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Research Article

SPILLOVERS BETWEEN INDONESIA'S GREEN INDEX, CONVENTIONAL INDEX AND GLOBAL STOCK INDEX: WHICH IS MORE STABLE?

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ABSTRACT

Background: The increasing global concern over climate change has accelerated the growth of sustainable investment, including the development of green stock indices such as Indonesia's SRI-KEHATI Index. However, despite their potential resilience and attractiveness, green indices remain exposed to volatility and interconnectedness with conventional and global financial markets. Therefore, understanding the dynamics of volatility and spillover effects between green, conventional, and global stock indices becomes crucial to assess their relative stability and investment potential.
Purpose: This study aimed to measure the level volatility, connectedness and spillovers between Indonesia green index, Indonesia conventional stock index, and some global stock price indices in the last decade.
Design/methodology/approach: Using daily return data from 2 February 2012 to 31 August 2022, this study used a rolling-samples of descriptive statistics approach and framework developed by Diebold and Yilmaz (2012) to measure the levels of volatility and spillovers between Indonesia's green index, Indonesia LQ45 index and several global stock indexes.
Findings: The results of the analysis showed that volatility and spillovers that have occurred between variables are dynamic over time. When the volatility values of the variables tend to be low, Indonesia return green index tends to be higher, and on the other hand, when volatility is high, Indonesian return green index tends to be lower than the conventional return index volatility. In addition, during the analysis period, the spillovers that occurred between variables experienced a significant increase several times and then decreased again after a certain period of time. In the long run, the returns of Indonesia's green index tend to experience negative spillovers where the spillovers caused by the returns of the green stock index to all variables tend to be smaller than the spillovers received by the returns of the green stock index. In addition, the return movement of Indonesia's green stock index is generally more explained by the return movement of global stock price indexes compared to conventional stock indexes of Indonesia.
Conclusion: The findings indicate that Indonesia's green stock index delivers higher average returns compared to the conventional index, although it exhibits slightly higher volatility over the study period. Furthermore, the results reveal that volatility spillovers are dynamic and largely driven by global market movements, with the green index tending to receive more spillovers than it transmits in the long run
Originality/value: This study compares the volatility and connectedness between Indonesia green index and Indonesia conventional stock index with several global stock indexes. As an index that was just launched about ten years ago, research on the Indonesian green index was still limited. In addition, the rolling sample method that measures the dynamics of parameter changes over time such as time varying volatility and the Diebold and Yilmaz (2012) framework provide something new in the time series research method.

ARTICLE INFO

Keywords:
green stock index, spillover, rolling samples, diebold-yielmaz, level volatility, descriptive statistics

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INTRODUCTION

The greatest threat facing humanity in modern history is global warming. Global temperatures have increased by 2°C since the pre-industrial era (1880-1900). This increase in temperature has caused chaos on Earth, causing extreme temperatures, melting of glaciers, ice caps and polar caps, intensifying rainfall and changing the habitats of plants and animals (Chakrabarti & Sen, 2021). The world is not standing still on the issue of climate change. The 2015 Paris Climate Conference (COP21) is a crucial agreement on climate change since the 1997 Kyoto Protocol. The agreements brought about at COP21 include limiting global temperature rise to 2°C above the pre-industrial levels and financial development in line with low greenhouse gas emissions and climate-resilient development (UNFCCC, 2015). This was the first time that the United Nations Framework Convention on Climate Change (UNFCCC) has emphasized the importance of climate-friendly funding in development goals (Lundgren et al., 2018). Since COP21, renewable energy stocks have strengthened, and the importance of investing in green or climate-friendly company stocks has been established. In this paper, we refer to the joint stock price for companies that have implemented the principles of sustainability and concern for the environment as a "green index".

Investing in the green index should have a special market share because investors are fanatical and naive in responding to news or new things (Pedersen, 2022). In general, investors' decisions to invest in a stock market are based on the amount of profitability or return earned. The ideal stock is a stock that has rising price trend performance and resistance to shocks. It is a characteristic of stocks that provide high profit opportunities (Reiter-Gavish et al., 2022). Therefore, green stocks can be an investment destination option if they provide attractive returns for investors. In several studies, it was found that the green index was defensive or had extraordinary resilience during several financial crises. Noticeable resilience or stability can attract investment in green index stocks (Adamska & Dąbrowski, 2021; Castro et al., 2021).

The green stock index in Indonesia is represented in the SRI-KEHATI Index. This index was formed in collaboration between the Indonesia Stock Exchange (IDX) and the Indonesian Biodiversity Foundation (KEHATI - Yayasan Keanekaragaman Hayati Indonesia). SRI is short for Sustainable Responsible Investment. The SRI-KEHATI index is a representation/ reflection of the stock prices of 25 issuers selected by considering criteria such as: total company assets, price earning ratio, and free float. This index is expected to provide additional information to investors who wish to invest in companies that have excellent performance in promoting sustainable business, as well as having awareness of the environment and implementing good corporate governance (Qoyum et al., 2021). In the last 10 years, the SRI-KEHATI Index has had a higher return performance than the LQ45 Index. The average daily return for the SRI-KEHATI index is 0.025 percent while the LQ45 index is 0.014 percent.

Fluctuating financial markets cause investment instruments in the stock market to have risks (Kumar, 2014). Likewise, the green stock index also has risks. Most recent findings (Cornell, 2021) suggested that a positive preference among investors for companies with an ESG (Environmental, Social and Governance) rating, which includes green companies, will lead to a risk-adjusted expected return on green stocks that is lower than balance or average. In other words, green index stocks tend to be more stable. The findings by Chakrabarti & Sen (2021) also showed that green stock market risks are reduced because green stocks act as a hedging instrument in the face of crises. The observed resilience of green stocks in crises may be enough to gain investors' confidence in them. The only risk to watch out for is the chaotic and unpredictable nature of green index stocks. They often have asymmetric movements (Chakrabarti & Sen, 2021). This requires more caution for investors before investing in green stocks.

As previously stated, the stability of the green index can attract investors as a safe and profitable investment option. Even though it is said to be resistant to shocks, the findings by Chakrabarti & Sen (2021) showed that the green index still has asymmetric movements so that it is a risk in itself. This phenomenon may be the same in every green index market in the world or it may be different. Therefore, this study aimed to analyse the comparison of the level of volatility of returns on the Indonesia's green index with the conventional index, as well as to measure the spillover occurring between the green stock returns in Indonesia, namely SRI-KEHATI and the return movement of conventional index and global stock index. This analysis would reveal which index has more stable movement and which provides higher profits.

METHODS

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

To analyze spillover between Indonesia's green index and other variables, this study used daily data from SRI-KEHATI index return (R_KEHATI) which was a proxy for Indonesia green index from 2 January 2012 to 31 August 2022. Other variables in the study as a proxy for Indonesia's conventional index used the LQ45 index (R_LQ45). Meanwhile, the global stock price indexes were chosen to represent the movement of global stock prices as a whole. In this study, the Dow-Jones stock price index (R_DJIA) was used to represent the United States, the Euro stock price index (R_EURO) to represent Europe, the Singapore stock price index (R_MSCI) as a proxy to represent ASEAN region stock prices, and the Nikkei stock price index (R_NIKKEI) to represent stock indexes in East Asia. In the analysis process, all variables were expressed in the form of daily return, so all discussion in this paper talks about the return spillovers between variables.

Volatility is difficult to observe, so a proxy to measure volatility is needed. Namely, conditional mean is zero and quadratic return provides a true unbiased estimator of the underlying volatility process. Therefore, volatility in the stock market is often observed by looking at the variations of return of stock prices. The approach used to measure return volatility in this study was the standard deviation value of stock return using the formula:

$$s = \sqrt{\frac{\sum(r_t - \bar{r})^2}{n}} \qquad (1)$$

where s is the standard deviation value, r_t is the return value in observation *t*, r is the average return in the observation period and n is the total observations analyzed.

The return value itself was calculated using the formula:

$$r_t = 100*((X_t - X_{t-1})/X_{t-1}) \qquad (2)$$

where r_t is the daily return of all variables analyzed, X_t is the stock price index in period t, and X_{t-1} is the stock price index one day before.

To find out the relationship between the variables analyzed and to measure the occurring spillovers, this study adopted the spillover approach developed by Diebold and Yilmaz (2012). The spillover approach by Diebold and Yilmaz is based on the original design of the generalized vector autoregressive (VAR) model used to calculate the forecast error variance decomposition (FEVD). This approach has many advantages over other spillover techniques developed previously. First, the results do not depend on the order of the variables because they do not use the Cholesky factor identification from the VAR model. Second, it allows tracing connectedness at different levels, from pair to the whole of the system of equations in a coherent and consistent way. In addition, this spillover is dynamic, compared to other static models which fail to take into account variations over time.

Spillover between variables can be explained from the general idea of the variance decomposition associated with the N-variable of VAR. Diebold and Yilmaz (2012) focused on total spillover in a simple VAR framework, by measuring directional spillovers in the general VAR framework that eliminates the possibility of dependencies. Consider the covariance of N-stationary variable VAR(p), $x_t = \sum^{p}_{i=1} Ø_i x_{t-i} + ε_t$, where $ε \sim (0,Σ)$ is shock vector or independently and identically distributed shock. The representation of moving average is $x_t = \sum^{\infty}_{i=0} A_i ε_{t-i}$ where matrix A_i with coefficient NxN follow the recursion $A_i = Ø_1 A_{i-1} + Ø_2 A_{i-2} + \ldots + Ø_p A_{i-p}$ with A_0 becoming the identity matrix of NxN and with $A_i = 0$ for $i < 0$. The coefficient moving average is the key to understanding dynamical systems. The decomposition of the variance makes it possible to decompose the estimated error variance of each variable into parts caused by various shocks to the system.

To calculate spillover between variables, the part of the variance of the variable itself was defined as the fraction of the error variance in forecasting caused by the shock to xi, for i = 1, 2, . . . , N, and the cross-division of variance, or spillovers, as a fraction of the error variance H-step-ahead in forecasting xi caused by the shock to xj, for i, j = 1, 2, . . . , N, such that i≠j. KPPS H-step-ahead Forecast error variance decompositions by , for H = 1, 2, . . ., formulated as:

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

where $\sum$ is the variance matrix for error vector e, σ_{jj} is the standard deviation of the error term equation j^{th} and e_i is the selected vector, with one as the th element and zero otherwise. As explained above, the number of elements in each row of the variance decomposition table is not equal to 1: $\sum_{j=i}^{N}\theta_{ij}^{g} \neq 1$. In order to use the information available in the variance decomposition matrix in the calculation of the spillovers one must normalize each entry of the variance decomposition matrix by the number of rows:

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

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

Using the volatility contribution from the variance decomposition, the total spillover could be calculated by the formula:

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

No matter how big the shock to spillover across the main variables is, the VAR approach makes it possible to study the directional spillovers in all variables used. The directional spillovers received by the variables, or in the context of this study is the stock market *i* from all other markets *j*, was formulated as:

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

In the same way, measuring directional spillovers transmitted by stock market *i* from all other markets *j* was formulated as:

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

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

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

RESULTS

Comparative Dynamics of Green and Conventional Indices in Indonesia

Prior to conducting a more in-depth analysis, this section provides a comparative overview of the characteristics of green and conventional stock indices in Indonesia, serving as a foundation for subsequent empirical investigation.

The Figure 1 illustrates the comparative dynamics of green and conventional stock indices in Indonesia over the period 2012–2022, represented by the KEHATI index and the LQ45 index, respectively. Overall, both indices exhibit a similar upward trend, indicating a general growth in the Indonesian equity market during the observed period. However, differences in their movements reflect varying responses to market conditions and external shocks.

The green index (KEHATI) tends to follow the general pattern of the conventional index (LQ45), suggesting a degree of co-movement between sustainable and conventional investments. Notably, both indices experienced a significant decline during the 2020 period, corresponding to the global economic disruption caused by the COVID-19 pandemic, followed by a recovery phase in subsequent years.

Despite their similar trajectories, the conventional index appears to exhibit slightly higher fluctuations at certain periods, while the green index demonstrates relatively stable growth over time. This pattern indicates that although both indices are influenced by common market factors, their sensitivity to shocks and market dynamics may differ.

Table 1 presents the summary statistics of returns for the green index (R_KEHATI) and the conventional index (R_LQ45). In terms of mean returns, R_KEHATI exhibits a higher average return (0.025) compared to R_LQ45 (0.014), indicating that the green index provides relatively greater returns over the observed period.

Table 1. Comparison of average return, standard deviation, and coefficient of variation (CV)

	R_KEHATI	R_LQ45
Mean	0.025	0.014
Std. Dev.	1.286	1.275
CV	0.019	0.011

In terms of volatility, both indices display very similar standard deviation values, with R_KEHATI at 1.286 and R_LQ45 at 1.275. This suggests that the level of risk associated with both indices is nearly identical. However, when considering the coefficient of variation (CV), R_LQ45 (0.011) shows a lower value compared to R_KEHATI (0.019), implying that the conventional index offers a more favorable risk-return trade-off.

Overall, although the green index yields higher returns, it is accompanied by relatively higher variability per unit of return, whereas the conventional index appears to be more efficient in terms of risk-adjusted performance. To compare the stability of the two indices, rolling standard deviations of returns were computed using a 200-observation window. Figure 2 illustrates the evolution of return volatility for Indonesia's green index and the conventional index over the study period.

Figure 2 illustrates the trends in return volatility for the green index (KEHATI) and the conventional index (LQ45) in Indonesia, measured using a rolling standard deviation approach. Overall, both indices exhibit highly similar volatility patterns over time, indicating a strong co-movement in risk dynamics between green and conventional assets.

Several periods of heightened volatility can be observed, particularly around 2013–2014, 2015–2016, and most prominently during 2020–2021 (Putera et al., 2022). The sharp increase in volatility during 2020 reflects the impact of the global COVID-19 pandemic, which significantly disrupted financial markets worldwide. Following this period, volatility gradually declined, suggesting a recovery phase in market stability.

Despite the general similarity in their movements, minor deviations between the two indices can still be observed, indicating that while both are influenced by common market shocks, there may be differences in their sensitivity and adjustment processes. Overall, the evidence suggests that the green index does not exhibit substantially different volatility behavior compared to the conventional index, reinforcing the notion of close integration between the two markets.

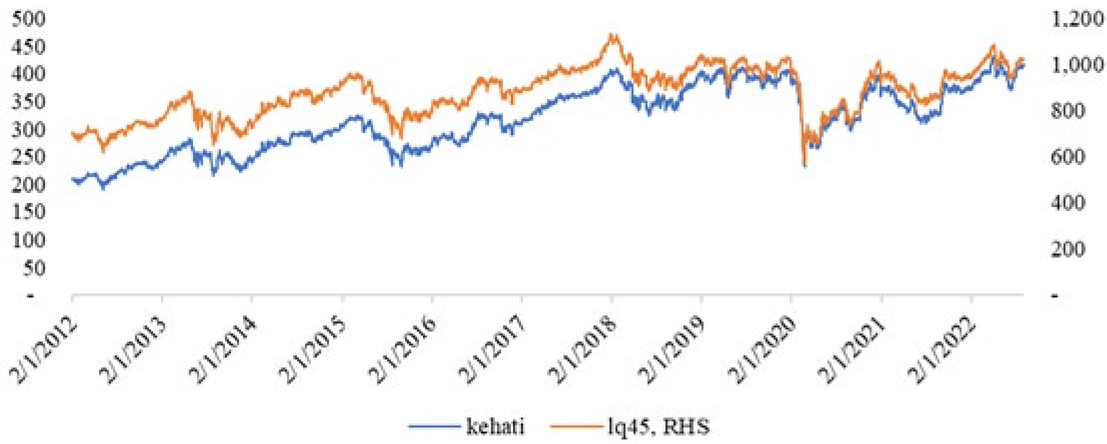

Figure 1. Trend of green index vs non-green index in Indonesia

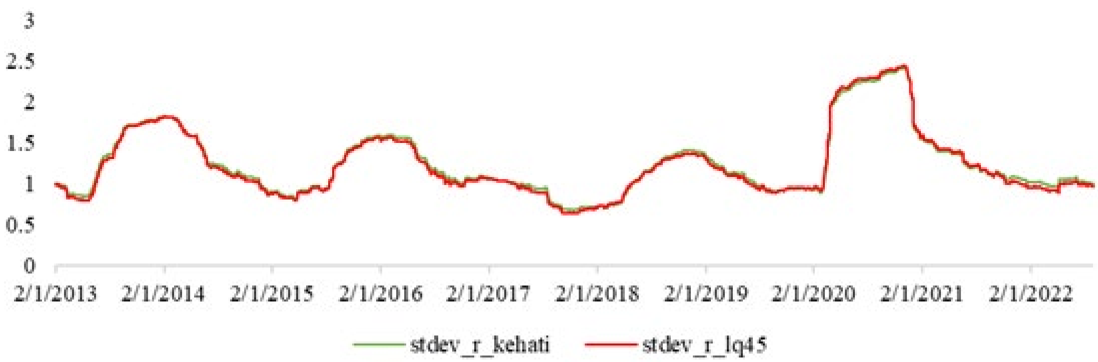

Figure 2. Trends in the return volatility of green index and conventional index in Indonesia

Green Index and Volatility of Other Asset Classes

In the initial stage, a descriptive analysis of the daily return data for all variables was conducted, followed by stationarity tests. Based on Table 2, all stock index returns in this study are stationary at the level, as indicated by the ADF test probability values. Therefore, the returns are directly used to estimate a VAR model, which is subsequently employed to measure spillovers among the stock market indices. Based on the standard deviation values, the volatility of R_KEHATI, R_LQ45, R_EURO, and R_NIKKEI appears relatively similar, with only minor differences. Among the six stock markets, R_KEHATI exhibits the highest volatility (1.286). Consistent with the earlier discussion, R_KEHATI is not only more volatile but also more persistent to shocks. In contrast, the lowest volatility is observed in R_DJIA (1.051) and R_MSCI (0.873).

Total (The Full-Sample) Volatility Spillover

Before conducting the spillover analysis, the optimal VAR specification was selected. The lag length criteria suggest a maximum lag of 49, while the Schwarz Criterion (SC) identifies lag 1 as the most appropriate. Table 3 presents the spillover effects across stock markets over the full sample period from February 2012 to August 2022. The off-diagonal elements, labelled as ‘contribution to others,’ capture directional spillovers transmitted from one market to others, while the row sums, labelled as ‘contribution from others,’ represent spillovers received by each market. The difference between transmitted and received spillovers defines the net spillover for each market.

The total spillover index, reported in the lower-right corner of the table, measures the overall level of spillover in the system as the share of cross-market (off-diagonal) forecast error variance relative to the total variance, expressed as a percentage. Furthermore, the spillover table provides a decomposition of volatility spillovers, reflecting the input–output structure of shock transmission across markets.

Table 2. Summary statistics, daily return of the variables

	R_KEHATI	R_LQ45	R_DJIA	R_EURO	R_MSCI	R_NIKKEI
Mean	0.025	0.014	0.033	0.013	-0.005	0.042
Median	0.000	0.000	0.033	0.029	0.000	0.000
Maximum	14.729	13.908	10.764	8.834	6.502	7.731
Minimum	-8.188	-8.622	-13.842	-13.241	-7.411	-8.253
Std. Dev.	1.286	1.275	1.051	1.229	0.873	1.271
Skewness	0.158	0.014	-1.030	-0.721	-0.295	-0.254
Kurtosis	12.981	12.292	28.816	12.808	10.274	7.533
Jarque-Bera	11,468	9,929	77,133	11,302	6,125	2,393
Observations	2760.0	2760.0	2760.0	2760.0	2760.0	2760.0
ADF Test	-50.186	-50.276	-16.317	-53.945	-34.591	-35.765
Prob ADF	0.000	0.000	0.000	0.000	0.000	0.000

Table 3. Spillover (connectedness) table between variables

	R_KEHATI	R_LQ45	R_DJIA	R_EURO	R_MSCI	R_NIKKEI	From Others
R_KEHATI	43.3	41.6	4.9	3.6	5.5	1	56.7
R_LQ45	41.2	42.9	5.2	3.8	5.7	1.2	57.1
R_DJIA	3.4	3.7	56.8	22.6	8.4	5.2	43.2
R_EURO	2.7	2.9	22.8	55.6	10.3	5.8	44.4
R_MSCI	6.3	6.6	13.8	13.3	51.9	8.1	48.1
R_NIKKEI	1.7	1.9	15.9	15.8	9.7	55.1	44.9
Contribution to others	55.3	56.7	62.5	59.1	39.6	21.2	294.5
Contribution including own	98.6	99.6	119.3	114.7	91.4	76.3	49.10

Directional spillover (gross and net) is the main thing that can be seen from the Table 3. Based on the "directional to others" line, it can be seen that the transmission of spillover from one stock market to another stock market has too many different relative values. Markets that contributed through relatively large spillover transmission to other markets were DJIA and EURO, respectively 62.5 and 59.1 percent. Furthermore, based on the "directional from others" column, it can be seen that the spillovers from other stock markets received by KEHATI and LQ45 were relatively large, namely 56.7 and 57.1 percent. Net directional volatility spillovers can be different from directional to others and directional from others. Net directional volatility spillovers of DJIA was 19.3 percent (62.5 – 43.2). Meanwhile, the net directional volatility spillover of LQ45 was -0.4 percent (56.7-57.1). A negative value means that the stock index receives more spillover than transmits spillover. The KEHATi index was not much different from the LQ45, having a net value of -1.4 percent. Of the six indexes, NIKKEI was the index most influenced by other markets with net volatility spillovers of -23.7 percent.

DJIA has contributed the most to the equation system to DJIA itself. In total, DJIA had a contribution value of 119.3 percent of FEVD. Next was the total (non-directional) volatility spillover, which is a distillation of various directional volatility spillovers into one index. The total volatility spillovers can be seen in the lower right corner of table 4, which indicates that the average of all samples in the study period used was 49.10 percent of the entire market. Based on this, the directional spillovers of KEHATI and several other stock markets are quite high compared to the total spillovers index of all samples.

The Rolling-Sample Total Volatility Spillover Plot

The spillover calculation process as described in the previous section can actually be done repeatedly for different times. With the availability of 2761 observations, this study calculated the spillover index values dynamically using 200 observations of the rolling-sample calculation. Thus, about 2561 spillover indices were obtained as shown in Figure 3. We can see that the values of the spillover index between the variables used vary over time. The results reveal substantial variation in spillover dynamics over time, reflecting the impact of major global events, including financial disturbances and the COVID-19 pandemic. While the full-sample spillover table provides an average measure of interconnectedness, Figure 3 illustrates its time-varying behavior.

In general, the spillover index fluctuates within a moderate range, suggesting a relatively stable level of integration under normal market conditions. However, sharp increases are observed during periods of financial stress. A notable spike occurs in September 2015, when the spillover index rises to 54.39%, reflecting heightened market uncertainty associated with the Chinese stock market turbulence (Ahmed & Huo, 2019).

A more pronounced surge is evident in early 2020, where the spillover index peaks at 70.66%. This period coincides with the outbreak of the COVID-19 pandemic, which triggered a global financial crisis and significantly intensified cross-market volatility transmission.

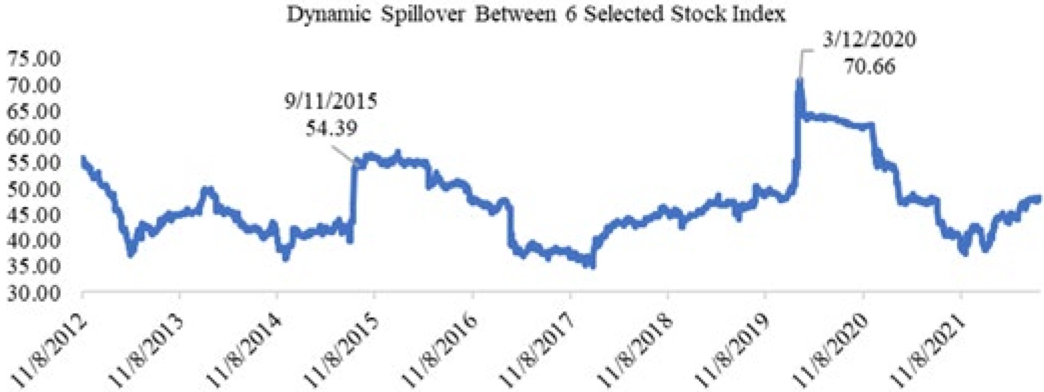

Figure 3. Total volatility spillovers, between variables

Following this peak, the spillover index gradually declines, indicating a partial restoration of market stability. Nevertheless, the level of interconnectedness remains elevated compared to pre-crisis periods. Overall, these findings highlight the time-varying and asymmetric nature of volatility spillovers, where interconnectedness strengthens significantly during crisis periods, signaling an increased risk of financial contagion across markets.

The Rolling-Sample Gross Directional Volatility Spillover Plots

This section will specifically discuss the directional volatility spillover of the six indexes. Directional volatility spillover was obtained by using rolling data of 200 samples which were observed during the study period. Figure 4 shows the directional volatility spillover that is transmitted by each index to other indexes. The KEHATI and LQ45 indexes are relatively stable over time and the pattern is relatively the same. The increase in spillover from KEHATI and LQ45 to other indexes only occurred during the Chinese stock market crisis and the COVID-19 pandemic. At that time, the directional spillover index increased to 70 percent. Meanwhile, global indexes have had highly fluctuating directional volatility spillover all the time. The DJIA and EURO indexes have had high directional spillover indexes while the MSCI and NIKKEI are seen to be lower than all indexes. The increase in directional spillover on global indexes occurred several times not only during the financial crisis.

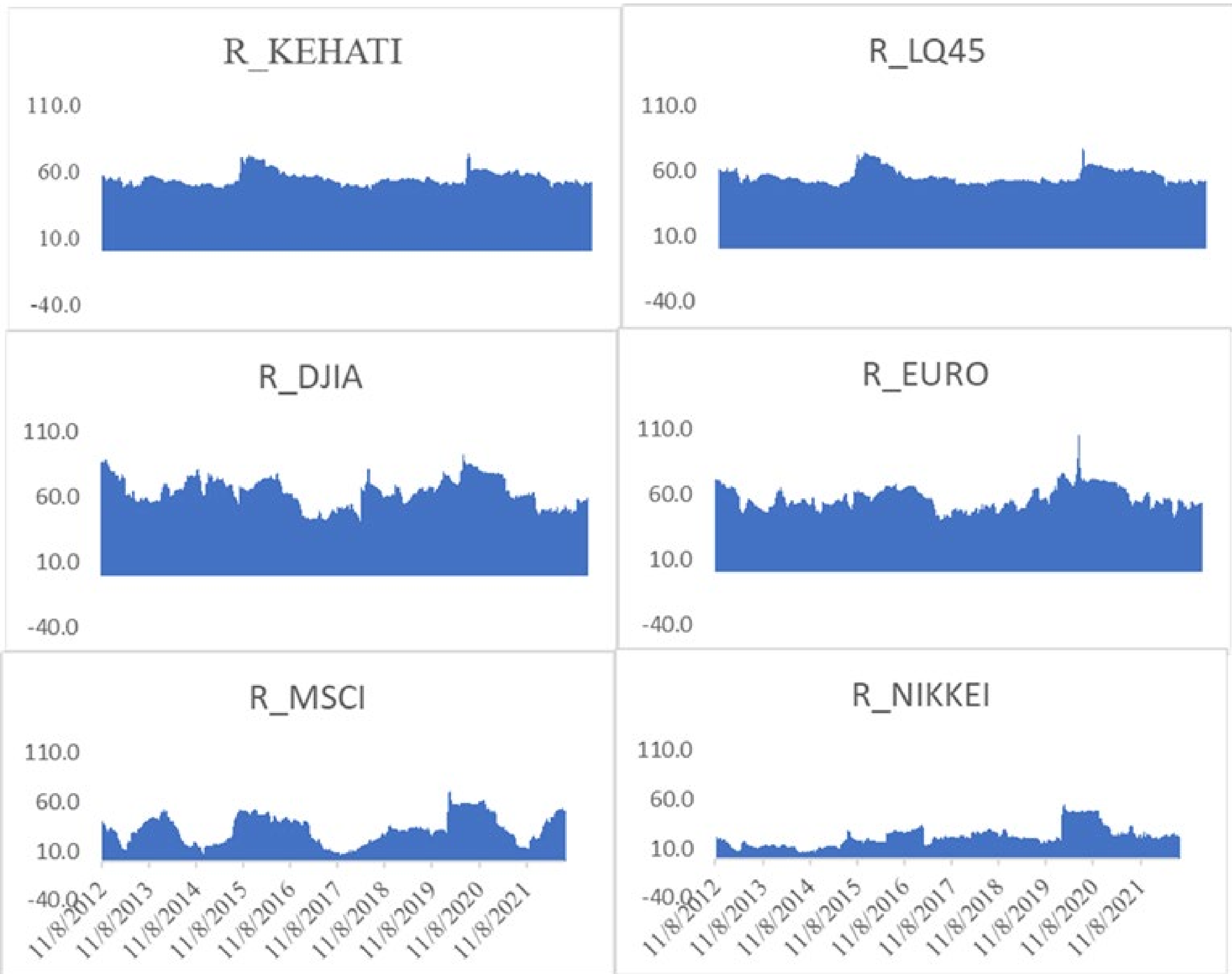

Figure 4. Directional return spillovers, FROM each variable

From the opposite point of view, Figure 5 shows the directional spillovers that each index received from other indexes. The pattern is relatively similar to the phenomena in Figure 4. The local indexes, namely KEHATI and LQ45 tend to be stable, but the received directional spillover values were not much different from those transmitted. Then there was a significant increase during the crisis period reaching the directional spillover value of 70 percent. For global indexes, for example DJIA and EURO, the received directional spillover still fluctuated but its value was lower than that which was transmitted. In contrast, MSCI and NIKKEI received greater directional spillover than was transmitted. To see directional spillover in two directions, it was necessary to calculate the net directional spillover value.

Net volatility spillovers are the difference between directional spillovers transmitted to other stock indexes and those received from other stocks. Based on Figure 6, it can be seen that the net volatility spillovers of local indexes, namely the green SRI-KEHATI index and the conventional LQ45 index, fluctuate around zero. There are specific patterns that are evident in times of crisis and outside of crises. Before there was a crisis, the value of the local index's net volatility spillovers was negative, while during the crisis it was positive. This means that during a crisis the local index transmits shocks to other indexes. There is an asymmetric effect from the crisis incident which causes spillover changes from local indexes to other stock indexes.

However, when viewed from the value of the local index's net volatility spillovers, it is still not as high as the global indexes, namely the DJIA and EURO. The DJIA and EURO indexes are always positive from time to time and their value is higher than the net volatility spillovers of local indexes and other global indexes. Meanwhile, other global indexes MSCI and NIKKEI have negative net volatility spillovers from time to time. From these results, it is generally revealed that the movement of the green stock index is more explained by the movement of the global stock price index compared to Indonesia's conventional stock index.

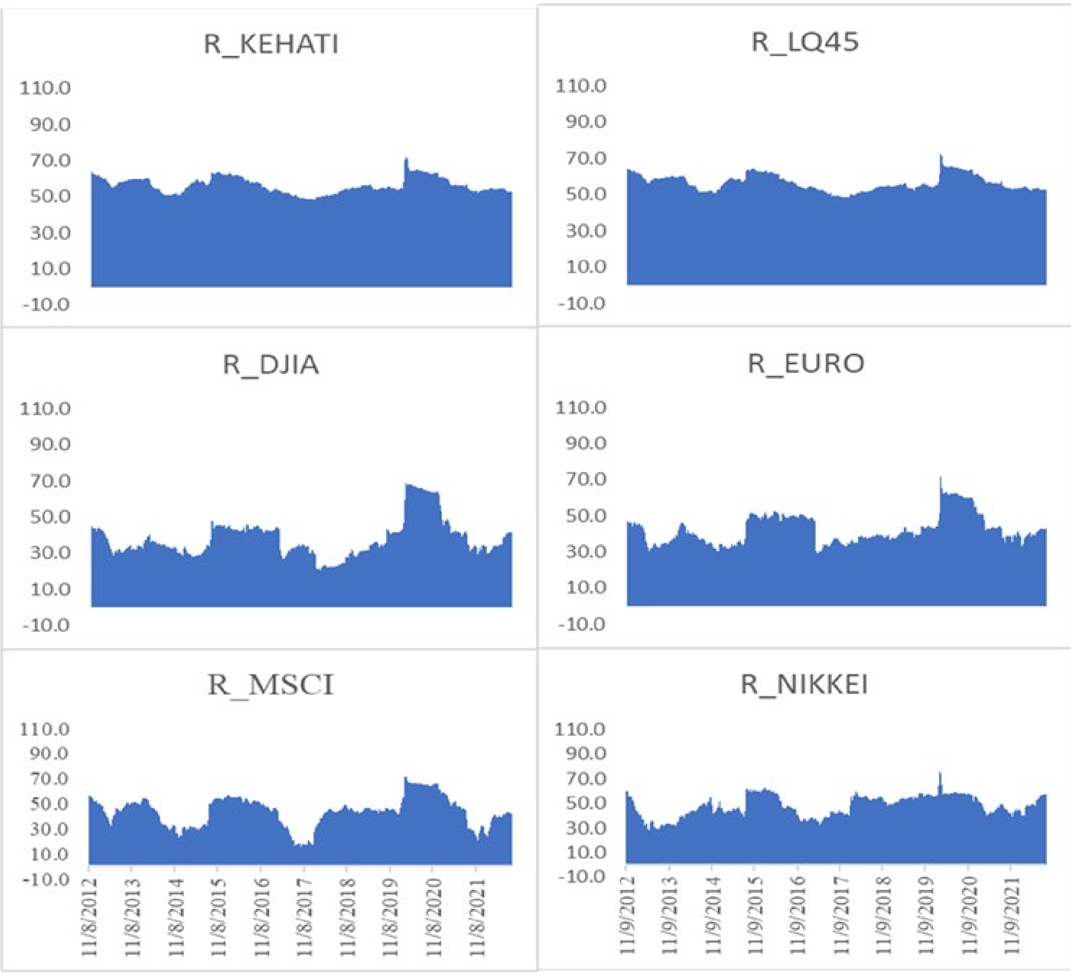

Figure 5. Directional return spillovers, TO each variable

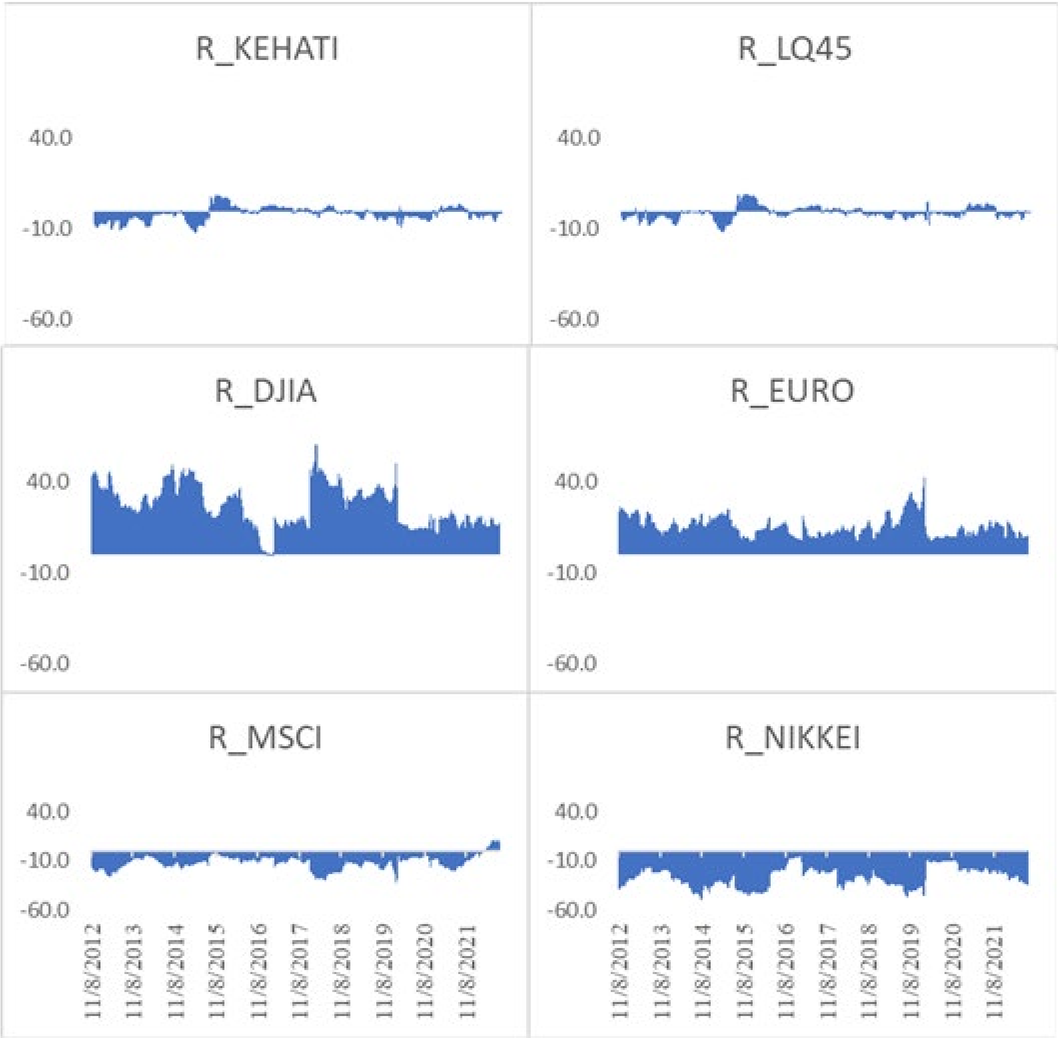

Figure 6. Dynamic Net volatility spillovers, TO each variable

The volatility of the green index in Indonesia is not much different from the conventional stock index in Indonesia. Volatility can be said to be more stable than the global stock index but it is not proof that the green stock index is more stable than the overall stock price index in this study. The study by Chakrabarti & Sen (2021) showed that the green stock index is resistant to shocks. From net volatility spillovers, this is true because it has a positive value during times of crisis, but this also happens to conventional stocks in Indonesia. The risk that can occur in the green index, from several previous studies, is transmitted by energy market volatility (Dutta et al., 2021; Mzoughi et al., 2022).

CONCLUSIONS

The results of the analysis using daily return data from 2 February 2012 to 31 August 2022 showed that Indonesia's green index has a better performance compared to other stock indexes in Indonesia such as the LQ45. It is shown that during the study period, the average daily return value for the green index was 0.025 percent while the LQ45 index was 0.014 percent. However, it turns out that the green index has a higher standard deviation and coefficient of variation than the LQ45 index. The standard deviation of the SRI-KEHATI and LQ45 indexes is 1.286 and 1.275 respectively with CV values of 0.019 and 0.011 respectively. This shows that the green index tends to be more volatile. In addition, the movement between Indonesia's green index and conventional index tends to be similar. This indicates connectedness between the two stocks during the study period.

Using the Diebold and Yilmaz (2012) approach, this study tried to measure how spillovers occurred between Indonesia's green index and LQ45 and several global stock indexes. The results of the analysis showed that the spillovers occurring between variables are dynamic over time. During the analysis period, the spillovers that occurred between the variables experienced a significant increase several times and then decreased again after a certain period of time. In the long term, the returns of Indonesia's green index tend to experience negative spillovers where spillovers caused by the returns of the green stock index to all variables tend to be smaller than spillovers received by the returns of the green stock index. In addition, the return movement of Indonesia's green stock index is generally more explained by the return movement of the global stock price index compared to the conventional stock index of Indonesia.

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