatility spillover approach [8], [9] measures the total volatility of spillover and examines the dynamics over time in the direction of the *spillover volatility*.

The study results showed that the DJIA and the EURO are the strongest stock markets with the strongest spillover transmission to other large markets. This is not a surprising result because DJIA and EURO are the stock markets of large and dominant countries in the world, so their influence is also significant to other markets [25], [26]. Meanwhile, JKSE, as an emerging market, is the smallest in comparison to other markets included in this study.

Using *the time-varying total volatility spillover*, it can be seen that the connectedness fluctuates over time, with the highest spillover existing during the COVID-19 pandemic (around March 2020). This event suggests that connectedness in financial markets tends to vary over time, depending on global market conditions. This phenomenon shows the *asymmetric effect* of COVID-19, where *volatility spillover* tends to be different during and outside the COVID-19 Pandemic [27]. It also signals that *risk contagion* will increase during the presence of COVID-19 [31].

The results of this study can be beneficial both for policymakers and regulators. Empirical results indicate that policymakers should focus on the Indonesian stock market's interconnectedness with the global market. With each appropriate policy, shocks in the worldwide market can be better managed and responded to. On the other hand, investors should consider risk transmission from other markets when diversifying their portfolios. Furthermore, from a scientific perspective, it would be interesting to extend this research to the sectoral stock market in future studies. The impact of volatility spillover on Indonesian sectoral stocks may vary between sectors.

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