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Measuring Asian Stock Market Integration by Using Orthogonal Generalized Autoregressive Conditional Heteroscedasticity

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ABSTRACT

This study investigates Asian stock market integration during the period of 1999 to 2018. The analysis technique used was Orthogonal Generalized Autoregressive Conditional Heteroscedasticity (OGARCH). OGARCH is a combination of GARCH and Principal Component Analysis (PCA) methods. The benefit of employing OGARCH in a stock market integration study is that it could estimate the degree of stock market integration precisely and how many components are related to it. In order to deepen the analysis, this study also does an analysis based on pre, during and post the GFC. The result shows that not all stock markets studied were integrated. Singapore, Hong Kong, Japan, Taiwan, Thailand, and South Korea stock markets tended to integrate, while the ones in Indonesia, Philippine, and Malaysia did not. This shows that stock markets in Asia were not fully integrated. Stock market integration during the Global Financial Crisis (GFC) period is higher than the pre-GFC period and post-GFC period. Investment managers who have the ability to form international portfolios can diversify existing stocks in Indonesia, Malaysia, and the Philippines even Japan by considering country risk because their stock markets tend to be segmented. Investment managers also need to conduct special studies before investing in Asian stock markets that have proven to be integrated.

INTRODUCTION

The covariance matrix of all assets in a portfolio has a strong connection with portfolio risks that the creation of large covariance matrix and semi-definite positive is highly crucial in risk management (Bai, 2011) and investment analysis (Alexander, 2001b, Torres, 2013). Unfortunately, the large covariance matrix creation and semi-definite positive has been a very own challenge for practitioners in the portfolio management field. Whereas, the covariance matrix has a pivotal role in investment analysis and the use of risk factor model do not suffice for the brokers to assess their portfolios (Alexander 2001a). As times go by, experts in statistics and econometrics attempted to develop an analysis tool that could accommodate the issue, one of whom was Alexander (2001a) who developed Orthogonal Generalized Autoregressive Conditional Heteroscedasticity (OGARCH). This OGARCH model can also be applied to calculate *Value-at-Risk* (VaR) (Holton 2014). The VaR model has been widely used either by practitioners or academicians in finance as a tool of quantitative risk measurement (Simons, 1996). In practice, the utilization of OGARCH in VaR is often associated with market risk, volatility (Bai, 2011) and portfolio strategy (Luo, 2015).

One of the studies applying the OGARCH method was conducted by Bai (2011). In the research, He provides empirical evidence that OGARCH was also able to reduce the complexity of calculations, count volatility and correlation of all assets and even control *residual* or *noise* as long as the existing assets had high correlations. Bai (2011) conducted a study on energy shares such as Exxon Mobil, Shell, Chevron, BP, Conoco Phillips. The stocks were selected because they were deemed to have a high degree of correlation. Robiyanto (2017) estimated the ASEAN-5 stock markets (Indonesia, Malaysia, Singapore, Thailand, and the Philippines) integration. Torres (2013) estimated covariance matrix in the pension funds' portfolio. In addition, Byström (2004) studied Nordic stock markets during the Asian Financial Crisis (AFC). The benefit of employing OGARCH in a stock market integration study is that it could estimate the degree of stock market integration precisely and how many components are related to it.

This study uses the OGARCH method used in Bai (2011) and Robiyanto (2017). However, unlike Bai (2011) which scrutinized the energy sector stocks and Robiyanto (2017) which studied the ASEAN-5 stock markets, this study extended its stock markets on the available ones in Asia, such as the ASEAN-5 stock markets plus several prominent stock markets (Hong Kong, South Korea, Japan and China). The underlying reason was that the stock markets in Asia had proven to have a high correlation and were integrated. It was supported by researches such as by Click and Plummer (2005), Karim and Karim (2012), Karim and Ning (2013), Robiyanto and Ernayani (2018), Suganda and Soetrisno (2016), Suganda and Hariyono (2018), Surianshah, Karim, and Khalid (2017). Hence, the implementation of the OGARCH model for Asian stock markets is very feasible.

In this research, the orthogonal approach was done with the GARCH and then followed by principal component analysis (PCA) as the solution for dimensionality problems. The OGARCH researches involving stock markets in the Asian level are still rare to find. To strengthen this study's contribution in stock markets integration studies, this study also dividing the research period into three periods, namely pre-GFC period, during GFC period, and post-GFC period.

1. LITERATURE REVIEW

1.1 Orthogonal Generalized Autoregressive Conditional Heteroscedasticity (OGARCH)

OGARCH depends on the use of PCA in summarizing factors that explain variations in a time series of data and then apply the covariance matrix of a principal component to adjust with the initial data covariance matrix. OGARCH can be used to solve practical problems in finance because of its ability to reduce the dimensions of the covariance matrix that should be estimated (Bai 2011, Iqbal, 2013; Lanne and Saikkonen, 2007; Weide, 2002). Luo (2015) explained that in an OGARCH model, the observed time series data is linearly transformed into a series of independent time series data by using PCA. The OGARCH model introduced by Alexander (2001a) is as follows (it has been adjusted with the monthly data used in this research):

If Y_t is multivariate time series data of monthly return with a zero average on k asset and the length of T with column $y_t,\dots, y_k$. Therefore, matrix X_t T X K with column $x_t,\dots, x_k$ can be formulated into the following equation:

$$x_t = \frac{y_t}{\sqrt{v_i}}$$

Where $V = diag(v_1, \dots, v_m)$ with v_1 is the sample of variance in column ith Y_t. If L indicates eigenvector matrix of population correlation x_t and $l_m = (l_{1,m},\dots,l_{k,m})$ is column mth. l_m is eigenvector k X 1 relates to λ_m. The column L has been chosen so that $\lambda_1 > \lambda_2 > \dots > \lambda_k$. If D is diagonal eigenvalue matrix, the principal component mth of the system can be explained as

$$p_m = x_1 l_{1,m} + x_2 l_{2,m} + \dots + x_k l_{k,m}$$

If each principal component vector p_m is placed as column in matrix P T X k, so

$$P = XL$$

If principal component column is modeled by GARCH (1,1)

$$p_t \mid \psi_{t-1} \sim N(0, \Sigma_t)$$

$$p_{i,t} = \epsilon_{i,t}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

where Σ_t diagonal matrix of principal component conditional variance P. ψ_{t-1} which contains all available information until t-1. Conditional variance matrix X_n is $D_t = L\,\Sigma_t L_n^T$ so the covariance conditional matrix of Y is as follows:

$$H_t = \sqrt{V} D_t \sqrt{V}$$

The more detailed estimation procedure will be shown in the next section.

1.2 Estimation Model in OGARCH

If Y becomes matrix T X k of monthly return k asset on T month, then the monthly return can be calculated by using the natural algorithm of the next monthly closing price divided by the monthly closing price. The formulation is as follows (Alexander, 2001b, a; Robiyanto, 2017):

$$y_i = log\frac{P_{i+1}}{P_i}$$

Where P_i is the monthly closing price in period i.

First step: Standardizing data into matrix X T X k with the variance estimated, the average for each y_i and obtain correlation matrix XX'.

Second step: Analyzing principal component (PCA) in XX' to acquire eigenvalue vector and eigenvalue. This eigenvector is notated with L and its column mth with $l_m = (l_{1,m},\dots,l_{k,m})$, eigenvector K X 1 is correlated with eigenvalue λ_m. Thus, this column becomes $\lambda_1 > \lambda_2 > \dots > \lambda_k$.

Third step: Determining the number of principal components to use. If the first principal component is selected, then the principal component mth of the system is as follows:

$$p_m = x_1 l_{1,m} + x_2 l_{2,m} + \ldots + x_k l_{k,m}$$

Where x_i is column ith from column X_n, matrix TXn and then extracted from X. Hence, the matrix of principal component P is shown by matrix T X n and obtained $P = X_n W_n$.

Fourth step: Conditional variance of the principal component ith p_i, i = 1, N is estimated with GARCH (1,1):

$$p_{i,t} = \epsilon_{i,t}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

$$\Sigma_t = diag(\sigma_{1,t}^2, \ldots \sigma_{n,t}^2)$$

Fifth step: Conditional covariance matrix X_n is $D_t = W_n \Sigma_t W_n^t$ and conditional variance matrix Y is:

$$H_t = \sqrt{V} D_t \sqrt{V}$$

Where $W_n = L_n diag(\sqrt{\lambda_1}, \ldots, \sqrt{\lambda_n}$

Accuracy of conditional covariance matrix V_t of original return is determined of how many component n is chosen to represent the available system.

1.3 Asian Stock Markets Integration

Stock market integration still becomes an interesting topic in finance, especially in portfolio management. Several scholars try to give a description of stock market integration. Emiris (2001) stated that the stock market was integrated if the price only common risk factor. While Bekaert and Harvey (1995) described that the stock market would be integrated if several similarities in risk associated with return were found. This statement is also supported by Hedi (2005) and Robiyanto (2018a). Stock market integration viewed has an important role in both international and national economics (Suryanta, 2011). Stock market integration could provide the possibility of the lower cost of fund, better capital allocation and also better portfolio diversification (Boyle, 2009). Stock market integration was also boosted by capital flow relaxation in some countries (GIH, 2008; Muharam, 1999; Park and Lee, 2011).

Studies on Asian stock markets integration were flourished before and after the AFC and the GFC occurred. Palac-McMiken (1997) conducted a study of capital market integration in ASEAN-5 member countries using data from January 1987 to October 1995 which were analyzed by co-integration analysis. This study concludes that all stock markets in ASEAN-5 countries, except Indonesia, had links with each other. In line with the study, Roca, Selvanathan and Shepherd (1998) found consistent results. Roca, Selvanathan and Shepherd (1998) examined the relationship between several stock markets in ASEAN-5 member countries in the period of 1988 – 1995. The result shows that the Indonesian stock market was not at all connected with the stock markets in other ASEAN member countries in the long and short term.

After the AFC, Karim and Karim (2012) conducted a study of capital market integration in several ASEAN member countries such as Indonesia, Malaysia, Singapore, Thailand and the Philippines using data from January 1988 to December 2010. The research period was then divided into before and after 1997 and the period after the GFC. Karim and Karim (Ibid.) concluded that capital markets in ASEAN member countries were increasingly integrated, especially after the GFC. This finding is also supported by the results of Robiyanto (2018b) study which used dynamic methods in predicting capital market integration in ASEAN countries. Robiyanto (2018b) found that capital markets in ASEAN countries tended to have stronger dynamic correlations after the GFC.

In addition, Kim and McKenzie (2008) conducted a study of stock market integration in nine stock markets in Asia and found that not all stock markets were integrated, only relatively advanced capital markets were mutually integrated. Kim and McKenzie (2008) provided an explanation that in a relatively advanced capital market, foreign investors had a relatively important role and would tend to be more flexible in managing the cash flow. This finding is also supported by Park (2013), Muharam, Anwar and Robiyanto (2019) who found that stock market integration in Indonesia, Malaysia, Philippines, and Thailand tended to be different from other Asian countries. Findings by Najmudin et al. (2019), Wahyudi et al. (2018), Muharam et al. (2019) also supported the previous findings, concluding that the Indonesian and Philippine stock markets tended to be segmented compared to other ASEAN stock markets.

2. METHOD

2.1 Data

The data used in this research was stock price index data of monthly closing of stock markets in Asia (Singapore, Malaysia, Indonesia, Philippines, Thailand, South Korea, Japan, China, and Hong Kong) during the period of January 1999 to December 2018. The overall data were obtained from Bloomberg. In order to deepen the analysis, this study also does an analysis based on pre, during and post the GFC. The period division in this study followed the Robiyanto (2018b), Majid and Kassim (2009), Karim, Kassim, and Arip (2010). There are three periods, namely the pre-GFC period (January 1999-June 2007), during the GFC period (July 2007-December 2008) and post-GFC period (January 2009-December 2018).

2.2 Methodology

In mathematics, PCA is often defined as a procedure that uses orthogonal transformation to summarize important information of a series of interconnected variables into fragmented variables. The new orthogonal variables are then referred to as principal components (PC) and the number of PCs will be less than the number of initial variables (Bai, 2011). For example, if K is the number of variables and M is the number of principal components, the M is expected to be less than K because it is expected that the noise of the data will be released and can simplify the calculation. Meanwhile, the number of principal components used in the analysis will be determined by the accuracy of calculation for PCA which indicates how many total variations in the initial data can be explained by each principal component. Hence, in general, the principal components must calculate the highest variance that may arise and any variance that follows has the possibility of becoming the highest variance by looking at the limitations into orthogonal of the previous components.

3. RESULTS AND DISCUSSION

3.1 All Research Period (January 1999-December 2018)

Bai (2011) and Robiyanto (2017) suggested that OGARCH techniques would work well in a correlated data series. Therefore, it was necessary to do correlation analysis for stock market returns in the Asian region studied before conducting the OGARCH analysis. The analysis of the correlation between Asian stock market returns is presented in Table 1.

Table 1. Correlation of Asian Stock Markets

	HSI	JCI	KLCI	KOSPI	NIKKEI225	PSEI	SETI	STI	TAIPEI
HSI	1.000	0.500	0.434	0.659	0.527	0.468	0.558	0.758	0.596
JCI	0.500	1.000	0.533	0.524	0.399	0.630	0.637	0.635	0.426
KLCI	0.434	0.533	1.000	0.391	0.263	0.401	0.465	0.523	0.477
KOSPI	0.659	0.524	0.391	1.000	0.530	0.485	0.623	0.673	0.627
NIKKEI225	0.527	0.399	0.263	0.530	1.000	0.347	0.448	0.518	0.455
PSEI	0.468	0.630	0.401	0.485	0.347	1.000	0.615	0.613	0.428
SETI	0.558	0.637	0.465	0.623	0.448	0.615	1.000	0.670	0.565
STI	0.758	0.635	0.523	0.673	0.518	0.613	0.670	1.000	0.591
TAIPEI	0.596	0.426	0.477	0.627	0.455	0.428	0.565	0.591	1.000

Source: Bloomberg, processed.

Based on Table 1., it can be seen that, in general, the stock market returns in Asia studied tend to correlate with each other so that the OGARCH analysis is suitable. Furthermore, based on the results of the OGARCH analysis (which combines GARCH and PCA), conditional variance returns of the stock markets in Asia forms two principal components. This finding is different from research results by Park (2013) which found five principal components because the research period used was the period of 1991-2011 where the information technology level was not as advanced as it is today. The detail can be seen in Table 2. and Table 3., while the Ordered Eigenvalue and Eigenvalue Cumulative Proportion can be seen in Figure 1. and Figure 2.

Table 2. Principal Component Analysis Result

Principal Component	*Eigenvalue*	*Proportion*	*Cumulative Value*	*Cumulative Proportion*
1	5.267	0.585	5.267	0.585
2	0.881	0.098	6.149	0.683

Source: Bloomberg, processed.

Table 3. Eigenvector (*Loadings*)

Variable	PC 1	PC 2
RESID_1_01 (HSI)	0.352	-0.279
RESID_2_01 (JCI)	0.335	0.407
RESID_3_01 (KLCI)	0.279	0.417
RESID_4_01 (KOSPI)	0.352	-0.278
RESID_5_01 (NIKKEI225)	0.280	-0.529
RESID_6_01 (PSEI)	0.316	0.385
RESID_7_01 (SETI)	0.356	0.144
RESID_8_01 (STI)	0.383	-0.018
RESID_9_01 (TAIPEI)	0.327	-0.229

Source: Bloomberg, processed.

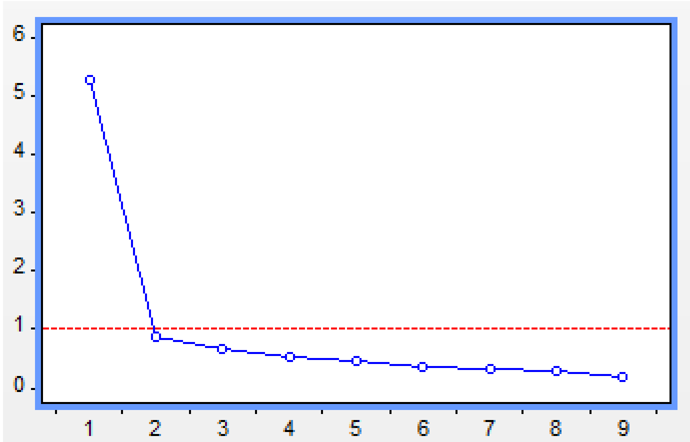

Figure 1. Scree Plot (Ordered Eigenvalue)

Source: Bloomberg, processed.

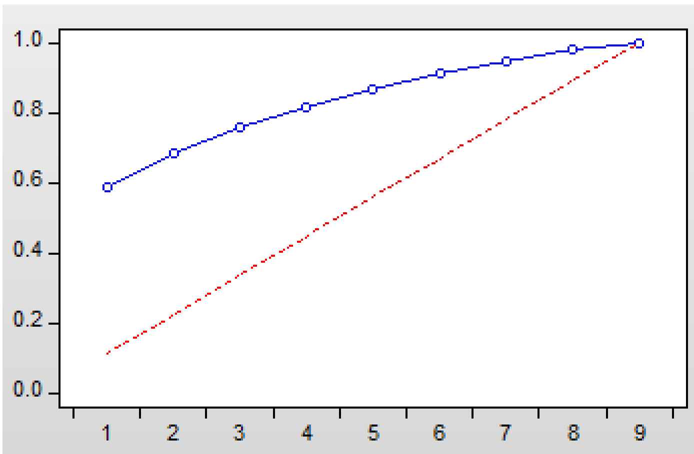

Figure 2. Eigenvalue Cumulative Proportion

Source: Bloomberg, processed.

The principal component (PC) 1 has an eigenvalue with a value of 5.267. The proportion of PC 1 is 0.585, indicating that the stock markets had the same main explanatory variance return. PC 1 is able to explain 58.5% of the amount of variance in the stock market returns in Asia. This shows that the stock markets had the same main risk factor and accounted for 58.5% of the size of the conditional variance of each of the stock market returns.

Meanwhile, the principal component (PC) 2 has an eigenvalue of 0.881 with a proportion of 0.098. This second factor is able to explain 9.8% of the variance in the Asian stock markets. This shows that there were other factors that had the same role in determining the amount of variance in the stock markets. The risk factor for the PC2 contributed 9.8% to the size of the conditional variance of each of the stock market returns.

Eigenvector shows that HSI, KOSPI, NIKKEI225, SETI, STI, and TAIPEI are stock markets that form PC1 with a high eigenvalue and contribute 58.5% of all existing proportions. This means that the Hong Kong, South Korea, Japan, Thailand, Singapore, and Taiwan stock markets were highly integrated capital markets with a high degree of integration. Most of these stock markets were relatively more advanced compared to the others. The stock markets also tended to have a larger market capitalization. This is consistent with researches conducted by Kim and McKenzie (2008) and Park (2013).

The study also found that the PC2 was formed from the stock markets in Indonesia, Malaysia, and the Philippines with a relatively small proportion of 9.8%. This means that they had a minimal level of co-movement and tended to be segmented from other stock markets. This finding supports the results of studies by Najmudin et al. (2019), Palac-McMiken (1997), Roca, Selvanathan, and Shepherd (1998), Wahyudi et al. (2018), Muharam et al. (2019) who also found that the Indonesian capital market tended to be segmented, and so was the Philippine stock market (Najmudin et al., 2019, Robiyanto, 2017). They tended to be segmented because the factors influencing the movement of these stocks during the observation period were dominated by internal factors rather than external factors, especially the regional ones such as political factors.

3.2 Pre-GFC Period (January 1997 – June 2007)

The analysis of the correlation between Asian stock market returns during the pre-GFC period is presented in Table 4. Table 4. shows that the stock market returns in Asia in the pre-GFC period tend to correlate with each other so that the OGARCH analysis is suitable.

Table 4. Correlation of Asian Stock Markets

	HSI	JCI	KLCI	KOSPI	NIKKEI225	PSEI	SETI	STI	TAIPEI
HSI	1.000	0.401	0.345	0.651	0.428	0.358	0.490	0.694	0.494
JCI	0.401	1.000	0.458	0.442	0.315	0.559	0.548	0.585	0.291
KLCI	0.345	0.458	1.000	0.296	0.155	0.305	0.387	0.466	0.447
KOSPI	0.651	0.442	0.296	1.000	0.529	0.447	0.597	0.622	0.563
NIKKEI225	0.428	0.315	0.155	0.529	1.000	0.336	0.369	0.404	0.365
PSEI	0.358	0.559	0.305	0.447	0.336	1.000	0.593	0.574	0.367
SETI	0.490	0.548	0.387	0.597	0.369	0.593	1.000	0.634	0.506
STI	0.694	0.585	0.466	0.622	0.404	0.574	0.634	1.000	0.480
TAIPEI	0.494	0.291	0.447	0.563	0.365	0.367	0.506	0.480	1.000

Source: Bloomberg, processed.

Same with all period used in this study, based on the results of the OGARCH analysis (which combines GARCH and PCA), conditional variance returns of the stock markets in Asia form two principal components. The detail can be seen in Table 5. and Table 5, while the Ordered Eigenvalue and Eigenvalue Cumulative Proportion can be seen in Figure 3. and Figure 4.

Table 5. Principal Component Analysis Result

Principal Component	*Eigenvalue*	*Proportion*	*Cumulative Value*	*Cumulative Proportion*
1	4.731	0.525	4.731	0.525
2	0.989	0.109	5.720	0.635

Source: Bloomberg, processed.

Table 6. Eigenvector (*Loadings*)

Variable	PC 1	PC 2
RESID_1_01 (HSI)	0.349	-0.280
RESID_2_01 (JCI)	0.325	0.417
RESID_3_01 (KLCI)	0.264	0.488
RESID_4_01 (KOSPI)	0.369	-0.342
RESID_5_01 (NIKKEI225)	0.270	-0.529
RESID_6_01 (PSEI)	0.322	0.265
RESID_7_01 (SETI)	0.368	0.114
RESID_8_01 (STI)	0.392	0.063
RESID_9_01 (TAIPEI)	0.317	-0.159

Source: Bloomberg, processed.

The principal component (PC) 1 has an eigenvalue with a value of 4.731. The proportion of PC 1 is 0.525, indicating that the stock markets had the same main explanatory variance return. PC 1 is able to explain 52.5% of the amount of variance in the stock market returns in Asia. This shows that the stock markets had the same main risk factor and accounted for 52.5% of the size of the conditional variance of each of the stock market returns. This is slightly lower than all period. This condition shows that during the GFC, the level of Asian stock markets integration is lower than all period. This finding is consistent with Robiyanto (2018b)'s finding which used the Dynamic Conditional Correlation (DCC). Meanwhile, the principal component (PC) 2 has an eigenvalue of 0.989 with a proportion of 0.109. This second factor is able to explain 10.9% of the variance in the Asian stock markets. This shows that there were other factors that had the same role in determining the amount of variance in the stock markets. The risk factor for the PC2 contributed 10.9% to the size of the conditional variance of each of the stock market returns. This is higher than all period analysis result.

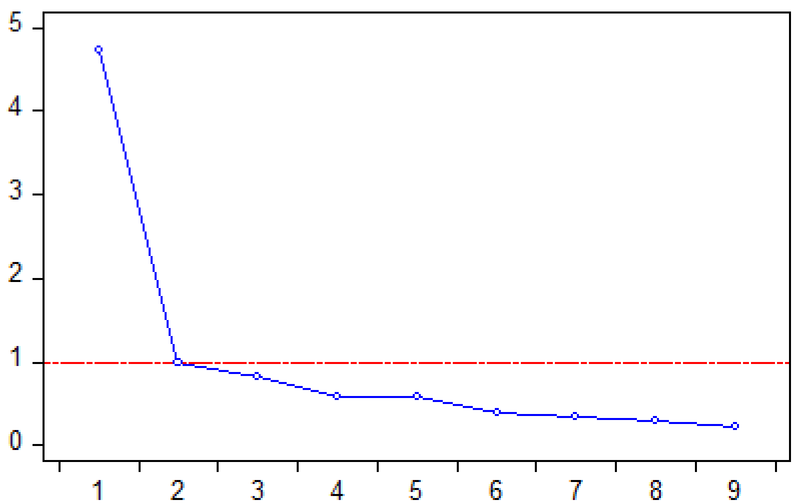

Figure 3. Scree Plot (Ordered Eigenvalue)

Source: Bloomberg, processed.

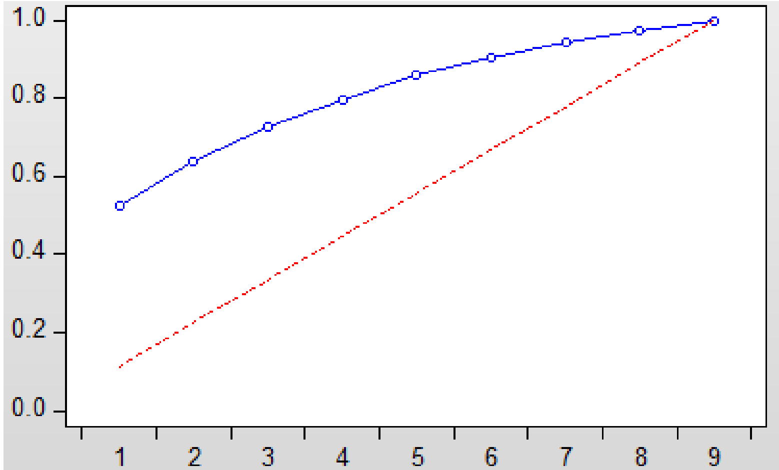

Figure 4. Eigenvalue Cumulative Proportion

Source: Bloomberg, processed.

Eigenvector shows that HSI, KOSPI, NIKKEI225, PSEi, SETI, STI and TAIPEI are stock markets that form PC1 with a high eigenvalue and contribute 52.5% of all existing proportions. This means that the Hong Kong, South Korea, Japan, the Philippines, Thailand, Singapore, and Taiwan stock markets were highly integrated capital markets with a high degree of integration. While the PC2 which formed from the stock markets in Indonesia and Malaysia with a relatively small proportion of 9.8%. This means that before the GFC, Indonesia and Malaysia had a minimal level of co-movement and tended to be segmented from other stock markets. This finding supports the results of studies by Najmudin et al. (2017), Najmudin et al. (2019), Wahyudi et al. (2018), Roca, Selvanathan and Shepherd (1998), Palac-McMiken (1997) who also found that the Indonesian capital market tended to be segmented. This finding also supports Karim, Kassim and Arip (2010), which found there is no contagion effect in Islamic financial markets which consists of Indonesia and Malaysia.

3.3 During the GFC Period (July 2007 – December 2008)

The analysis of the correlation of Asian stock market returns during the GFC period is presented in Table 7. Table 7. shows that the stock market returns in Asia during the GFC period tend to correlate with each other so that the OGARCH analysis is suitable. Same with all period and pre-GFC period used in this study, based on the results of the OGARCH analysis (which combines GARCH and PCA), conditional variance returns of the stock markets in Asia forms two principal components. The detail can be seen in Table 8. and Table 9., while the Ordered Eigenvalue and Eigenvalue Cumulative Proportion can be seen in Figure 5. and Figure 6. The principal component (PC) 1 has an eigenvalue with a value of 6.927. The proportion of PC 1 is 0.769, indicating that the stock markets had the same main explanatory variance return. PC 1 is able to explain 76.9% of the amount of variance in the stock market returns in Asia. This shows that the stock markets had the same main risk factor and accounted for 76.9% of the size of the conditional variance of each of the stock market returns. This is higher than all period and pre-GFC period. This finding also consistent with Robiyanto (2018b). Meanwhile, the principal component (PC) 2 has an eigenvalue of 0.717 with a proportion of 0.079. This second factor is able to explain 7.9% of the variance in the Asian stock markets. This shows that there were other factors that had the same role in determining the amount of variance in the stock markets. The risk factor for the PC2 contributed 7.9% to the size of the conditional variance of each of the stock market returns.

Table 7. Correlation of Asian Stock Markets

	HSI	JCI	KLCI	KOSPI	NIK-KEI225	PSEI	SETI	STI	TAIPEI
HSI	1.000	0.715	0.779	0.820	0.801	0.596	0.749	0.895	0.774
JCI	0.715	1.000	0.868	0.733	0.719	0.674	0.870	0.791	0.603
KLCI	0.779	0.868	1.000	0.733	0.767	0.681	0.767	0.796	0.551
KOSPI	0.820	0.733	0.733	1.000	0.737	0.567	0.863	0.857	0.744
NIK-KEI225	0.801	0.719	0.767	0.737	1.000	0.621	0.763	0.887	0.666
PSEI	0.596	0.674	0.681	0.567	0.621	1.000	0.575	0.700	0.426
SETI	0.749	0.870	0.767	0.863	0.763	0.575	1.000	0.820	0.817
STI	0.895	0.791	0.796	0.857	0.887	0.700	0.820	1.000	0.798
TAIPEI	0.774	0.603	0.551	0.744	0.666	0.426	0.817	0.798	1.000

Source: Bloomberg, processed.

Table 8. Principal Component Analysis Result

Principal Component	Eigenvalue	Proportion	Cumulative Value	Cumulative Proportion
1	6.927	0.769	6.927	0.769
2	0.717	0.079	7.644	0.849

Source: Bloomberg, processed.

Table 9. Eigenvector (*Loadings*)

Variable	PC 1	PC 2
RESID_1_01 (HSI)	0.344	-0.153
RESID_2_01 (JCI)	0.336	0.259
RESID_3_01 (KLCI)	0.335	0.331
RESID_4_01 (KOSPI)	0.341	-0.210
RESID_5_01 (NIKKEI225)	0.336	0.019
RESID_6_01 (PSEI)	0.278	0.631
RESID_7_01 (SETI)	0.349	-0.170
RESID_8_01 (STI)	0.364	-0.057
RESID_9_01 (TAIPEI)	0.308	-0.570

Source: Bloomberg, processed.

Eigenvector shows that HSI, JCI, KLCI, KOSPI, NIKKEI225, SETI, STI and TAIPEI are stock markets that form PC1 with a high eigenvalue and contribute 76.9% of all existing proportions. This means that the Hong Kong, Indonesia, Malaysia, South Korea, Japan, Thailand, Singapore, and Taiwan stock markets were highly integrated capital markets with a high degree of integration during the GFC period. Surprisingly, the stock market which is not integrated in the pre-GFC periods such as Indonesia and Malaysia, become integrated during the GFC period. This may occur because there was existed extreme fear which pushes stock markets to move downward simultaneously. This finding supports Adas and Tussupova (2016), Mustafa et al. (2015).

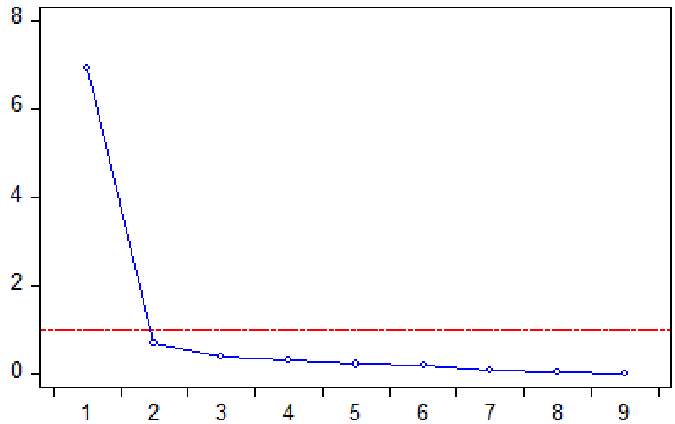

Figure 5. Scree Plot (Ordered Eigenvalue)

Source: Bloomberg, processed.

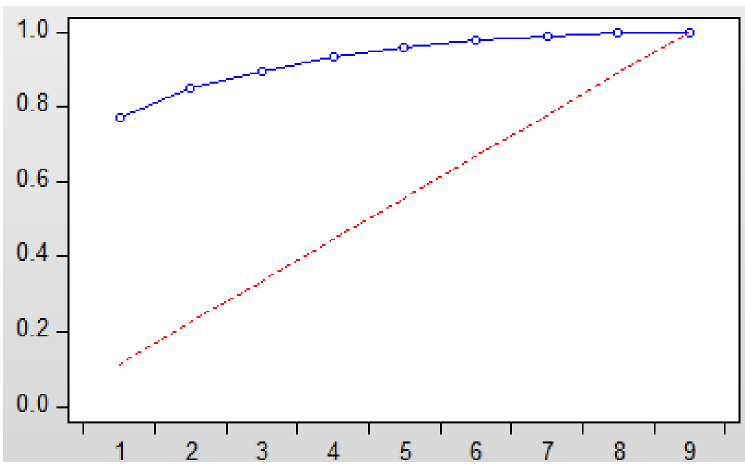

Figure 6. Eigenvalue Cumulative Proportion

Source: Bloomberg, processed.

The study also found that the PC2 was formed from the stock markets in the Philippines with a relatively small proportion of 7.9%. This means that the Philippines had a minimal level of co-movement and tended to be segmented from other stock markets. This finding supports the results of studies by Najmudin et al. (2017) and Robiyanto (2017) who also found that the Philippine stock market tended to be segmented.

3.4 Post-GFC Period (January 2009 – December 2018)

The analysis of the correlation of Asian stock market returns post- GFC period is presented in Table 10. Table 10. shows that the stock market returns in Asia in the post-GFC period tend to correlate with each other so that the OGARCH analysis is suitable, this is consistent with other periods. Same with other period used in this study, based on the results of the OGARCH analysis (which combines GARCH and PCA), conditional variance returns of the stock markets in Asia form two principal components. The detail can be seen in Table 11 and Table 12, while the Ordered Eigenvalue and Eigenvalue Cumulative Proportion can be seen in Figure 7 and Figure 8.

Table 10. Correlation of Asian Stock Markets

	HSI	JCI	KLCI	KOSPI	NIK-KEI225	PSEI	SETI	STI	TAIPEI
HSI	1.000	0.521	0.527	0.669	0.498	0.541	0.579	0.770	0.693
JCI	0.521	1.000	0.571	0.607	0.330	0.703	0.667	0.610	0.587
KLCI	0.527	0.571	1.000	0.517	0.279	0.515	0.530	0.570	0.503
KOSPI	0.669	0.607	0.517	1.000	0.467	0.495	0.554	0.711	0.732
NIK-KEI225	0.498	0.330	0.279	0.467	1.000	0.210	0.393	0.482	0.478
PSEI	0.541	0.703	0.515	0.495	0.210	1.000	0.623	0.606	0.479
SETI	0.579	0.667	0.530	0.554	0.393	0.623	1.000	0.647	0.532
STI	0.770	0.610	0.570	0.711	0.482	0.606	0.647	1.000	0.670
TAIPEI	0.693	0.587	0.503	0.732	0.478	0.479	0.532	0.670	1.000

Source: Bloomberg, processed.

Table 11. Principal Component Analysis Result

Principal Component	Eigenvalue	Proportion	Cumulative Value	Cumulative Proportion
1	5.474	0.608	5.474	0.608
2	0.969	0.107	6.444	0.716

Source: Bloomberg, processed.

Table 12. Eigenvector (*Loadings*)

Variable	PC 1	PC 2
RESID_1_01 (HSI)	0.357	0.207
RESID_2_01 (JCI)	0.344	-0.330
RESID_3_01 (KLCI)	0.305	-0.246
RESID_4_01 (KOSPI)	0.354	0.184
RESID_5_01 (NIKKEI225)	0.243	0.655
RESID_6_01 (PSEI)	0.318	-0.475
RESID_7_01 (SETI)	0.339	-0.202
RESID_8_01 (STI)	0.374	0.082
RESID_9_01 (TAIPEI)	0.349	0.227

Source: Bloomberg, processed.

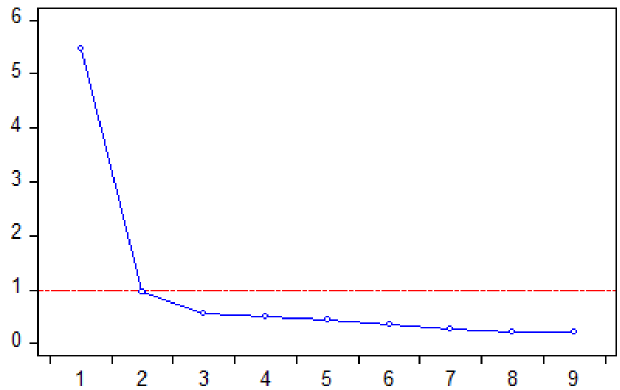

Figure 7. Scree Plot (Ordered Eigenvalue)

Source: Bloomberg, processed.

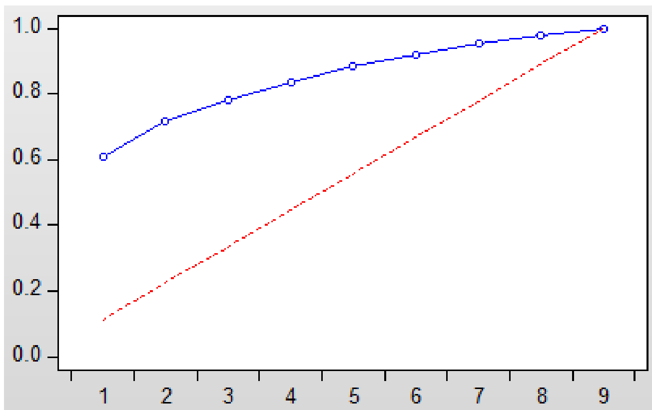

Figure 8. Eigenvalue Cumulative Proportion

Source: Bloomberg, processed.

The principal component (PC) 1 has an eigenvalue with a value of 5.474. The proportion of PC 1 is 0.608, indicating that the stock markets had the same main explanatory variance return. PC 1 is able to explain 60.8% of the amount of variance in the stock market returns in Asia. This shows that the stock markets had the same main risk factor and accounted for 60.8% of the size of the conditional variance of each of the stock market returns. This is higher than all period and pre-GFC period, but lower than during the GFC period. This finding shows that after the GFC, Asian stock markets integration become lower but still higher than before the GFC period.

Meanwhile, the principal component (PC) 2 has an eigenvalue of 0.969 with a proportion of 0.107. This second factor is able to explain 10.7% of the variance in the Asian stock markets. This shows that there were other factors that had the same role in determining the amount of variance in the stock markets. The risk factor for the PC2 contributed 10.7% to the size of the conditional variance of each of the stock market returns.

Eigenvector shows that all Asian stock markets except Japan form PC1 with a high eigenvalue and contribute 60.8% of all existing proportions. This means that all Asian stock markets except Japan were highly integrated capital markets with a high degree of integration. This study also found that the PC2 was formed from the stock market Japan with a relatively small proportion of 10.7%. This means that Japan had a minimal level of co-movement and tended to be segmented from other stock markets after the GFC.

CONCLUSION

In general, it can be concluded that not all stock markets in Asia were integrated and only the Singapore, Hong Kong, Japan, Taiwan, Thailand, and South Korea stock markets tended to be integrated for the whole research period. The Indonesian, Philippine and Malaysian stock markets tended not to be integrated with most stock markets in Asia. For this reason, it can be stated that the Asian stock markets were not fully integrated during the research study.

The Asian stock markets integration tend to evolve during the research period. Its integration was at the highest level during the GFC period, While, the Asian stock markets integration in the pre-GFC period is lower than the post-GFC period. This finding shows that integration is dynamic and follows the stock market condition generally.

Investment managers who have the ability to form international portfolios can diversify existing stocks in Indonesia, Malaysia, and the Philippines even Japan by considering country risk because their stock markets tend to be segmented. Investment managers also need to conduct special studies before investing in Asian stock markets that have proven to be integrated. Analysis of the correlation of individual shares across countries can be recommended given there is a relatively high level of integration in the Hong Kong, Singapore, Japan, South Korea, Taiwan and Thailand stock markets for certain periods.

This research has not involved the stock market in China which has been highly developed in the past few years. Therefore, future researchers can involve various stock markets in China and use the latest analytical techniques, such as wavelet.

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