Chapter 5

Examining Volatility Spillovers across International Gold Market and ASEAN Emerging Stock Markets

Nowadays, it is now widely accepted that financial volatilities tend to move together over time across assets and markets. Perhaps, this is due to the financial globalization, so an economic shock to a certain market often causes increasing volatility in that market then the volatility may easily spill over to other markets. Studies on volatility spillovers have been conducted not only on the financial area but have been extended to other areas such as commodity markets (oil, agricultural products, etc.), tourism arrivals, political election, environment, and so on. However, Volatility spillovers across the gold and ASEAN emerging stock markets have been unknown, so this chapter is planned for this issue. The empirical results show the evidences of shock and volatility spillovers across the sample markets, as well as the implications of the differences in immunization and absorbability of shocks and volatility transmitted to each of ASEAN emerging stock markets from the other markets.

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Abstract

The paper attempts to examine the possible shock and volatility spillover effects across the international gold and 5 ASEAN emerging stock markets (Indonesia, Malaysia, Philippines, Thailand and Vietnam), using daily data. Two multivariate GARCH extensions, namely the VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model of McAleer *et al.* (2009) are employed. We find that the VARMA-AGARCH dominates VARMA-GARCH in the Indonesia, Malaysia, Philippines and Thailand stock markets, while the contradiction exists in the Vietnam stock market. Moreover, some evidences of the shock and volatility spillovers are observed between the gold and each selected stock markets, while clear evidences of the spillovers are found among ASEAN emerging stock markets. However, among these markets, Thailand and Philippines stock markets play a major role in terms of volatility spillovers to all other stock markets, while the least volatility spillover to other markets is observed in the Vietnam stock market. On the other hand, Malaysia, Thailand and Vietnam are major sources of the shocks influencing almost all other stock markets, whereas shocks to Indonesia have no impact on other markets.

5.1 Introduction

Volatility is simply defined as a time varying conditional variance of market returns that is not directly observable and is a measure of the uncertainty of the investment rate of return. When an economic shock to a certain market often causes increasing volatility in that market, the volatility may easily spill over to other markets. This often happens during the economic crises, leading to high volatility and strong declining in global stock markets. Commonly, high volatility is considered as a signal of market distortion *i.e.,* unfair pricing of securities, this could be due to lacks of a well-functioning and efficient capital market. Moreover, it is now widely accepted that financial volatilities tend to move together over time across assets and markets. Realizing this feature through a multivariate modelling framework leads to more relevant empirical models than working with separate univariate models (Bauwens *et al.,* 2006). In economics, a shock relates to an expected and unpredictable event that affects equilibrium in an economy. Such a shock can be positive or negative and technically refers to unpredictable change in exogenous factor.

In recent years, financial and economic crises have occurred over the world that affected most stock markets, especially in developing countries. In the Association of South East Asian Nations (ASEAN), emerging stock markets such as Vietnam, Thailand, Philippines, Malaysia and Indonesia have suffered severely from the crisis *e.g.,* their stock markets are highly volatile, which has discouraged investors. Beside that, the international gold market has abnormal movements, because the investors are very concerned about a long economic crisis. However, the related issues on how volatility transmission across ASEAN emerging stock markets and international gold market occurs and whether or not, shocks to a market affect the volatility in the other markets, have not been known. This is very crucial for investors in financial markets. Moreover, the inclusion of the Vietnam stock market as a younger emerging one in ASEAN and gold market in our study is of interests since no such study has been done in the literatures. Usually, studies on stock markets in ASEAN seem to be very rare to appear Vietnam stock market, they often relates with developed markets.

In fact, there have been a number of studies in financial markets relating to cross border volatility transmission such as in stock markets (Hamao *et al.,* 1990; King and Wadhwani, 1990; Karolyi, 1995; Longin and Solnik, 1995; Koutmos and Booth, 1995), in foreign exchange markets (Bollerslev, 1990; Baillie *et al.*, 1993; Kearney and Patton, 2000; Hong, 2001), and in interest rate markets (Tse and Booth, 1996), among many others. Seemingly, such issues on the gold market have not been paid much attention by the researcher yet. The main difficulty relating to the multivariate models of market volatility transmission is that the large number of parameters has to be estimated, as we include a lot of markets in the models. Actually, a typical model specifies first and second order conditional moments such as an ARMA for the mean and a GARCH for the variance. In practice, the number of included assets or markets is limited to no more than 5. To deal with the case of over 5, a second-best approach is to estimate several small size models bearing on different combinations of assets (Bauwens *et al.,* 2003).

The purpose of this paper is to examine the possible shock and volatility spillover effects across international gold and ASEAN emerging stock markets, and test for asymmetric effects of positive and negative shocks with the same magnitude. Two multivariate volatility models, namely the vector autoregressive moving average

GARCH (VARMA-GARCH) model, and VARMA asymmetric GARCH (VARMA-AGARCH) mode are employed. The remainder of the paper is organized as follows: Section 5.2 provides data and basic statistics. Section 5.3 presents the model specifications. Section 5.4 discusses the empirical results. Finally, Section 5.5 draws concluding remarks.

5.2 Data

The data set used comprises daily closing stock market indexes from 5 ASEAN emerging stock exchanges: (1) JKSE Index (Indonesia), (2) KLSE Index (Malaysia), (3) PSE Index (Philippines), (4) SET index (Thailand) and (5) VN index (Vietnam), and together with (6) daily prices of the PM London Gold Fix (World reference gold market). The sample period for analysis is from July 28, 2000 (marking the time that Vietnam stock market has formally operated as a new market in ASEAN) to March 31, 2009. All the 5 stock indexes were obtained from Reuter, while the gold prices were downloaded at www.kitco.com.

Prior to doing time series analysis, the data should be checked the statistical adequacy *i.e.*, to see whether or not the time series data used in the research are stationary. The augmented Dickey–Fuller (ADF) and Perron-Phillips (PP) tests were employed. Results of the tests indicate that the null hypothesis of a unit root in the 6 level series cannot be rejected, implying that the 5 stock market indexes and gold prices are nonstationary. However, the null hypothesis of the presence of a unit root in the daily return series of the 6 markets is clearly rejected, so all these return series are stationary. The detail results of the tests are not reported here but are available upon request. For each market, we calculate the daily return, $r_{i,t}$, in percent between trading day *t-1* and *t* as $r_{i,t} = 100 \times [\log(p_{i,t} / p_{i,t-1})]$, where $p_{i,t}$ denotes the closing index of market *i* on day *t*.

5.3 Model Specifications

Since the well-known autoregressive conditional heteroscedasticity (ARCH) model was first introduced by Engle (1982) and developed then by Bollerslev (1986) to be the GARCH model, a numerous empirical researches have been found in the literatures relating to these models. Recently, the univariate GARCH model have been extended to the multivariate GARCH (MGARCH) cases to examine the volatility spillovers as well as the conditional correlations between the markets. Actually, in dealing with these issues in the financial markets, there are alternative MGARCH models that have been developed by the researchers for various purposes such as VECH and Diagonal VECH (Bollerslev, Engle, and Wooldridge, 1988), BEKK (Engle and Kroner, 1995), CCC (Bollerslev, 1990), DCC (Engle, 2002), VARMA-GARCH (Ling and McAleer, 2003), VARMA-AGARCH (McAleer *et al.,* 2009), *etc*. As discussed in Bauwens *et al*.(2006), the spillover effects across markets are measured by lags in shocks and the conditional variances of a market (direct effects) or the covariance of two markets (indirect effects), which appear significantly in the conditional variance equation of other markets.

In our study, two constant conditional correlation MGARCH models, namely VARMA-GARCH (symmetry) and VARMA-AGARCH (asymmetry), are employed in order to measure spillovers across the selected markets and to capture the possible asymmetric effects. The default equation for the means in the MGARCH models can be constant, or AR(*p*), or ARMA(*p,q*). In general, the conditional mean equations of daily returns of the markets under the consideration in MGARCH models can be written as follows,

$$r_{it} = E(r_{it} \mid \Psi_{t-1}) + \varepsilon_{it}, \quad with\ \varepsilon_{it} \mid \Psi_{t-1} \sim N(\mu_{it}, h_{it}) \tag{5.1}$$

$$\varepsilon_{it} = \sqrt{h_{it}} z_{it}, \qquad with\ z_{it} \sim iid(0,1).$$

Let $i = 1 \ldots s$ be the number of the sample markets, $t = 1 \ldots n$ the number of observations, r_{it} return series of the sample markets, $\varepsilon_{it} = r_{it} - \mu_{it}$ the innovations or shocks to the market returns, h_{it} the univariate conditional variances of the market returns, Ψ_{t-1} the past information available at time t, $z_{it} = \varepsilon_{it} / \sqrt{h_{it}}$ the standardized innovations to the market returns.

Since the constant conditional correlation (CCC) is maintained in both VARMA-GARCH and VARMA-AGARCH models, we should take a view on how to construct the CCC multivariate GARCH model of Bollerslev (1990). As defined in (1), the conditional covariance matrix, H_t , in the CCC model is written as follows,

$$H_t = E(\varepsilon_t \varepsilon_t' \mid \Psi_{t-1}) = E(D_t z_t z_t' D_t) = D_t E(z_t z_t') D_t = D_t R D_t \,. \tag{5.2}$$

Let $D_{it} = diag(\sqrt{h_{it}})$ be a diagonal matrix of the univariate conditional variances of the sample markets, $R = E(z_t z_t') = D^{-1} H_t D^{-1} = (\rho_{ik})$ a symmetric positive definite matrix that $(\rho_{ik}) = (\rho_{ki})$ with $\rho_{ik} = 1\ \forall\ i=k$ (for $i, k = 1, \ldots, s$). Hence, R is the matrix of the constant conditional correlations, ρ_{ik} , between different pairs of the market returns. In the CCC model, the univariate conditional variance for the return series, h_{it}, follows a univariate GARCH process (Bollerslev, 1986) as

$$h_{it} = \omega_i + \sum_{j=1}^{p} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q} \beta_{ij} h_{i,t-j} \qquad (5.3)$$

Let $i = 1 \ldots s$ be the number of the selected markets, α_{ij} the ARCH effects implying the short-run effects of shocks, β_{ij} the GARCH effects or the contribution of such shocks to long-run persistence ($\alpha_{ij} + \beta_{ij}$). The simplest case is GARCH(1,1), *i.e.*, $h_t = \varpi + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$, but has been most widely used in practice.

As specified in (5.3), the CCC model assumes that return volatility in each market is independent from others, so there are no shock and volatility spillovers across the sample markets. However, this assumption may not be realistic, particularly in the context of international integration and market liberation. To capture possibilities of the spillovers across markets, Ling and McAleer (2003) built the VARMA-GARCH model that the lags in shocks and variances of other markets are added in the conditional variance of a market. As explained in equations (5.1) and (5.3) for the parameters and notations that are continuously used, the multivariate conditional variances of the VARMA-GARCH model can be expressed as,

$$h_{it} = \omega_i + \sum_{i=1}^{s} \sum_{j=1}^{k} \alpha_{ij} \varepsilon_{it-j}^2 + \sum_{i=1}^{s} \sum_{j=1}^{k} \beta_{ij} h_{it-j} \qquad (5.4)$$

The existence of asymmetry in the volatility is an important characteristic in the financial markets. It exists if the positive and negative shocks with an equal magnitude have different effects on the conditional volatility of a market. It is interesting to realize that both CCC and VARMA-GARCH models do not take the possible asymmetric effects into account. Therefore, McAleer *et al.* (2009) introduced the VARMA-AGARCH model, for which the CCC and VARMA-GARCH models are nested within the VARMA-AGARCH. The multivariate conditional variances of the VARMA-AGARCH model can be expressed as,

$$h_{it} = \omega_i + \sum_{i=1}^{s}\left[\sum_{j=1}^{k}\alpha_{ij} + \sum_{j=1}^{k}\gamma_{ij} I(\varepsilon_{i,t-j} \leq 0)\right]\varepsilon_{i,t-j}^{2} + \sum_{i=1}^{s}\sum_{j=1}^{k}\beta_{ij} h_{i,t-j} \tag{5.5}$$

In equation (5.5), $I(\square_{i,t-j} \leq 0)$ is the indicator function, taking the values of 1 if $\varepsilon_{i,t-j} \leq 0$ (*i.e.,* bad news) and zero, otherwise. It is obviously that the multivariate equation in (5.5) is simplified to the univariate asymmetric case of Glosten, Jagannathan and Runkle (1992) *i.e.,* GJR model, if $s=1$ (a single market only). If $\gamma_i = 0$ for all the cases, VARMA-AGARCH becomes VARMA-GARCH. The parameters in (5.1), (5.4) and (5.5) can be obtained from the quasi maximum likelihood estimator (QMLE), see Ling and McAleer (2003) and McAleer *et al.* (2009) for the details. And, the estimates of the VARMA-GARCH and VARMA-AGARCH are obtained using the program codes in RATS 6.2 (Doan, 2006).

5.4 Empirical Results and Discussions

Regarding to the VARMA-GARCH and VARMA-AGARCH specifications mentioned in Section 5.3, we recognize that the multivariate volatility equation of the VARMA-GARCH model is constructed, based on the univariate GARCH model, while the VARMA-AGARCH is modelled, based on the univariate asymmetric GJR model. It is widely recognized by the researchers that GARCH(1,1) is the simplest GARCH model, but it has become the most popular application in modelling the time-varying conditional volatility. Similarly, we employ the GJR(1,1) model for capturing the asymmetric volatility for the simplicity. Therefore, in the section, we first provide the estimates of the univariate conditional variance models by using the GARCH(1,1) and GJR(1,1) models in the selected markets based on the ARMA(1,1) processes for mean equations so that we can check the properties of the univariate volatility models of the selected markets before conducting the estimations of the multivariate models for them *i.e.,* VARMA-GARCH(1,1) and VARMA-AGARCH(1,1). All the estimates of the parameters for the univariate conditional volatility of the selected markets are obtained using the Marquardt optimization algorithm in Eviews 6. Results of the estimates are presented in Tables 5.1-5.2.

Tables 5.1-5.2 report the estimated parameters in mean and variance equations of the selected market returns. The estimates of variance equations in the GARCH(1,1) and GJR(1,1) models show that all the estimates of the unconditional variance (ω), the ARCH (α) and the GARCH (β) effects are positive and significant. Especially, volatility in the gold market shows the largest GARCH effect (β=0.957), meaning that shocks to its conditional variance take a long time to die out, so its volatility is persistent. Meanwhile, volatility in the Vietnam stock market contains the largest effect of the shocks (α =0.313) as compared to those of other markets, implying that its volatility could react quite intensely to market movements and tends to be more spiky. The estimates of the GJR(1,1) model given in Table 5.2 indicate that the asymmetric effects (γ) of positive and negative shocks with equal magnitudes on conditional volatility are significant for all the markets, except in Vietnam. Therefore, the GARCH(1,1) and GJR(1,1) specifications are statistically adequate for the conditional variance of those markets.

Table 5.1: Estimates of the GARCH(1,1) Model for the Selected Markets

Market returns	Mean equation			Variance equation		
	Constant	AR(1)	MA(1)	ω	α	β
GoldFix	0.0708	0.9551	-0.9838	0.0104	0.0396	0.9546
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Indonesia	0.1359	0.0436	0.0869	0.1367	0.1405	0.8080
	(<0.001)	(0.823)	(0.664)	(<0.001)	(<0.001)	(<0.001)
Malaysia	0.0257	0.3197	-0.1746	0.0106	0.1349	0.8682
	(0.212)	(0.053)	(0.318)	(<0.001)	(<0.001)	(<0.001)
Philippines	0.0694	0.1754	-0.0688	0.2177	0.1352	0.7678
	(0.038)	(0.438)	(0.769)	(<0.001)	(<0.001)	(<0.001)
Thailand	0.0727	0.0667	0.0508	0.4218	0.1632	0.6384
	(0.076)	(0.756)	(0.814)	(<0.001)	(<0.001)	(<0.001)
Vietnam	0.0076	0.0696	0.2264	0.0314	0.3147	0.7149
	(0.732)	(0.406)	(0.016)	(<0.001)	(<0.001)	(<0.001)

Notes: The figures in parentheses are the p-values.

However, we need to check the structural properties for the existence of the first and second moments in the return series, Jeantheau (1998) constructed the log-moment condition for the GARCH(1,1), *i.e.,* $E(\log(\alpha_1 z_t^2 + \beta_1)) < 0$, while Ling and

McAleer (2002) developed the log-moment condition for the GJR(1,1), *i.e.,* $E(\log((\alpha_1 + \gamma_1 I(\varepsilon_t < 0))z_t^2 + \beta_1)) < 0$, which are sufficient for consistency and asymptotic normality of the QMLE for GARCH(1,1) and GJR(1,1). However, the second moment regularity conditions, $\alpha_1 + \beta_1 < 1$ for GARCH(1,1) and $\alpha_1 + \gamma/2 + \beta_1 < 1$ for GJR(1,1), are also sufficient for those properties of the QMLE. Actually, the log-moment condition is a weaker regularity condition than the second moment condition and so the log-moment condition may not be violated even when $\alpha_1 + \beta_1 > 1$ for GARCH(1,1) and $\alpha_1 + \gamma/2 + \beta_1 > 1$ for GJR(1,1).

Table 5.2: Estimates of the GJR(1,1) Model for the Selected Markets

Market returns	Mean equation			Variance equation			
	Constant	AR(1)	MA(1)	ω	α	γ	β
GoldFix	0.0768	0.9571	-0.9849	0.0101	0.0597	- 0.0432	0.9565
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Indonesia	0.0933	0.1823	-0.0461	0.1949	0.0527	0.1578	0.7830
	(0.017)	(0.317)	(0.803)	(0.863)	(0.002)	(<0.001)	(<0.001)
Malaysia	0.0127	0.3538	-0.2132	0.0119	0.1021	0.0698	0.8641
	(0.558)	(0.042)	(0.248)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Philippines	0.0270	0.2215	-0.1123	0.1817	0.0519	0.1299	0.8010
	(0.376)	(0.278)	(0.602)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Thailand	0.0303	0.0745	0.0507	0.4690	0.0305	0.2933	0.6033
	(0.450)	(0.695)	(0.793)	(<0.001)	(0.171)	(<0.001)	(<0.001)
Vietnam	0.0057	0.0687	0.2271	0.0313	0.3110	0.0083	0.7149
	(0.832)	(0.416)	(0.015)	(<0.001)	(<0.001)	(0.819)	(<0.001)

Notes: The figures in parentheses are the p-values.

Results in Tables 5.1-5.2 imply that the second moment conditions are not satisfied in the Malaysia and Vietnam stock markets, which are consistent with earlier findings of Do *et al.* (2009), however, the author showed that the log-moment conditions are negative and satisfied with these markets. Thus, the properties of univariate models are satisfied, so returns of the selected markets are characterized by a heteroscedastic process. Then, it would be appropriate to extend the models to their multivariate counterparts.

A main restriction of the univariate volatility models examined above is that they are estimated independently from others. Thus, MGARCH models can potentially overcome these deficiencies with their univariate counterparts. Assuming that, a shock to a market may increase the volatility in that market as well as in other markets differentially and high volatility in a market may also spill over to the other markets. In examining shock and volatility spillover effects across the sample markets, actually, we aim to a set of the 6 markets (5 ASEAN emerging stock and international gold markets). However, estimations of the multivariate volatility models for the case of over 5 markets together are very hard to get the models converged as many parameters have to be estimated in the model. A summary of the number of parameters estimated in various MGARCH models can be seen in McAleer *et al.* (2009). Therefore, our interest is to work on the 2 smaller size models such as bivariate model for each selected stock market coupled with the gold market and 5-variate model for the 5 ASEAN emerging stock markets together. By doing so, the shock and volatility spillovers between the gold and each selected stock market are estimated through the bivariate VARMA(1,1)-GARCH and VARMA(1,1)-AGARCH models. On the other hand, we attempt to capture possible shock and volatility spillover effects across the 5 ASEAN emerging stock markets, so the 5-variate VARMA(1,1)-GARCH and VARMA(1,1)-AGARCH models are employed for this purpose.

A summary of the estimates of bivariate VARMA-GARCH and VARMA-AGARCH models for the 5 market pairs is presented in Table 5.3, including the directions of shock and volatility spillovers, and the asymmetric effects. For the bivariate VARMA-GARCH estimates, there are few evidences of shock and volatility spillovers between the market pairs. For instance, the Vietnam stock market volatility is affected by the 1 day lagged shocks to the gold market only, whereas the gold market volatility is influenced by the 1 day lagged shocks to the Philippines stock market. Meanwhile, volatility spillovers appear only between the Thailand stock and gold markets under bi-direction effects. No shock or volatility spillovers are found between the gold and Indonesia as well as Malaysia stock markets.

Table 5.3: Summary of the Bivariate Estimates between Gold and Stock Markets

Pair returns	Direction of spillovers				Asymmetric effects
	VARMA-GARCH		VARMA-AGARCH		
	Shock	Volatility	Shock	Volatility	
GoldFix, Indonesia	−	−	−	→	significant
GoldFix, Malaysia	−	−	−	←	significant
GoldFix, Philippines	←	−	←	−	significant
GoldFix, Thailand	−	↔	→	↔	significant
GoldFix, Vietnam	→	−	↔	−	significant

Notes: The arrows (*i.e.,* ↔, → and ←) denote the significant directions, and (−) denotes not significant direction of spillovers between pairs of market returns.

For the bivariate VARMA-AGARCH estimates, we find that the Thailand and Vietnam stock market volatility is affected by the 1 day lagged shocks to the gold market, while volatility in the gold market spills over to the Indonesia and Thailand stock market volatility in the next trading days. On the other hand, the gold market volatility is influenced by the 1 day lagged shocks to the Philippines and Vietnam stock markets and the 1 day lagged volatility in the Malaysia and Thailand stock markets. Moreover, asymmetric effect exists in all the 5 cases. It is clear that, bivariate VARMA-AGARCH can capture better the shock and volatility spillovers between the market pairs than bivariate VARMA-GARCH (Table 5.3).

Table 5.4 provides the estimates of the 5-variate VARMA-GARCH model for the 5 ASEAN emerging stock markets. The estimates of the conditional variance show that all the sample market volatilities are influenced by their own 1 day lagged shocks (α) and 1 day lagged volatility (β). Beside that, results also show the empirical evidences of shock and volatility spillovers across the sample markets. For instance, it can be observed in the Indonesia stock market that its return volatility is affected by the 1 day lagged shocks to the Philippines and Thailand stock market, and the 1 day lagged volatility in the Vietnam stock market. Moreover, the Malaysia stock market volatility is affected by the 1 day lagged shocks to the Vietnam stock market, and the 1 day lagged volatility in the Indonesia, Philippines and Thailand stock markets. Meanwhile, the Thailand stock market volatility is influenced by the 1 day lagged return volatility in all other sample stock markets and the 1 day lagged shocks to the Malaysia stock market. On the other hand, for the Philippines stock market, its returns are affected by the 1 day lagged return volatility in the Malaysia and Thailand stock markets, no shocks to the other sample markets are transmitted to this market. Finally, the Vietnam stock market volatility is affected by the 1 day lagged shocks to the Malaysia and Thailand stock markets, and the 1 day lagged volatility in all other sample stock markets returns.

The estimates of a more sophisticated 5-variate VARMA-AGARCH model for the 5 ASEAN emerging stock markets are reported in Table 5.5. Similar to the 5-variate VARMA-GARCH, the estimates of the conditional variance for the sample markets show that all the sample market volatilities are affected by their own 1 day lagged shocks as well as their own 1 day lagged volatility. Beside that, the empirical evidences of shock and volatility spillovers are also found among the sample markets. For instance, the Indonesia stock market volatility is affected by the 1 day lagged shocks to and the 1 day lagged volatility in all the sample stock markets, except the 1 day lagged volatility in the Malaysia stock market. Moreover, the Malaysia stock market volatility is affected by the 1 day lagged volatility in all other sample stock markets and the 1 day lagged shocks to the Philippines and Vietnam stock markets. On the other hand, the Thailand stock market volatility is influenced by the 1 day lagged volatility in all other sample stock markets and the 1 day lagged shocks to the Malaysia stock market. Meanwhile, the Philippines stock market volatility is affected by the 1 day lagged volatility in the Malaysia and Thailand stock markets, and the 1 day lagged shocks to the Vietnam stock market. Finally, the Vietnam stock market volatility is affected by the 1 day lagged shocks to the Malaysia and Thailand stock markets, and the 1 day lagged volatility in all other sample stock markets returns.

Table 5.4: VARMA-GARCH Estimates in the Selected Stock Markets

Market returns	Parameters in the variance equations										
	Constant	Shock spillover effects					Volatility spillover effects				
	ω	α_I	α_M	α_T	α_P	α_V	β_I	β_M	β_T	β_P	β_V
Indonesia	-0.0335	0.2089	-0.0465	-0.0464	-0.0941	-0.0397	0.4393	-0.5369	0.8998	0.6904	-6.4120
	(0.739)	(<0.001)	(0.396)	(0.002)	(0.012)	(0.200)	(0.002)	(0.505)	(0.277)	(0.190)	(0.018)
Malaysia	-0.1340	-0.0010	0.1474	-0.0134	-0.0182	0.0728	-0.2394	-0.3503	2.3020	0.5094	-2.1945
	(<0.001)	(0.926)	(<0.001)	(0.157)	(0.193)	(<0.001)	(0.053)	(<0.001)	(<0.001)	(<0.001)	(0.104)
Thailand	0.5507	0.0067	-0.0943	0.0919	-0.0180	-0.0330	0.5507	4.9503	-0.4975	-1.1628	7.9017
	(<0.001)	(0.667)	(0.011)	(<0.001)	(0.349)	(0.233)	(0.031)	(<0.001)	(<0.001)	(<0.001)	(0.001)
Philippines	0.3302	0.0565	-0.0911	0.0262	0.1463	-0.0771	-0.0722	2.8508	-0.7217	0.3011	0.4729
	(0.003)	(0.155)	(0.290)	(0.500)	(<0.001)	(0.113)	(0.816)	(<0.001)	(0.045)	(0.056)	(0.643)
Vietnam	-0.0106	-0.0423	0.0602	0.0556	-0.0118	0.3503	7.5556	7.3521	26.4327	-2.7987	0.5872
	(0.050)	(0.277)	(<0.001)	(0.081)	(0.619)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.059)	(<0.001)

Notes: The figures in parentheses are the p-values.
The subscripts (*i.e.,* I, M, T, P and V) of the estimates denote for Indonesia, Malaysia, Thailand, Philippines and Vietnam, respectively.

Interestingly, it can be seen that the estimated asymmetric effects (γ) in the selected stock markets are statistically significant, except in Vietnam stock market, so positive and negative shocks with an equal magnitude have different effects on the conditional volatility in those markets. Consequently, the VARMA-AGARCH dominates VARMA-GARCH in the Indonesia, Malaysia, Philippines and Thailand stock markets, while the contradiction exists in the Vietnam stock market. These findings are also associated with the better estimates through higher significant levels of the estimated parameters and/or more significant variables in the dominant model as compared to its counterpart. Moreover, both VARMA-GARCH and VARMA-AGARCH models cause similar spillovers to the Vietnam stock market, in which the market volatility behaves symmetrically, whereas the estimates of spillovers given by the two models can be different for the cases that the asymmetric effects exist, except in the Thailand stock market (see Tables 4-5).

Overall, the 1 day lagged shocks to the Malaysia, Thailand and Vietnam stock markets have a wider spillover to 3 over 4 markets, while those to the Philippines stock market transmit to 2 over 4 markets. However, the 1 day lagged shocks to the Indonesia stock market are immunized by all the other markets. On the other hand, the 1 day lagged volatility effects in the Thailand and Philippines stock markets are found with the widest spillover to all other 4 markets, followed by those to the Indonesia and Malaysia stock markets that have spillovers to 3 over 4 markets. Finally, the narrowest spillover is observed for the 1 day lagged volatility in the Vietnam stock market, 2 over 4 markets. Furthermore, in terms of sign and size effects of the shock and volatility spillovers from one market to the other markets, we can observe different levels of both negative and positive effects (Table 5.5). Actually, less volatility of a market may be associated with negative effects of shock and volatility spillovers from other markets to that market and vice versa. This exhibits absorbability/weak resistance of a market for the shock and volatility spillovers from other markets. Recognizing these features is very important for investors and fund managers when they invest in the regional markets, especially when a certain market experiences a high volatility.

Since the multivariate GARCH models estimated in the paper assume the constant conditional correlations between the markets, to examine the validation of the assumption, we apply the rolling windows approach. Commonly, estimation of GARCH models requires large sample sizes to obtain the efficient maximum likelihood function, since estimation of the models may take hundreds of iterations to get converged, particularly when we estimate MGARCH models. However, to determine the optimal window size for modeling volatility, Yew *et al*. (2002) used recursive estimation of GARCH model by showing the dynamic paths of the estimated parameters and their corresponding t-scores to derive the smallest range of robust window samples. Their finding suggests that the optimal window size is from 3 to 4 years, as the recursive plots reveal significant robustness in the estimated parameters for these periods. In our research, the rolling window with a rolling sample size of 1000 observations was employed to examine the time varying conditional correlations between the markets, using the VARMA-GARCH and VARMA-AGARCH models. The loop procedure was programmed in RATS6.2. It begins with estimation of the first 1000 observations and then the estimation interval is moved one-day into the future by deleting the first observation and adding an extra observation at the end of the sample window. The procedure is repeated until the last observation of the entitle sample.

Table 5.5: VARMA-AGARCH Estimates in the Selected Stock Markets

Market returns	Parameters in the variance equations											
	Constant	Shock spillover effects					Asymmetric	Volatility spillover effects				
	ω	α_I	α_M	α_T	α_P	α_V	γ	β_I	β_M	β_T	β_P	β_V
Indonesia	0.0497	0.1078	-0.0869	-0.0560	-0.0896	-0.1025	0.1965	0.2037	-0.1688	0.5313	1.4605	0.7386
	(0.360)	(<0.001)	(0.085)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.275)	(<0.001)	(<0.001)	(0.043)
Malaysia	-0.0861	-0.0033	0.1091	-0.0156	-0.0320	0.0809	0.0598	0.0852	0.0941	1.1841	0.4089	-0.1311
	(<0.001)	(0.787)	(<0.001)	(0.015)	(0.006)	(<0.001)	(0.027)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.201)
Thailand	0.5334	-0.0347	-0.1795	0.0905	0.0139	-0.0311	0.0939	0.4429	3.7677	-0.0489	-1.6205	2.7989
	(<0.001)	(0.113)	(<0.001)	(<0.001)	(0.505)	(0.301)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Philippines	0.2994	0.0237	-0.0953	0.0407	0.1150	-0.0912	0.0795	-0.1208	2.2806	-0.4876	0.3623	0.5554
	(<0.001)	(0.504)	(0.240)	(0.244)	(<0.001)	(0.006)	(0.028)	(0.541)	(<0.001)	(0.032)	(<0.001)	(0.152)
Vietnam	-0.0116	-0.0388	0.0766	0.0531	-0.0194	0.3502	-0.0061	-1.2302	3.8813	6.6302	-1.3766	0.5908
	(0.013)	(0.220)	(0.087)	(0.046)	(0.529)	(<0.001)	(0.872)	(0.004)	(0.027)	(<0.001)	(<0.001)	(<0.001)

Notes: The figures in parentheses are the p-values.
The subscripts (*i.e.,* I, M, T, P and V) of the estimates denote for Indonesia, Malaysia, Thailand, Philippines and Vietnam, respectively.

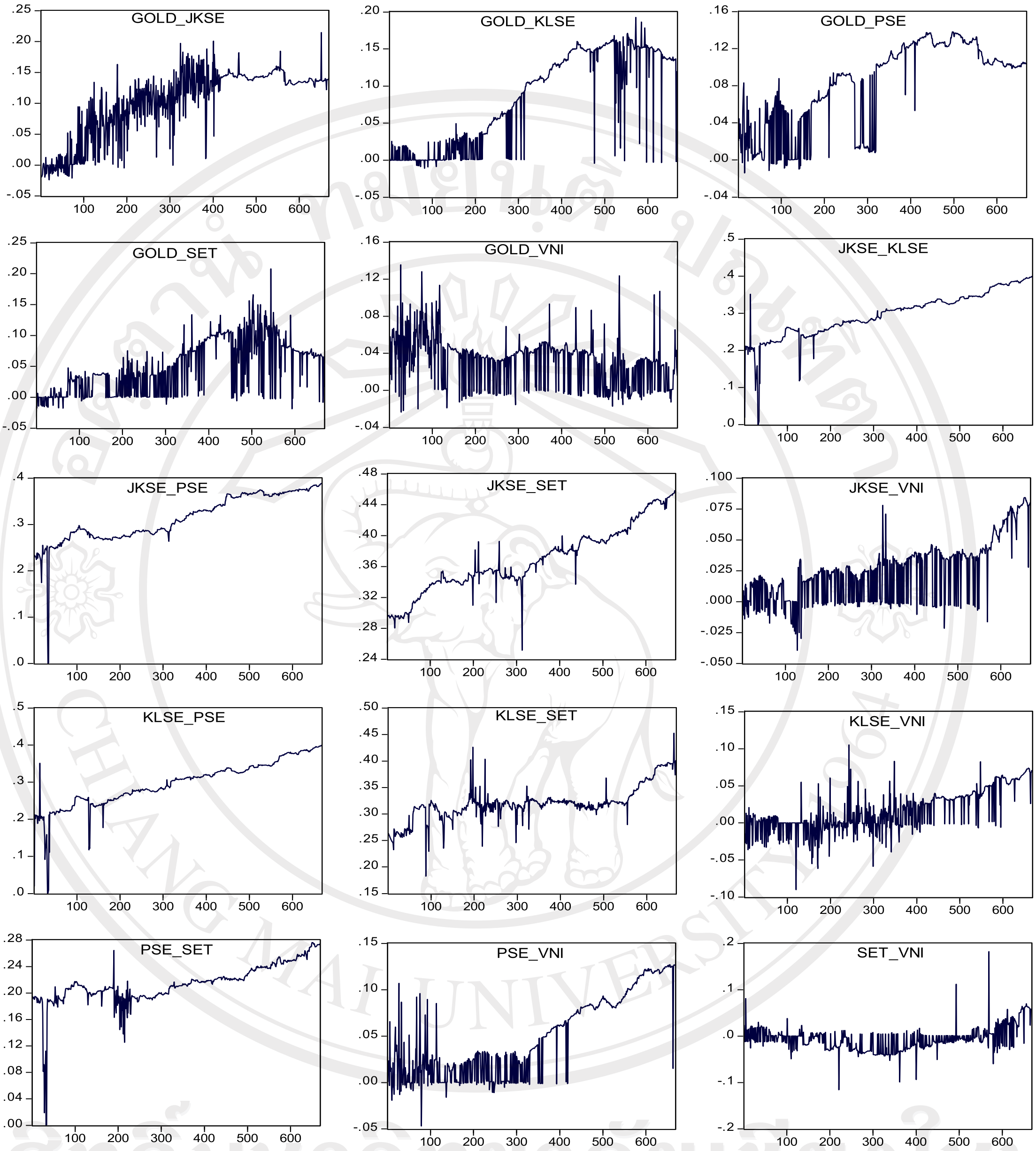

Figure 5.1: Dynamic Paths of Pair Return Conditional Correlations based on VARMA-GARCH (window size=1000 and moving windows=668)

After the completion of the rolling windows for the 15 market pairs based on the two models, all the estimated conditional correlations are collected and plotted in Figure 5.1 for VARMA-GARCH and Figure 5.2 for VARMA-AGARCH, for which the dynamic paths of the rolling conditional correlations in each market pair are quite similar between two models. It reveals that rolling conditional correlations illustrate considerable variability and/or consistent growths in all the 15 market pairs for both models over the time paths, which imply that the restrictive assumption of constant conditional correlation is no longer valid. Such a result may be used to motivate the estimation of dynamic conditional correlation models to provide an in-depth analysis for interdependencies among the sample markets.

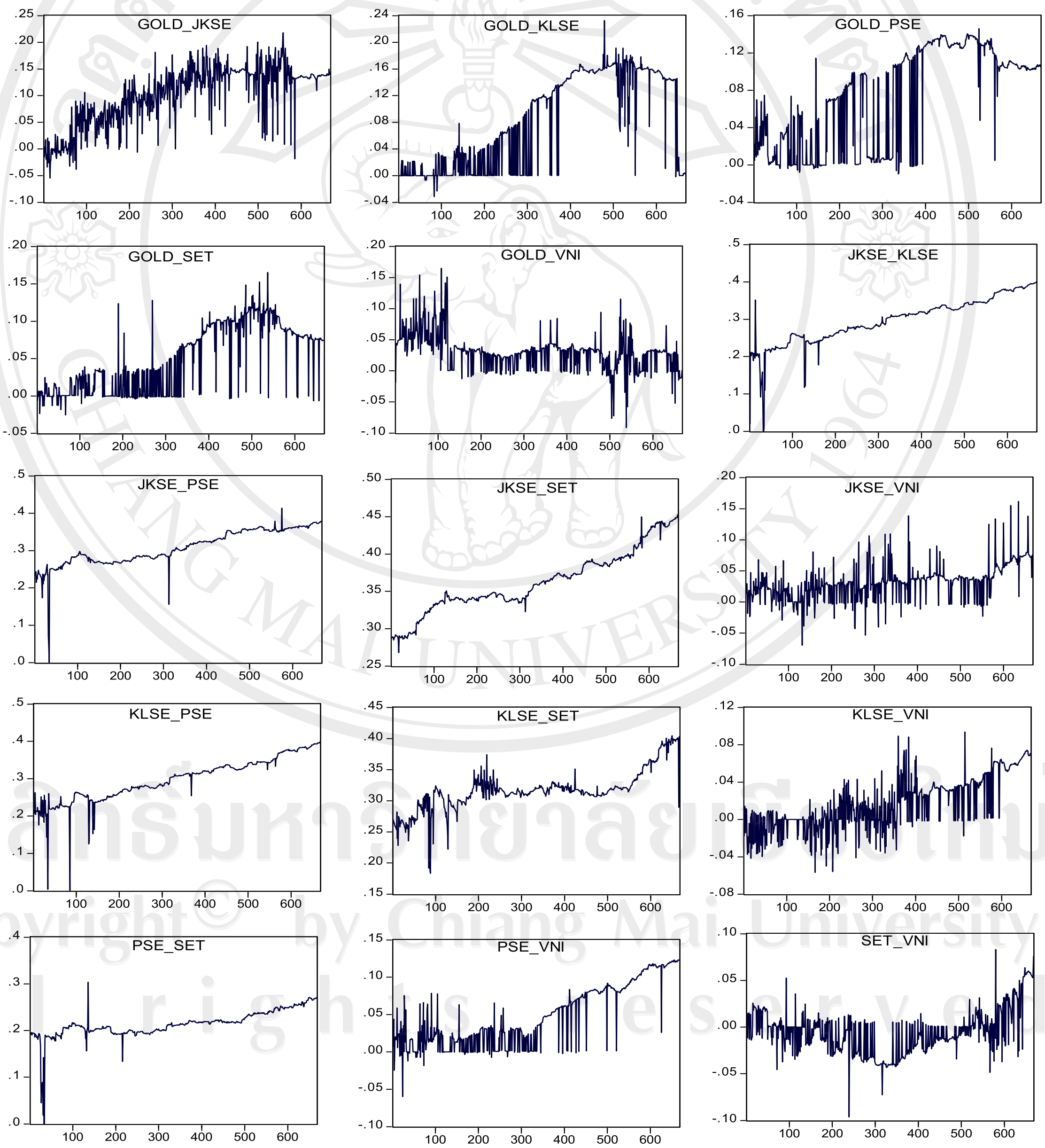

Figure 5.2: Dynamic Paths of Pair Return Conditional Correlations based on VARMA-AGARCH (window size=1000 and moving windows=668)

5.5 Concluding Remarks

This paper used two multivariate constant conditional correlation models, namely the VARMA-GARCH and VARMA-AGARCH to examine shock and volatility spillover effects across the sample markets, asymmetric effects of positive and negative shocks with the same magnitude to market volatility, and the conditional correlations between the selected markets. Daily data for the selected market returns covering the period 28 July 2000 to 31 March 2009 were used to estimate time the varying conditional volatility and multivariate conditional volatility models.

The estimates of bivariate VARMA-AGARCH and VARMA-GARCH models between the gold and 5 ASEAN emerging stock markets provide some evidences of shock and volatility spillovers, seeming that gold and the 5 ASEAN stock market volatilities are partly interdependent. Meanwhile, the estimates of the conditional variances obtained from the 5-variate VARMA-GARCH and VARMA-AGARCH models show strong evidences of both shock and volatility spillovers across the 5 ASEAN emerging stock markets. To evaluate the possible spillovers across the sample markets, the VARMA-AGARCH can capture better the shock and volatility spillover effects to the Indonesia, Malaysia, Philippines and Thailand stock markets than the VARMA-GARCH. On the contrary, a symmetric VARMA-GARCH should be appropriate for the Vietnam stock market.

The empirical evidences also imply that ASEAN emerging stock markets reacted to shock and volatility spillovers from the international gold market and from themselves differently. This is highlighted through their suffering, immunization and absorbability of shocks and volatility transmitted from other markets to each of ASEAN emerging stock markets.