Journal of Multidisciplinary Academic Business Studies (JoMABS)
ISSN 3032-3169, Vol 2, No 2, 2025, 371-384 *https://doi.org/10.35912/jomabs.v2i2.2682*

Financial contagion analysis on asset return of S&P 500 Index, Shanghai Index, and Hang Seng Index with Jakarta Composite Index for the period 2017 – 2023

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Article History
Received on 1 January 2025
1st Revision on 8 January 2025
Accepted on 20 January 2025

Abstract

Purpose: Using the co-volatility contagion test investigation method developed by Fry-McKibbin (2018), this study analyzes financial contagion, which is how risk and instability spread from one market to another, especially during periods of economic crises.

Method: The subject of this research is the asset return of four global stock markets represented by the S&P 500 Index (SPX, United States), the Shanghai Composite Index (SCI, China), the Hang Seng Index (HSI, Hong Kong), and the Jakarta Composite Index (JCI/JCI, Indonesia) from January 2017 to December 2023.

Results: Utilizing the contagion co-volatility test developed by Fry-McKibbin (2018), this study successfully finds contagion from the SPX, SCI, and HSI indices to the JCI index with varying co-volatility values. The difference in co-volatility values between the SPX and JCI indices is significantly positive; it decreases during a crisis, meaning that both indices tend to move in the same direction and independently during periods of global uncertainty. Meanwhile, the difference in the co-volatility values between the SCI and JCI indices is significantly negative, indicating that the index tends to move in opposite directions during a crisis or independently. However, the magnitude is small during non-crisis and crisis periods. For the HSI and JCI, the difference in the co-volatility values is also significantly negative and decreases. This shows that the Hong Kong and Indonesian markets are becoming less connected with each market moving in opposite directions, reflecting different sensitivities to global uncertainty risk. These differences in market characteristics can provide valuable insights for market participants, investors, and policymakers, enhancing their understanding of risk preferences and volatility transmission between stock markets, thereby supporting informed investment decision making based on historical data analysis.

Keywords: *financial contagion, co-volatility, return*

How to cite: Fardian, F., & Rikumahu, B. (2025). Financial contagion analysis on asset return of S&P 500 Index, Shanghai Index, and Hang Seng Index with Jakarta Composite Index for the period 2017 – 2023. *Journal of Multidisciplinary Academic Business Studies*, 2(2), 371-384.

1. Introduction

One of the instruments of investment is the stock market or capital market, which has now become one of the backbones of the economy, both in Indonesia and around the world. Companies compete to register their names on the stock market, obtain capital that can be used for the development of business capital, and increase the level of production and income of the company. Technological developments, financial deregulation, and the increasing integration of the world's capital markets have created an environment in which investors can easily access stock markets across countries. This process drives what is known as financial globalization. Currently, the flow of capital transfers between countries occurs rapidly. Investors, both individuals and large institutions, are increasingly looking for profit by taking advantage of a wider market, not just limited to the domestic market.

Meanwhile, in Indonesia, the Jakarta Composite Stock Price Index (JCI), or in this study, is referred to as JCI, which is the main reflection of domestic capital market performance. JCI is growing rapidly as part of emerging *markets* that are increasingly attracting global investors. However, due to Indonesia's economic dependence on exports and foreign capital flows, JCI movements are often severely affected by changes in sentiment in the global capital market, especially in the United States, China, and East Asia.

The stock market index in the United States, the S&P 500 (SPX), experienced a consistent rise from the beginning of 2020, before dropping to a low of $2,237 on March 23, 2020, which is down 23.2% from the daily average value of $2,913 in 2019. After the end of 2020, the index generally rose to a high of $4,794 in early 2022, but after that it declined again and fluctuated in the range of $3,500 to $4,500 until finally rising again to the price of $4,783 at the end of the 2023 observation period, which shows the strength of the post-pandemic recovery of the US stock market.

In the Hong Kong stock market, the HSI began to record a price decline in early January 2020 when the Covid-19 pandemic began to spread, until it fell to its lowest point of HK$21,696 on March 23, 2020, which means a decrease of 21.3% from the daily average value of HK$27,576 in 2019. Although the HSI Index shows high volatility, it managed to recover in early 2021 to above HK$30,000, which exceeded the daily average price in 2019. Just a few months later, the index then returned and continued to decline from mid-2021 until the end of the 2023 observation period, as shown in Figure 1.4 (*finance.yahoo.com*).

In Indonesia, the JCI index began to record a decline in early January 2020 until it fell to its lowest point of Rp 3,938 on March 24, 2020, a decrease of 37.5% from the daily average value of Rp 6,296 in 2019. Along with the various policies that the government has taken to restore the Indonesian economy, it can be seen from the JCI price chart in Figure 1.5 that the market started to rise again since the enactment of *the new normal* on June 1, 2020.

Then, in a press release from the Coordinating Ministry for Economic Affairs of the Republic of Indonesia on September 12, 2023, Indonesia and the People's Republic of China agreed to cooperate in the field of Digital Economy. In the field of investment, the development of *integrated Electric Vehicle* (EV) battery production, the development of the petrochemical industry, and the construction of glass factories. The infrastructure sector includes the construction of high-speed trains and the development of the National Capital City (IKN). The two leaders target bilateral trade between the two countries to increase by more than 100 billion US dollars (Limanseto, 2023; Sulistiowati, Adisa, & Caturiani, 2021).

Many researchers have conducted studies on the relationship between capital markets, both during crises and non-crises, using various econometric methods to explore the relationship between capital markets. For example, the vector autoregression (VAR) method by C. Li, Su, Altuntaş, and Li (2022) analyzes how changes in one market affect other markets. Meanwhile, Asai, Gupta, and McAleer (2019) conducted a study on two different types of assets (oil prices and gold futures prices) to find out that variations *in jumps* and *leverage* have a significant impact on co-volatility using four *Heterogeneous Auto Regressive* (HAR) models. Mulyadi (2009) analyzes volatility and changes in conditional variance in a stock market, as well as the relationship between volatility between stock markets. The development of the GARCH method, namely *Dynamic Conditional Correlation – GARCH* (DCC-GARCH), was used by Nguyen, Phan, and Nguyen (2022) to find contagion from the US stock market to the stock market of emerging countries in Asia during the GFC. In addition, Zehri (2021) showed that there was a significant *spillover* effect from the United States market to the East Asian market, especially during the pandemic period using the GARCH-Copula CoVaR method approach, this method is suitable for capturing extreme dependence such as during the financial crisis.

Meanwhile, Fry-McKibbin, Hsiao, and Martin (2018) offer a new series of tests to look at financial market contagion based on changes in extreme dependency defined as co-volatility and co-curtosis. This approach is useful for capturing changes in various aspects of asset yield relationships such as cross-market volatility (co-volatility) and *cross-market averages and* skewness (*co-kurtosis*). Fu, Liu, and Wei (2021) also conducted a study of stock markets in fifteen countries representing each of the Asian continents, Europe, North America, and South America using an *extreme dependence* methodology calculated based on *co-curtosis* and co-volatility during the pandemic.

A newer approach in the analysis of inter-market relationships is the co-volatility method introduced by Fry-McKibbin et al. (2018). Co-volatility is a concept used to measure how volatility in one market interacts with volatility in other markets simultaneously. This is in contrast to traditional volatility analysis which focuses on only one market, where co-volatility takes into account the dynamic relationships between the volatility of multiple markets at once.

Based on research from Fry-McKibbin et al. (2018) which can measure how volatility in one market can interact with volatility in other markets simultaneously, the author tries to raise the topic of *financial contagion analysis* research based on volatility in the yield levels of SPX, SCI, and HSI Index assets, with the JCI Index using the co-volatility method. Therefore, this study is titled "*Analysis of Financial Contagion in Asset Returns on the S&P 500 Index, Shanghai Index, and Hangseng Index with the Indonesia Composite Stock Price Index for the 2017–2023 Period"*.

1.1. Problem Formulation

Based on the background that has been described earlier, the formulation of research problems and questions that will be discussed in this study is as follows:

1. Will there be *a contagion* from the SPX market to the JCI market in the 2017-2023 period?
2. Will there be *a contagion* from the SCI market to the JCI market in the 2017-2023 period?
3. Will there be *a contagion* from the HSI market to the JCI market in the 2017-2023 period?

2. Literature Review

2.1 Stock Indices

The country's economy is currently heavily influenced by the capital market. The capital market allows those who have excess funds to invest their funds in various securities in the hope of obtaining returns, while those who need funds can use these funds to develop their projects. Alternative funding from the capital market can be used by companies for operations and business development, and the government can finance its various activities that can improve the national economy and general prosperity (Abu, 2024; Akabom & Ejabu, 2018).

According to Law No. 8 of 1995 concerning the Capital Market, the capital market is defined as all activities related to the offering and trading of general securities, securities related to the public companies that issue them, as well as institutions and professions related to these securities. Indonesia's capital market is designed to connect investors (financiers) with companies or government institutions, as indicated by its definition of value. Both investors and companies or government institutions need funds for various projects (Ameliah & Jatnika, 2024).

2.2 Return

Return is the level of profit expected by investors from the investment made. If the investment does not provide any benefits then the investor will not make the investment. In practical terms, the rate of return on an investment is a percentage of the total income over a given period compared to the purchase price of the investment (Alfredo, 2023). The goal of investors investing in stocks, bonds, and others is to make a profit or *return* in the future that can guarantee their lives in the future. *Return* is the result or profit obtained by investors who have invested in the capital market. Motivation to earn *return* Stocks encourage investor interest in investing in the stock market. In theory, the higher the level of *return* The stocks that investors expect, the higher the risk that must be faced, and vice versa. Important information for investors in assessing the company's financial performance can be seen from the performance of the company's financial statements. In order for the calculation *return* Stocks become more precise, investors need to conduct a ratio analysis to the company's financial statements. The results of measuring financial ratios can show the ability of a company's financial performance, so it can be a reference for investors in the decision-making process to invest (Alfredo, 2023).

2.3 Volatility

Volatility is *a* statistical measure of the price fluctuations of an asset or financial instrument over a certain period of time (Fry-McKibbin & Hsiao, 2018). Meanwhile, according to Hsu (2022), volatility refers to the level of instability or price fluctuations in the financial market which reflects how much the price of an asset changes over time, especially when there are risky global events. Volatility is often used to measure risk, where a high level of volatility indicates that the price of an asset is undergoing rapid and significant changes in a short period of time. On the contrary, low volatility indicates that prices tend to be stable. In the context of financial markets, volatility is usually calculated as a standard deviation from a change in the price or *return of an asset*. Volatility can also create opportunities for investors who are able to take advantage of rapid price changes to make a profit. There are two main types of volatility: historical volatility, which is calculated based on past price data or returns, and implicit volatility, which reflects the market's expectations for future volatility based on option prices. Factors that affect volatility include macroeconomic conditions, changes in interest rates, government policies, as well as global events such as financial crises or geopolitical tensions. Volatility is also often affected by market sentiment and reactions to specific news or events.

2.4 Contagion and Spillover

Contagion In the context of volatility, financial markets refer to the spread of volatility shocks from one market to another, especially during periods of crisis. This phenomenon occurs when extreme changes in volatility in one market trigger changes in volatility in another, exceeding the normal economic relationships that usually occur (Rigobon, 2019). Platonov (2024) describes *Contagion* As a rapid decline in national equity prices: if one country experiences a financial crisis, then other countries may get negative sentiment from it which can cause the country to experience a similar financial crisis. It is often caused by irrational market behavior, such as panic or massive selling, which then spreads to the global market. Classic example of *Contagion* Volatility was the 2008 global financial crisis, in which volatility in the United States financial markets quickly spread to European and Asian markets, although not all markets have direct economic linkages. This shows that *contagion* often involves changing risk perceptions globally, leading to higher volatility across markets (Fry-McKibbin & Hsiao, 2018).

While *Spillover* Volatility refers to the transmission of volatility between markets through more normal economic and financial channels, often occurring during periods of stability as well as instability. Volatility can also be used to measure the risk of a single stock market, and that risk can be contagious among stock markets, which is defined as *Spillover* volatility (C. Li et al., 2022). Research by Diebold and Yilmaz (2009) shows that *Spillover* Volatility can occur through trade relationships, capital flows, or shared exposure to global risks. For example, the increase in the relationship between volatility in the commodity market and the volatility of the stock market of exporting and importing countries of the commodity. *Spillover* volatility is usually more predictable compared to *Contagion*, and often reflect the structural relationships between existing markets. However, during periods of crisis, the difference between *Spillover* and *Contagion* can be biased because the transmission of volatility can occur through a variety of more complex paths (Cotter, Hallam, & Yilmaz, 2023).

2.5 Spillover Effects

Spillover effects or *spillover* effects refer to the impact of volatility shocks from one market to another, this indicates the transmission of risk between markets where fluctuations in one market can cause the impact of stability or uncertainty in another market (Hsu, 2022). Meanwhile, according to Nguyen et al. (2022), the *spillover effect* refers to the impact transmitted from one market to another, especially when a crisis occurs. This effect is indicated by price movements or volatility in one market spreading out and triggering similar changes in other markets.

Meanwhile, according to Yurastika and Wibowo (2020), the spillover *effect* refers to a phenomenon where volatility or instability in one financial market can affect volatility in another financial market, so that both markets experience similar volatility or affect each other.

2.6 Co-Movement

According to research conducted by Ang, Hodrick, Xing, and Zhang (2006), significant *co-movements* between stock market indices from different countries show a strong correlation on global financial markets. In terms of risk management and global portfolio diversification, these relationships can have a significant impact.

Bekaert, Harvey, and Lundblad (2011) investigated global variables that interact with *the phenomenon of co-movement* in the stock market. In the study, they emphasized that global variables such as changes in the global economy, political uncertainty, and the movement of international capital flows can affect how much movement the market has. Their analysis also provides an in-depth understanding of the complex relationships that occur in the stock market globally that affect the dynamics of the global economy as a whole, not just local variables. These results have great benefits for market participants and decision-makers, in terms of managing risk and creating effective and optimal investment and diversification strategies in the midst of uncertain global markets.

2.7 Behaviour of Financial Contagion

Referring to the research of Fry-McKibbin et al. (2018), *financial contagion* behavior is a way of spreading risk and instability from one market to another, especially during periods of financial crisis. The main characteristic of this behavior is that there is an increase in correlation during crisis periods, which means that during crisis periods, correlations between markets tend to increase, indicating that these markets are increasingly interconnected. Then there is increased co-volatility, where volatility in various markets moves together. This provides evidence that *the contagion* effect is shown by a surge in volatility in one market often followed by a surge in volatility in another.

2.8 Framework of Thought

The financial linkage between asset returns on the SPX, SCI, and HSI indices against the *Jakarta Composite Index* (JCI) during the 2017–2023 period reflects the high level of interdependence of global financial markets. During this period, the three major indices have been an important source of volatility and *spillover* for JCI, given the increasingly close economic connectivity between Indonesia and other countries, especially in Asia and the United States. The Hang Seng and Shanghai indices play a significant role due to Indonesia's economic linkages with China and Hong Kong through trade and investment, while the S&P 500 reflects the global impact of the United States economy on financial markets around the world, including Indonesia.

The framework of thinking in this study focuses on two independent *variables*. In this study, the SPX Index, SCI Index, HSI Index, and JCI Index are independent variables, which are derived into the co-volatility of the SPX and JCI Indices, the co-volatility of the SCI and JCI Indices, the co-volatility of the HSI and JCI Indices before and during the Covid-19 crisis which can be described as follows:

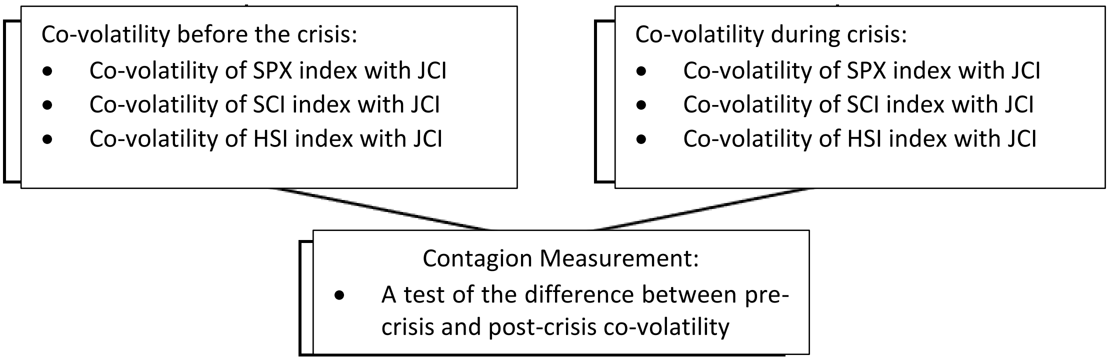

Figure 1. Framework of Thought

2.9 Research Hypothesis
There is a *volatility spillover* between the US market, the Japanese market, and the Indonesian market (Mulyadi, 2009). Meanwhile, there was a *two-way volatility spillover* in the stock market and bond market in Indonesia (Yurastika and Wibowo, 2020). Using the VAR method, Y.-M. Li and Bai (2021) found that there is a *mean spillover effect*, and through the perspective of the GARCH model, *the volatility spillover* effect is significant among the Chinese stock market and the ASEAN-5 stock market, including Indonesia. Meanwhile, Fu et al. (2021) found that there was a significant *financial contagion* during the Covid-19 pandemic with different impacts on each region, with countries in Asia tending to be stronger than countries in South America and Europe.

In this study, the definition of *contagion* is based on Forbes and Rigobon (2002) which states a significant increase in correlation between markets during periods of crisis. In other words, if the correlation between two markets is moderate in a stable period and shocks in one market cause a surge in *co-movement* in the other, then *contagion* occurs.

Using the *return*, average, and volatility data of each SPX, SCI, HSI, and JCI Index, the correlation value of each SPX, SCI, and HSI Index with the JCI Index can be determined. Then the amount of co-volatility of each SPX, SCI, and HSI Index with the JCI Index can be known for the period before and during the Covid-19 crisis. Based on this, the following research hypotheses can be developed:
1. SPX Index and JCI Index
   H1: There is a difference in co-volatility before and during the Covid-19 crisis in the SPX Index and the JCI Index.
2. SCI Index and JCI Index
   H2: There is a difference in co-volatility before and during the Covid-19 crisis in the SCI Index and the JCI Index.
3. HSI Index and JCI Index
   H3: There is a difference in co-volatility before and during the Covid-19 crisis in the HSI Index and the JCI Index.

3. Research Methodology
3.1. Type of Research
This study uses a type of explanatory research with a quantitative approach. This type of research was chosen because it aims to provide a general understanding of the data being analyzed, by using historical data in the form of numbers in a certain period of time. The paradigm used is positivism which argues that facts can be measured and understood through observation and analysis of empirical data. Based on the involvement of the researchers, the researchers did not intervene with the analysis units in the study being the S&P 500 (SPX), Shanghai (SCI), Hang Seng (HSI), and JCI (JCI) stock market indices. The background of this research is *non-contrived,* which means that the data used is stock market data that occurs naturally without any intervention from the researcher. Based on the time of the study is longitudinal. The following is a table of research characteristics:

Table 1. Table of Research Characteristics

It	Research Characteristics	Kind
1	By Method	Quantitative Methods
2	By Purpose	Verifiable Descriptive Research
3	Based on Paradigm	Positivism
4	Based on Approach	Deductive
5	Based on Researcher Involvement	Not Intervening with Data
6	By Unit of Analysis	Stock market indices
7	Based on Research Background	*Non-Contrived Setting*
8	Based on Implementation Time	Longitudinal

Source: data has been processed by the author

3.2. Variable Operationalization

In this study, the variables that will be operationalized are as follows:

Table 2. Table of Operational Variables

It	Variable	Sub Variables	Operational Definition (Indicator)	Scale
1	Return SPX Index	Return of the SPX Index before the crisis SPX Index Return during a crisis	The closing price of the Index at t-1 compared to the closing price of the Index at t-1 of the SPX Index from 1 January 2017 to 31 December 2023	Ratio
2	Return SCI Index	Return of SCI Index before the crisis SCI Index Returns in Crisis	The closing price of the Index at time *t* compared to the closing price of the Index at time *t-1 of the SCI Index from January 1, 2017 to December 31, 2023*	Ratio
3	HSI Index Return	HSI Index Return before the crisis HSI Index Return during a crisis	The closing price of the Index at t-1 compared to the closing price of the Index at t-1 of the HSI Index from 1 January 2017 to 31 December 2023	Ratio
4	JCI Index Return	JCI Index Return before the crisis JCI Index Returns during a crisis	The closing price of the Index at time *t* compared to the closing price of the Index at time *t-1 of the JCI Index from January 1, 2017 to December 31, 2023*	Ratio

3.3. Population and Sample

Population is the entire element that will be used as a generalization area. The population element is the entire subject to be measured, which is the unit being studied (Sugiyono, 2017). The selected population in this study is the limit of what is produced from this study. In this study, there are four selected population groups, namely the S&P 500 stock market price index (SPX), Shanghai (SCI), HangSeng (HSI), and JCI (JCI).

In this study, a non-random sampling technique or *non-probability sampling* was used, which according to Sugiyono (2017) is a sampling technique that does not provide the same opportunity/opportunity for each element of the population to be used as a sample. So the sample used in this study is the daily closing prices of the four stock market indices SPX, SCI, HSI, and JCI in the time period from January 1, 2017 to December 31, 2023.

3.4. Data Analysis Techniques

In the process of data analysis in this study, a series of analysis techniques used are:

1. Data Collection: The first step in the study is the collection of the fourth daily return data of the SPX, SCI, HSI, and JCI Indices in the period 2017–2023 taken from *finance.yahoo.com sources.*
2. Descriptive Statistics: The next step in this data analysis is to provide an overview of the characteristics of the dataset. Descriptive statistics are used to describe the distribution of data by calculating the mean, median, mode, and standard deviation of the relevant variables.
3. Return Calculation: Calculate the return of each SPX, SCI, HSI, and JCI Index before and during the crisis using the formula (2.4).
4. Calculation of Average Return Index: Calculate the average return of each SPX, SCI, HSI, and JCI Index before and during the crisis using the formula (2.5).
5. Volatility Calculation: Calculate the volatility of each of the SPX, SCI, HSI, and JCI Indices before and during the crisis using the formula (2.6).
6. Correlation Calculation: Perform correlation calculations from the SPX and JCI Indices, SCI and JCI Indices, and HSI and JCI Indices before and during the crisis using the following formula:

$$\rho_{(x,y)} = \frac{\sum\left(R_{t,i} - \bar{R}_i\right)\left(R_{t,j} - \bar{R}_j\right)}{\sqrt{\sum\left(R_{t,i} - \bar{R}_i\right)^2 \sum\left(R_{t,j} - \bar{R}_j\right)^2}} \quad (3.1)$$

Where:

$\rho_{(i,j)}$ = Correlation of Index *i* and *Index j*

$R_{t,i}$ dan $R_{t,j}$ = Daily return of market *i* and market *j*

$\bar{R}_i \; dan \; \bar{R}_j$ = Average *return* of market *i* and market *j*

7. Correlation adjustment during a crisis: Adjusting the correlation value during a crisis due to heteroscedasticity, namely using the following formula:

$$\nu_y = \frac{\rho_y}{\sqrt{1 + \frac{\sigma_{yi}^2 - \sigma_{xi}^2}{\sigma_{xi}^2}\left(1 - \rho_y^2\right)}} \quad (3.2)$$

Where:

ν_y = Correlation adjusted crisis period

ρ_y = Correlation of crisis periods

σ_{yi} = Volatility value of the market crisis period *i*

σ_{xi} = Volatility value of the non-crisis period of the market *i*

8. Co-volatility calculation: Perform the co-volatility calculation of the SPX and JCI Indices, SCI and JCI Indices, and HSI and JCI Indices before and during the crisis, using the formula (2.7).
9. Time Series Analysis: When the dataset used relates to data collected over a specific time range, time series analysis is used. This analysis helps in identifying patterns of change in the data over the time of observation, especially during the pre-crisis period (2017-2019) and during the crisis (2020-2023).
10. Differential test: Measure the differential test of co-volatility before and during the crisis using the following statistical hypotheses:

a) SPX Index and JCI Index

H0: There was no significant difference between the co-volatility before and during the Covid-19 crisis on the SPX Index and the JCI Index.

H1: There is a significant difference between the co-volatility before and during the Covid-19 crisis on the SPX Index and the JCI Index.

b) SCI Index and JCI Index

H0: There was no significant difference between the co-volatility before and during the Covid-19 crisis on the SCI Index and the JCI Index.

H1: There is a significant difference between the co-volatility before and during the Covid-19 crisis on the SCI Index and the JCI Index.

c) HSI Index and JCI Index

H0: There was no significant difference between the co-volatility before and during the Covid-19 crisis on the HSI Index and the JCI Index.

H1: There is a significant difference between the co-volatility before and during the Covid-19 crisis on the HSI Index and the JCI Index.

11. Hypothesis test: Conducting a statistical hypothesis test using Chi Squared to test the comparative hypothesis of two Index samples with nominal data and a large number of samples. The following formula is used to test the hypothesis:

$$\chi^2 = \left(\frac{\xi_y - \xi_x}{\sqrt{\frac{4v_y^4+16v_y^2+4}{T_y} + \frac{4\rho_x^4+16\rho_x^2+4}{T_x}}} \right)^2 \sim \chi^2(1) \qquad (3.3)$$

Where:
ξ_y = co-volatility of crisis periods
ξ_x = co-volatility of non-crisis periods
ν_y = Correlation adjusted crisis period
ρ_x = Correlation of non-crisis periods
T_y = Number of sample data for the crisis period
T_x = Number of sample data for the non-crisis period

4. Result and Discussion

4.1 Data Characteristics

Furthermore, to be able to understand the characteristics of the data used in this study, it is necessary to conduct a descriptive analysis. Descriptive analysis is conducted with the aim of providing an overview of the closing price of the shares of each index studied. The following is a table of descriptive statistical characteristics from the closing price data of the SPX, SCI, HSI, and JCI Indices for the period January 2017 – December 2023:

Table 3. Descriptive statistics of SPX, SCI, HSI, and JCI indices 2017-2023

Index Variables	***Mean***	***Median***	***Minimum***	***Maximum***	***Standard Deviation***
SPX	3.426,62	3.278,65	2.237,40	4.796,56	755,78
SCI	3.168,06	3.197,90	2.464,36	3.715,37	262,28
HSI	24.930,59	25.657,54	14.687,02	33.154,12	3.954,19
JCI	6.200,05	6.209,12	3.937,63	7.318,02	627,17

In Table 3 above, you can see some descriptive statistics from the index, including the average closing price of the SPX Index is 3,426.62, while the median value describing the middle value of the observation data is 3,278.65. As for the maximum price is 4,796.56 and the minimum price is 2,237.40. And also a standard deviation of 755.78 which indicates the level of volatility or price fluctuations from the average value.

In the JCI index, the average value of the index is 6,200.05 and the median value representing the middle point of the data distribution is 6,209.12. While the lowest price was 3,937.63 and the highest price was 7,318.02. The standard deviation results in a figure of 627.17 which describes the level of volatility or price fluctuations from its average value.

Next, *the* calculation of the daily return of each SPX, SCI, HSI, and JCI index using the formula (2.4) to then make descriptive statistics as seen in Table 4 The average *return* of the SPX index is greater than the average *return* of other indices, which reflects the average profit opportunity is greater among other indices. The SPX and SCI indices show more stable market conditions with few large movements. The standard deviation shows that the dispersion rate of *the HSI* index return is greater than that of other indices, which is 0.0133, which means that the HSI index is more dynamic with a large level of fluctuation. Meanwhile, the JCI index is the index with the smallest standard deviation of 0.0093 which shows that the index tends to be stable with small price fluctuations, but has greater growth potential compared to other indices.

Table 4. Descriptive statistics *of return* of SPX, SCI, HSI, and JCI indices 2017-2023

Index Variables	***Mean***	***Median***	***Minimum***	***Maximum***	***Standard Deviation***
SPX	0,0005	0,0005	-0,1198	0,0938	0,0120
SCI	0,0000	0,0000	-0,0772	0,0571	0,0100
HSI	-0,0001	0,0000	-0,0636	0,0908	0,0133
JCI	0,0002	0,0000	-0,0658	0,1019	0,0093

Then the correlation matrix between the indices is made using the formula (3.1) the results of which can be seen in Table 5 In general, the SPX and JCI indices have a positive correlation that shows a stronger unidirectional relationship (0.59), this relationship shows that both indices tend to move in the same direction, when the volatility of one index moves up, then the other index also moves up. This positive correlation may be contributed by similar economic factors and policies implemented in both countries. This is similar to the correlation of the SCI and JCI indices with a positive value but smaller at 0.15 which means that the correlation relationship between the indices tends to move in the same direction, but is quite weak. Inversely proportional to the correlation between HSI and JCI which is negative (-0.42), it shows that the two indices tend to move in opposite directions or in other words, when the volatility of one index moves up, the other index moves down, or vice versa. This negative correlation may be influenced by different economic and policy factors between Hong Kong and Indonesia that make the index fluctuate in opposite directions.

Table 5. Correlation matrix of SPX, SCI, HSI, and JCI indices 2017-2023

Index Variables	**SPX**	**SCI**	**HSI**	**JCI**
SPX	1,00			
SCI	0,49	1,00		
HSI	-0,55	0,06	1,00	
JCI	0,59	0,15	-0,42	1,00

4.2 Financial contagion analysis

The analysis was carried out by calculating volatility, average, correlation, and adjusted correlation, with the number of samples during the non-crisis period (stable, x) being 827 samples and the crisis period (unstable, y) being 992 samples, to obtain the co-volatility values of the market indices compared, namely: SPX and JCI, SCI and JCI, as well as HSI and JCI. The non-crisis and crisis periods are differentiated based on an official announcement from the *World Health Organization* (WHO) on March 11, 2020 which declared Covid-19 a global pandemic (WHO, 2023).

4.3 Volatility and average analysis

The analysis begins by calculating the volatility of the index, the results of which can be seen in Table 6 The small difference in volatility of the SPX and JCI indices in the non-crisis period (0.92% for SPX and 0.81% for JCI) shows that SPX has greater fluctuations compared to JCI. Where SPX is more sensitive to very dynamic global market issues, while JCI is more stable with more dominant domestic factors. At the time of the crisis, both indices experienced increased volatility (1.39% for the SPX and

1.02% for the JCI) indicating that global economic uncertainty and instability are increasing in both markets. The SPX index has experienced a more significant increase compared to the JCI index. This is in line with the concept of *the spillover effect*, where global markets respond faster to crisis dynamics compared to local markets that may have better resilience to global capital flows.

With a similar calculation method, the SCI Index shows a volatility of 1.04%, higher than the JCI index (0.81%), which can be interpreted that the Chinese market has a greater level of uncertainty than the Indonesian market during the non-crisis period. A different thing happened when entering the crisis period, the volatility of the SCI index decreased to 0.95% while the volatility of the JCI index increased to 1.02%. The decline in the SCI index reflects that the Chinese market is relatively more stable in the face of the crisis made possible by the intervention of policymakers to bring the economy under control. Meanwhile, the increase in volatility of the JCI index illustrates that the Indonesian market is more vulnerable to the impact of the global crisis with its dependence on foreign capital flows.

The average yield of the HSI index experienced a significant decrease in the crisis period, from 0.02% to -0.03%, which means that this index recorded a loss in the average yield. Meanwhile, the JCI index is the opposite of the HSI index, which has experienced an increase in the average yield from 0.00% to 0.04%, which means that this index is more resistant to crisis shocks that occur or there are domestic factors that hold back the index's performance during the crisis.

Table 6. Volatility and average analysis

Index Variables	**Era**	**Volatility**		**Average**	
		(i)	***(j)***	***(i)***	***(j)***
SPX (*i*) and JCI (*j*)	Non-crisis (x)	0.92%	0.81%	0.03%	0.00%
	Crisis (y)	1.39%	1.02%	0.06%	0.04%
SCI (*i*) and JCI (*j*)	Non-crisis (x)	1.04%	0.81%	0.00%	0.00%
	Crisis (y)	0.95%	1.02%	0.00%	0.04%
HSI(*i*) and JCI(*j*)	Non-crisis (x)	1.01%	0.81%	0.02%	0.00%
	Crisis (y)	1.54%	1.02%	-0.03%	0.04%

4.4 *Correlation and co-volatility analysis*

The next step is to determine the correlation and correlation is adjusted between indices to obtain a co-volatility value. The results of the analysis can be seen in Table 4.5. The result of the calculation of the correlation of the yields of the SPX and JCI indices in non-crisis times was 0.19, while in times of crisis it was 0.22. There is a correlation of the index when the crisis increases. However, as introduced by Forbes and Rigobon (2002), adjustments need to be made regarding the heteroscedasticity of the correlation of crisis periods. So that adjustments are needed to the correlation calculation calculated using formula 3.2. So that the correlation between the SPX and JCI indices after adjustment during the crisis was obtained at 0.15, and was smaller or weakened by 23.47% compared to the correlation in the non-crisis period. This means that the correlation of the SPX and JCI indices during the crisis shows a positive relationship so that it tends to move in one direction, but with the strength of the relationship weakening or contagion decreasing. The reduction in correlation at the time of the crisis which reached 23.47% compared to the time of the non-crisis shows that the volatility of the yields of each SPX and JCI index tends to move with their respective movement patterns (*independent*).

With the same logic as before, calculations are carried out for the HSI and JCI indexes. The correlation between the HSI index yield and the JCI index seems to have weakened considerably during the crisis from 0.39 to 0.28 during the non-crisis or weakened by 28.5%. After adjustments related to heteroscedasticity, the correlation between the HSI and JCI indices during the crisis was obtained at 0.19, which means that the correlation between the HSI and JCI indices weakened to 52.1%. Or in other words, something that happens in one market is less disruptive to the other or *less contagion* . The reduction in correlation at the time of the crisis which reached 52.1% compared to the time of the non-crisis shows that the volatility of the yields of each HSI and JCI index tends to move with their respective movement patterns (*independent*).

Next, the co-volatility relationship between the HSI and JCI indices is seen to weaken, at non-crisis time it is -0.14 and at crisis time it is -0.37. The negative co-volatility value gives an idea that when the volatility of one index increases, then the movement of the other index tends to go in the opposite direction or down. Meanwhile, the value that fell from -0.14 to -0.37 at the time of the crisis shows that the opposite movement pattern between the two indices is getting stronger. This is possible due to different reactions to global economic sentiment or the flow of capital withdrawal from the HSI index to be placed in a more stable capital market.

Table 7. Correlation analysis, adjusted correlation, and co-volatility

Index Variables	Era	Correlation	Adjusted Correlation	Co-volatility
SPX and JCI	Non-crisis (x)	0,1913	0,1913	5,5623
	Crisis (y)	0,2188	0,1464	5,2222
SCI and JCI	Non-crisis (x)	0,2405	0,2405	-0,1322
	Crisis (y)	0,2241	0,2441	-0,8687
HSI and JCI	Non-crisis (x)	0,3922	0,3922	-0,1391
	Crisis (y)	0,2804	0,1878	-0,3696

4.5 Hypothesis testing

The next step is to conduct a statistical test of the co-volatility value obtained, using a *chi-squared* statistical test with one degree of freedom using the formula 3.3. The results of *the chi-squared* statistical test of the co-volatility of the SPX and JCI indices can be seen in Table 8, which is 11.6446. Then the calculation *of the p-value* value can be done using *a chi-squared* distribution with one degree of freedom, and produces a very small value, which is 0.0006. Based on the significance table of *chi-squared critical values,* this means that the co-volatility of the SPX and JCI indices during the crisis is significant. Thus, the results of the co-volatility differential test for H0 were rejected, so it can be concluded that there is a significant difference between the co-volatility before and during the Covid-19 crisis period in the SPX index and the JCI index. It can also be said that the SPX index and the JCI index are less responsive to each other's volatility when there is an increase in uncertainty or crisis.

Meanwhile, the results of *the chi-squared statistical test* of the co-volatility of the SPX and JCI indices are 4.2369. And the *p-value* is obtained a very small value, which is 0.0396, so this means that the co-volatility of the HSI and JCI indices during the crisis is significant. Thus, the results of the co-volatility differential test for H0 were rejected, so it can be concluded that there is a significant difference between co-volatility before and during the Covid-19 crisis period in the HSI index and the JCI index. It can also be said that the HSI index and the JCI index are less responsive to each other's volatility when there is an increase in uncertainty or crisis.

Table 8. Analysis of chi-squared and p-value hypothesis tests

Index Variables	*chi-squared*	*p-value*
SPX and JCI	11,64455773	0,000643906
SCI and JCI	49,41079069	2.07601E-12
HSI and JCI	4,23693293	0,03955356

5. Conlusion

5.1 Conclusion

Based on the analysis of the results of this study, the following conclusions are obtained:

1. The price movements and yields of the SPX index show an upward trend that is in line with increased volatility during times of crisis. The positive correlation between the SPX and JCI

indices shows the influence of the dominant global market on the Indonesian market. The co-volatility value of the SPX and JCI indices yields was positive but seemed to decrease during the crisis, inversely proportional to the increased volatility of each index. Based on the results of the co-volatility differential test, it can be concluded that there was *a contagion* from the SPX market to the JCI market in the 2017-2023 period.

2. Price movements and yields of the SCI index tend to move in a narrow range, reflecting domestic stability. The correlation between the SCI and JCI indices is positive, but with the strength of the relationship that tends not to change, or *the contagion remains.* The yield co-volatility value of the SCI and JCI indices looks weaker and shows a stronger negative correlation. Based on the results of the co-volatility differential test, the decline in the co-volatility of the SCI and JCI indices during the crisis is significant, although not too far away. So it can be concluded that there was *a contagion* from the SCI market to the JCI market in the 2017-2023 period.
3. Price movements and yields of the HSI index are the most volatile, with high sensitivity to global dynamics. The correlation between the HSI index yield and the JCI index is positive, but weakened considerably during the crisis. The yield co-volatility value of the HSI and JCI indices appears to weaken and shows a stronger negative correlation. Based on the results of the co-volatility differential test, the decrease in the co-volatility of the HSI and JCI indices during a crisis is significant. So it can be concluded that there was *a contagion* from the HSI market to the JCI market in the 2017-2023 period.

5.2 Suggestion

The suggestions from the results of the research are as follows:

5.2.1 For academics

For academics, this research can be used as input and consideration for further research. This research can be expanded by using more in-depth analysis methods, such as the GARCH or VAR model approaches, to understand the dynamics of volatility between indices in a more complex way. Future research may also explore the relationship between stock indices and macroeconomic factors, such as inflation, interest rates, and foreign capital flows, to broaden understanding the influence of external factors on the domestic market.

5.2.2 For Practitioners

For practitioners, the results of this research will be very useful for investors, portfolio managers, and policymakers in Indonesia. For investors, it is advisable to leverage domestic markets, such as JCI, as a portfolio diversification instrument to reduce risk during periods of global uncertainty. The stability of the JCI index is an opportunity for investors looking for security with moderate fluctuations. For global markets such as the SPX and HSI, investors with a higher risk tolerance can take advantage of it as a potential source of greater profits, especially during post-crisis recovery periods. For policymakers, it is important for governments and capital market regulators to strengthen domestic economic policy frameworks that can maintain market stability during global crises. Efforts such as interest rate adjustments, fiscal intervention, and flexible monetary policy are important steps to support market confidence. International cooperation needs to be increased to mitigate the impact of global economic *spillover* on the domestic market. This includes strengthening bilateral and multilateral agreements in the economic and trade fields.

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