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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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Abstract

Purpose: This study investigates financial contagion—the transmission of risk and instability between markets and using the co-volatility contagion test method developed by Fry-McKibbin (2018). This study aims to analyze the volatility linkages among major global stock markets and their impact on Indonesia's market during economic crises.

Research Methodology: This study examines daily asset returns from January 2017 to December 2023 for the S&P 500 Index (SPX, United States), Shanghai Composite Index (SCI, China), Hang Seng Index (HSI, Hong Kong), and Jakarta Composite Index (JCI, Indonesia). The co-volatility contagion framework measures changes in market correlations between crisis and non-crisis periods.

Results: The findings reveal contagion from SPX, SCI, and HSI to the JCI, with varying co-volatility patterns. The SPX–JCI relationship shows significantly positive co-volatility differences that decline during crises, indicating synchronized but independent movements under global uncertainty. The SCI–JCI differences were significantly negative with low magnitudes, suggesting opposite movement tendencies during crises. HSI–JCI differences were also significantly negative, reflecting reduced connectivity and divergent responses to global risks.

Conclusions: Distinct co-volatility patterns indicate different market sensitivities to global uncertainty, emphasizing the importance of tailored investment and policy strategies.

Limitations: This study focuses on four markets and a defined time span, potentially limiting generalizability. However, it does not account for sector-specific contagion effects.

Contribution: This study provides empirical evidence of volatility transmission mechanisms, offering valuable insights for investors, market participants, and policymakers to enhance risk assessment and investment strategies.

Keywords: *Co-Volatility, Financial Contagion, Return, Stock Market, Volatility Transmission*

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1. Introduction

One of the instruments of investment is the stock 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 their production and income levels.* 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 (Kristiyani, Marlissa, & Urip, 2025; Lani, Hutajulu, & Mollet, 2025; Wamaer, Umar, & Hafizrianda, 2025). *Currently, capital transfers between countries occur rapidly. Investors, both individuals and large institutions, are increasingly looking for profit by taking advantage of a wider market that is not 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. *The JCI is growing rapidly as part of emerging markets that are increasingly attracting global investors. However, owing 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. A few months later, the index 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 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 implemented 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. 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 (Sitepu & Soma, 2025). 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 and the relationship between volatility and 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, which is suitable for capturing extreme dependence, such as during the financial crisis (Restiani & Indiyati, 2024; Rosyadi, Gunarto, & Yuliawan, 2025).

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 studied stock markets in 15 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 to the analysis of inter-market relationships is the co-volatility method introduced by Fry-McKibbin et al. (2018). Co-volatility measures 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 considers the dynamic relationships between the volatility of multiple markets simultaneously. Based on research by Fry-McKibbin et al. (2018), which can measure how volatility in one market can interact with volatility in other markets simultaneously, this study attempts to raise the topic of *financial contagion analysis* 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 described earlier, the research problems and questions that will be discussed in this study are as follows:

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

2. Literature review

2.1 Stock Indices

The 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. Companies can use alternative funding from the capital market for operations and business development, and the government can finance its various activities to 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 public companies that issue them, and 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 value definition. Both investors and companies or government institutions require funds for various projects (Ameliah & Jatnika, 2024).

2.2 Return

Return is the level of profit expected by investors from their investments. If the investment does not provide any benefits, the investor will not invest. In practical terms, the rate of return on an investment is the percentage of the total income over a given period compared to the purchase price of the investment (Alfredo, 2023). Investors in stocks, bonds, and other assets aim 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 invest in the capital market. Motivation to earn *returns* encourages investors to invest in the stock market. In theory, the higher the level of *return* expected from the stocks, the higher the risk that must be faced, and vice versa. Important information for investors in assessing a company's financial performance can be seen from the company's financial statements. To make the calculation *of return* stocks more precise, investors need to conduct a ratio analysis of 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 (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). 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. In contrast, low volatility indicates that prices tend to be stable. In the context of financial markets, volatility is usually calculated as the standard deviation of a change in the price or *return of an asset*. Volatility can also create opportunities for investors who can 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 of future volatility based on option prices. Factors that affect volatility include macroeconomic conditions, changes in interest rates, government policies, and global events such as financial crises or geopolitical tensions. Volatility is often affected by market sentiment and reactions to specific news or events.

2.4 Contagion and Spillover

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 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 global markets. A 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 had direct economic linkages. This shows that *contagion* often involves changing risk perceptions globally, leading to higher volatility in markets (Fry-McKibbin & Hsiao, 2018).

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). Diebold and Yilmaz (2009) show that *Spillover* Volatility can occur through trade relationships, capital flows, or shared exposure to global risks. For example, the relationship between volatility in the commodity market and the volatility of the stock market of exporting and importing countries of the commodity increases. *Spillover* volatility is usually more predictable than *contagion* and often reflects 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 refer to the impact of volatility shocks from one market to another, indicating the transmission of risk between markets, where fluctuations in one market can cause stability or uncertainty in another market (Hsu, 2022). According to Nguyen et al. (2022), the spillover effect refers to the impact transmitted from one market to another, especially during a crisis. This effect is indicated by price movements or volatility in one market spreading and triggering similar changes in other markets. Meanwhile, according to Liu, Chen, Chen, and Yao (2022), 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 in global financial markets. These relationships can have a significant impact on risk management and global portfolio diversification. Bekaert, Harvey, and Lundblad (2011) investigate global variables that interact with *the phenomenon of co-movement* in the stock market. They emphasized that global variables, such as changes in the global economy, political uncertainty, and the movement of international capital flows, can affect the extent of market movement. Their analysis also provides an in-depth understanding of the complex relationships that occur in the stock market globally, which 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
According to 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 inter-connected. 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 the 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 because of 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 worldwide, including Indonesia.

The framework of 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, and the co-volatility of the HSI and JCI Indices before and during the Covid-19 crisis, which can be described as follows:

Co-volatility before the crisis:
- Co-volatility of SPX index with JCI
- Co-volatility of SCI index with JCI
- Co-volatility of HSI index with JCI

Co-volatility during crisis:
- Co-volatility of SPX index with JCI
- Co-volatility of SCI index with JCI
- Co-volatility of HSI index with JCI

Contagion Measurement:
- A test of the difference between pre-crisis and post-crisis co-volatility

Figure 1. Framework of Thought

2.9 Research Hypothesis
There is a *volatility spillover* between the US, Japanese, and Indonesian markets (Mulyadi, 2009). Meanwhile, there was a *two-way volatility spillover* in Indonesia’s stock and bond markets (Liu et al., 2022). 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 those in South America and

Europe. In this study, contagion is defined 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 were 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 and JCI indices.
2. SCI Index and JCI Index
   H2: There is a difference in co-volatility before and during the Covid-19 crisis in the SCI and JCI indices.
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 used 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, which were 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 are stock market data that occur naturally without any intervention from the researcher. Based on the time of the study, it was longitudinal. The following table presents the 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	The closing price of the Index at time *t* compared to the closing price of the	Ratio

		SCI Index Returns in Crisis	Index at time *t-1 of the SCI Index from January 1, 2017 to December 31, 2023*	
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

The 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 under study (Sugiyono, 2017). The selected population in this study is the limit of what was produced in this study. In this study, four population groups were selected: 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, does not provide the same opportunity for each element of the population to be used as a sample. Therefore, 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 were used.

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 for the period 2017–2023 from *finance.yahoo.com sources.*
2. Descriptive Statistics: The next step in the data analysis was to provide an overview of the dataset characteristics. Descriptive statistics were used to describe the distribution of data by calculating the mean, median, mode, and standard deviation of the relevant variables.
3. Return calculation: The return of each SPX, SCI, HSI, and JCI Index is calculated before and during the crisis using formula (2.4).
4. Calculation of Average Return Index: The average return of each of the SPX, SCI, HSI, and JCI indices is calculated before and during the crisis using 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 formula (2.6).
6. Correlation Calculation: Correlation calculations were performed for the SPX and JCI, SCI and JCI, and HSI and JCI indices before and during the crisis using the following formula:

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

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: The correlation value is adjusted during a crisis due to heteroscedasticity using the following formula:

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

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: The co-volatility calculation of the SPX and JCI Indices, SCI and JCI Indices, and HSI and JCI Indices before and during the crisis is performed using formula (2.7).
9. Time Series Analysis: When Time series analysis is used when the dataset relates to data collected over a specific time range. This analysis helps identify 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 and JCI Indices.

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

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 and JCI indices.

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

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 and JCI indices.

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

11. Hypothesis test: A statistical hypothesis test was conducted using the chi-squared test to test the comparative hypothesis of two index samples with nominal data and a large number of samples. The following formula was used to test the hypothesis:

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

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 understand the characteristics of the data used in this study, a descriptive analysis was conducted. A descriptive analysis was conducted to provide 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, some descriptive statistics from the index are presented, including the average closing price of the SPX Index, which is 3,426.62, while the median value describing the middle value of the observation data is 3,278.65. The maximum price is 4,796.56 and the minimum price is 2,237.40. The standard deviation is 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. 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 daily returns of each of the SPX, SCI, HSI, and JCI indices are calculated using formula (2.4) to obtain descriptive statistics, as shown in Table 4. The average *return* of the SPX index is greater than the average *return* of the other indices, which reflects that the average profit opportunity is greater than of that the other indices. The SPX and SCI indices show more stable market conditions with few large movements than the others. The standard deviation shows that the dispersion rate of *the HSI* index return is greater than that of other indices, at 0.0133, which means that the HSI index is more dynamic with a large level of fluctuation. Meanwhile, the JCI index has 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 than 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 created using formula (3.1), the results of which are shown in Table 5. In general, the SPX and JCI indices have a positive correlation that shows a stronger unidirectional relationship (0.59), indicating that both indices tend to move in the same direction; when the volatility of one index increases, the other index also increases. This positive correlation may be attributed to the 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 the HSI and JCI which is negative (-0.42), it shows that the two indices tend to move in opposite directions; in other words, when the volatility of one index increases, the other index decreases, or vice versa. This negative correlation may be influenced by the different economic and policy factors between Hong Kong and Indonesia that cause the index to 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 and the crisis period (unstable, y) being 992, 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 began by calculating the volatility of the index, the results of which are shown in Table 6. The small difference in the 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 than the JCI. SPX is more sensitive to dynamic global market issues, whereas JCI is more stable with 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 were increasing in both markets. The SPX index experienced a more significant increase than the JCI index. This is in line with the concept of *the spillover effect*, where global markets respond faster to crisis dynamics than local markets, which may have better resilience to global capital flows. Using a similar calculation method, the SCI Index shows a volatility of 1.04%, higher than the JCI index (0.81%), which can be interpreted as the Chinese market having a greater level of uncertainty than the Indonesian market during the non-crisis period. A different trend was observed during the crisis period, when 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.

The average yield of the HSI index experienced a significant decrease in the crisis period, from 0.02% to -0.03%, indicating 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, which is adjusted between indices to obtain a co-volatility value. The results of the analysis are presented 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 between the index and the increase in the crisis. However, as introduced by Forbes and Rigobon (2002), adjustments need to be made regarding the heteroscedasticity of the correlation of the crisis periods. Therefore, adjustments are needed for the correlation calculation calculated using formula 3.2. Therefore, the correlation between the SPX and JCI indices after adjustment during the crisis was 0.15, which was smaller or weakened by 23.47% compared to the correlation in the non-crisis period. This means that the correlation between the SPX and JCI indices during the crisis shows a positive relationship, tending 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*).

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 indicates that when the volatility of one index increases, 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 was getting stronger. This is possible due to different reactions to global economic sentiment or the flow of capital withdrawal from the HSI index to 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 was to conduct a statistical test of the co-volatility value obtained, using a *chi-squared* statistical test with one degree of freedom using formula 3.3. The results of *the chi-squared* statistical test of the co-volatility of the SPX and JCI indices are presented in Table 8, which is 11.6446. Then, the p-value can be calculated using *a chi-squared* distribution with one degree of freedom, which produces a very small value of 0.0006. Based on the significance table of *the chi-squared critical values,* this means that the co-volatility of the SPX and JCI indices during the crisis was significant. Thus, the results of the co-volatility differential test for H0 were rejected, and 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. The *p-value* is very small at 0.0396*,* indicating 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, and 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 and JCI indices 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. Conclusion

5.1 Conclusion

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

1. The price movements and yields of the SPX index show an upward trend, which 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 Indonesia's market. The co-volatility value of the SPX and JCI index 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 *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 the domestic stability. The correlation between the SCI and JCI indices is positive, but the strength of the relationship tends not to change, or *the contagion remains.* The yield co-volatility values of the SCI and JCI indices appear weaker and show 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 was significant, although not too far away. Therefore, it can be concluded that there was *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 the global dynamics. The correlation between the HSI index yield and the JCI index was positive but weakened considerably during the crisis. The yield co-volatility values of the HSI and JCI indices appear to weaken and show 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 during a crisis is significant. Therefore, it can be concluded that there was *contagion* from the HSI market to the JCI market in the 2017-2023 period.

5.2 Suggestion

The suggestions from the results of this study are as follows:

5.2.1 For academics

For academics, this research can be used as input and consideration for future 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 manner. Future research may also explore the relationship between stock indices and macroeconomic factors, such as inflation, interest rates, and foreign capital flows, to broaden our understanding of the influence of external factors on the domestic market.

5.2.2 For Practitioners

For practitioners, the results of this study will be useful for investors, portfolio managers, and policymakers in Indonesia. For investors, it is advisable to leverage domestic markets, such as the 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 in the stock price. For global markets such as the SPX and HSI, investors with 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 to maintain market stability during global crises. Efforts such as interest rate adjustments, fiscal intervention, and flexible monetary policy are important steps in supporting market confidence. International cooperation must be strengthened to mitigate the impact of global economic *spillovers* on domestic markets. This includes strengthening bilateral and multilateral agreements in the economic and trade sectors.

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