Return and volatility spillover between large and small stocks in Bursa Malaysia

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Abstract

The main concern for asset allocation is that if any return and volatility from a stock market spillovers into, return and volatility of another market. This paper investigates the existence of spillover effect in Malaysian market. Specifically, we study the return and volatility spillover effects between Bursa Malaysia Composite Index (KLCI) and Bursa Malaysia Second Board Index. Multivariate GARCH model has been employed in our study. We reveal that return transmission mechanisms between large and small stocks in Bursa Malaysia are reciprocal, where both types of stocks have significant spillover effects on each other; particularly during and after Asian financial crisis. On the other hand, volatility of large stocks has much more impact on volatility of small stocks. The dominance effect of large stocks in Malaysian market indicates that information is first incorporated into prices of larger stocks before being explicitly embedded into prices of smaller stocks. Hence, these stocks are interrelated and the spillover effect should be taken into consideration during investing in Malaysian market.

Keywords: Return spillover; Volatility spillover; Multivariate GARCH model; Bursa Malaysia Composite Index; Bursa Malaysia Second Board Index.

1. Introduction

Stock return volatility measures the random variability of the stock returns. More specifically, it is the standard deviation of daily stock returns around the mean. Volatility of stock returns has been mainly studied in the developed economies. Since the seminal work of Engle (1982), Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalized form (GARCH) by Bollerslev (1986) have captured much attention of academicians. Many empirical studies have employed these models and their extension models in studying return volatility (see Nicholls and Tonuri, 1995; Booth, Martikainen and Tse, 1997; De Lima, 1998; and Sakata and White, 1998). Spillover effect is a result or the effect of return and volatility of larger stocks that have spread to other smaller stocks, or vice versa. There are number of reasons that explained the importance of transmission mechanisms between the returns and volatilities of different stocks. Firstly, market efficiency is somehow explained by these transmission mechanisms. Existence of spillover effect in returns is the evidence against efficient market hypothesis. An exploitable trading strategy may exist to deliver the profits that exceed transaction costs. Furthermore, the knowledge of spillover effects may be useful in asset allocation process and thus help in portfolio management. Lastly, information about volatility spillover effects is of importance in financial applications that rely on conditional volatility, such as option pricing, portfolio optimization, value at risk (VaR) and hedging. Stock market volatility, in particularly, could harm the economy through a number of directions. Asian financial crisis 1997 that originated in Thailand had affected the financial market of neighboring countries is one of the apparent volatility spillover effects. The sudden bear markets occurred in the 1997-98 East Asia financial and currency crisis had caused the stock prices around Asian region to fluctuate greatly.

Many previous studies have documented that the returns of large and small stocks in the US and UK stock markets are cross-correlated (see, for example, Campbell, Lo and MacKinlay, 1997). Moreover, some studies showed that these cross-correlations are asymmetric.Very little empirical researches on this issue have been documented for emerging markets. Asian emerging markets are characterized by high risk high return. Hence, it is crucial to understand how these emerging markets are influenced by the return and volatility spillovers between large and small stocks. The Malaysian economy in recent years has been characterized by trends towards increased liberalization, greater openness to world trade, higher degree of financial integration and greater financial development. This possibly increases the exposure of Malaysian market to volatility spillover effects. This study aims to investigate the behavior of stock price return and volatility spillover effects between large and small stocks in Malaysian market. We seek to find out spillover directions of stock return and volatility. This paper is organized as follow. Section 2 reviews the literature on stock returns and volatility. Section 3 describes the empirical methodology employed in this study. Empirical results and discussions will be presented in Section 4 and conclusion comes into last section of this paper.

2. Literature review

Numerous studies have been conducted to examine the relationship between stock returns and volatility in developed markets, for instance French, Schwert and Stambaugh (1987), Baille and DeGennaro (1990), and so on for the cases of United States, United Kingdom, French and Germany stock markets. Theodossiou and Lee (1995) use the GARCH-M model to study the interdependence of U.S., U.K., Caanada, Germany and Japan stock markets. Weak statistically significant mean spillovers were found from U.S. stock market to U.K., Canada and Germany, and radiate from Japan to Germany stock market. They also documented a significant volatility spillovers radiate from U.S. stock market to all four stock markets. Yang and Bessler (2004) reveal that Japanese stock market does not influenced by other major stock indices future markets. U.S. and U.K. shown to be the leaders in the future markets with U.K. and Germany exert significant influences on most European markets. Some studies examine the spillover effect from developed markets to emerging markets. Eun and Shim (1989) employed the vector autoregressive regression (VAR) model to investigate the international transmission mechanism of stock market movements.

They found that US stock market had the most influence on each spot market and has the largest impact on other stock markets as compared to London, Frankfurt, Sydney, Hong Kong, Zurich and Tokyo. Methodologically, Wang, Gunasekarage and Power (2005) employed a more advance method, which is EGARCH model to investigate the volatility spillovers from U.S. and Japan stock markets to three South Asian capital markets. Both return and volatility of U.S. stock market were found to spillover to all three South Asian capital markets. Similarly, a significant spillover effect could be found from the US index futures market (Gannon, 2005). He also documented that Hang Seng index future has a one-way transmission effect on the fluctuation of the Hang Seng spot index. Some researchers took a further extent to study the relationship between stock returns and volatility in an international context. Among others, Corhay and Rad (1994), Theodossiou and Lee (1995), Paudyal and Saldanha (1997), Chiang and Doong (2001) and Li, et al. (2004) contribute to the literature on the relationship between stock returns and volatility.

Very little studies have emphasized on emerging markets, such as Asia (Malaysia, India, China, Taiwan, Korea), Latin America (Brazil, Argentina) and Europe/Middle-east (Greece, Turkey). Recently, there is an increasing works have been done on Great China region. Wei, Liu, Yang and Chaung (1995) find that return and volatility spillover from US to Taiwanese and Hong Kong markets. Yu (2002) also documented at the same conclusion on Taiwanese stock market, in which it being affected by US market. Contrarily, Hu et al. (1997) and Wang and Wang (2010) also examine the volatility spillover effect among US, Japan and Great China region and documented an opposite findings.Returns and volatility of developed market (US and Japan) and countries from Great China region have spillover effect on each other. Singh, Kumar and Pandey (2010), on the other hand find that a greater regional effect among Asian market. Japanese market that being affected by US and European market which in turns affect the other markets in Asia region. Other study that focus on emerging market include Qiao, Chiang and Wong (2008), Bhar and Nikolova (2009) and Johansson and Ljungwall (2009) and Beirne, Caporale and Schulze-Ghattas and Spagnolo (2010). However, this issue is yet to be tested in Malaysian market.

3. Empirical study

3.1. Description of data

The empirical analysis uses continuously compounded daily stock prices of the Bursa Malaysia Composite Index (also known as KLCI) and Bursa Malaysia Second Board Index from 1st April 1992 to 20th September 2005, obtained from METASTOCK (a total of 3,300 observations).

Both series are market-weighted indices which are generally accepted as the local (Malaysia) stock market barometer. Bursa Malaysia Composite Index is a capitalization-weighted index calculated from the 100 major companies from the Main Board. For the sub-period analysis, this study splits the full sample into two equal sub periods. The first sub-sample is from 1st April 1992 to 31st December 1996, which is before the Asia Financial Crisis in between 1997-1998; whereas the second sub-sample is from 2nd January 1997 until 20th September 2005 which encompass the period of Asia Financial Crisis and thereafter. Sub-period analysis uses short horizon returns which enable to analyze spillover effects in both the mean and volatility of the two series, but the time series variation in conditional volatility tends to be much weaker for longer horizon returns.The summary statistics of the stock indices are presented in Table 1. Mean of stock indices are quite small. It is also clear that return series of four stock indices are asymmetry and leptokurtic. Jarque-Bera test also strongly reject the null hypothesis, in which return distribution is non-normal.

Insert Table (1) about here

3.2. Methodology

We computed daily return for both indices follow the formulation below since the price series is non-stationary.

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

where P_t = Today's closing price for each indices

P_{t-1} = Yesterday's closing price for each indices.

3.2.1. Modeling the returns and volatilities of the stock indices

We first model the dynamic properties of the returns and volatilities of Bursa Malaysia Composite Index (KLCI) and Bursa Malaysia Second Board Index return series without spillover effects. Simplified multivariate AR (1) – GJRGARCH – M model is being used in this study with following formulation for both indices $i, j = 1,2$:

$$R_{i,t} = \alpha_{i,0} + \sum_{n=1}^{2} \alpha_{i,n} R_{i,t-n} + \gamma_i h_{ii,t} + \varepsilon_{i,t} \tag{2}$$

$$h_{ii,t} = \beta_{i,0} + \beta_{i,1} h_{ii,t-1} + \beta_{i,2} \varepsilon^2{}_{i,t-1} + \lambda_i I_{i,t-1} \varepsilon^2{}_{i,t-1} \tag{3}$$

$$h_{ij,t} = \rho_{ij}\left(\sqrt{h_{ii,t}}, \sqrt{h_{jj,t}}\right) \tag{4}$$

where $R_{i,t}$ is the return of portfolio i (EMAS (Exchange Main Board Share Index) for instance) in the period $t, \varepsilon_t \mid \psi_{t-1} \sim N(0, H_t), \psi_{t-1}$ is the set of all information available at time $t-1$ and $H_t = \lfloor h_{i,j,t} \rfloor$ is the conditional covariance matrix. $I_{i,t-1}$ is a dummy variable that is equal to one if the lagged squared residual, $\varepsilon_{i,t-1}$ is negative, and zero otherwise. As specified above, the conditional variance of each index has been included in return equation as an explanatory variable. The main benefit of using GARCH – M is to exploit as much information as we could in estimating expected returns, rather than to impose a particular or specific asset pricing restriction, and this seems to be a common view in literatures (see, Ng, Chang and Chou, 1991; Theodossiou and Lee, 1993). The equations (3) and (4) are the equations of conditional variance and conditional covariance in multivariate GARCH model. The conditional variance of each index is formulated as a univariate GARCH model with the conditional covariance of any two series i and j is the multiplication of conditional variances, $h_{ii,t}$ and $h_{jj,t}$, and the constant correlation coefficient, ρ_{ij}.

The CCOR model has the advantage of being parsimonious and hence greatly reduces the computational effort required to estimate the model, where a more reliable parameter estimates can be assured.This is specifically important in the present case owing to the large number of parameters to be estimated. Apparently, such greater advantage of CCOR model leads to the use of this model in our study; although we could have to choose other multivariate GARCH models with more complicated estimation procedure.To ensure the robustness of our results, we employed GJRGARCH (1,1) model (Glosten, Jagannathan and Runkle, 1993) in univariate GARCH estimation since the volatility responds asymmetrically to good and bad news. The volatility spillovers can be significantly underestimated if this asymmetric effect is ignored. $I[\varepsilon_{t-1} > 0]$ in equation (3) is the indicator function for negative return shocks, taking a value of 1 if $\varepsilon_{t-1} < 0$ and 0 otherwise.

Also, as for robustness, this study includes the full sample and two sub-periods analysis, which are pre-Asian Financial Crisis (1st April 1992 to 31st December 1996) and during and after Asian Financial Crisis, 2nd January 1997 until 20th September 2005, as previously mentioned.

3.2.2. Modeling spillover effects between the stock indices

The ultimate goal of this study is to analyze the return and volatility spillovers between large and small stocks in Bursa Malaysia. We modified the AR (2) – GJRGARCH – M model given in equations (2) to (4) by including the mean and variance equations for each index, the lagged shocks to the means and volatilities of both indices, in order to analyze the return and volatility spillovers between Bursa Malaysia Composite Index (KLCI) and Bursa Malaysia Second Board Index. In order to capture spillover effects in the mean equation for index i, specifically this study includes the first lag of the returns of each index, $i \neq j$. Also, in order to capture spillover effects in the volatility equation for index i, this study take into consideration the first lag of the squared return shocks of each index. The model including spillovers for indices i, j = 1, 2, 3 is therefore given by:

$$R_{i,t} = \alpha_{i,0} + \sum_{n=1}^{2} \alpha_{i,n} R_{i,t-n} + \gamma_i h_{ii,t} + \sum_{j=1, j\neq i}^{2} wi, jR_{j,t-1} + \varepsilon_{i,t} \quad (5)$$

$$h_{ii,t} = \beta_{i,0} + \beta_{i,1} h_{ii,t-1} + \beta_{i,2} \varepsilon^2{}_{i,t-1} + \lambda_i I_{i,t-1} \varepsilon^2{}_{i,t-1} + \sum_{j=1, j\neq i}^{2} z_{i,j} \varepsilon^2{}_{j,t-1} \quad (6)$$

$$h_{ij,t} = \rho_{ij} \left(\sqrt{h_{ii,t}}, \sqrt{h_{jj,t}} \right) \quad (7)$$

The partial impact on the returns of index i of past return shocks of the both indices was measured by the parameter, $w_{i,j}$; while the partial impact on the volatility of index i of past volatility shocks to the both indices was measured by the parameter, $z_{i,j}$. The estimation of the multivariate GARCH model, both with and without spillover effects can be done by quasi-maximum likelihood with a normal conditional distribution (Bollerslev and Woolridge, 1992). We also employed the BFGS algorithm with a convergence criterion of 0.00001 applied to the function value and the robust errors are computed, which are valid under non-normality (White, 1982).

4. Empirical result

4.1. Multivariate AR (2)-GJRGARCH (1,1)-M Results

Table 2 reports the first four autocorrelation coefficients for returns of each index, together with Ljung-Box portmanteau statistics. For these two indices, returns are serially correlated, although the magnitude of the serial correlation decreases with capitalization. Squared returns are highly serially correlated for all series indicating the presence of volatility clustering. Contrarily, the magnitude of the serial correlation in squared returns increases with capitalization, implying that ARCH effects are stronger for large stocks than for small stocks. This is align with the findings of Harris and Pisedtasalasai (2006), whereby the serial correlation for the returns of FSTE100, FSTE 250 and FSTE Small Cap is increasing with the capitalization to show that the ARCH effects are stronger for large stocks than for small stocks.

Insert Table (2) about here

Table 3 reports the estimated parameters of the multivariate AR (2)-GJRGARCH (1,1)-M model for both indices, given by equations (1), (2) and (3), together with Ljung-Box test statistics for the standardized residuals (LB(4)) and the squared standardized residuals ($LB^2(4)$). For both indices, the sum $\beta_{i,1} + \beta_{i,2} + \lambda_i/2$ suggests that volatility is not stationary but highly persistent.

This is exactly the true picture for Asian Emerging Markets, where these markets experienced high expected returns as well as unpredictable high volatility which may not be beneficial to the investors. This result is also contradicted with the findings in UK (Harris and Pisedtasalasai, 2006) whereby the volatility for FSTE100, FSTE 250 and FSTE Small Cap is stationary but highly persistent (constantly volatile). Particularly, the half life of volatility for the Bursa Malaysia Composite Index and Bursa Malaysia 2nd board index is -48.81 days and -12.12 days, respectively[1]. This result indicates that the return distribution is asymmetric.

Insert Table (3) about here

[1] The half-life is computed as hi = In(1/2)/In ($\beta_{i,1} + \beta_{i,2} + \lambda_i/2$) under the assumption that the return distribution is symmetric.

The GARCH-in-mean coefficient, γ_i, is significantly positive for both indices, implying that higher volatility is associated with higher expected returns, which is consistent with the explanation of risk aversion. The coefficient of the asymmetry term, $\lambda_{i,}$ is significantly positive for Bursa Malaysia Second Board Index followed by Bursa Malaysia Composite Index, implying that bad news or news propaganda has a larger impact on the volatility of Bursa Malaysia 2nd Board Index than good news does. Whereas, the asymmetry term, $\lambda_{i,}$ is less significantly positive for Bursa Malaysia Composite Index, implying that bad news or news propaganda has a smaller impact on the volatility of Bursa Malaysia 2nd Board Index. However, although the asymmetry term is positive for both indices but it is not statistically significant for Bursa Malaysia Composite Index. The estimated correlation coefficients, $\rho_{i,j}$, between the two indices are positive and highly significant as expected.

The LB^2 (4) statistics suggest that the multivariate GARCH (1,1) specification successfully captures the serial correlation in squared returns for each indices. On the other hand, LB (4) statistics show that there is significant serial correlation in the residuals for the two indices. However, it has been noticed in Table 3 that this serial correlation has increased once the return and volatility spillovers is included into the model. This explains alternatively, the ARMA specifications of the mean equation (specifically based on the AIC, which generally include longer lags of both the AR and MA components) tend to be succeeding in eliminating this serial correlation, as this is evidenced by the opportunities for diversification within East Asian. This result is in contrary to the findings done by Harris and Pisedtasalasai (2006) whereby the serial correlation is significantly reduced once the return and volatility spillovers is included into the model and the ARMA specifications of the mean equation are failed to eliminate the serial correlation.

4.2. Multivariate AR (2)-GJRGARCH (1,1)-M Results with spillover effects

The Table 4 reports the estimated parameters of the multivariate AR (2) – GJRGARCH (1,1) – M model with spillover effects for each of the two series. Comparing Table 3 and 4, it is noticed that the introduction of the spillover effects into the model generally reduced the estimated parameter values for the mean and variance equations of both indices. However, the introduction of spillover effects does increase the serial correlation in the residuals. This implying that the LB (4) statistic is now significant for Bursa Malaysia Composite Index (KLCI), and considerably increased for the Bursa Malaysia Second Board Index. Again, alternative ARMA specifications for the mean equation tend to be succeeding in eliminating the remaining serial correlation. Besides that, the choice of model for the mean return for both series does significantly affect the results on mean and volatility spillovers that are reported in Table 4, and changes some of the qualitative conclusion, such as the coefficient of the asymmetry term, λ_i. Table 4 shows that the spillover effects are reciprocal.

There are less significant return and volatility spillovers from the Bursa Malaysia Second Board Index to Bursa Malaysia Composite Index, but the opposite direction is being observed. This is true from the speculation activities in Malaysia that the news propaganda is affecting much in Bursa Malaysia Second Board Index than the Bursa Malaysia Composite Index. The coefficient of the asymmetry term, λ_i, is a significant negative value for both indices, implying that bad news that results in speculation activities, is affecting both of the volatility of both indices. For both indices under the spillovers effect, the sum $\beta_{i,1} + \beta_{i,2} + \lambda_i/2$ suggests that volatility is less stationary but highly persistent. However, the GARCH-in-mean coefficient, γ_i, is significantly positive for Bursa Malaysia 2nd Board Index, implying that higher volatility is associated with higher expected returns, which is consistent with the explanation of risk aversion.

Insert Table (4) about here

There are spillovers effects between the return of both indices. In particular, there are less significant (positive) spillover effects in returns from Bursa Malaysia Second Board Index to the Bursa Malaysia Composite Index.Table 4 also shows that there is a negative significant spillover effects from the return of Bursa Malaysia Composite Index to the return of Bursa Malaysia Second Board Index. There is a less positive spillover effects from the return of Bursa Malaysia Second Board to the return of Bursa Malaysia Composite Index. In terms of volatility impact, the volatility of smaller stock is less significant to spillover on to the larger stocks. However, the volatility of larger stocks have positive significant impact to spillover on to the smaller stocks. In order to shed more light on the observed spillover patterns, this study had included the same analysis using each of the two sub-samples.

4.3. Sub-Period analysis

The results for the sub-period analysis show that the pattern of return spillovers for both sub-periods is very similar to the results reported in the full sample. Again, based on the Table 5, 6, 7 and 8 below, this study finds that the spillover effects in return are reciprocal for 2nd sub-period, not for the 1st sub-period.

There are highly significant spillover effects in returns from the Bursa Malaysia Composite Index to Bursa Malaysia 2nd Board Index. The evidence of asymmetry is even more pronounced for the second sub-period, which is during and after the Asian Financial Crisis in 1997. There are less positive significant spillover effects in returns from Bursa Malaysia 2nd Board Index to Bursa Malaysia Composite Index in 2nd sub-periods. There are no statistical significant spillover effects in returns from Bursa Malaysia 2nd Board Index to Bursa Malaysia Composite Index in the 1st sub-period.For conditional volatility, the significant spillover effects from Bursa Malaysia Composite Index to Bursa Malaysia 2nd Board Index that presented in the full sample are also presented in the 2nd sub-period. The spillover from Bursa Malaysia 2nd Board to Bursa Malaysia Composite Index that is present in the full sample is significant for second sub-period, specifically due to the economic recession periods in the years of 97-98. The result of insignificant spillover effects in volatility from Bursa Malaysia 2nd Board Index to Bursa Malaysia Composite Index is also applies to both sub-periods.

This is due to the liquidity problem faced by the small stocks listed under Bursa Malaysia 2nd Board Index, particularly after the financial crisis in 97-98. The results of sub-period analysis therefore suggest that the spillover effects in returns and volatility from larger stock portfolios to smaller stock portfolios are robust in the Malaysia scenario with the respect to the time-period considered. The spillover in both returns and volatility tend to be stronger in the second sub-period than the first sub-period due to the economic recession periods during the years of 1997 and 1998. For both return and volatility, there are no significant spillover effects from the portfolios of smaller stocks to the portfolios of larger stocks, but these effects vary with the time-period considered. Although Harris and Pisedtasalasai (2006) explain that the negative spillover from smaller stocks (FSTE 250 index) to the larger stocks (FSTE 100 index) is casting doubt on its robustness and has spurious element. In fact, this is the truly reflect in Malaysia where there is a reciprocal effect between smaller stocks and larger stocks. The return volatility is spillover from larger stocks to smaller stocks and also from smaller stocks to larger stocks in Bursa Malaysia, particularly during and after the crisis period.

Insert Table (5,6,7 and 8) about here

5. Conclusions

This study investigates the return and volatility spillover effects between large and small stocks in Bursa Malaysia using the multivariate AR (2) – GJRGARCH (1,1) – M model. We find that the returns and volatilities of larger stocks are important in predicting the future dynamics of smaller stocks. Also, the return and volatilities of smaller stocks have much less impact on the future dynamics of larger stocks. However, the spillover effect for returns is reciprocal for both indices. Both returns of larger stocks and smaller stocks have spillover effects on each other.The return volatility of the penny stocks as characterized by the small stocks listed on Second Board is greater than the large stocks in Main Board. The small stocks that listed in the Bursa Malaysia whose situation is in the process of evolving from Second Board to the Main Board. These stocks has less government intervention, loosen listing requirements[2], short-term risk-averse investors who speculate the increase of the prices and allows the quick buys and sells activities for penny stocks, less long-term commitment on the stock holding, and are not capable to raise public funds for businesses. Hence, these penny stocks are characterized with high volatility that may eventually spillovers on the large stocks.

The empirical results from this study suggest that information flow and news propaganda have an influence on the pattern of the transmission mechanisms between small and large stocks. Therefore, the spillover for returns attempts to be reciprocal for both indices. The explanation for this study is consistent with that the market-wide information is first incorporated into the prices of large stocks before being incorporated into the prices of small stocks. However, during and after the financial crisis, the prices of smaller stocks respond with a delay to the arrival of larger stocks' information. Specifically, there are reciprocal significant spillover effects from the returns of large stocks to the returns of small stocks; and from the return on smaller stocks to the return of larger stocks after the financial crisis. The significant spillover effects form Bursa Malaysia Composite Index to Bursa Malaysia Second Board Index is align with the results from the developed countries such as US and UK (see Harris and Pisedtasalasai, 2006).

Table 1: Summary statistics of data on rate of returns from 1st April 1992 to 20th September 2005

Indices	Mean ($x 10^{-4}$)	Standard Deviation	Skewness	Kurtosis	Jarque-Bera (p-value)
KLCI	2.69	0.0164	1.5065	44.2748	0.0000*
Bursa Malaysia Second Board Index	0.95	0.02002	0.7257	12.9405	0.0000*

*Significant at 0.05 level of significance

[2] The loosen listing requirements in Bursa Malaysia Second Board compared to Bursa Malaysia Main Board can be obtained from the website, *www.bursamalaysia.com.my* , with up-to-date listing requirements.

Table 2: Autocorrelation coefficients for each stock index return

	R_t		R^2_t	
	BMCI	**BM2ndBoard**	**BMCI**	**BM2ndBoard**
ρ_1	0.084*	0.183*	0.483	0.380
ρ_2	0.030*	0.069*	0.289	0.229
ρ_3	0.007*	0.045*	0.213	0.164
ρ_4	-0.083*	0.065*	0.199	0.142
LB (4)	49.663*	146.89*	1327.4	790.65

* denote statistical significance at the 5% level of significance.

Table 3: The Multivariate AR (2)-GJRGARCH (1,1)-M Model, without Spillovers –Full Sample

Full Sample: 1st April1992 until 20th September 2005				
	KLCI		Bursa Malaysia Second Board Index	
	Coefficients	t-stat.	Coefficients	t-stat
$\alpha_{i,0}$	0.0003	1.6549	-0.0065	-3.0263**
$\alpha_{i,1}$	0.0546	4.1120**	0.1760	5.8184**
$\alpha_{i,2}$	0.1316	2.4551*	0.1052	1.5273
γ_i	0.0345	1.6745	0.1205	5.4155**
$\beta_{i,0}$	0.0004	2.8909*	-0.0007	-3.7785**
$\beta_{i,1}$	0.0002	0.9060	0.0023	[0.1104]
$\beta_{i,2}$	0.9976	356.2345**	0.9995	237.6131**
λ_i	0.0330	1.5507	0.1143	5.3804**
$\rho_{klci,2ndboard}$	0.8496	110.2679**		
LB(4)	99.7040	[0.0000]	134.1700	[0.0000]
$LB^2(4)$	1.9990	[0.5730]	1.8261	[0.6090]
Log-likelihood	10124.45		9101.808	
AIC	-6.136156		-5.515807	
SBC	-6.119502		-5.499154	

LB(4) and $LB^2(4)$ reports the first four autocorrelations for the returns of each index and forth-order Ljung-Box statistics. * and ** denote statistical significance at the 5% level and the 1% level respectively.

Table 4: The Multivariate AR (2)-GJRGARCH (1,1)-M Model with Spillovers – Full Sample

Full Sample: 1st April1992 until 20th September 2005				
	KLCI		Bursa Malaysia 2nd Board Index	
	Coefficient	t-stat.	Coefficient	t-stat
$\alpha_{i,0}$	0.0001	0.9167	-0.0008	-4.2624**
$\alpha_{i,1}$	0.1906	4.2332**	0.5355	7.0540**
$\alpha_{i,2}$	0.0173	0.2649	-0.1837	-1.8737
γ_i	0.0287	1.3971	0.0972	4.9303**
$w_{i,KLCI}$	-	-	-0.4808	-6.5152**
$w_{i,2ndBoard}$	0.1909	2.1961*	-	-
$\beta_{i,0}$	0.0002	1.1688	-0.0007	-4.0346**
$\beta_{i,1}$	0.1869	4.1652**	0.5229	6.6800**
$\beta_{i,2}$	0.0201	0.3117	-0.1920	-1.9702
λ_i	-0.1536	-3.4656**	-0.4661	-6.1268**
$z_{i,KLCI}$	-	-	0.3930	3.8571**
$z_{i,2ndboard}$	-0.1027	-1.5444	-	-
$\rho_{klci,2ndboard}$	0.8499	106.3132**		
LB(4)	101.9600	[0.0000]	137.7100	[0.0000]
$LB^2(4)$	0.0718	[0.9950]	8.2058	[0.0420]
Log-likelihood	10140.78		9161.129	
AIC	-6.145454		-5.551185	
SBC	-6.12695		-5.532681	

LB(4) and $LB^2(4)$ reports the first four autocorrelations for the returns of each index and forth-order Ljung-Box statistics. * and ** denote statistical significance at the 5% level and the 1% level respectively.

Table 5: The Multivariate AR (2)-GJRGARCH (1,1)-M Model without Spillovers–Sub-period1

	Sub-period 1: 1st April1992 until 31st December 1996			
	KLCI		Bursa Malaysia 2nd Board Index	
	Coefficient	t-stat.	Coefficient	t-stat
$\alpha_{i,0}$	0.000673	2.600532*	0.000251	1.419136
$\alpha_{i,1}$	0.053676	2.532871*	0.104071	3.917474**
$\alpha_{i,2}$	0.150326	2.022695*	0.107096	1.095221
γ_i	-0.005044	-0.155747	0.082115	2.288762*
$\beta_{i,0}$	0.0000656	2.482772*	0.000635	1.888287
$\beta_{i,1}$	0.000163	1.378403	0.001883	0.114513
$\beta_{i,2}$	0.990957	92.74505**	0.999260	154.9995**
λ_i	-0.014558	-0.433084	0.064745	1.912996
$\rho_{klci,2ndboard}$	0.935502	94.02950**		
LB(4)	34.102	[0.0000]	53.923	[0.0000]
$LB^2(4)$	0.3601	[0.948]	3.1860	[0.364]
Log-likelihood	3671.114		3236.434	
AIC	-6.330362		-5.578969	
SBC	-6.291051		-5.539659	

LB(4) and $LB^2(4)$ reports the first four autocorrelations for the returns of each index and forth-order Ljung- Box statistics. * and ** denote statistical significance at the 5% level and the 1% level respectively.

Table 6: The Multivariate AR (2)-GJRGARCH (1,1)-M Model with Spillovers – Sub-period 1

	Sub-period 1: 1st April1992 until 31st December 1996			
	KLCI		Bursa Malaysia 2nd Board Index	
	Coefficient	t-stat.	Coefficient	t-stat
$\alpha_{i,0}$	0.000584	2.241792*	0.000200	0.643645
$\alpha_{i,1}$	0.168523	2.275246*	0.339710	3.944138**
$\alpha_{i,2}$	0.059559	0.602986	-0.094913	-0.802684
γ_i	-0.005221	-0.160485	0.052056	1.666828
$w_{i,KLCI}$	-	-	-0.298352	-3.445459**
$w_{i,2ndBoard}$	0.040352	0.362072	-	-
$\beta_{i,0}$	0.000597	2.299674*	0.000179	0.644690
$\beta_{i,1}$	0.151577	2.111474*	0.308738	3.705449**
$\beta_{i,2}$	0.071900	0.745815	-0.080508	-0.717906
λ_i	-0.108144	-1.463902	-0.278093	-3.288670**
$z_{i,KLCI}$	-	-	0.264850	1.082263
$z_{i,2ndboard}$	-0.072122	-1.090274	-	-
$\rho_{klci,2ndboard}$	0.936766	90.82600**		
LB(4)	36.439	[0.0000]	57.354	[0.0000]
$LB^2(4)$	1.9252	[0.588]	5.9372	[0.115]
Log-likelihood	3673.991		3250.153	
AIC	-6.333606		-5.600956	
SBC	-6.289927		-5.557277	

LB(4) and $LB^2(4)$ reports the first four autocorrelations for the returns of each index and forth-order Ljung-Box statistics. * and ** denote statistical significance at the 5% level and the 1% level respectively.

Table 7: The Multivariate AR (2)-GJRGARCH (1,1)-M Model without Spillovers–Sub-period 2

	Sub-period 2: 2nd January1997 until 20th September 2005			
	KLCI		Bursa Malaysia 2nd Board Index	
	Coeff	t-stat.	Coeff	t-stat
$\alpha_{i,0}$	0.0000464	0.235625	-0.001446	-5.405693**
$\alpha_{i,1}$	0.060912	3.573747**	0.232828	4.686469**
$\alpha_{i,2}$	0.125211	1.742444	0.086901	0.954498
γ_i	0.053961	2.051493*	0.135960	4.913629**
$\beta_{i,0}$	0.0001999	1.119619	-0.001481	-6.401118**
$\beta_{i,1}$	0.000770	0.129065	0.001633	0.096267
$\beta_{i,2}$	0.999558	295.2729**	0.999457	176.6474**
λ_i	0.056913	2.121258*	0.131657	4.937154**
$\rho_{klci,2ndboard}$	0.831355	94.84993**		
LB(4)	63.124	[0.0000]	84.953	[0.0000]
$LB^2(4)$	2.4668	[0.481]	1.1597	[0.763]
Log likelihood	6454.647		5879.877	
AIC	-6.029605		-5.491934	
SBC	-6.005746		-5.468076	

LB(4) and $LB^2(4)$ reports the first four autocorrelations for the returns of each index and forth-order Ljung-Box statistics.
* and ** denote statistical significance at the 5% level and the 1% level respectively.

Table 8: The Multivariate AR (2)-GJRGARCH (1,1)-M Model with Spillovers – Sub-period 2

	Sub-period 2: 2nd January1997 until 20th September 2005			
	KLCI		Bursa Malaysia 2nd Board Index	
	Coeff	t-stat.	Coeff	t-stat
$\alpha_{i,0}$	-0.000116	-0.592800	-0.001571	-6.397059**
$\alpha_{i,1}$	0.199617	3.494359**	0.691103	6.298640**
$\alpha_{i,2}$	0.004246	0.050565	-0.288360	-2.116955*
γ_i	0.033137	1.285627	0.108895	4.328065**
$w_{i,KLCI}$	-	-	-0.629399	-6.002921**
$w_{i,2ndBoard}$	0.310702	2.459304*	-	-
$\beta_{i,0}$	-0.000071	-0.376430	-0.001474	-6.782238**
$\beta_{i,1}$	0.201740	3.498473**	0.647663	5.533925**
$\beta_{i,2}$	-0.002156	-0.026022	-0.276284	-1.988365
λ_i	-0.194221	-3.451225**	-0.513336	-5.164356**
$z_{i,KLCI}$	-	-	0.489456	3.535463**
$z_{i,2ndboard}$	-0.161696	-1.613457	-	-
$\rho_{klci,2ndboard}$	0.831495	93.53910**		
LB(4)	61.643	[0.0000]	85.831	[0.0000]
$LB^2(4)$	2.1053	[0.551]	5.7887	[0.122]
Log likelihood	6468.858		5929.767	
ACI	-6.041962		-5.537668	
SBC	-6.015453		-5.511159	

LB(4) and $LB^2(4)$ reports the first four autocorrelations for the returns of each index and forth-order Ljung-Box statistics.
* and ** denote statistical significance at the 5% level and the 1% level respectively.

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