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Spillover Effects between Developed Stock Markets and ASEAN-5 Stock Markets

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ABSTRACT

Understanding the volatility spillover is crucial for asset allocation decisions, in executing hedging strategies and for devising policies related to capital inflow in the market. This paper examines the mean and volatility spillover effects from the developed countries, namely the US, the UK and Japan to five ASEAN countries; Malaysia, Thailand, Indonesia, Singapore and the Philippines. Investigation has also been carried out on the spillover effect from the ASEAN countries to the developed countries. This study considers the spillover effect across markets in time-varying volatility framework since the findings reveal the unsuitability of constant variance ARMA model. The empirical results show that the returns at ASEAN stock markets are more influenced by Japan and the US than the UK. Significant volatility spillover is observed from regional leading market, Japan to all ASEAN countries. In terms of volatility, the world leading market, the US and the UK only affect certain ASEAN markets. On the influence of smaller markets on larger markets, the returns of Japan stock market are positively and significantly influenced by all five ASEAN markets. Meanwhile, the returns of the US and the UK stock markets are affected by Thailand, Singapore and the Philippines stock markets. In general, the volatility in ASEAN markets does not spill to the developed markets under investigation.

Keywords: Spillover effect, ARMA-GARCH, leverage effect

INTRODUCTION

Understanding the behavior of return volatility is essential for investors in making asset allocation decisions, in executing hedging strategies and for devising policies related to capital inflow in the market. The co-movements of financial markets in return and volatility are due to the emergence and reaction to information originating aboard through the transmission channels. Gebka and Serwa (2007) highlighted that the macroeconomic news in one country influences the value of domestic and foreign as far as there are real linkages between the countries. Kodres and Pritsker (2002) among others, suggested that the motivation of investors to rebalance their global portfolio, cross-country hedging policies which reveal the reaction of investors to foreign news, the foreign trade or investment linkages between countries, and common lenders constitute potential channels for spillover to exist.

The tendency towards world economy globalization and certain dramatic episodes have prompted a number of studies to understand the volatility spillover effect across international markets. Black (1976) originated the study on the relation between stock returns and volatility. He found that volatility was typically higher after the stock market falls than after it rises, so future conditional stock volatility was negatively linked with the current stock return. Black argued that the phenomenon may be due to the increase in leverage surfacing when the market value of a firm declines. Schwert (1989) supports the findings of Black (1976).

Substantial literature exists on return and volatility among developed markets. Eun and Shim (1989) documented the innovations occurring in the US market transmitted to other markets. In contrast, the information transmission from small markets to big markets was found to be weak. Hamao *et al.*(1990), Koutmos & Booth (1995), Baele (2003) among others also found that the US is the dominate influence in the countries under investigation. With regards to the spillover effect from developed to emerging markets, Ng (2000), and Chelly-Stelly (2004) fond that the emerging markets are more influenced by country-specific shock or regional shock rather than the global shock. However, Karolyi (2004) and Kim (2005) argued that there is significant impact of the developed markets on emerging markets.

This paper examines the transmission mechanism of the first and second moments of daily return between the developed markets; the US, the UK and Japan and the five ASEAN markets; Malaysia, Thailand, Indonesia, Singapore and the Philippines. Specifically, this study is interested in whether the ASEAN markets are more influenced by the Asian leading market (Japan) or the world leading markets (the US and the UK). Furthermore, this study investigates whether the lagged linkages in returns and volatility of developed markets are independent from the ASEAN markets.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology used, Section 3 discusses the result and Section 4 concludes the paper.

DATA AND METHODOLOGY

The data employed is daily closing stock prices of eight national stock indices. The chosen indices are Kuala Lumpur Composite Index (KLCI), Stock Exchange of Thailand Index (SETI), Jakarta Composite Index (JCI), Singapore Straits Times Index (STI) and Philippines Composite Index (PSI) for the ASEAN markets of Malaysia, Thailand, Indonesia, Singapore and the Philippines; Nikkei 225 Stock Index (JNK), Dow Jones Industrial Average (DJIA) and Financial Times Stock Index (FTSE) for the developed markets of Japan, the United States and the United Kingdom. The data covers from January 1994 to May 2009. The analysis will be based on the percentage daily returns of the data, which is calculated as follows:

$$R_t = \log\left(P_t \big/ P_{t-1} \right) \times 100$$

where R_t is the daily return on day t and P_t is the stock markets closing price on day t.

Augmented Dickey Fuller (ADF) test proposed by Dicky and Fuller (1981) has been employed in this study to test the existence of unit root in a series. By considering the series have an ARMA structure, the test examines the null hypothesis that a series has a unit root, $I(1)$ versus the alternative that it is stationary, $I(0)$. The ADF test is based on estimating the regression:

$$\Delta Y_t = \mu + \alpha_1 t + \rho Y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \varepsilon_t$$

where Y_t is time series observation, t is a time trend and ε_t is a white noise process.

Autoregressive Moving Average (ARMA) model was developed by Box and Jenkins (1976) and it is used to capture the linear dependency of current returns on past returns and / or past errors. An ARMA model can be written as:

$$R_t = \phi_1 R_{t-1} + \phi_2 R_{t-2} + \ldots + \phi_p R_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - -\theta_q \varepsilon_{t-q}$$

where ε_t is a series of independent and identically normal distributed white noise with mean zero and variance. The ARMA model is a second order stationary process; which means that the mean, variance and covariance must be constant.

Engle (1982) proposed an Autoregressive Conditional Heteroskedasticity (ARCH) model to encounter the weakness of ARMA model. Under the ARCH(s) process, the noise series is distributed as:

$$\varepsilon_t \left| \psi_{t-1} \sim N(0, \sigma_t^2) \right. \text{ where } \sigma_t^2 = \alpha_0 + \sum_{i=1}^{s} \alpha_i \varepsilon_{t-i}^2 + w_t$$

where ψ_{t-1} is the information available up to time t-1 and w_t is a random component with white noise properties. The ARCH model is assumed to be a linear function of past squared innovations and it can be interpreted as daily news, information or shocks contributing to the volatility.

Bollerslev (1986) extended the ARCH(s) to GARCH (r, s) which is written as:

$$\sigma_t^2 = \alpha_0 + \sum_{m=1}^{s} \alpha_m \varepsilon_{t-m}^2 + \sum_{n=1}^{r} \beta_n \sigma_{t-n}^2.$$

Note that the current conditional variance is described by the previous information about the volatility and the past conditional variance. The sum of $\sum_{m=1}^{s} \alpha_m$ and $\sum_{n=1}^{r} \beta_n$ measure the level of volatility persistency such that the volatility persistency increases when the sum approaches unity. Besides that, the half-life which measures the number of day taken for the volatility to decay to half of its original level can be calculated as follows:

$$\text{Half} - \text{life} = \frac{\ln 0.5}{\ln(\alpha_1 + \beta_1)}$$

The studies of Nelson (1991) showed that the ARCH and GARCH models do not capture the leverage /asymmetric effect of stock return data. This effect occurs when an unexpected drop in price (bad news) increases conditional volatility more than an unexpected increase in price (good news). Nelson introduced Exponential GARCH (EGARCH) which allows asymmetric shocks and the EGARCH (1,1) can be written as:

$$\log \sigma_t^2 = \alpha_0 + \delta \log \sigma_{t-1}^2 + \tau \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

where negative value of γ represents the existence of leverage effect. A negative γ associated with positive τ indicates that a bad news ($\varepsilon_{t-1} < 0$) will increase the volatility more than the good news ($\varepsilon_{t-1} < 0$) of same magnitude, or else being equal.

To scrutinize the mean and volatility spillover effects from external indices into a particular index, the daily returns of the external indices and their corresponding estimated conditional variance on the present day, t or on the previous day, t-1 are considered as the influence of external factors on a particular market. The general equations for mean and volatility spillovers from external indices into a particular stock market can be represented as:

$$R_t^i = \sum_{i=1}^{p} \phi_i R_{i,t-1} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{i,t-j} + \sum_{j=1}^{k} \lambda_t^j R_t^j + \sum_{j=1}^{k} \lambda_{t-1}^j R_{t-1}^j$$

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 \varepsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2 + \sum_{j=1}^{k} \psi_t^j \varepsilon_t^{2j} + \sum_{j=1}^{k} \psi_{t-1}^j \varepsilon_{t-1}^{2j}$$

where i is the individual index. Significant λ_t^j and/or λ_{t-1}^j indicate the presence of mean spillover from market j to market i while significant ψ_t^j and/or ψ_{t-1}^j represent the existence of volatility spillover from market j to market i.

After estimating the coefficients, diagnostic checking is carried out to examine the adequacy of the model. Ljung-Box Q-statistics is used to verify the presence of autocorrelation among residuals of ARMA-GARCH model. The Q-statistics at lag k is a test statistic for the joint null hypothesis that there is no autocorrelation up to order k:

$$H_0\text{:}\ \rho_1^{\varepsilon} = \rho_2^{\varepsilon} = \ldots = \rho_k^{\varepsilon} = 0$$

In addition, the ARCH test is designed to examine the presence of time-varying variance (ARCH effect) in a time series. Regression below is run to test the null hypothesis that there is no ARCH effect up to order p in the residuals.

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \upsilon_t$$

where ε_t is the residual at time t. The null hypothesis to be tested is given by:

$$\alpha_1 = \alpha_2 = \ldots = \alpha_p = 0$$

RESULT AND DISCUSSION

Unit Root Test

Examination of data stationarity is essential since most of the time series econometrics models assume the underlying series to be stationary. Table 1 displays the results of ADF unit root test. The results show that all logarithmic stock indices are non-stationary at level as the null hypotheses of unit root are accepted at 5% significance level. On the contrary, the null hypotheses are rejected for all series after first differencing at 5% significant level. The results imply that all the series become stationary after first differencing. The (percentage) return of the series will be used for subsequent analyses since the (percentage) first difference of the series are equivalent to the returns.

Table 1: ADF unit root test of stock indices

Series	Level				1st difference			
	lag	Without trend	lag	trend	lag	Without trend	lag	trend
KLCI	1	-2.124	1	-2.269	0	-51.218[1]	0	-51.228[1]
SETI	1	-2.163	1	-1.851	0	-51.428[1]	0	-51.456[1]
JCI	1	-0.515	1	-2.001	0	-46.442[1]	0	-46.456[1]
STI	1	-1.904	1	-2.124	0	-50.867[1]	0	-50.864[1]
PSI	1	-1.882	1	-1.759	0	-49.443[1]	0	-49.450[1]
JNK	0	-1.415	0	-2.084	0	-57.425[1]	0	57.420[1]
DJIA	0	-2.381	0	-1.275	0	-57.412[1]	0	-57.481[1]
FTSE	2	-1.858	2	-1.484	1	-42.563[1]	1	-42.581[1]

Note: [1] denotes significant at 5%

ARMA Model

In this section, analysis is carried out by using ARMA model to get a closer picture of the linear dependencies in the return series. Due to parsimony principle, the number of coefficients will be restricted to $\{p + q \leq 3\}$, giving a number of tentative models for each of the stock index. Among the tentative models, the best tentative model is the ARMA (p,q) model with significant p^{th} and q^{th} parameters and with the smallest Akaike Information Criterion (AIC). Diagnostic checking on residual will then be conducted on the best tentative model to ensure the model is statistically adequate.

Table 2 displays the estimated coefficients of the best fitted ARMA models. The results show that KLCI, PSI, JNK and DJIA returns are solely affected by the previous error while JCI, STI and FTSE are affected by both previous returns and error. Note that the negative sign of $ø_2$ for STI implies that the stock prices are expected to increase (fall) if the stock prices on previous day fall (decrease). The best tentative model for SETI suggests that the stock prices will continue to increase after two consecutive days of price increase and vice versa.

The results of Lagrange Multiplier (LM) test shows that the null hypotheses of no autocorrelation among residuals are accepted for all indices, with the exception of SETI and JCI. This suggests that the respective fitted models for these two markets are inadequate to explain the autocorrelation among the returns and higher order of ARMA model is needed. In general, the results of Q-statistics are consistent with the LM test. The ARCH tests and Q-squared statistics are significant for all indices recommend that the variance of the return series are time-varying and thus employing GARCH approach to model the return series is necessary.

Table 2: Estimated coefficients for the best fitted ARMA model: ASEAN + developed

Index	KLCI	SETI	JCI	STI	PSI	JNK	DJIA	FTSE
ARMA	(0,2)	(2,0)	(2,1)	(1,2)	(0,1)	(0,2)	(0,2)	(1,2)
$ø_1$		0.070[1]	0.760[1]	-0.541[2]				0.380[1]
		(0.018)	(0.222)	(0.280)				(0.165)
$ø_2$		0.050[1]	-0.143[1]					
		(0.018)	(0.035)					
θ_1	0.074[1]		-0.582[1]	0.625[1]	0.113[1]	-0.044[1]	-0.041[1]	-0.391[1]
	(0.018)		(0.223)	(0.279)	(0.018)	(0.018)	(0.018)	(0.165)
θ_2	0.044[1]			0.082[1]		-0.044[1]	-0.037[1]	-0.081[1]
	(0.018)			(0.024)		(0.018)	(0.018)	(0.020)
Q-Stat	1.399	3.706	17.618[1]	2.887	2.630	6.201	1.893	1.031
LMTest	0.500	2.295[1]	7.164[1]	0.786	0.557	1.458	0.400	0.246
Q-sq	389.80[1]	122.280[1]	303.970[1]	267.54[1]	74.513[1]	915.810[1]	1352.200[1]	847.79[1]
ARCH	43.017[1]	18.600[1]	35.869[1]	32.543[1]	9.728[1]	115.748[1]	127.214[1]	85.917[1]
AIC	3.904	4.240	4.149	3.804	3.999	3.912	3.354	3.422

Note: [1] and [2] denote significant at 5% and 10% respectively, standard errors are given in parentheses

GARCH and EGARCH Model

Since the ARCH test on ARMA models showed ARCH effect, the analysis proceeds to the ARMA-(E) GARCH modeling which explains the conditional heteroskedasticity inherent in return series. Table 4 tabulates the estimated coefficients for the best fitted ARMA-(E)GARCH models. By comparing the AIC values in Table 2 and 3, it can be found that the AIC values for ARMA-(E) GARCH models are smaller than the ARMA models. This implies that the mean and stochastic behavior of volatility in the return series are better fitted by the ARMA-(E) GARCH models than the pure ARMA models.

Based on Table 3, all the return series are fitted in EGARCH models with the exceptional for DJIA, meaning that seven of the return series have asymmetrical nature of volatility. Furthermore, the negative and significant γ coefficient for the return series shows the existence of leverage effect, that is bad news in the markets are followed by higher volatility than good news of the same magnitude. In addition, FTSE has the highest ratio of $|-1+\gamma|/(1+\gamma)$among the return series, that is approximately 1.26, indicating that the impact of bad news on current conditional volatility are 26% greater than the good news in FTSE of the same magnitude.

Table 3: Estimated coefficients for the best fitted (E)GARCH type model: ASEAN + developed

Index	KLCI	SETI	JCI	STI	PSI	JNK	DJIA	FTSE
ARMA	(1,1)	(2,0)	(2,1)	(2,1)	(1,2)	(1,1)	(1,1)	(0,2)
GARCH/EG	EG(1,1)	EG(1,1)	EG(1,1)	EG(1,1)	EG (1,1)	EG (1,1)	G (1,1)	EG (1,1)
$\o_1$	0.661[1]	0.102[1]	-0.695[1]	1.004[1]	-0.649[1]	-0.913[1]	0.842[1]	
	(0.095)	(0.018)	(0.079)	(0.033)	(0.207)	(0.084)	(0.095)	
$\o_2$		0.061[1]	0.160[1]	-0.042[1]				
		(0.019)	(0.026)	(0.020)				
θ_1	-0.574[1]		0.896[1]	-0.949[1]	0.792[1]	0.906[1]	-0.849[1]	-0.0002
	(0.106)		(0.075)	(0.029)	(0.207)	(0.087)	(0.094)	(0.019)
θ_2					0.117[1]			-0.029[2]
					(0.030)			(0.018)
α_0	-0.091[1]	-0.094[1]	-0.150[1]	-0.171[1]	-0.100[1]	-0.104[1]	0.018[1]	-0.084[1]
	(0.005)	(0.005)	(0.008)	(0.028)	(0.005)	(0.011)	(0.002)	(0.008)
α_1							0.079[1]	
							(0.006)	
β_1							0.911[1]	
							(0.007)	
τ	0.133[1]	0.237[1]	0.242[1]	0.255[1]	0.209[1]	0.167[1]		0.114[1]
	(0.007)	(0.012)	(0.012)	(0.011)	(0.009)	(0.015)		(0.011)
γ	-0.037[1]	-0.037[1]	-0.026[1]	-0.098[1]	-0.081[1]	-0.080[1]		-0.115[1]
	(0.004)	(0.008)	(0.006)	(0.005)	(0.007)	(0.007)		(0.008)
δ	0.993[1]	0.939[1]	0.978[1]	0.973[1]	0.951[1]	0.973[1]		0.985[1]
	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)		(0.002)
Persistency	0.993	0.939	0.978	0.973	0.951	0.973	0.990	0.985
Half-life	95.937	10.979	31.261	25.540	13.758	25.135	68.058	45.961
Q-Stat	1.603	2.998	17.618[2]	3.806	2.039	1.227	3.849	8.950[2]
Q-Sq.	1.459	1.240	12.429[1]	0.440	2.722	8.510[2]	3.575	7.827[2]
ARCH	0.240	0.208	1.989[2]	0.081	0.121	1.368	0.590	1.290
AIC	3.321	4.042	3.812	3.424	3.818	3.678	3.013	2.989

Note: [1] and [2] denote significant at 5% and 10% respectively

The volatility persistency for all the return series are recorded at an acceptable level since none of them exceeds one. KLCI and DJIA shows the highest and second highest of persistency, implying that the volatility of these two indices decay at a slower pace as compared to the others. Moreover, the value of half-life for KLCI is extremely high, of approximately 96 days. This recommends that the volatility takes more than three months to decay by half of its original value. The Q-statistics in Table 3 shows the order of ARMA is found to be sufficient for most of the return series since the autocorrelation among the residuals has been eliminated except JCI and FTSE. Higher order of ARMA model is necessary for JCI and FTSE to get rid of the autocorrelation among the residuals. Furthermore, the ARCH test result shows the low order of GARCH (1,1) or EGARCH (1,1) model is sufficient for fitting the series with time-varying volatility. All of the return series do not present ARCH effect, with the exception of JCI.

Analysis of Spillover Effect from Developed Countries to ASEAN Countries

The analysis is extended with the consideration of the mean and volatility spillover effects from the developed countries to ASEAN countries and vice versa. Due to the time differential between the countries under investigated, the lagged DJIA and lagged FTSE will be used as the shock from DJIA and FTSE is expected to reflect in ASEAN countries on the following day. On the other hand, the contemporaneous JNK will be used since the trading hours of JNK and ASEAN countries overlap greatly. The order of ARMA is restricted to $p = 1$ and $q = 0$ since the results have proved that low order of ARMA model is sufficient. Furthermore, the order of ARMA component is expected to be lower than those in the previous sections after the introduction of spillover effect, that is the high degree of autocorrelation in a particular series is infect due to the spillover effect from other stock indices.

Refer to Table 3 and Table 4, it can be observed that the ARMA-GARCH-type model for JCI and STI have altered from EGARCH model to GARCH model after the introduction of mean and volatility spillover effect from the developed markets. Also, it can be found that the AIC values for all models are smaller than those models which are not encountered for the spillover effect. Table 4 shows that JNK and DJIA have significant and positive influence on the returns of all the five ASEAN indices. However, the mean spillover from FTSE only has significant impact on JCI. Besides that, it can be observed that the AR(1) coefficient ($\o_1$) is smaller than the estimated mean spillover from JNK and DJIA ($\lambda_{jnk,t}$ and $\lambda_{djia,t-1}$) for all indices except JCI. This implies that the returns of the ASEAN markets are more influenced by the foreign markets than their own market. Note that the AR(1) coefficient for STI is insignificant and the Q-statistics shows that the order of ARMA model is sufficient, indicating that the return of STI is solely affected by spillover effect.

Table 4: Estimated mean and volatility spillover from Developed to ASEAN countries

Index	KLCI	SETI	JCI	STI	PSI	Index	KLCI	SETI	JCI	STI	PSI
ARMA	(2,0)	(1,0)	(1,0)	(1,0)	(1,0)	ARMA	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)
(E)GARCH	EG(1,1)	EG(1,1)	G(1,1)	G(1,1)	EG(1,1)	(E)GARCH	EG(1,1)	EG(1,1)	G(1,1)	G(1,1)	EG(1,1)
$\o_1$	0.078^{1}	0.072^{1}	0.193^{1}	0.010	0.091^{1}	α_0	-0.156^{1}	-0.106^{1}	0.054^{1}	0.030^{1}	-0.150^{1}
	(0.019)	(0.020)	(0.018)	(0.021)	(0.019)		(0.008)	(0.009)	(0.010)	(0.007)	(0.011)
$\lambda_{jnk,t}$	0.167^{1}	0.287^{1}	0.220^{1}	0.338^{1}	0.192^{1}	α_1			0.143^{1}	0.153^{1}	
	(0.010)	(0.019)	(0.017)	(0.014)	(0.015)				(0.010)	(0.013)	
$\lambda_{djia,t-1}$	0.118^{1}	0.075^{1}	0.187^{1}	0.193^{1}	0.231^{1}	β_1			0.790^{1}	0.726^{1}	
	(0.017)	(0.025)	(0.025)	(0.022)	(0.021)				(0.010)	(0.013)	
$\lambda_{ftse,t-1}$	-0.020	0.004	-0.042^{2}	-0.013	0.018	τ	0.210^{1}	0.242^{1}			0.285^{1}
	(0.015)	(0.023)	(0.023)	(0.020)	(0.019)		(0.011)	(0.016)			(0.014)
						γ	-0.052^{1}	-0.043^{1}			-0.086^{1}
							(0.005)	(0.009)			(0.008)
						δ	0.980^{1}	0.918^{1}			0.899^{1}
							(0.002)	(0.004)			(0.004)
						$\psi_{jnk,t}$	0.012^{1}	0.016^{1}	0.050^{1}	0.060^{1}	0.017^{1}
							(0.001)	(0.001)	(0.006)	(0.004)	(0.001)
						$\psi_{djia,t-1}$	-0.007^{1}	-0.013^{1}	0.028^{1}	0.004	-0.004
							(0.002)	(0.002)	(0.010)	(0.009)	(0.003)
						$\psi_{ftse,t-1}$	-0.007^{1}	-0.0044^{2}	-0.004	0.019^{1}	-0.009^{1}
							(0.002)	(0.0025)	(0.008)	(0.009)	(0.003)
						Persistency	0.980	0.918	0.933	0.880	0.899
						Half-life	34.981	8.101	10.018	5.402	6.501
						Q-Stat	15.160^{1}	9.035	9.014	2.631	4.887
						Q-Sq.	2.618	1.332	10.986^{1}	1.203	1.107
						ARCH	0.433	0.226	1.798^{2}	0.217	0.190
						AIC	3.177	3.917	3.691	3.130	3.674

Note: ^{1} and ^{2} denote significant at 5% and 10% respectively

On top of that, all ASEAN indices also experience volatility spillover from JNK. However, there is no volatility spillover from DJIA to STI and PSI and from FTSE to JCI. Based on Table 4, the magnitude of estimated coefficients for JNK are larger than DJIA and FTSE for almost all the cases, indicating that the ASEAN countries are more influenced by the Asian leading market than the world leading markets. The γ coefficient for KLCI, SETI and PSI is negative and significant indicates that leverage effect presents in these markets. Note that some of the coefficients of volatility spillover are negative implying that the volatility is not necessarily bad, a shock in a particular market may be transmitted as a positive shock to another market. The Q-statistics in Table 4 shows that the order of ARMA model is sufficient for all indices except KLCI. ARMA model with higher order is needed to eliminate the autocorrelation among the residuals. The Q-squared statistics and ARCH test shows that the low order (E)GARCH model is sufficient in modeling the time-varying volatility of the series except JCI.

Analysis of Spillover Effect from ASEAN Countries to Developed Countries

There is a common believe that the spillover effect is transmitted from dominant markets to smaller markets. However, there is a possibility that the opposite effect to occur. In this section, the existence of spillover effect from ASEAN countries to developed countries is investigated. The smaller AIC values in Table 3 as compared to Table 5 suggest that the introduction of spillovers in model has produced a relatively better fit model. Table 5 shows that the mean return of JNK is significantly and positively influenced by the five ASEAN markets. On top of that, recall the results in Table 4 that JNK has significant impact on ASEAN markets; the findings provide strong evidence that ASEAN region and Japan have very close relationship. In addition, both DJIA and FTSE receive mean spillover from SETI, STI and PSI. This is a surprise since the world leading market, FTSE are influenced by these three ASEAN countries but not the opposite (refer Table 4).

Table 5 shows that the variance equation provided lesser evidence of spillover effect if compared to the mean equation. JNK is only affected by the volatility transmitted from STI and PSI, DJIA is only influenced by the spillover from STI and none of the ASEAN countries impacts FTSE significantly in terms of volatility. The γ coefficient for DJIA and FTSE is negative, indicating the leverage effect exists in these two indices. Although the AR(1) coefficient for JNK is not significant, the Q-statistics shows that there is no remaining serial correlations in the residuals, meaning that the mean returns for JNK is purely affected by spillover effect but not the previous returns or error. On the contrary, the Q-statistics for DJIA and FTSE suggests that the mean equation provides an inadequate description of the data and hence higher order of ARMA model is needed. Furthermore, both Q-squared statistics and ARCH test show that the ARCH effect has been successfully fitted for all three series.

Table 5: Estimated mean spillover and volatility spillover from ASEAN to developed countries

Index	JNK	DJIA	FTSE	Index	JNK	DJIA	FTSE
ARMA	(1,0)	(1,0)	(1,0)	ARMA	(1,0)	(1,0)	(1,0)
(E)GARCH	G(1,1)	EG(1,1)	EG(1,1)	(E)GARCH	G(1,1)	EG(1,1)	EG(1,1)
$ø_1$	-0.029	-0.067[1]	-0.059[1]	α_0	0.015[1]	-0.097[1]	-0.106[1]
	(0.020)	(0.019)	(0.019)		(0.006)	(0.009)	(0.009)
$\lambda_{klci,t}$	0.034[1]	0.007	-0.002	α_1	0.072[1]		
	(0.017)	(0.011)	(0.012)		(0.008)		
$\lambda_{seti,t}$	0.045[1]	0.020[1]	0.037[1]	β_1	0.899[1]		
	(0.013)	(0.008)	(0.009)		(0.010)		
$\lambda_{jci,t}$	0.049[1]	0.009	0.015	τ		0.130[1]	0.126[1]
	(0.015)	(0.010)	(0.010)			(0.012)	(0.012)
$\lambda_{sti,t}$	0.401[1]	0.113[1]	0.203[1]	γ		-0.105[1]	-0.107[1]
	(0.020)	(0.013)	(0.014)			(0.009)	(0.010)
$\lambda_{psi,t}$	0.089[1]	0.038[1]	0.026[1]	δ		0.971[1]	0.976[1]
	(0.014)	(0.010)	(0.010)			(0.003)	(0.004)
				$\psi_{klci,t}$	-0.0004	0.0002	0.0002
					(0.002)	(0.001)	(0.001)
				$\psi_{seti,t}$	-0.0003	0.0001	-0.0002
					(0.001)	(0.001)	(0.001)
				$\psi_{jci,t}$	-0.001	-0.001	0.001
					(0.002)	(0.001)	(0.001)
				$\psi_{sti,t}$	0.020[1]	0.003[1]	0.001
					(0.004)	(0.001)	(0.001)
				$\psi_{psi,t}$	0.0031[2]	-0.0003	0.001
					(0.0018)	(0.001)	(0.001)
				Persistency	0.971	0.971	0.976
				Half-life	23.787	23.892	29.014
				Q-Stat	0.683	12.835[1]	12.515[1]
				Q-Sq.	1.081	3.795	0.865
				ARCH	0.173	0.604	0.145
				AIC	3.400	2.930	2.864

Note: [1] and [2] denote significant at 5% and 10% respectively

CONCLUSION

This paper contributes to the understanding of return and volatility spillovers between the developed markets and ASEAN markets. The results from pure ARMA model show that the return series exhibit time-varying volatility and therefore the GARCH-type models are implemented. With the exception of DJIA, all markets under study exhibits leverage effect where investors react more towards bad news rather than good news.

Furthermore, the combination of ARMA-GARCH-type models is used to investigate the mean and volatility spillover effects between stock markets. Japanese and the US market show strong impact on the returns of ASEAN markets in terms of mean spillover. However, the UK market only affects the return of Indonesia. This may be due to the fact that Japan and the US play a more important role in ASEAN countries in terms of import and foreign direct investment as compared to the UK. Apart from the significant mean spillover, it is found that the volatility from Japan has transmitted to all ASEAN markets. In contrast, the volatility spillover effect from the US and the UK only present in certain ASEAN countries. This means that the role of Japan as a regional leading market is more influential than the world leading markets in ASEAN countries.

On the influence of ASEAN markets to developed markets, the mean spillover effect present from all ASEAN countries to Japan. Besides, certain ASEAN countries affect the return of the US and the UK markets. Generally, the volatility of ASEAN markets does not spill to developed markets. In brief, ASEAN countries have certain influential on the developed markets although the effect is not as strong as the effect from the developed markets to ASEAN markets.

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