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Analysis of the effect of Regional Stock Market on the Jakarta Composite Index using Markov Regime Switching Regression

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Abstract

Purpose: In the current era of information, global stock market interconnections significantly influence investment decisions. Changes in one market rapidly affect others. The co-movement of stock markets presents challenges and opportunities for investors, whereas volatility spillovers complicate risk management and investment strategies.

Research Methodology: This study examines the influence of the Nikkei 225, Straits Times Index, and Shanghai Composite Index on the Jakarta Composite Index across the pre-pandemic, pandemic, and post-pandemic phases.

Results: Utilizing the hidden Markov model with regime-switching regression, this study identifies changes in market behavior due to economic shifts during the pandemic, revealing two regimes: synchronization and desynchronization.

Limitations: Pre-COVID-19, the Jakarta Composite Index shows strong synchronization with the Nikkei 225 and Straits Times Index, while the Shanghai Composite Index has an insignificant impact. During the COVID-19 pandemic, frequent desynchronization occurred due to high uncertainty and volatility, with only the Straits Times Index significantly influencing the Jakarta Composite Index. Post-pandemic, synchronization between the JCI and regional markets strengthened again. This study highlights the consistent influence of the Nikkei 225 and Straits Times Index, while the Shanghai Composite Index remains insignificant.

Contributions: This study contributes significantly to the understanding of regional stock market relationships and offers valuable insights for academia and practice.

Keywords: *Capital Markets, Comovement, Volatility Spillover, Regime Switching Regression, Hidden Markov Model*

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1. Introduction

The rapid flow of information heavily influences capital markets. In today's era of technology and internet connectivity, events in one location can quickly affect the situation in another. Leiwakabessy, Patty, and Baretha (2021) notes that investors often base their decisions on the latest information. For example, changes in government policies or strong company performance in one market can influence investors' decisions in another market. An increase in interest rates in one country may cause capital to move to markets with higher interest rates (Amin & Herawati, 2012). This rapid flow of information creates strong interconnectedness between global markets, influencing investor behavior and global market dynamics around the world.

In "International Political Economy Dynamics" by Djirimu and Tombolotutu (2023), significant events such as the European debt crisis, Brexit, the US-China trade war, and the oil crisis have affected capital markets. The COVID-19 pandemic has been particularly disruptive, causing severe global health and economic impact (Kusno, 2020). Investors face high volatility and uncertainty, which complicate risk management strategies. Research by Phan and Narayan (2021) highlights market reactions to unexpected events such as COVID-19. Rizvi, Juhro, and Narayan (2021) find that fiscal policy is effective in mitigating the negative impact of the pandemic on ASEAN capital markets. Globally, the pandemic has increased market volatility, with stock markets such as the Nikkei 225, STI, and Shanghai Composite Index exhibiting connectedness dynamics (Baker, Bloom, Davis, & Terry, 2020; Larasati, Irwanto, & Permanasari, 2013). Post-pandemic analysis is important to understand market synchronization and new behavioral patterns (Zhang, Hu, & Ji, 2020).

To analyze the synchronization between the Jakarta Composite Index (JCI) and the Nikkei 225, the Straits Times Index (STI), and the Shanghai Composite Index, this study uses the Hidden Markov Model (HMM) and regime-switching regression. The HMM, as explained by Rabiner (1989), identifies hidden patterns in financial data and captures changes in market conditions that cannot be directly observed through stock prices. This model assumes that the observed data are influenced by hidden states that change over time, providing a deeper insight into market dynamics.

Regime Switching Regression, highlighted by Hamilton (1989), identifies the relationships between stock indices over different periods by allowing the model to switch between regimes based on economic conditions. This technique is useful for detecting structural shifts in financial data, such as those caused by pandemics. Krolzig (2013) and Guidolin and Timmermann (2006) find that this technique reveals complex co-movement patterns in financial markets that cannot be captured by conventional models.

The model identifies different regimes in the data, such as synchronous and asynchronous stock markets, with each regime having different statistical parameters (Ang & Bekaert, 1999; Goutte, 2014). The transitions between regimes are governed by a Markov process that estimates the probability of switching from one regime to another. Using the Expectation-Maximization (EM) algorithm, the model estimates the parameters for each regime and identifies regime shifts (Goutte, 2014).

This study aims to understand how movements in one market can affect other markets, with a particular focus on Indonesia and other Asian countries, such as Japan, Singapore, and China. This study explores the characteristics of the relationship between the Indonesian stock market and the Nikkei 225, the Straits Times Index, and the Shanghai Composite Index. Changing market conditions before, during, and after the pandemic require investigation into the impact of these three indices on the Jakarta Composite Index (JCI). This study uses the Hidden Markov Model (HMM) and regime-switching regression as the main analysis tools to provide deeper insights into detecting and modeling hidden regimes in stock market movements between Indonesia and Japan, China, and Singapore.

2. Literature Review

2.1 Volatility Spillover and Contagion in the Stock Market

Volatility spillover refers to the phenomenon in which volatility in one financial market impacts other markets. This occurs when fluctuations in asset prices or risks in one market spread to other markets, creating a domino effect that affects the overall performance and stability of the market. Diebold and Yilmaz (2009) define volatility spillover as the effect of volatility in one market on another and develop a method to measure its direction and strength through a spillover index, which captures both direct and indirect impacts. There are two types of volatility spillover: positive and negative. A positive spillover indicates that an increase in volatility in one market leads to an increase in volatility in another market, while a negative spillover indicates the opposite. Wegener, Kruse, and Basse (2019) introduce the concept of "spillovers of explosive regimes," which explains how one crisis can trigger another, emphasizing the interconnectedness of financial crises.

"Wegener's "Butterfly Effect" describes how small changes in one part of a system can trigger significant changes elsewhere, such as an economic crisis in one country affecting global market sentiment. This interconnectedness, reinforced by globalization, means that changes in one market can quickly spread to other markets, amplifying the butterfly effect. Understanding these factors is critical for managing risk and increasing global financial market resilience.

During a financial crisis, the term "contagion" refers to the increasing interdependence between markets. Rigobon (2019) notes that, although spillovers occur in both good and bad times, contagion is more pronounced during the crisis, showing a significant increase in the spread of shocks. Understanding contagion is essential for policymakers and regulators to manage systemic risks and design-responsive economic policies.

2.2 Stock Market Co-movement
Co-movement in stock market indices refers to the tendency of stocks to move together over time. This phenomenon reflects the degree of correlation between the changes in stock prices in the index. Factors, such as economic conditions, monetary policy, and global events, can affect the level of co-movement.

Chen, Roll, and Ross (1986) suggested that comovement may be related to asymmetric information among investors. Market information can trigger simultaneous reactions, leading to uniform movements in stock indices. Therefore, understanding comovement involves economic factors, as well as the behavioral and psychological aspects of market participants.

Ang, Hodrick, Xing, and Zhang (2006) highlight that significant co-movement between stock indices from different countries indicates strong integration in global financial markets. Connectivity has implications for global portfolio diversification and risk management. Campbell, Lettau, Malkiel, and Xu (2001) find that macroeconomic factors, such as interest rates and inflation, drive co-movement in stock indices. Understanding these factors helps develop better investment strategies to reduce portfolio risk amidst market fluctuations.

Global financial market integration means that events or factors affecting one market can spill over to other markets, creating challenges and opportunities. Bekaert, Harvey, and Lundblad (2011) investigated the global factors affecting co-movement, such as economic changes, political uncertainty, and international capital flows. Their analysis highlighted the complexity of inter-market relationships at the global level, showing that co-movement dynamics are influenced by both local and global economic factors. These findings are important for market participants and financial decision makers in managing risk and designing effective investment strategies in globally connected markets.

2.3 Hidden Markov Model
Hidden Markov Models (HMM) are statistical models in which a system is assumed to follow a Markov process with unobservable states (Prasetyo, 2011). This model represents a system with hidden state transitions, allowing inferences regarding internal conditions based on observable data. The core concept of the HMM provides a powerful framework for analyzing the dynamics of systems with hidden states. In the context of finance, HMMs are used to identify changes in market conditions that are not directly visible in historical data.

HMMs consist of two sets of states, namely hidden states and observations. Hidden states reflect the internal conditions of the system that are not directly known, whereas observations are the data that are visible and associated with these hidden states. This model includes the following main components: the Transition Matrix, which represents the probability of moving from one hidden state to another; the Emission Matrix, which determines the probability of observation based on hidden states; and the Initial Probability Matrix, which shows the initial probability of each hidden state. These components allow HMMs to infer hidden states based on the observed data.

The HMM extends the Markov Model, which is typically used for time-series data. In a standard Markov Model, future states depend only on the current state and not on the past states. HMM improves on this by including five parameters: M and N as fixed parameters, and A, B, and π as variable parameters, providing greater flexibility in modeling state relationships (Himawan, Indriyani, & Rahmawati, 2017). Overall, the HMM is a powerful tool for representing systems in which the observed data are generated from underlying, unseen processes, making it invaluable for analyzing complex financial dynamics.

2.4 Regime Switching Regression

Regime Switching Regression (RSR) is a statistical approach that models changes in the behavior of economic variables by identifying and measuring different regimes. In the context of stock markets, the RSR allows for a deeper analysis of co-movement dynamics, reflecting the extent to which stocks in a market index move together over time. This approach is based on the understanding that relationships between economic variables can change regimes due to external factors, such as global economic conditions, monetary policy, or crises. For example, Panopoulou and Pantelidis (2015) highlighted the ability of RSR to capture changes in market behavior, providing insight into the factors that influence comovement under different market conditions. RSR helps identify critical periods during which stock relationships shift, helping researchers and investors understand the factors that drive these changes, such as global economic events, monetary policies, or crises. Thus, RSR is an important tool for navigating the dynamic financial market landscape.

RSR works by identifying and modeling multiple regimes in the data. Ang and Bekaert (1999) note that RSR assumes that data can be in multiple regimes, such as synchronous and asynchronous stock market movements. Goutte (2014) study of the UK and US stock markets shows that each regime has different statistical parameters, such as mean and variance, reflecting different economic conditions. Transitions between regimes are governed by Markov processes, which determine the probability of switching from one regime to another based on available information. Using algorithms such as expectation-maximization (EM), RSR can estimate the parameters for each regime and identify regime shifts.

Ang and Bekaert (1999) use RSR to examine differences in volatility and correlation among international stock markets, finding increased correlations during the financial crisis, indicating stronger co-movement in poor economic conditions. Similarly, Bekaert and Harvey (2003) used RSR to evaluate the impact of globalization on stock market synchronization and found higher correlations among major markets due to increased global integration. These studies emphasize the importance of RSR in analyzing the dynamic interactions between global financial markets.

Lucey and Voronkova (2008) investigate the synchronization between Russian and international equity markets using RSR, revealing an increase in short-term synchronization during the 1998 Russian financial crisis. This model allowed them to assess regime shifts, highlighting periods of increasing or decreasing market synchronization.

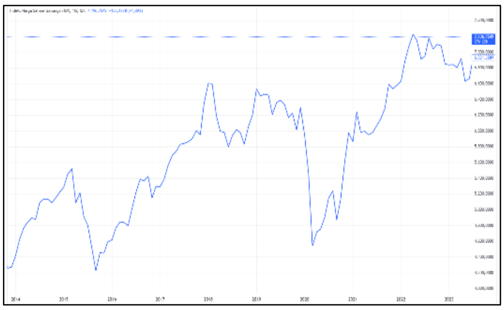
Ahmad and Sehgal (2015) analyzed regime shifts and stock market volatility in the “BRIICKS” economies (Brazil, Russia, India, Indonesia, China, South Korea, and South Africa) from February 1996 to January 2012. Using a Markov regime-switching regression model in a mean-variance framework, they identified two regimes in each market and found inconsistent levels of synchronization across these markets.

Finally, Rikumahu and Anggraeni (2021) explored the influence of the Hang Seng Index (Hong Kong), S&P500 (US), and SET (Thailand) on the Jakarta Composite Index using the Hidden Markov Model (HMM) with a focus on Markov regime-switching regression. Their findings indicate the presence of a dominant synchronization state from January 2016 to December 2020. Markov Regime Switching Regression (MRSR) combines linear regression with the Markov switching mechanism to identify regime changes in variable relationships. It excels in the simplicity of interpretation and its effectiveness in identifying structural changes (Hamilton, 1989). Therefore, MRSR is the most suitable method for assessing cross-country stock market synchronization because of its ability to provide clear and interpretable insights into regime changes and the dynamics of international stock market relationships, making it a valuable tool for analyzing stock market synchronization.

3. Research Methods

3.1 Data

Data were collected by obtaining stock closing price data from the Nikkei 225 (Japan), Straits Times Index (Singapore), Shanghai Composite Index (China), and Jakarta Composite Index from 2014 to 2023. Figure 1 shows the stock closing price graphs for the four indices.



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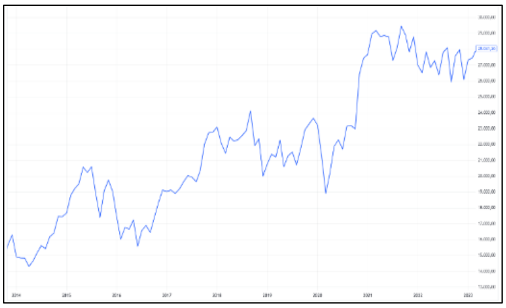

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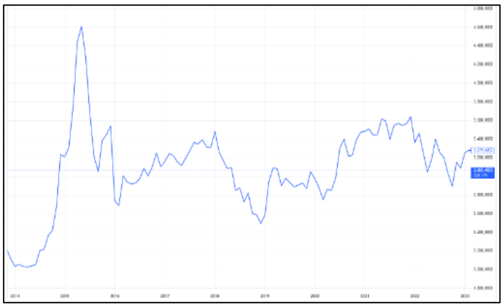

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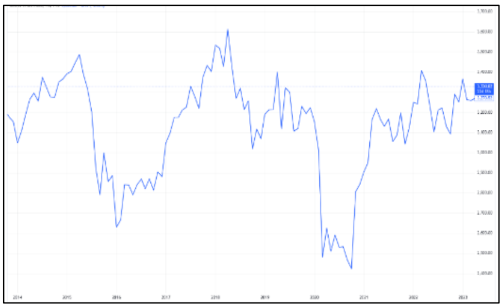

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Figure 1. Stock Index Closing Price Charts: a: JCI; b: N225; c: SCI; d: STI.

3.2 Methodology

Regime Switching Regression analysis is a statistical technique that allows modeling of the relationship between independent and dependent variables by considering changes in regimes or conditions in the data. Regime Switching Regression is used to model how changes in the Nikkei 225, Shanghai Composite Index, and Straits Times Index relate to changes in the market conditions in the Jakarta Composite Index. The regime-switching regression analysis process involves estimating parameters of the regression model that vary for each regime. The conceptual model of the regime-switching regression is shown in Figure 2.

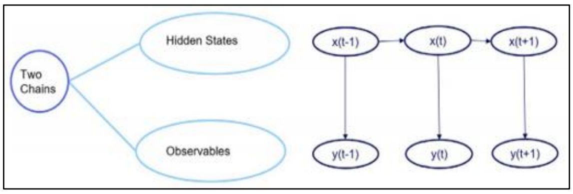


Figure 2. Conceptual Model

The Markov Regime Switching Regression model was used to estimate the synchronization and desynchronization of the Jakarta Composite Index (JCI) with the Nikkei 225, Shanghai Composite Index (SCI), and Straits Times Index (STI) before, during, and after the COVID-19 pandemic. This model assumes the existence of two unobserved states influenced by the Markov process. The presence of the two states in this model reflects the difference in market dynamics, indicating periods of synchronization and desynchronization between JCI and other stock market indices. During the synchronization period, the JCI moves in line with the other indices, whereas during the desynchronization period, the JCI moves independently of the indices. The conceptual model and data used in this study are shown in Figure 3.

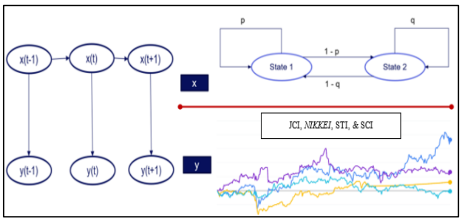


Figure 3. Conceptual Model and Data

When $S_t = 1$, changes in JCI are not affected by changes in other indices such as Nikkei 225, STI, and SCI. This means that other factors affect changes in the JCI, which is called desynchronization. Conversely, when $S_t = 2$, changes in JCI are affected by changes in other indices such as Nikkei 225, STI, and SCI. This condition is called synchronization.

In regime 1, the first differentiation changes of JCI (y_t) is expressed as:

$$y_t = \alpha_1 + \beta_1 x_t + \epsilon_{1t} \qquad (1)$$

Where ϵ_{1t} follows a normal distribution with mean zero and variance σ_1^2 when $S_t = 1$. In regime 2, the first differentiation change JCI (y_t) is expressed as:

$$y_t = \alpha_2 + \beta_2 x_t + \epsilon_{2t} \qquad (2)$$

Where ϵ_{2t} me follows a normal distribution with mean zero and variance σ_2^2 when$S_t = 2$.
Markov Regime Switching Regression model is used to estimate the synchronization and desynchronization of JCI with Nikkei 225, SCI, and STI. In this model, the first differentiation change

of JCI (ΔR_{JCI}) is expressed as:

$$\Delta R_{JCI} = \alpha_1 + \epsilon_t \qquad (3)$$

When $S_t = 1$, where ϵ_t men follows a normal distribution with mean zero and variance σ_1^2. When $S_t = 2$, the first differentiation change of JCI (ΔR_{JCI}) is expressed as:

$$\Delta R_{JCI} = \alpha_1 + \epsilon_t \qquad (3)$$

where ϵ_{2t} follows a normal distribution with mean zero and variance σ_2^2. The variable ΔR_{JCI} represents the first differentiation change of the Jakarta Composite Index, ΔR_{NIK} represents the first differentiation change of the *Nikkei 225*, ΔR_{SCI} represents the first differentiation change of the Shanghai Composite Index, and ΔR_STI represents the first differentiation change of the Straits Times Index. The coefficients $\alpha_2, b_{21}, b_{22}, b_{23}$ are the estimated regression parameters.

The probability of transition between regimes is determined by

$$\Pr(S_t = 1 | S_{t-1} = 1) = p_{11} \qquad (5)$$
$$\Pr(S_t = 2 | S_{t-1} = 1) = 1 - p_{11} \qquad (6)$$
$$\Pr(S_t = 2 | S_{t-1} = 2) = p_{22} \qquad (7)$$
$$\Pr(S_t = 1 | S_{t-1} = 2) = 1 - p_{22} \qquad (8)$$

where p_{11} and p_{22} are the probabilities of staying in the same regime. The transition matrix shows the probability of moving from one state to another. For example, p_{11} is the probability of transitioning from state 1 to state 1, p_{12} is the probability of transitioning from state 1 to state 2, p_{21} is the probability of transitioning from state 2 to state 1, and p_{22} is the probability of transitioning from state 2 to state 2. These probabilities were calculated using the following formula:

$$P_{ij} = \frac{the\ number\ of\ transitions\ from\ State\ i\ to\ State\ j}{Total\ number\ of\ transitions\ from\ State\ i} \qquad (9)$$

where P_{ij} is the probability of moving from state i to state j in historical data.

In addition, the expected duration measurement in the Markov-switching model helps understand how long, on average, the system will remain in a given state before switching to another state. This expected duration provides an insight into the stability and volatility of the state. The expected duration of state i is calculated using the following formula:

$$Expected\ Duration = \frac{1}{1 - P_{ii}} \qquad (10)$$

By using the Markov Regime Switching Regression model, we can identify the synchronization and desynchronization periods between the JCI and other stock market indices and understand the dynamics of the stock market during the period before, during, and after the COVID-19 pandemic. The results of this analysis were then carefully interpreted to draw valid conclusions and answer the research questions posed.

4. Result and Discussion

4.1 Stationarity Test

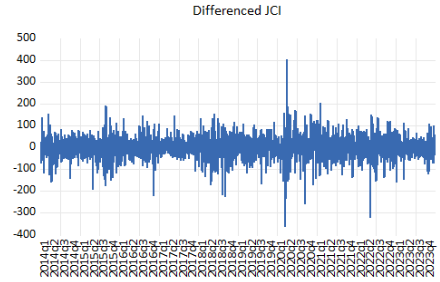
To perform a valid analysis, it is important to determine whether the data are stationary, meaning that they have a constant mean, variance, and autocorrelation over time. If the data are not stationary, the analysis may produce biased or invalid results; therefore, data transformation is needed to achieve stationarity before further analysis. In this study, the Augmented Dickey-Fuller (ADF) test was used to assess the stationarity of data. The ADF test is commonly used to detect the presence of a unit root in a time series to indicate whether the data are stationary. Data were considered stationary if the probability value (p-value) of the ADF test was < 0.05. If $p < 0.05$, the null hypothesis that the data have a unit root (is not stationary) is rejected, indicating that the data are stationary. Conversely, if $p > 0.05$, then the null hypothesis cannot be rejected, indicating that the data are not stationary.

Table 1. Augmented Dickey Fuller Test Results

Index	***p-value***	
	Level	***First differentiation***
JCI	0.4554	0.0000
N225	0.8173	0.0001
STI	0.1104	0.0000
SCI	0.0331	-

The ADF test result for the JCI closing prices from 2014 to 2023 shows a p-value of 0.4554, indicating non-stationarity. The first differentiation was applied, resulting in a p-value of 0.0000, confirming stationarity. Similarly, the N225 closing price was non-stationary ($p = 0.8173$) but became stationary after differentiation ($p = 0.0001$). The STI closing price also became stationary after differentiation (from $p = 0.1104$ to $p = 0.0000$). However, the SCI closing price is stationary ($p = 0.0331$), without differentiation.

Because time series analysis requires stationary conditions for JCI, N225, and STI, the analysis is continued using the first differentiation index, except for SCI, as shown in Figure 4.



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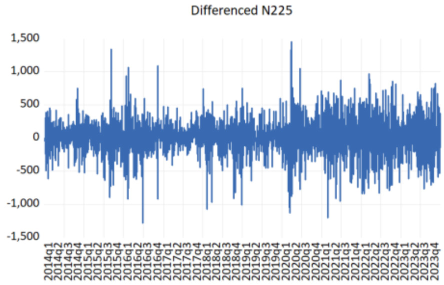

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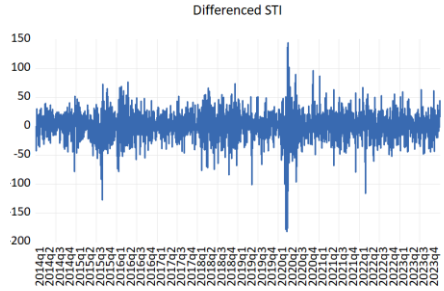

c

Figure 4. First Differentiation Index: a: JCI, b: N225 c: STI

4.2 Markov Switching Regression Results

The results of the Markov Switching Regression between the first-differentiated closing price of the Jakarta Composite Index (DJCI) and the first-differentiated closing price of the Nikkei 225 (DN225), the Shanghai Composite Index (SCI), and the first-differentiated closing price of the Straits Times Index (DSTI) are shown in Table 2.

Table 2. Markov switching regression results

Variable	*State* 1	*State* 2
DN225	0.0209 (0.0000)	0.0419 (0.0692)
SCI	-0.0034 (0.0751)	-0.0029 (0.9181)
DSTI	0.6644 (0.0000)	0.6281 (0.0002)

4.3 State Identification

In State 1, two variables, N225 and STI, were significant, with p-values less than 0.05, indicating synchronization. N225 has a coefficient of 0.020948, and STI has a coefficient of 0.664448, indicating a significant positive effect on JCI. SCI, with a p-value of 0.0751, was not statistically significant. Thus, during this state, DJCI is affected by N225 and STI but not by SCI.

In State 2, only STI remained significant, with a p-value less than 0.05, indicating desynchronization. N225 showed a positive effect, but with a lower significance (p-value of 0.0692), while SCI was not significant (p = 0.9181). This suggests that the DJCI is less influenced by the global market and more influenced by other domestic or regional factors.

4.4 Transition Matrix and Constant Expected Duration

The transition matrix for the state switching is shown in Figure 5.

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = j)

	1	2
1	0.986788	0.013212
2	0.731065	0.268935

Figure 5. Transition Matrix

Figure 5 shows the transition probabilities between the states. In State 1 (synchronization), there is a probability of 0.986788 remaining in synchronization and a probability of 0.013212 switching to desynchronization. In State 2 (desynchronization), there was a probability of 0.268935 remaining in desynchronization and a probability of 0.731065 to switch back to synchronization. This shows that the JCI tends to remain in synchrony with the N225 and STI, reflecting the strong influence of these regional indices. In desynchronization, JCI movements were more variable and did not move together with the N225 and STI.

The constant expected durations for the synchronization and desynchronization periods are shown in Figure 6.

Constant expected durations:

	1	2
	75.68889	1.367868

Figure 6. Duration of expectations

Figure 6 shows that the average duration of synchronization (75.68889 days) was significantly longer than that of desynchronization (1.367868 days). This indicates that DJCI tends to stay synchronized with the N225 and STI markets for a longer period, reflecting the higher stability and significant influence of these indices. In contrast, the desynchronization period is shorter, indicating that the instability and varying influence of regional indices on DJCI do not last long.

4.5 Smoothed Regime Probability

Smoothed Regime Probabilities estimate the probability that the system is in a particular state at a particular time using all available data. In Markov Regime Switching, these probabilities help to determine the state of the data over time. Figure 7 illustrates the Smoothed Regime Probabilities for State 1 (synchronization).

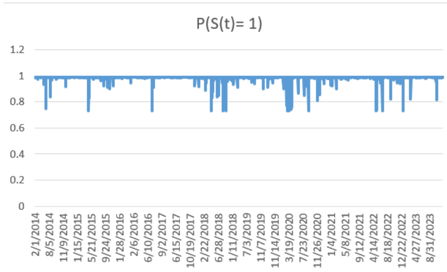

Figure 7. Markov Switching Probability Smoothed Regime

From 2016 to 2020, the probability was mostly above 0.8, indicating that the JCI was mostly affected by the N225 and STI. However, after the declaration of COVID-19 as a global pandemic in early March 2020, desynchronization periods became more frequent and the synchronization duration shortened, reflecting increased market uncertainty and volatility. Desynchronization was dominant from March 2020 to April 2021. After April 2021, the synchronization probability increased again, indicating that the JCI was more frequently affected by changes in the N225 and STI until December 2023.

5. Conclusion

Smoothed regime probabilities above 0.8. N225 and STI have a positive and significant impact on JCI, whereas SCI has a negative but insignificant impact. During the pandemic period from March 2020 to April 2021, the market experienced more frequent desynchronization, reflecting high uncertainty and volatility. During this period, the impact of the N225 became less significant, SCI remained insignificant, and only STI continued to have a significant impact on JCI. After April 2021, synchronization strengthened again, along with global economic recovery and vaccine rollout. JCI was significantly affected by N225 and STI, showing a consistent and significant impact during the synchronization period, whereas SCI remained insignificant in both periods.

This study has limitations, such as potential inaccuracies in secondary data and the limited analysis period from 2014 to 2023. Future research should extend this period, consider external factors such as economic policies and global conditions, and use primary data for greater accuracy. For policymakers, monitoring global and regional market dynamics is essential to maintain domestic stock market stability. For investors, understanding the synchronization and desynchronization periods helps risk management and portfolio optimization. Academically, this study enhances the understanding of regional stock market relationships and serves as a reference for further research, making significant contributions to both the academic and practical fields.

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