Integration of ASEAN Banking Sector Stocks

Jones Odei MENSAH [a,*] and Gamini Premaratne [b]

[a] *Wits Business School, University of the Witwatersrand, 2 St Davids Place, Parktown, Johannesburg 2193, South Africa*
** Corresponding author.*
[b] *School of Business and Economics, University of Brunei Darussalam, Jalan Tungku Link, Gadong BE 1410, Brunei Darussalam*
E-mail addresses: jones.mensah@wits.ac.za (J. O. Mensah), gamini.premaratne@ubd.edu.bn (G. Premaratne),

Abstract

Over the past decades, ASEAN countries have made wide-ranging commitments and concerted efforts to achieve greater financial integration. Despite these efforts, the extant literature on equity market integration does not say much about how the banking sector, in particular, has been evolving over the years. Moreover, very little is known about the level of spillover effects in volatility and conditional asymmetry across banking sector returns. This paper sets out to address these issues using DCC-GARCH framework, and Granger-causality approach. We apply a quantile-based estimate of conditional asymmetry and examine its propagation across markets. Our findings confirm the evolving nature of financial integration in the banking sector through rising correlation. However, the correlation is of low magnitude across both ASEAN banking sector returns and returns of non-ASEAN countries and irrespective of whether we use a bivariate or multivariate model. This suggest possible gains in diversification. The Granger-causality model supports the existence of feedback between the volatilities of banking returns, where volatility in banking sector returns spillover across the ASEAN markets and between ASEAN and other markets outside the region. These volatility spillovers between the banking sector returns suggest the possibility of a systemic event, although with a relatively low probability. On the other hand, we find little evidence of spillover in terms of conditional asymmetry, which suggests that asymmetry is mostly a local phenomenon.

Keywords: banking sector stocks; conditional asymmetry; spillover; dynamic correlation

1. Introduction

Financial markets across the globe have experienced rapid integration over the past four decades, mainly spurred by the gradual loosening of controls on movement of capital and foreign exchange transactions, deregulation and relaxation of banking restrictions, globalization and advances in information technology. A major benefit of financial integration is that it generally improves risk sharing across national borders since restrictions on investment are removed; this is shown in the earlier works of Obstfeld (1994) and more recent works by Wright (2005), Gourinchas and Jeanne (2006), and Bekaert, Harvey and Lundblad (2006). Integration reduces the impact of regional shocks in domestic consumption, which has the potential of affecting long-term growth by altering resource allocation and savings rates. However, greater financial integration also leads to stronger co-movement between markets and increases the chances of cross-border contagion. Examples include the global repercussions of the stock market crash in 1987, the 1997 Asian crisis and the recent global financial crisis of 2008. In a broader sense, this affects the gains from international diversification, which hinge on the co-movement between markets.

There are both economic and financial reasons to investigate the integration of equity markets in South East Asia, considering the wide-ranging commitments and concerted efforts being made for economic and financial integration in the region. For instance, the region is considering various areas under its financial integration frameworks including financial services, payments and settlements, capital account and capital markets. In April 2011, the ASEAN Central Bank governors endorsed the ASEAN Banking Integration Framework, which sets out to harmonize five regulatory areas, namely bank accounting standards and disclosure requirements, minimum capital requirements, prompt corrective action and methodologies for the resolution of failed banks, restrictions on large exposure, and anti-money laundering and consumer protection regulations (Vinayak & Thompson, 2014). As a further step in pursuing financial integration, the ASEAN trading link was launched in 2012 to integrate equity markets in Malaysia, Singapore and Thailand. These efforts suggest that member states are determined to explore the potential gains from deeper integration. The question that naturally rises is whether these wide-ranging concerted efforts have led to greater financial integration in the region.

The objective of this paper is to investigate the extent of financial integration across the banking sector in the ASEAN region as well as with other influential

Asian markets and global markets. Even though ASEAN markets have experienced economic integration into regional and global markets in recent decades, there is limited empirical evidence on the extent of financial integration in the sub-region, particularly one involving the banking sector. This paper intends to fill this gap by addressing the following questions: To what extent are the banking sectors in the sub-region integrated? Is the banking sector in the sub-region integrated with other influential regional and global markets? How are shocks transmitted within and across the banking sector in the sub-region?

The extant literature provides several dimensions and definitions of financial integration, such as free movement of capital, relaxation of capital controls, financial openness, and integration of financial services. A broad of range of measuring criteria exists, ranging from evaluation of spillovers of shocks and volatilities, to studying return co-movements and international capital flows (Boubakri and Guilaumin, 2015). For instance, Mensah and Alagidede (2017) and Mensah and Premaratne (2018) study the co-movement of stock markets using copula techniques. Lean and Teng (2013) study the co-movement of Malaysian stock market and other emerging markets. Boubakri and Guilaumin (2015) employ GARCH models to assess the dynamics of regional financial integration on East Asian countries. Our study contributes to the strand of literature investigating the time-varying level of financial integration employing dynamic multivariate GARCH models. The main similarity with existing literature is that we examine the integration of financial markets in Asia, which is addressed in Sharma and Wongbangpo, 2002; Click and Plummer, 2005; Jeon, Oh & Yang, 2006; Lee, 2008; Yu, Fung and Tam, 2010; Claus and Lucey, 2012; and Wang, 2014.

The contribution of this study is the focus on integration across banking sector indices, unlike previous studies that deal with the entire stock market indices. There are several reasons for the chosen sector. Unlike other sectors, the banking sector plays a major role in the financial system and the economy by allocating funds from savers to borrowers in a manner that makes the overall economy more efficient, motivating the need to study the dynamic interdependence of the sector in a regional context. In addition, the global financial system has experienced several episodes of banking crises, affecting both advanced and emerging economies. Even the recent global financial crisis with its bitter and slow recovery had big banks as its major cause. Asian banks have recorded a total of 22 banking crises between 1945 and 2008 and its total share of years in a banking crisis since 1945 is 12.4%, the highest of all regions (Reinhart & Rogoff, 2009; Mensah and Premaratne, 2017). High capital mobility, which is the result of increased financial integration, is known to be correlated with banking crisis. We examine the changing integration of the banking sector in the aftermath of banking crisis episodes.

Beyond the methodologies and sectoral focus, this paper also contributes in the manner it addresses spillovers across the various markets. Previous empirical research addresses this issue mainly in the mean and volatility of returns. , These past studies are generally driven by implications for risk management, asset allocation and the development and implementation of regulatory frameworks. By contrast, we take a further step to analyse the degree of co-movement and spillover in conditional asymmetry among the banking sectors in Asia. In line with Ghysels, Plazzi and Valkanov (2011), we employ conditional quantile techniques to estimate the conditional asymmetry for each banking sector index and estimate the causal effect among the banking sector stocks in our results we observe that integration patterns are upward trending although the observed correlations are not at high levels. We also find evidence of significant causal linkages, in terms of volatility, to and from the ASEAN banking sector. However, we find little evidence of conditional asymmetry spillover.

The remainder of the paper is structured as follows. Section 2 presents the methodology. Section 3 discusses the data and some preliminary analyses of the data series covered in the study. Section 4 presents the estimation results. Section 5 provides concluding remarks.

2. Methodology

Existing integration measures can be classified into three categories: (i) price-based measures; (i) quantity-based measures and (iii) regulatory measures. The price-based measures are the most popular in the existing literature that examine integration in Asia. As argued by the Adam et al (2002), the usefulness of an integration measure is based on four main criteria, namely: data availability, reliability of the data on which the indicator is based, economic meaning of the indicator and the ease of building and updating the indicator. Priced-based indicators largely satisfy these criteria and for that reason, we follow that strand of literature.

From a methodological point of view, previous studies on financial integration have mostly relied on price-based measures such as Vector Auto-Regression (VAR) models, standard cross-correlation, cointegration and error-correction models (Chan et al., 1992; Vo, 2009). However, these methods have a number of drawbacks. For instance, cointegration and VAR models are unable to produce a numerical value for financial integration (Billio et al., 2017). In addition, cointegration methods are static and do not capture the evolving nature of financial integration. The standard correlation measure also assumes a static relationship between variables and ignores possible volatilities.

In view of the above, we rely on the dynamic conditional correlation model of Engle (2002) in order to quantify the level of integration and trace out its dynamics over time. We also employ the Granger causality method to trace out the causal linkages between the various markets. In addition, we employ a quantile-based measure of conditional asymmetry in line with (Ghysels, Plazzi and Valkanov, 2011). This allows us to quantify conditional asymmetry and subsequently measure its spillover across the banking sectors of the countries examined. Details on the models are explained in the ensuing subsections.

2.1 Dynamic Conditional Correlation

Generally, high correlation among international markets suggests high co-movement and thus greater financial integration. For this reason, we employ the dynamic conditional correlation (DCC) model (Engle, 2002; and Tse & Tsui, 2002), which is one of the most widespread proxies for measuring financial markets co-movement and consequently financial integration. DCC overcomes the problems of simple correlation, accounts for heteroscedasticity and captures the time dependence of integration. Following Engle (2002), we assume the returns from N assets, r_t, are multivariate normally distributed as

$$r_t|\emptyset_{t-1} \sim N(O, H_t), \qquad (1)$$

The conditional covariance matrix, H_t, is formulated by :

$$H_t = D_t R_t D_t \qquad (2)$$

where $D_t = (\sqrt{h_{1t}}, \sqrt{h_{2t}}, \dots, \sqrt{h_{Nt}})$ is a diagonal matrix with the ith diagonal element $\sqrt{h_{it}}$ (i.e. conditional standard deviations), and $R_t = (\rho_{ij,t})$ refers to the correlation matrix of dimension $N \times N$, which implies that $\rho_{ii,t} = 1\ \forall_i$ and $\forall_t$. The conditional variance, h_{it}, must be positive for all *i*, and R_t must be positive-definite to ensure that the covariance matrix, H_t, is also positive-definite.

The conditional variances, h_{it}, are obtained by fitting GARCH(1,1) to each of the return series as follows:

$$h_{it} = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \text{ for } i = 1,2, \dots, N \qquad (3)$$
$$\omega_i > 0\ , \alpha_{ip} \geq 0, \text{and } \beta_{iq} \geq 0$$

where ω_i, α_{ip}, β_{iq} are the unknown coefficients to be estimated and satisfy the "non-explosivity" condition $\alpha_{ip} + \beta_{iq} < 1$, which ensures non-negativity and stationarity in variance. The correlation matrix, R_t, is specified in a way that ensures it is positive-definite and does not depend on so many parameters to estimate. We define the dynamic process on the covariance matrix of the standardized residuals, $\tilde{\varepsilon}_t$ (i.e $\tilde{\varepsilon}_t = D_t^{-1}\varepsilon_t$), denoted Q_t, and transform it to the correlation matrix, R_t :

$$Q_t = (1-\gamma-\delta)\bar{Q} + \alpha(\tilde{\varepsilon}_{t-1}\tilde{\varepsilon}'_{t-1}) + \beta Q_{t-1}, \tag{4}$$

$$R_t = diag(Q_t)^{-1}Q_t diag(Q_t)^{-1} \tag{5}$$

where $\bar{Q}$ is an $N \times N$ symmetric unconditional correlation matrix of the standardized residuals, and γ and δ are non-negative scalar parameters which satisfy $\gamma + \delta < 1$. The parameter γ shows the sensitivity of the co-movements to news, and δ represents the decay of past co-movement. Q_t is symmetric and positive-definite if Q_0 is positive-definite and the condition, $\gamma + \delta < 1$, is met. Hence, R_t will be positive-definite and represents the correlation matrix at each point in time.

Note that the normality assumption in Eq. (1) implies that we maximize log-likelihood over the parameters of the model as follows:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + \log|H_t| + r_t'H_t^{-1}r_t) \tag{6}$$

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \tilde{\varepsilon}_t R_t^{-1}\tilde{\varepsilon}_t') \tag{7}$$

Engle (2002) proposes a two-step procedure that gives simple but inefficient parameters of the model. This involves a two-stage estimation of the conditional variance model and conditional correlation model, giving rise to two sub-divisions of the log-likelihood function: L_V and L_C for the conditional variance and conditional correlation parts respectively. Let θ denote the vector of parameters of the conditional variances contained in D_t and λ is the vector of the parameters of the conditional correlation matrix, R_t. Thus,

$$L(\theta,\lambda) = L_V(\theta) + L_C(\theta,\lambda), \tag{8}$$

$$L_V(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + 2\log|D_t| + r_t'D_t^{-2}r_t) \tag{9}$$

$$L_C(\theta,\lambda) = -\frac{1}{2}\sum_{t=1}^{T}(log(|R_t|) - \tilde{\varepsilon}_t'\tilde{\varepsilon}_t + \tilde{\varepsilon}_t'R_t^{-1}\tilde{\varepsilon}_t) \tag{10}$$

We first estimate Eq. (9) with a univariate GARCH model and once θ is estimated, the value can be inserted into Eq. (10) and then maximized with respect to λ. The two-stage quasi-maximum likelihood (QML) estimator of DCC is consistent and asymptotically normal under broad conditions although the parameter estimates are inefficient.

The DCC model enables us to model the conditional correlation of a pair of stock indices in conjunction with how their correlation evolves over time. The dynamic correlation estimated from the DCC model measures market integration. Markets become more integrated when the conditional correlation increases over time. The modelling process begins by formulating appropriate ARMA (p,q)-models for each of the banking sector returns. Next, we determine the optimal lag-length for the univariate GARCH-models and fit bivariate DCC(1,1).

It is important to note that the DCC-GARCH captures only pairwise conditional correlation. For this reason, we also employ the Dynamic EquiCorrelation (DECO) model of Engle & Kelly (2012). The DECO captures time-varying correlation between two or more return pairs at a time, thus providing a holistic view of financial integration across many markets. Details on the DECO model are provided in the appendix.

2.2 Conditional Asymmetry

Other than examining the extent of integration, this paper seeks to quantify the level of asymmetry and subsequently measure its spillover across the banking sector stocks. To achieve this, we rely on the quantile-based asymmetry measure (Ghysels, Plazzi and Valkanov, 2011), which tests whether the interval between conditional quantiles $1-\theta$ and θ is positioned at the conditional median of $r_{t,n}$. Suppose, we consider the difference between the upper and lower quartiles of the conditional distribution of $r_{t,n}$, then the return distribution is asymmetric if at time t, the midspread is not centred at the median. The quantile-based measure of conditional asymmetry given information I_{t-1} is specified as:

$$CA_{\theta,t}\big(r_{t,n}\big) = \frac{\big(q_{\theta,t}(r_{t,n})-q_{0.50,t}(r_{t,n})\big)-\big(q_{0.50,t}(r_{t,n})-q_{1-\theta,t}(r_{t,n})\big)}{q_{\theta,t}(r_{t,n})-q_{1-\theta,t}(r_{t,n})} \qquad (11)$$

where $q_{\theta,t}\big(r_{t,n}\big) = F^{-1}_{t,n|t-1}(r)$ is the conditional quantile θ of return $r_{t,n}$. Denote $q_{\theta,t}\big(r_{t,n}\big)$ by $q_{\theta,t}\big(r_{t,n};\delta_{\theta,n}\big)$, where the vector, $\delta_{\theta,n}$, captures the unknown parameters of the quantile model. This measure captures the asymmetry of quantiles $q_{1-\theta,t}\big(r_{t,n}\big)$ and $q_{\theta,t}\big(r_{t,n}\big)$ with respect to the median, which is $q_{0.50,t}\big(r_{t,n}\big)$. The function q can be estimated at various quantiles θ and the vector of parameters $\delta_{\theta,n}$ could vary across quantiles and horizons. In the empirical analysis, we set $\theta = 0.75$ to denote the interquartile range, which results in a conditional version of the Bowley's (1920) statistic. The denominator normalizes the statistic to lie between -1 and 1 and ensures that is unit-free. If at time t, $CA = 0$, then the return distribution is symmetric whereas values close to -1 or 1 suggests left and right skewness respectively. We model $q_{\theta,t}(r_{t,n};\delta_{\theta,n})$ as a function of financial and economic state variables $(M_{\theta,t-1})$, contained in the vector $M_{\theta,t-1}$:

$$q_{\theta,t}(r_{t,n};\delta_{\theta,n}) = \alpha_{\theta,n} + \beta_{\theta,n}M_{\theta,t-1} \tag{12}$$

where $\delta_{\theta,n} = \alpha_{\theta,n},\ \beta_{\theta,n}$ are the unknown parameters to be estimated and state variables $M_{\theta,t-1}$, which capture the fluctuations in the quantiles of n-period returns, are allowed to vary across quantiles. More details on the state variables are provided in section 3.

2.3 Granger Causality Test

In addition to the extent of integration, we are also interested in finding out how the banking sector stocks volatility and conditional asymmetry spillover across countries. To fulfil this, we employ the Granger causality test (Granger, 1969, 1980 and 1988). Explicitly, X is said to "Granger-cause" Y if previous values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone. The form of the Granger-causality equation is specified as

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \epsilon_t \tag{13}$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \omega_t \tag{14}$$

where m denotes the maximum lag length and ϵ_t and ω_t are two uncorrelated white noise processes. Y is said to cause X when b_j is not equal to zero. Similarly, X causes Y when c_j is different from zero, that is, if the p-value is less than 5%. When both statements hold, then there is a feedback relationship between the two time series. Y and X refers to either conditional volatility or conditional asymmetry, within the context of this study.

3. Data and Preliminary Observations

The data set employed for this study consist of banking sector indices for the following countries: Singapore, Malaysia, Philippines, Thailand, Indonesia, Hong Kong, Japan, China, India, and U.S.A.[1] The data are collected from

[1] We have provided the names, and mnemonics of the banking sector indices in the appendix. The Thompson Reuters indices usually have two versions, i.e. Price Return and Total Return, depending on whether dividend is adjusted or not. Further information on the

DataStream and comprise of 3390 daily observations based on closing prices from January 4, 2000 to December 31, 2012. The summary statistics are reported in Table 1. Judging by the mean returns and volatility, the markets generally do not follow the standard risk-return trade-off where high standard deviation is expected to be accompanied by high returns. For instance, Malaysia has the lowest standard deviation although it ranks second in terms of returns whereas U.S.A has the highest standard deviation although it ranks ninth in terms of returns. The markets with negative skewness include Hong Kong, India, Malaysia, and Thailand; the rest of the markets have positive skewness. Reasons for high negative skewness include relatively high turnover and uncommon high returns over previous periods. The degree of skewness is also related to stock capitalization (Hashmi and Tay, 2012). The kurtosis coefficients provide evidence of fat-tails in the return distributions. The Jarque-Bera statistic, which is not reported, strongly rejects the null hypothesis of normality in the return distributions. Finally, the ARCH-LM test of order 10 strongly confirms the presence of ARCH-effects in the individual series, justifying the employment of GARCH models for the conditional variance of the returns.

Table 2 shows the correlation coefficients. The correlation coefficients across all the banking sector stocks in our sample tend to be positive, with the exception of correlation between U.S.A and China. The correlation ranges from -0.0057 to 0.5114, which indicates weak co-movement across the markets. For the ASEAN markets, which are the focus of this paper, we can say that proximity does not necessarily imply stronger ties, as the correlation coefficients are weak in all cases. The low correlations also suggest that there could be low risk for financial losses that may arise due to adverse movements in correlation between the markets. At the level of country pairs, Singapore and Hong Kong shows a relatively greater correlation, 0.5114, compared to the others. This could possibly be because the two markets have more developed financial systems. The correlation coefficient of China with U.S. banking sectors tend to be the least, -0.0057. In effect, this low correlation presents an escape route for investors in the event of adverse shocks in one of the markets. However, these coefficients are static and since correlations are time-varying, it is important that we model the stochastic processes, which by construction are time dependent. We estimate the dynamic correlation in the empirical section using the DCC model.

calculation methods is available here:
https://www.thomsonreuters.com/content/dam/openweb/documents/pdf/tr-com-financial/methodology/global-equity-index-methodology-oct-2015.pdf

To estimate expression 12, we employ a set of lagged state variables $M_{\theta,t-1}$ based on economic theory and previous evidence on stock return predictability. We consider two financial state variables – conditional volatility of stocks and stock return turnover – as well as two macroeconomic indicators (short-term interbank or government bond yield and the spread between a long-term and the short-term rate). The factors include:

a. **Financial Variables:** Conditional Volatility of stock market index from each country, estimated with a GARCH model. This is used as a proxy for economic uncertainty and also captures the leverage effect for each market (Ghysels, Plazzi and Valkanov, 2011).
   The second financial variable considered is turnover, which is defined as the log of the ratio of total value of shares traded to average market capitalization for the period. This is used as a proxy for the degree of financial development or the intensity of disagreement among investors (Ghysels, Plazzi and Valkanov, 2011; Bekaert, Harvey, Lundblad, and Siegel, 2011; Chen, Hong, and Stein, 2001).
b. **Economic Variables**: We also consider the short-term interbank or government bond yield as well as the spread between long-term and short-term rate, which capture changes in the investment opportunity set. Engle and Rangel (2008), Ghysels, Plazzi and Valkanov (2011), Bekaert, Harvey, Lundblad, and Siegel (2011) have also used these variables in recent studies.

Ghysels, Plazzi and Valkanov (2011) use the above variables and additional variables to capture the dynamics in conditional asymmetry. This study however employs these variables to capture the time variation in the conditional moments of the returns.

Table 1. Summary statistics of returns of Banking Sector Indices

	Mean	Std.Dev.	Skewness	Kurtosis	ARCH test Q2(10)
Singapore	0.0001	0.0149	0.0021	7.4488	0.0000
Malaysia	0.0003	0.0104	-0.3263	9.4668	0.0000
Thailand	0.0002	0.0191	-0.3055	11.1406	0.0000
Philippines	0.0002	0.0129	0.2307	13.3943	0.0000
Indonesia	0.0002	0.0235	0.2199	9.1878	0.0000
Japan	-0.0003	0.0189	0.0888	7.5193	0.0000
Hong Kong	0.0000	0.0154	-0.8656	27.6498	0.0000
China	0.0001	0.0178	0.3217	7.6169	0.0000
India	0.0007	0.0208	-0.1556	8.0315	0.0000
U.S.A	-0.0001	0.0238	0.1386	17.9743	0.0000

Notes: The table reports the summary statistics for the log returns of the 12 Asian Banking indices at daily frequency from January 2000 to December 2012. ARCH test Q2(10) shows the p-values for the Engle(1982) test for heteroscedasticity at 10 lags.

Table 2 Correlation Coefficients across Asian Banking Sector 2000-2012

	Singapore	Malaysia	Thailand	Philippines	Indonesia	Japan	Hong Kong	China	India
Malaysia	0.3488								
Thailand	0.3752	0.2964							
Philippines	0.2347	0.2629	0.2260						
Indonesia	0.2619	0.2121	0.2193	0.2278					
Japan	0.3272	0.2328	0.2459	0.2563	0.2186				
Hong Kong	0.5091	0.3014	0.3600	0.2772	0.2451	0.3872			
China	0.1811	0.1373	0.1436	0.1191	0.1191	0.1608	0.2253		
India	0.3438	0.2065	0.2658	0.1673	0.2043	0.1894	0.3134	0.1573	
U.S.A	0.1586	0.0368	0.0762	0.0042	0.0378	0.0545	0.1038	-0.0031	0.1586

Notes: The table presents the estimated correlations among the Asian banking sector indices over the period January 2000 to December 2012.

4. Empirical Results

4.1 Financial Integration

Table 3 reports the estimated univariate GARCH(1,1) model parameters and the log-likelihood values for the respective banking sector stocks. Panel A shows results for the conditional mean equation, which has significant parameters for most of the countries. Panel B reports the estimates of the conditional variance parameters ω, α and β from equation 3. According to Bollerslev (1986), the following inequality restrictions must be satisfied to ensure that the GARCH (1,1) model is not misspecified: (i) $\varpi_0 \geq 0$ (ii) $\alpha_1 \geq 0$ (iii) $\beta_j \geq 0$ (iv) $\alpha_1 + \beta_1 < 1$. In this regard, all the estimated coefficients satisfy the standard regularity conditions. The volatility updating parameter, α_1, ranges between 0.0366 to 0.1079 whereas the autoregressive variance parameter, β_1, ranges from 0.8433 to 0.9589. The parameter estimates indicate that the GARCH model captures the high volatility persistence in the 10 banking sectors and is correctly specified. The sum of the ARCH and GARCH coefficients, $\alpha_1 + \beta_1$, indicates that shocks to volatility have a persistent effect on the conditional variance. In other words, periods of high volatility in the prices will last for a long time.

Table 4 presents the maximum likelihood estimates for the multivariate DCC-GARCH model for the ASEAN-5 markets. With the exception of Singapore-Thailand, all the DCC(1,1) parameters, α and β, are statistically significant for all market-pairs, which suggests considerable time-varying co-movement. The persistence measure $(\gamma + \delta)$ is mostly close to one, suggesting a very slow mean-reversion in the conditional correlations. This explains the upward trending correlations observed in the evolution of the DCC(1,1) shown in Figure 1 and Figure 2. Maximum likelihood estimates of the DCC-GARCH for ASEAN with other influential markets are shown in Table 5. The first two rows of each panel shows the estimates of the DCC(1,1) parameters γ and δ in Equation 5. Both parameters are statistically significant for many of the pairs, indicating significant time-varying co-movement. The persistence measure is also high for most of the pairs examined.

Figure 1 presents the pairwise time-varying correlations for the ASEAN-5 countries. Generally, an upward trend is observed although the correlation coefficients are at moderate levels. This upward movement in correlation suggests that integration among the banking sectors in the ASEAN region has been rising for the period analysed. However, the magnitude of rising correlation is moderate. These findings further suggest that diversification benefits for portfolios that contain assets from these sectors may have decreased during the past one and half decade. In particular, we observe similar upward movement and an abrupt rise during the early 2000s crisis, the sub-prime crisis, the collapse of Lehman Brothers on September 15, 2008 and the European sovereign debt crisis, which began in 2010. At a country level, the degree of correlation between Singapore-Malaysia and Malaysia-Thailand increased by an average of only 6% after 2001, whereas the rise for the remaining pairs is as follows: Singapore-Thailand (51%), Singapore-Philippines (273%), Singapore-Indonesia (135%), Malaysia-Philippines (103%), Malaysia-Indonesia (110%), Thailand-Philippines (15%), Thailand-Indonesia (73%) and Philippines-Indonesia (60%). Figure 2 shows the evolution of the estimated conditional correlation coefficients between the ASEAN-5 countries and other influential markets. Similar to figure 1, the correlation is not so pronounced for the various pairs although the trend is upwards. The magnitudes of the correlation coefficients are below 0.5 for most the pairs, with the exception of Singapore-Hong Kong where it peaks around 0.6 and Thailand-Hong Kong where it peaks around 0.55. These plots reveal a common upward movement for all the correlations pairs, and they reach their peak in the second half of 2008.

Table 3. Estimation Results of ARMA(p,q)-GARCH(p,q) Models

	Singapore	Malaysia	Thailand	Philippines	Indonesia	Japan	Hong Kong	China	India	U.S.A
Panel A: Conditional Mean Equation										
C	0.0003	0.0006	0.0008	0.0005	0.0010	0.0002	0.0003	0.0000	0.0012	0.0003
	(0.0002)[c]	(0.0002)[b]	(0.0003)[b]	(0.0002)[b]	(0.0003)[a]	(0.0003)	(0.0002)[b]	0.0002	(0.0003)[a]	(0.0002)[c]
AR(1)	-0.0123	-0.4429	0.0722	0.2833	0.0216	0.0967	0.0209	-0.0326	0.1038	-0.0450
	(0.0184)	(0.2939)	(0.0193)[a]	(0.1361)[b]	(0.0177)	(0.0178)[a]	(0.0186)	(0.0171)[b]	(0.0176)[a]	(0.0182)[b]
MA(1)		0.5602		-0.1705						
		(0.2941)[b]		(0.1412)						
MA(2)		0.0659								
		(0.0388)[c]								
MA(3)		0.0503								
		(0.0177)[b]								
Panel B: Conditional Variance Equation										
Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]	(0.0000)[a]
ARCH	0.0958	0.0724	0.0718	0.1038	0.1079	0.0742	0.0821	0.0366	0.0906	0.0843
	(0.0074)[a]	(0.0044)[a]	(0.0061)[a]	(0.0062)[a]	(0.0058)[a]	(0.0057)[a]	(0.0044)[a]	(0.0022)[a]	(0.0063)[a]	(0.0048)[a]
GARCH	0.8995	0.9264	0.8959	0.8433	0.8839	0.9180	0.9188	0.9589	0.8910	0.9172
	(0.0069)[a]	(0.0037)[a]	(0.0089)[a]	(0.0098)[a]	(0.0061)[a]	(0.0055)[a]	(0.0038)[a]	(0.0022)[a]	(0.0072)[a]	(0.0042)[a]
Ljung–Box Q-statistics Q(10)	0.1110	0.614	0.2570	0.2590	0.9370	0.7150	0.5140	0.1340	0.3010	0.5750
ARCH test Q2(10)	0.2381	0.1484	0.9979	0.5512	0.4663	0.8734	0.4082	0.2971	0.3946	0.4304

Notes: The table presents results for daily returns on the Asian banking sector indices over the period January 2000 to December 2012. The top panel presents the parameter estimates for the conditional mean, modelled by an ARMA(p,q) model; the second panel presents parameter estimates from GARCH(1,1) models for the conditional variance. Values shown in parenthesis are the t-values. [a] and [b] indicates statistical significance at 5% and 10% respectively

In order to have a holistic view, we present results for the DECO-GARCH. The DECO correlation, shown by the lower panel of Figure 3, reveals that correlation between the ASEAN and other markets increased by 269% from the start of the sample to the peak in 2008. The second half of 2008 marks the period when stocks and commodities around the globe experienced sharp reductions in value, which culminated with a global systemic crisis and led the failure and takeover of key financial institutions in the US and Europe such as Lehman Brothers, AIG, Merrill Lynch, Glitnir bank, Kaupthing bank and Landsbanki. It was around the same period that the Indonesia stock exchange halted trading after a 10% drop in one day and the Bank of East Asia in Hong Kong experienced a brief run on deposits at some branches immediately after the collapse of Lehman Brothers. The common upward movement in correlations of ASEAN banking sector as well as with other Asian markets suggest rising integration of banks within the region. High correlation among the Banking-sector is a conduit for the easy spread of negative economic shocks, which in extreme cases could be systemic with dire consequences across the regional banking sector. However, one cannot be sure of the probability of such an extreme event occurring and subsequently spreading across the ASEAN banking sector, as correlations remain at moderate levels. The mild upward trend suggests the existence of common regional factors, which drive correlation in the ASEAN banking-sector, and could possibly be the result of contractual links among the banks (Adrian & Brunnermeier, 2010) or a common interbank market. It is also possible that there are similarities in how the banks conduct their business and if such closeness in behaviour strengthens over time, it could make the regional financial sector prone to systemic risk.

Table 4. DCC results for ASEAN

	γ	δ	$\gamma + \delta$	DF	LL
SIN-MAL	0.0377 (3.2470)[a]	0.9292 (31.24)[a]	0.9668	6.1203	21516.9350
SIN-THA	0.0194 (1.2160)	0.9711 932.83)[a]	0.9905	6.8440	19316.7940
SIN-IND	0.0122 (1.8070)[c]	0.9865	0.9986	6.8595	18837.5390
MAL-THA	0.0236 (2.0330)[b]	0.9286 (118.30)[a]	0.9522	4.9570	20508.9650
MAL-IND	0.0072 (2.1010)[b]	0.9918 (17.76)[a]	0.9990	5.1281	20030.0070
THA-PHI	0.0117 (4.0530)	0.9792 (190.20)[a]	0.9908	5.4634	19464.8140
PHI-IND	0.0059 (1.8760)[c]	0.9932 223.50[a]	0.9991	5.2427	19066.6070
THA-IND	0.0151 (2.6410)[a]	0.9787 (107.60)[a]	0.9938	5.4944	17803.9420
MAL-PHI	0.0056 (1.8040)[c]	0.9921 (195.40)[a]	0.9977	5.0043	21741.0810
SIN-PHI	0.0111 (2.5660)[b]	0.9781 (103.30)[a]	0.9892	6.3617	20464.7710

Notes for Table 4: This table shows the evolution parameters for the DCC GARCH model with t-values in parenthesis. DF and LL denotes degree of freedom and log-likelihood values; $\gamma + \delta$ shows the degree of persistence. [a, b,] and [c] implies statistical significance at 1%, 5% and 10%, respectively. SIN, MAL, THA, PHI, IND refers to Singapore, Malaysia, Thailand, Philippines, and Indonesia in that order.

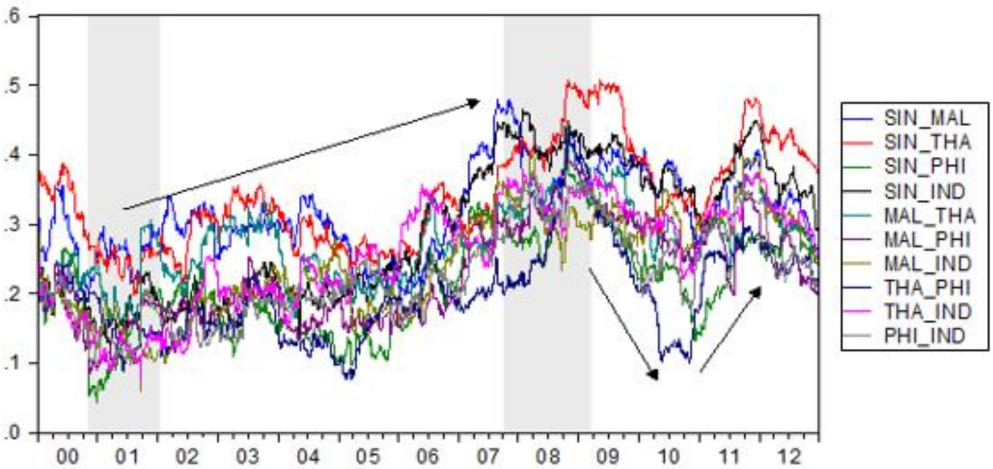

Figure 1 DCC-GARCH Model Estimates for ASEAN countries

Notes: The Figure shows the conditional correlations between banking sector indices overtime, 2000–2012. SIN, MAL, THA, PHI, IND refers to Singapore, Malaysia, Thailand, Philippines, and Indonesia in that order.

Table 5. DCC Results for ASEAN and other markets

	Japan	Hong Kong	China	India	U.S.A
Panel A: Singapore-Related Pairs					
γ	0.0153 [c]	0.0152 [c]	0.0042 [b]	0.0061 [a]	0.0000
δ	0.9766 [a]	0.9806 [a]	0.9954 [a]	0.9930 [a]	0.6531
$\gamma + \delta$	0.9920	0.9958	0.9996	0.9991	0.6531
DF	8.1986	5.9229	6.0860	7.9616	7.6320
LL	19339.7920	20998.0400	19386.6100	18961.7950	19532.7390
Panel B: Malaysia-related pairs					
γ	0.0246	0.0218	0.0181 [a]	0.0156 [c]	0.0048
δ	0.9532 [a]	0.9543 [a]	0.9498 [a]	0.9492 [a]	0.9813 [a]
$\gamma + \delta$	0.9778	0.9761	0.9679	0.9649	0.9861
DF	5.8257	5.0743	4.7058	6.0821	5.7397
LL	20498.3940	21962.3810	20654.2150	20089.8250	20758.7890
Panel C: Thailand-related pairs					
γ	0.0042	0.0259	0.0054 [a]	0.0063 [a]	0.0016
δ	0.9939 [a]	0.9533 [a]	0.9917 [a]	0.9926 [a]	0.9972 [a]
$\gamma + \delta$	0.9982	0.9792	0.9971	0.9989	0.9987
DF	6.3477	5.3272	4.9210	6.1820	6.2459
LL	18263.8530	19794.8060	18418.9910	17920.3900	18517.1390
Panel D: Philippines-related pairs					
γ	0.0181	0.0066 [a]	0.0058 [b]	0.0069 [b]	0.0000
δ	0.9734 [a]	0.9909	0.9898 [a]	0.9798 [a]	0.8703 [a]
$\gamma + \delta$	0.9915	0.9975	0.9956	0.9867	0.8703
DF	6.0004	5.0697	4.6490	6.1360	6.1725
LL	19569.0210	20956.5640	19716.5200	19118.4430	19797.9010
Panel E: Indonesia-related pairs					
γ	0.0120 [b]	0.0160	0.0086 [b]	0.0062 [b]	0.0000
δ	0.9794 [a]	0.9813 [a]	0.9889 [a]	0.9923 [a]	0.8811
$\gamma + \delta$	0.9914	0.9973	0.9975	0.9986	0.8811
DF	6.6559	5.3935	5.1142	6.2416	6.3423
LL	17800.5250	19304.1660	17970.5550	17456.8950	18070.8440

Notes: This table shows the evolution parameters for the DCC GARCH model with t-values in parenthesis. DF and *LL* denotes degree of freedom and log-likelihood values; $\gamma+\delta$ shows the degree of persistence. [a, b,] and [c] implies statistical significance at 1%, 5% and 10%, respectively.

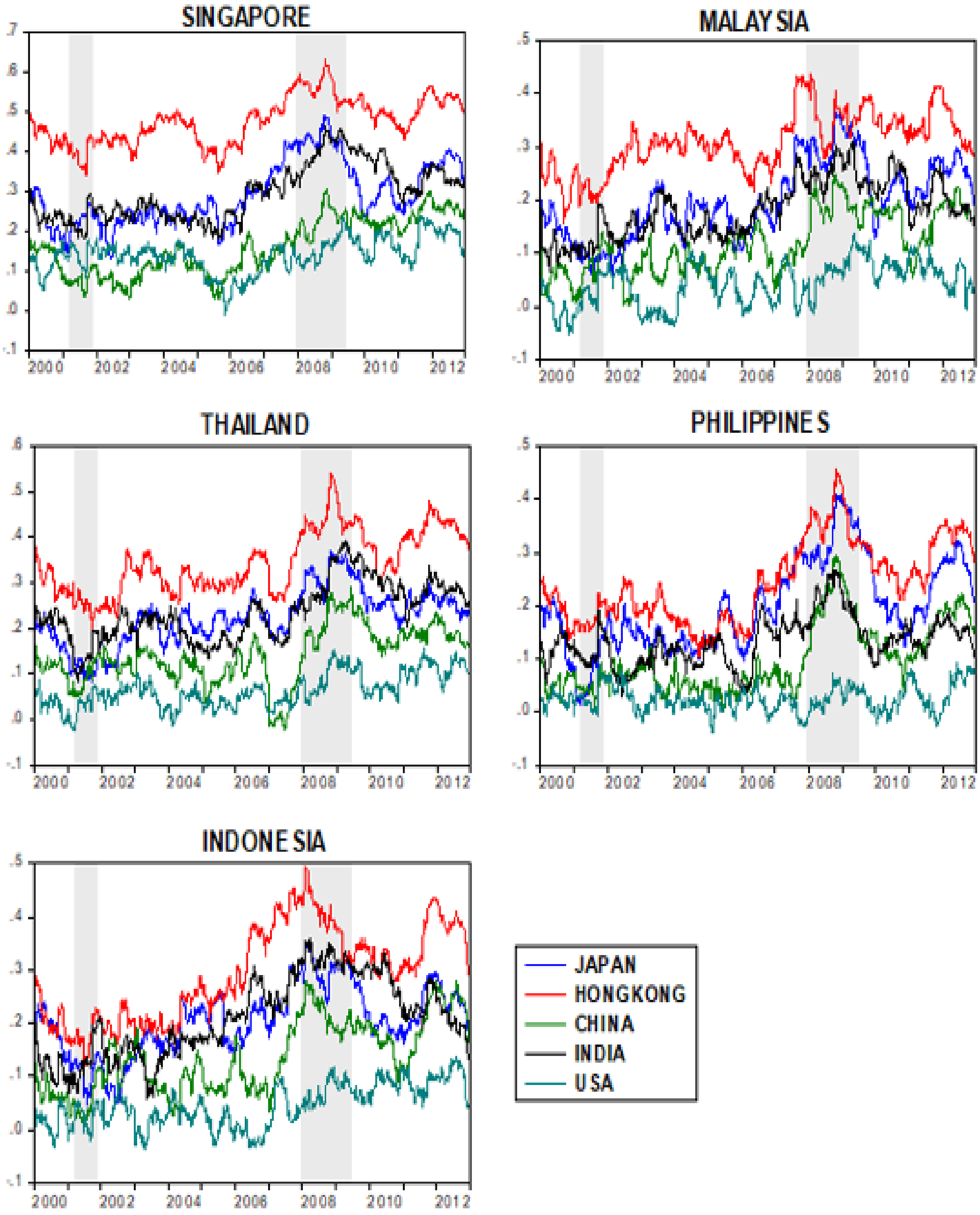

Figure 2 DCC-GARCH Model Estimates for ASEAN and Other Countries

Notes: The Figure shows the conditional correlations between banking sector indices overtime, 2000–2012.

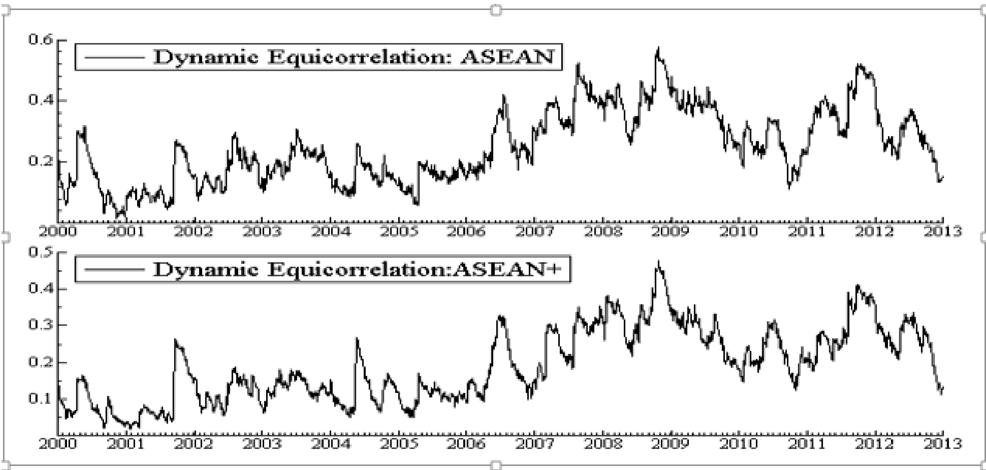

Figure 3 DECO coefficients among the banking sector indices, 2000-2012

4.2 Spillover in Volatility and Conditional Asymmetry: Granger Causality

To gain more insight into the dynamic relationship between the banking sectors, we apply the Granger-causality test for the entire sample of banking sector indices in ASEAN as well as the U.S.A and other Asian markets. We investigate causality for conditional variance and conditional asymmetry. Table 6 presents the Granger-causality test results for the conditional volatilities of the ASEAN banking sector indices as well as with that of the other influential markets. The results show that volatility of the Singapore banking sector affects volatility in Malaysia, Thailand, Japan, Hong Kong and vice versa. The volatility of the Malaysian and Indonesian banking sectors also spills over to each other. Volatility in Philippines and Indonesia also affects volatility in Singapore. There is a two-way causality between Indonesia and Thailand. These findings imply that some extent of volatility spillover occurs within the ASEAN region.

After including U.S.A and the other influential markets in East Asia, we observe significant causal linkages, in terms of volatility, to and from the ASEAN banking sector. For instance, Japan Granger-causes Singapore and Malaysia, volatility in Hong Kong spills over to Singapore and Indonesia while China affects the banking sectors in Philippines, Thailand and Indonesia. These results indicate that the information set provided by other influential markets can predict the future fluctuations of the banking sector stocks in the ASEAN region. Interestingly, India and the U.S banking sectors do not Granger-cause any of the ASEAN banking sectors.

The results up until now suggest volatility spill over between the ASEAN banking sector stocks and other influential markets in Asia and the U.S. The asymmetric feature of stock returns implies that the first and second moments do not suffice in describing the risk faced by investors in those markets (Ghysels, Plazzi and Valkanov, 2011). Therefore, as a next step, we examine whether the spillovers observed for the mean and conditional variance are also present in the conditional higher moments of the banking sector stocks. In particular, we rely on the quantile-based conditional asymmetry measure presented in equation 11 and 12. First, we estimate the 25th, 50th and 75th conditional quantiles in equation 11 and proceed to substitute them into expression 12 to obtain the time-series of conditional asymmetry values. Next, we run Granger causality tests using the conditional asymmetry series.

Table 7 presents the results. Generally, we observe mixed results. Considering only ASEAN, we do not find evidence of spillover effects in the conditional asymmetry of banking sector returns for most of the pairs with the exception of Malaysia-Indonesia, Malaysia-Thailand, Thailand-Indonesia, and Indonesia-Singapore. Considering the other influential markets, we note the following causal relations: Singapore-US, US-Singapore, Malaysia-India, India-Singapore, Philippines-India, Indonesia-India, Japan-Singapore, Hong Kong-Singapore, Hong Kong-Malaysia, and India-Thailand. In the absence of significant Granger-causal relations for most of the pairs, it may be concluded that asymmetry is mostly a local phenomenon, which is in line with the findings by Hashmi & Tay (2012).

So far, we find that correlations fell to pre-crisis levels post the GFC period. Similarly, correlations rose during the European sovereign debt crisis but fell after this period. This result is contrary to self-fulling prophecy phenomenon popularised in the literature (Dalkir, 2009). Essentially, the argument of the self-fulling prophecy phenomenon is that traders' belief that different markets are highly correlated during a crisis becomes reality due to their correlated actions; eventually, stopping correlation falling to pre-crisis levels.

We also argue that the integration process may have been amplified by the GFC and the Euro debt crises, on the basis that correlations were strong during the Global financial crisis and the European sovereign debt crisis. To some extent, it suggests that the ASEAN banking sector is relatively not well protected against a Global Financial crisis. The mostly below 0.5 but positive correlation between markets indicate limited risk of contagion, but this is possible in the future and could expose the regional banking sector to systemic risk, if the comovements strengthen over time. As seen from the Granger causality results, there is a tendency towards volatility transmission across some markets in the ASEAN region. To this end, policy makers should be watchful to the behaviour of the banking sector in their design and implementation of appropriate regulatory measures.

Moreover, the findings from this study have significant implications for portfolio managers. The benefits of diversification hinge on low correlation (Markowitz 1952; Sharpe 1964). So far, the evidence points to a time-varying upward trending correlations for both the ASEAN-5 countries and, between the ASEAN-5 countries and other influential markets. Although, the correlations remain at moderate levels (mostly below 0.5 for most pairs), the upward trend suggest that opportunities to take advantage of international diversification may have declined in recent times. Ideally, a negative correlation is preferable from a risk management perspective, as it could help reduce overall portfolio risk, in the sense that if one asset price decreases, the other asset on average increases. Contrary to this, we find positive correlations and this could potentially lead to upward adjustments in the levels of risk for equity investors, possibly leading to financial losses. These results should alert investors to pay close attention to banking sector stock behaviour within the ASEAN region and relative to other influential markets.

Table 6. VAR Granger Causality for conditional variance

Dependent	Excluded	Chi-sq	Prob.	Dependent	Excluded	Chi-sq	Prob.
Singapore	Malaysia	21.626	0.000[a]	Japan	Singapore	124.091	0.000[a]
Singapore	Thailand	10.449	0.005[a]	Japan	Malaysia	18.338	0.000[a]
Singapore	Philippines	0.370	0.831	Japan	Thailand	2.585	0.275
Singapore	Indonesia	1.221	0.543	Japan	Philippines	27.459	0.000[a]
Singapore	Japan	7.540	0.023[b]	Japan	Indonesia	3.711	0.156
Singapore	Hong Kong	47.590	0.000[a]	Japan	Hong Kong	43.310	0.000[a]
Singapore	China	0.706	0.703	Japan	China	0.760	0.684
Singapore	India	9.665	0.008[a]	Japan	India	32.745	0.000[a]
Singapore	USA	80.346	0.000[a]	Japan	USA	157.340	0.000[a]
Malaysia	Singapore	9.121	0.011[b]	Hong Kong	Singapore	81.619	0.000[a]
Malaysia	Thailand	5.929	0.052	Hong Kong	Malaysia	1.481	0.477
Malaysia	Philippines	8.719	0.013[b]	Hong Kong	Thailand	0.948	0.623
Malaysia	Indonesia	14.755	0.001[a]	Hong Kong	Philippines	1.692	0.429
Malaysia	Japan	2.800	0.247	Hong Kong	Indonesia	13.935	0.001[a]
Malaysia	Hong Kong	4.616	0.100	Hong Kong	Japan	12.393	0.002[a]
Malaysia	China	1.226	0.542	Hong Kong	China	6.311	0.043[b]
Malaysia	India	0.881	0.644	Hong Kong	India	2.211	0.331
Malaysia	USA	50.148	0.000[a]	Hong Kong	USA	141.203	0.000[a]
Thailand	Singapore	7.122	0.028[b]	China	Singapore	0.276	0.871
Thailand	Malaysia	0.229	0.892	China	Malaysia	2.732	0.255
Thailand	Philippines	3.559	0.169	China	Thailand	9.876	0.007[a]
Thailand	Indonesia	6.874	0.032[b]	China	Philippines	22.823	0.000[a]
Thailand	Japan	1.362	0.506	China	Indonesia	8.549	0.014[b]
Thailand	Hong Kong	9.618	0.008[a]	China	Japan	5.742	0.057
Thailand	China	4.065	0.131	China	Hong Kong	9.555	0.008[a]
Thailand	India	3.871	0.144	China	India	2.441	0.295
Thailand	USA	8.554	0.014[b]	China	USA	4.397	0.111

Philippines	Singapore	171.670	0.000[a]	India	Singapore	0.737	0.692
Philippines	Malaysia	3.731	0.155	India	Malaysia	3.799	0.150
Philippines	Thai	0.002	0.999	India	Thailand	0.815	0.665
Philippines	Indonesia	1.522	0.467	India	Philippines	4.235	0.120
Philippines	Japan	1.769	0.413	India	Indonesia	0.733	0.693
Philippines	Hong Kong	7.734	0.021[b]	India	Japan	13.898	0.001 [a]
Philippines	China	28.561	0.000[a]	India	Hong Kong	23.296	0.000 [a]
Philippines	India	21.732	0.000[a]	India	China	10.860	0.004 [a]
Philippines	USA	67.687	0.000[a]	India	USA	18.407	0.000 [a]
Indonesia	Singapore	29.628	0.000[a]	USA	Singapore	0.160	0.923
Indonesia	Malaysia	15.861	0.000[a]	USA	Malaysia	0.195	0.907
Indonesia	Thailand	9.507	0.009[a]	USA	Thailand	1.599	0.450
Indonesia	Philippines	2.619	0.270	USA	Philippines	2.533	0.282
Indonesia	Japan	5.260	0.072	USA	Indonesia	1.083	0.582
Indonesia	Hong Kong	18.226	0.000[a]	USA	Japan	0.755	0.686
Indonesia	China	0.462	0.794	USA	Hong Kong	1.542	0.463
Indonesia	India	9.375	0.009[a]	USA	China	49.833	0.000 [a]
Indonesia	USA	22.112	0.000[a]	USA	India	0.411	0.814

Notes: The table shows the Granger Causality evolution parameters for conditional variance of banking sector returns, 2000-2012. Testing is based on the null hypothesis of no Granger causality against the alternative hypothesis of Granger causality. [a] and [b] denotes statistical significance at 1% and 5%, respectively.

Table 7. VAR Granger Causality for conditional Asymmetry

Dependent	Excluded	Chi-sq	Prob.	Dependent	Excluded	Chi-sq	Prob.
Singapore	Malaysia	5.831	0.054	Japan	Singapore	14.413	0.001[a]
Singapore	Thailand	0.040	0.980	Japan	Malaysia	3.208	0.201
Singapore	Philippines	3.060	0.217	Japan	Thailand	4.182	0.124
Singapore	Indonesia	0.469	0.791	Japan	Philippines	3.165	0.205
Singapore	Japan	1.154	0.562	Japan	Indonesia	1.694	0.429
Singapore	Hong Kong	2.418	0.299	Japan	Hong Kong	6.331	0.042[b]
Singapore	China	0.586	0.746	Japan	China	0.849	0.654
Singapore	India	1.347	0.510	Japan	India	62.289	0.000[a]
Singapore	USA	18.405	0.000[a]	Japan	USA	10.451	0.005[a]
Malaysia	Singapore	4.380	0.112	Hong Kong	Singapore	13.720	0.001[a]
Malaysia	Thailand	26.268	0.000[a]	Hong Kong	Malaysia	8.115	0.017 [b]
Malaysia	Philippines	3.044	0.218	Hong Kong	Thailand	0.628	0.731
Malaysia	Indonesia	7.761	0.021[b]	Hong Kong	Philippines	2.409	0.300
Malaysia	Japan	0.365	0.833	Hong Kong	Indonesia	4.520	0.104
Malaysia	Hong Kong	0.228	0.892	Hong Kong	Japan	1.424	0.491
Malaysia	China	5.937	0.051	Hong Kong	China	1.248	0.536
Malaysia	India	15.121	0.001[a]	Hong Kong	India	10.264	0.006[a]
Malaysia	USA	1.028	0.598	Hong Kong	USA	1.463	0.481

Thailand	Singapore	9.920	0.007[a]	China	Singapore	0.178	0.915
Thailand	Malaysia	1.069	0.586	China	Malaysia	2.616	0.270
Thailand	Philippines	0.279	0.870	China	Thailand	0.921	0.631
Thailand	Indonesia	19.288	0.000[a]	China	Philippines	3.889	0.143
Thailand	Japan	1.978	0.372	China	Indonesia	2.372	0.305
Thailand	Hong Kong	0.730	0.694	China	Japan	0.503	0.778
Thailand	China	0.681	0.711	China	Hong Kong	0.025	0.987
Thailand	India	3.634	0.163	China	India	5.631	0.060
Thailand	USA	1.258	0.533	China	USA	3.694	0.158
Philippines	Singapore	4.390	0.111	India	Singapore	7.711	0.021[b]
Philippines	Malaysia	1.161	0.560	India	Malaysia	1.400	0.497
Philippines	Thai	0.512	0.774	India	Thailand	7.560	0.023[b]
Philippines	Indonesia	5.134	0.077	India	Philippines	3.334	0.189
Philippines	Japan	2.948	0.229	India	Indonesia	3.163	0.206
Philippines	Hong Kong	4.289	0.117	India	Japan	11.826	0.003[a]
Philippines	China	5.648	0.059	India	Hong Kong	2.125	0.346
Philippines	India	17.463	0.000[a]	India	China	4.172	0.124
Philippines	USA	1.358	0.507	India	USA	3.412	0.182
Indonesia	Singapore	11.305	0.004[a]	USA	Singapore	13.920	0.001[a]
Indonesia	Malaysia	11.225	0.004[a]	USA	Malaysia	2.250	0.325
Indonesia	Thailand	1.230	0.541	USA	Thailand	16.582	0.000[a]
Indonesia	Philippines	1.810	0.405	USA	Philippines	0.417	0.812
Indonesia	Japan	1.722	0.423	USA	Indonesia	7.766	0.021[b]
Indonesia	Hong Kong	0.026	0.987	USA	Japan	7.918	0.019[b]
Indonesia	China	0.664	0.718	USA	Hong Kong	0.927	0.629
Indonesia	India	10.055	0.007[a]	USA	China	3.517	0.172
Indonesia	USA	2.916	0.233	USA	India	8.366	0.015[b]

Notes: The table shows the Granger Causality evolution parameters for conditional asymmetry of banking sector, 2000-2012. Testing is based on the null hypothesis of no Granger causality against the alternative hypothesis of Granger causality. [a] and [b] denotes statistical significance at 1% and 5%, respectively.

5. Summary and Conclusions

Over the recent decades, member states of the Association of South East Asian States (ASEAN) have taken steps to deepen regional integration. A few of these include the goal of forming the ASEAN Economic Community (AEC) by 2015, the Initiative for ASEAN Integration (IAI),as well as other areas under its financial integration frameworks including financial services, payments and settlements, capital account and capital markets. Despite these efforts, the extant literature on equity market integration does not say much about how the banking sector, in particular, has been evolving over the years. Again, little is known about how shocks, in particular conditional asymmetry, are transmitted within and outside the region.

In this paper, we have examined financial integration within and across the banking sector of five ASEAN markets, namely Singapore, Malaysia, Thailand, Indonesia and Philippines, as well as other influential markets, which include the U.S.A, Japan, China, India, and Hong Kong. In particular, we have employed univariate and multivariate models to examine how the integration dynamics of the ASEAN banking sector stocks have changed over time. Notably we applied a quantile-based estimate of conditional asymmetry and examined its propagation across markets.

Our findings confirm the evolving nature of financial integration in the banking sector; in particular, the study shows evidence of time-varying rising correlation, which suggest rising integration. Nevertheless, this rising integration is of low magnitude due to the relatively low correlations observed. This trend appears consistent across both ASEAN banking sector returns and returns of non-ASEAN countries and irrespective of whether we use bivariate or multivariate modelling techniques. We also note that the integration process of the ASEAN banking sector is amplified by crisis events; we observe relatively higher correlations during the global financial crisis and the European debt crisis, which is line with the literature. This suggests that the ASEAN banking sector is not immune to global financial crisis. Importantly, the results from the Granger causality estimations indicate the presence of volatility spillovers within the ASEAN banking sector and across the ASEAN and banking sectors from other regions. Therefore, although correlations are mild (mostly below 0.5) and may not indicate serious risk of contagion in the present moment, there is still the need for careful attention from policy makers to put forth measures to curb any potential systemic events that may results from adverse movements in correlations in future.

Furthermore, the results from this study have important implications for portfolio managers. The theory of portfolio selection makes a strong case for the role of low correlation (preferably negative correlations) in reducing portfolio risk. Adverse movements in correlation between two or more financial assets could lead to the risk of financial loss. The upward trending correlations, although mild, suggest that diversification benefits for portfolios that contain ASEAN banking sector stocks may have declined overtime. Also, the fact that correlations are amplified by crisis events imply that risk managers who have in their portfolios low correlated ASEAN banking sector stocks could suddenly witness these stocks decline together, eventually resulting in losses. These findings call for alertness from investors and policy makers towards the behaviour of banking sector stocks within and across the ASEAN region.

References

Adam, K., Jappelli, T., Menichini, A., Padula, M., Pagano, M. (2002). Analyse, compare and apply alternative indicators and monitoring methodologies to measure the evolution of capital market integration in the European Union. University of Salerno. Centre for Studies in Economics and Finance (CSEF).

Adrian, T., & Brunnermeier, M. (2010). CoVaR. (Working Paper). Federal Reserve Bank of New York.

Aielli, G. (2009). Dynamic conditional correlations: on properties and estimation. (Working Paper). University of Florida.

Azad, A. (2009). Efficiency, cointegration and contagion in equity markets: Evidence from China, Japan and South Korea. Asian Economic Journal, 23(1), 93–118.

Bekaert, G., Erb, C., Harvey, C. R., & Viskanta, T. (1998). Distributional characteristics of Emerging Market returns and asset allocation. Journal of Portfolio Management, 24(2), 102–116.

Bekaert, G., Harvey, C., & Lundblad, C. (2006). Growth volatility and financial liberalization. Journal of International Money and Finance, 25(3), 370–403.

Billio, M., Donadelli, M., Paradiso, A., & Riedel, M. (2017). Which market integration measure? Journal of Banking and Finance, 76, 150-174.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31 (1), 307–327.

Boubakri, S., & Guilaumin, C. (2015). Regional integration of the East Asian stock markets: An empirical assessment.. Journal of International Money and Finance, 57, 136-160.

Bowley, A. (1920). Elements of statistics (4th ed.). New York: Charles Scribner's Sons.

Chan, C.K., Gup, B.E., and Pan, M.S. (1992). An empirical analysis of stock prices in major Asian markets and the United States. Financial Review, 27 (2), 289-307.

Claus, E., & Lucey, B. M. (2012). Equity market integration in the Asia Pacific region: Evidence from discount factors. Research in International Business and Finance, 26, 137–163.

Click, R. W., & Plummer, M. G. (2005). Stock market integration in ASEAN after the Asian financial crisis. Journal of Asian Economics, 16, 5–28.

Dalkir, M. (2009). Revisiting stock market index correlations. Finance Research Letters, 6, 23-33.

Engle, R. (1999). Cointegration, causality and forecasting. Oxford: Oxford University Press.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339–350.

Engle, R., & Kelly, B. (2012). Dynamic equicorrelation. Journal of Business & Economic Statistics, 30(2), 212–228.

Ghysels, E., Plazzi, A., & Valkanov, R. (2011). Conditional Skewness of Stock Market Returns in Developed and Emerging Markets and its Economic Fundamentals. (Research Paper No. 11-06). Swiss Finance Institute, Geneva, Switzerland.

Gourinchas, P.-O., & Jeanne, O. (2006). The elusive gains from international financial integration. The Review of Economic Studies, 73(3), 715–741.

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica, 37, 424–438.

Granger, C. (1980). Testing for causality: A personal view. Journal of Economic Dynamics and Control, 2, 329–352.

Granger, C. (1988). Causality, cointegration and control. Journal of Economic Dynamics and Control, 12, 551–559.

Hashmi, A. R., & Tay, A. S. (2012). Mean, volatility and skewness spillovers in equity markets. In L. Bauwens, C. Hafner, & S. Laurent, Handbook of Volatility Models and Their Applications (pp. 127–145). New Jersey: Wiley & Sons, Inc.

Lean, H. H., & Teng, K. T. (2013). Integration of world leaders and emerging powers into the Malaysian stock market: A DCC-MGARCH approach. Economic Modelling, 32, 333–342.

Lee, J. (2008). Patterns and determinants for cross-border financial asset holdings in East Asia. (Working paper series on regional economic integration 13). Asian Development Bank.

Markowitz, H. M. (1952). Portfolio Selection. Journal of Finance, 7, 77–91.

Mensah, J.O., & Alagidede, P. (2017). How are Africa's emerging stock markets related to advanced markets? Evidence from copulas. Economic Modelling, 60, 1–10.

Mensah, J. O. & Premaratne, G. (2018). Dependence patterns among Asian banking sector stocks: A Copula Approach. Research in International Business and Finance, 45, 357-388.

Mensah, J. O. & Premaratne, G. (2017). Systemic interconnectedness among Asian Banks. Japan and the World Economy, 41, 17-33

Obstfeld, M. (1994). Risk-taking, global diversification, and growth. American Economic Review, 84(5), 1310-329.

Reinhart, C. M., & Rogoff, K. S. (2009). This Time is Different: Eight Centuries of Financial Folly. Princeton University Press.

Sharma, S. C., & Wongbangpo, P. (2002). Long-term trends and cycles in ASEAN stock markets. Review of Financial Economics, 11, 299–315.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. Journal of Finance 19, 425–442.

Tse, Y., & Tsui, A. (2002). A multivariate GARCH model with time-varying correlations. Journal of Business and Economic Statistics, 20, 351–362.

Vinayak, H., & Thompson, F. (2014). In Brief - Southeast Asia At The Crossroads: Three Paths To Prosperity. 20th ASEAN Banking Conference & 44th

ASEAN Banking Council Meeting (p. 4). Cebu: SC (Sang Choy) International Pte Ltd.
Vo, X.V. (2009). International financial integration in Asian bond markets. Research in International Business, 23(1), 90-106.
Wang, L. (2014). Who moves East Asian stock markets? The role of the 2007-2009 global financial crisis. Journal of International Financial Markets, Institutions and Money, 28, 182–203.
Wright, M. L. (2005). On the gains from international financial integration. Economics Letters, 87(3), 379–386.
Yu, I.-W., Fung, K.-P., & Tam, C.-S. (2010). Assessing financial market integration in Asia – Equity markets. Journal of Banking & Finance, 34, 2874–2885.

Appendix

A. Dynamic EquiCorrelation (DECO)

Following Enlge & Kelly (2012), we specify the dynamic process generating the equicorrelation matrix by

$$R_t^{DECO} = (1 - \rho_t)I_N + \rho_t J_{N\times N} \tag{15}$$

where ρ_t is the equicorrelation (scalar), I_N refers to the $N \times N$ identity matrix, and $J_{N\times N}$ denotes the $N \times N$ matrix of ones. For each time period, we take the cross-sectional average of the DCC conditional correlation matrix of Engle (2002) and its cDCC modification proposed by Aielli (2009) to arrive at the equicorrelation matrix, ρ_t,

$$\rho_t = \frac{1}{N(N-1)}(J_{1\times N} R_t^{DCC} J_{N\times 1} - N), \tag{16}$$

The determinant of the DECO correlation matrix is given by

$$\left|R_t^{DECO}\right| = (1 - \rho_t)^{N-1}(1 + (N-1)\rho_t) \tag{17}$$

Hence, the inverse of the equicorrelation matrix is given by

$$(R_t^{DECO})^{-1} = \frac{1}{(1-\rho_t)} I_N + -\frac{\rho_t}{1+(N-1)\rho_t} J_{N\times N} \tag{18}$$

The two-stage quasi-maximum likelihood (QML) estimator of DCC is consistent and asymptotically normal under general conditions. The simple structure of the inverse correlation matrix guarantees that the model can be estimated for a large dimension unbiased correlation parameters, α and β using maximum likelihood estimation. Within the DECO framework, all returns share an equal correlation on a given day, but this correlation differs over time thus allowing us to have a dynamic average correlation across several markets.

Table A3. Name of Banking Sector Indices

NAME OF SERIES	MNEMONIC
Singapore-datastream banks	BANKSSG
Malaysia-datastream banks	BANKSMY
Philippines-datastream banks	BANKSPH
Thailand-datastream banks	BANKSTH
Indonesia-datastream banks	BANKSID
Hong kong-datastream banks	BANKSHK
Japan-datastream banks	BANKSJP
China A-datastream banks	BANKSCA
India-datastream banks	BANKSIN
United States-datastream danks	BANKSUS

Notes: The table reports the names and mnemonics of the banking sector indices. All data was sourced from Thompson Reuters Datastream. The Thompson Reuters indices usually have two versions, i.e. Price Return and Total Return, depending on whether dividend is adjusted or not. Further information on the calculation methods is available here: https://www.thomsonreuters.com/content/dam/openweb/documents/pdf/tr-com-financial/methodology/global-equity-index-methodology-oct-2015.pdf

Table A. 2. Dynamic Conditional Equi-Correlation Results

	α	(Prob)	β	(Prob)	$\alpha + \beta$	DF	LL
ASEAN	0.0234	3.2370	0.9726	91.630	0.9959	6.7073	50235.1490
ASEAN+	0.0260	2.4060	0.9714	61.420	0.9975	8.7842	98082.8770
ASEAN+CHIINA	0.0281	3.0210	0.9673	73.620	0.9954	6.8033	59548.0680
ASEAN+INDIA	0.0190	1.7310	0.9798	69.610	0.9988	7.6642	59120.4440
ASEAN+HKG	0.0270	3.6990	0.9695	90.740	0.9965	6.7519	61271.0340
ASEAN+JAP	0.0275	4.6290	0.9668	116.500	0.9943	7.5160	59585.9370
ASEAN+USA	0.0106	2.2100	0.9888	178.600	0.9994	7.1897	59505.8920

Notes: This table shows the evolution parameters for the DECO GARCH model. ASEAN comprise of member states of the Association of Southeast Asian Nations (Indonesia, Malaysia, Philippines, Singapore, and Thailand). DF and LL denotes degree of freedom and log-likelihood values; α+β shows the degree of persistence.