Changes in the Nature of Financial Spillover after the Asian Crisis

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by

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Abstract:
This paper examines equity spillover among Asian countries using the ARFIMA-GARCH model. We consider two types of spillover (price and volatility spillover), and, based on post-crisis data, we confirm the findings of existing studies analyzing pre-crisis data that price spillover often exists between countries. However, unlike previous literature, volatility spillover is absent during our sample period, and no unidirectional spillover is found except in a few cases. Our results thus support a change in the nature of the spillover after the crisis. Finally, this paper also provides evidence to support the hypothesis that the Philippines' equity market is less efficient than other Asian emerging markets since its data alone exhibit a long-memory process.

Keywords: Equity returns, ARFIMA-GARCH

JEL classification: F36, G14, G15

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I. Introduction

This paper examines the spillover effects of equity price and volatility among Asian financial markets after the 1997 crisis. Some research has been conducted to examine possible changes in the economic behavior of countries that were adversely affected by the Asian crisis. For example, economic growth and investment patterns before and after the crisis were studied by Barro (2002), and trade performance by Higgins and Klitgaard (2000). However, to our knowledge, no study has been conducted to investigate possible changes in the financial spillover effects for these countries. It is therefore important to revisit this topic since the institutional and legal frameworks of financial markets in these countries have changed since 1997.[1]

Research conducted prior to the eruption of the Asian crisis has frequently reported evidence of equity price and volatility spillover effects among industrialized countries. For example, Hamao *et al* (1990) studied the independence of equity indices in terms of equity returns and volatility. They provided evidence in support of price and volatility spillover from New York and London to Tokyo, particularly after the equity price crash of 1987. However, developments in the Tokyo market have become increasingly influential over other markets over time (Hamao *et al* 1991), and Lin *et al* (1994) show evidence of the New York and Tokyo markets affecting one another. However, unidirectional spillover seems to be found only rarely among large financial markets such as London, New York, and Tokyo, and volatility spillover is very slight, lasting only about one hour (Susmel and Engle 1994).

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[1] See several issues of the IMF's Article IV consultation papers that discuss structural changes in economies during and after the crisis.

But, clearer examples of spillover have been observed more frequently from large financial markets to small ones. For instance, Jochum (1999) has shown evidence of spillover from the major financial markets (Frankfurt, London, New York, and Tokyo) to the Swiss market. A so-called "small" financial market can also refer to an emerging economy. Kim and Rogers (1995) document volatility spillover from Tokyo and New York to Korea. Wei *et al* (1995) find spillover effects from markets in developed countries (New York, Tokyo, London) to emerging markets (Hong Kong and Taiwan). They conclude that the Taiwanese market is more sensitive than Hong Kong's to equity return and volatility developments in industrialized countries. Furthermore, in contrast to Engle and Susmel (1993), they suggest that the geographically more distant market, New York, influenced these Asian countries more than Tokyo.

Against this background, this paper will conduct a comprehensive study of Asian equity indices covering both industrialized nations (Japan and the US) and emerging economies (Hong Kong, Korea, and the Philippines). While focusing mainly on these four Asian markets, this study also includes US equity data that were discussed as being influential over some emerging economies (Wei *et al* 1995). Our study differs from previous research in a number of ways. First, this paper focuses on the post-Asian crisis period by which time the financial markets of these countries are thought to have become more liberal. Now, there are enough post-crisis observations in order to obtain statistically reliable results using high frequency data. Secondly, our specification includes short-term interest rates to represent the stance of monetary policies in these countries, and also allows us to capture both price and volatility dynamics. Previous research often analyzed equity price or volatility spillover alone, and thus these results may be biased due to mis-specification in the model. Finally, in contrast to previous studies, we do not make any assumptions regarding the statistical properties of the data (i.e., the order of integration, $I(d)$). Rather, we estimate the order d by employing the Auto-Regressive Fractionally Integrated Moving Average (ARFIMA)-General Auto-Regressive Conditional Heteroschedasticity (GARCH) specification (Baillie *et al* 1996) in order to capture the long-memory process of the equity data. This method also allows us to analyze the efficiency of the markets using the criterion posited by the efficient market hypothesis (i.e., the size of d).

This paper consists of four more sections. Section 2 defines the concept of equity price and volatility spillover using the framework of the ARFIMA-GARCH model. Section 3 provides a data description and discusses the fundamental time-series properties of the data. The main empirical results are reported in Section 4, and the paper concludes with Section 5.

2. The Definition of Price and Volatility Spillover, and the ARFIMA-GARCH

So far, the term, price and volatility spillover, has been used without any specific definition, and therefore this section explains the concept using the statistical model (ARFIMA-GARCH). The GARCH-type models have been used to examine financial spillover by several researchers (Hamao *et al* 1990, Kim and Rogers 1995, Ramachand and Susmel 1998). The ARFIMA-GARCH was proposed by Baillie *et al* (1996) as it could accommodate the long-memory process of equity price movements. It is difficult to differentiate the unit root from the near unit root cases, and therefore, this model is useful when the data indeed belong somewhere between $I(0)$ and $I(1)$. The order of integration of the data is estimated by the model and thus it does not need to be pre-determined. Let me then discuss the ARFIMA-GARCH model itself.

The general specification of the model, ARFIMA(*p*, *d*, *q*)-GARCH(*k*, *l*) consists of the mean and conditional variance equations. The ARFIMA component can be expressed as:

$$\phi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \qquad (1)$$

where ε_t is a residual and is temporally assumed to follow the normal distribution since the ARFIMA model has been developed within this framework. Of course, this assumption of a constant variance will shortly be relaxed to allow the time-varying conditional variance that is required for the ARFIMA-GARCH model. The *L* is a lag operator so that $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots \phi_p L^p$, $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots \theta_q L^q$. All the roots of $\phi(L)$ and $\theta(L)$ lie outside the unit circle. The fractional differencing parameter, *d*, measures the level of integration of the equity index data, i.e., $y_t \sim I(d)$, and $(1-L)^d$ is defined by a binomial series.

$$(1-L)^d = \sum_{j=0}^{\infty} (-1)^j \binom{d}{j} L^j = \sum_{j=0}^{\infty} \frac{\Gamma(j-d)}{\Gamma(-d)\Gamma(j+1)} L^j$$

where Γ is the standard gamma function. Process (1) may have a long-memory process because a shock at time *t* has a long-lasting influence on the future value of the time-series compared with the case of a stationary ARIMA. When the process, y_t, follows the random walk process ($d = 1$), the autocorrelation function remains around unity as $t \to \infty$. In contrast, when $d = 0$ and y_t is white noise, the autocorrelation function exponentially converges to zero ($\rho_j = c\theta^j$ with $|\theta| < 0$). The long-memory process emerges because *d* no longer needs to be an integer. For ARFIMA (0, *d*, 0) and $d \in (-0.5, 0.5)$, the process y_t is weekly stationary and invertible.[2] In the case of $d < 0.5$ and $d \neq 0$, the covariance (3) and correlation (4) functions of y_t can be written respectively as follows (Granger and Joyeux 1979, Hosking 1981):

$$\gamma_j = \mathrm{cov}(\varepsilon_t, \varepsilon_{t-j}) = \frac{\sigma^2}{2\pi}\sin(\pi d)\frac{\Gamma(j+d)}{\Gamma(j+1-d)}\Gamma(1-2d) \tag{3}$$

$$\rho_j = \frac{\gamma_j}{\gamma_0} = \frac{\Gamma(1-d)}{\Gamma(d)}\frac{\Gamma(j+d)}{\Gamma(j+1-d)} \tag{4}$$

where Γ is a gamma function. Based on Sterling's theorem that $\Gamma(j+d)/\Gamma(j+v) \approx j^{d-v}$ as $j \to \infty$, the autocorrelation function of the time-series can be simplified to $\rho_j \approx cj^{2d-1}$ as $j \to \infty$ where *c* is the ratio of gamma functions, which indicates that the autocorrelation function hyperbolically converges to zero with the speed dependent on the size of *d*. Equation (4) suggests that the speed of convergence is much slower than that of the white noise.

The adjustment speed measured by *d* has an implication for the efficient market hypothesis (EMH) that asserts that the equity data is a random walk. It follows that the equity

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[2] Sowell (1990), furthermore, shows that the variance of the partial sums of y_t ($Y_T = \sum_{t=1}^{T} y_t$) increases at the speed of $O(T^{2d+1})$. It follows that the variance grows linearly at $O(T)$ for $d = 0$. The speed of growth for the process with $d \in (-0.5, 0)$ is slower than the case of $d = 0$, and that with $d \in (0, 0.5)$ is faster than a linear rate.

return data should be stationary (i.e., d = 0).[3] While a number of other criteria such as unbiasedness, independence, and the efficiency of the time-series properties of the equity indices need to be considered, the shorter the memory process, the closer the time-series process follows the conditions established for the EMH.

The ARFIMA-GARCH model extends the above model by allowing the variance of ε_t ($\varepsilon_t = v_t\sigma_t$) to follow the standard GARCH process:

$$\beta(L)\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \zeta z_t \tag{5}$$

where $\beta(L) = 1 - \beta_1 L - \beta_2 L^2 - \cdots \beta_k L^k$, and $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \cdots \alpha_l L^l$. The definition of v may differ according to researchers' assumptions with respect to the statistical distribution. The GARCH process is important in explaining the equity data due to the existence of a risk premium and irrational expectations (see Cuthbertson 1996).

Equations (1) and (5) consider the case where the equity indices may be affected by several other economic variables, and thus y_t in equation (1) may be expressed as: $y_t = \Delta p_t - a - b' x_t$, where x_t includes the equity returns of a home country (Δp) and other countries (Δp^*) and the interest rates of domestic and other countries. Similarly, equation (2) includes a vector of extra variables, z_t, which is expected to influence the volatility of Δp and consists of the equity volatility of other countries.

[3] See Cuthbertson (1996) for a comprehensive review of the efficient market hypothesis.

So what then is the difference between price and volatility spillover? Actually, the above-mentioned additional variables help distinguish equity price and volatility spillovers. Equity price spillover is defined as the case where a home stock return, Δp_t, is affected by the returns of other countries, Δp_t^*, which is one of several variables included in the vector *x*. Thus, the existence of this channel is confirmed by the statistical significance of this variable in (1). Similarly, equity volatility spillover is defined as the equity volatility of one country being affected by those of other countries, and thus statistically significant parameters on z_t provide evidence of the existence of volatility spillover.

For the estimation, the conditional distribution is assumed to be the Student-*t* with the number of the degree of freedom, *DF*, following Susmel and Engle (1994). Parameters are estimated by maximizing the following logarithmic likelihood.

$$\begin{aligned}\log L(\phi, d, a, b, \theta, \beta, \omega, \alpha, \zeta) &= T\{\log\Gamma((DF+1)/2) - \log\Gamma(DF/2) - 0.5\log\pi(DF-2)\} \\ &= -0.5\{\sum_{t=1}^{T}\log(\sigma_t^2) + (DF+1)\log(1+v_t^2/(DF-2))\end{aligned} \tag{6}$$

3. Data Description

The data used in this study are daily (5 days a week), cover the sample period 2000:1:3-2002:5:1, and are obtained from DATASTREAM. The starting date has been chosen in order to avoid any chaotic movements of equity indices during the Asian crisis. The equity indices are the Nikkei225 (Japan), the S&P500 (US), the KOSPI (Korea), the Philippines' composite, and the Hang Seng composite (Hong Kong). The equity return is here defined as $\Delta p_t = \ln(P_t / P_{t-1}) \times 100$. It is important to note that this paper employs price returns on equity indices following the literature of equity spillover (e.g., Susmel and Engle 1994, and Koutmos and Booth 1995). Thus, our study is not directly comparable with those using absolute returns ($|\Delta p_t|$) that have been frequently examined and found to possess a long memory process using the ARFIMA model (e.g., Granger and Ding 1996).

In addition, interest rate data are included to capture the stance of the monetary policies of the countries, which are the overnight call rates (Japan and Korea), the federal funds rate (US), the T-bill rate (the Philippines), and the interbank rate (Hong Kong). The inclusion of the interest rates helps differentiate equity index movements that are attributable to changes in interest rates (or more generally monetary policy) and other factors.

Table 1 summarizes the time-series characteristics of changes in the equity indices. It reports that all data are not normally distributed and their mean values are negative, which indicates that the equity indices (in levels) have a declining trend during our sample period. The non-normality of equity returns is reported by a number of researchers (e.g., Koutmos and Booth 1995; Booth *et al* 1997). This table also shows the relatively high correlation between the Nikkei225, the KOSPI, and the Hang Seng composite indices. The low correlation between the Philippines and the other Asian markets likely occurs because of its relatively low level of economic development and the substantially smaller size of its financial market with respect to the number of companies listed, the size of market capitalization, and total turnover.

Finally, for illustrative purposes, the lower half of Table 1 presents the results of the Augmented Dickey-Fuller (ADF) test that examines the order of integration for our data. This table shows that all differenced data are stationary (d = 0) regardless of the lag lengths used in the tests. While it is widely known that unit root tests lack the statistical power to distinguish between stationary and non-stationary data (e.g., Campbell and Perron 1991), our results are consistent with the use of differenced data in previous studies using the GARCH models (e.g., Hamao *et al* 1990). However, as discussed, in order to allow for a possible non-integer order of integration, the next section uses the ARFIMA model that allows us to estimate an order of integration that could be a non-integer, and as will be explained shortly can capture the possible long-memory process of the data.

4. Empirical results

Using the ARFIMA(0, *d*, 0)-GARCH(1, 1) method, this section analyzes the spillover effects of equity price and volatility across countries, and studies the direction, if any, of spillover. Previous research concludes that the stock movements of industrialized countries affect those of emerging markets. Therefore, a desirable specification of emerging markets needs to incorporate the equity stock data of industrialized countries. However, while data on stock returns are readily available, data on the time-varying variance of equity indices are not and thus need to be obtained by some other means. Thus before embarking on an examination of emerging market data, we will, first of all, estimate the volatility of the Nikkei225 and the S&P500.

4.1 Spillover between the Tokyo and New York markets.

This sub-section analyzes the spillover effects between the Tokyo and New York markets under three scenarios: (1) no spillover effects between either market, (2) no spillover originating in Tokyo and transferring to New York, and (3) no spillover from New York to Tokyo. Thus, this part of the paper assumes that the Tokyo and New York equity markets are not influenced by those of Korea, Hong Kong, or the Philippines. This assumption will be relaxed later. The standard ARFIMA-GARCH, without extra vectors (x_t and z_t), is therefore used for (1). Scenario (2) is consistent with previous findings (Hamao *et al* 1990) that spillover effects exist from New York to Tokyo markets.

The model specifications are summarized in Table 2. Notably, all US explanatory variables included in the Nikkei225 equation have a one-day lag because of the time difference between the Tokyo and New York markets.[4] The specification of all models, in general, seems appropriate. The parameters for ARCH and GARCH terms are all statistically significant and within the expected range. The terms representing the degrees of freedom are also significant, thereby implying the importance of a non-normality assumption. Table 2 also shows that, using the five percent criterion, there is no evidence of autocorrelation in the standardized and squared standardized residuals with one exception. The sign bias tests (Engle and Ng 1993) generally suggest that no size bias exists in either a positive or negative direction. Furthermore, although somewhat model sensitive, the estimated sizes of d are, in several cases, statistically significant and all within $-0.5 < d < 0$. In contrast, the results from (1), in particular, indicate that the first differences of equity data are stationary.[5] In short, this table does not provide clear evidence whether the Japanese or the US market follows the EMH.

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[4] US data at time t contains future information that is only available at time $t+1$ to investors in the Tokyo market.

[5] We have also examined the memory length of the absolute returns of our data during our sample period, and found that the absolute returns of all indices follow the long memory process. Using the ARFIMA(0, d, 0)-GARCH(1, 1), the estimated size of d ranges from 0 to 0.5 (0.023 for the Nikkei225, 0.052 for the KOSPI, 0.093 for the Philippine composite, 0.058 for the S&P500, and 0.056 for the Hang Seng composite).

Table 2 indicates that there are price spillovers, but no clear direction indicated between Tokyo and New York during our sample period. With respect to scenario (2), our results show that there is price spillover from New York to Tokyo: the S&P500 is significant in the mean equation of the Nikkei225. However, neither Japanese nor US interest rates are statistically significant determinants of equity returns for either the Nikkei225 or the S&P500. This would suggest that the stance of monetary policy, which is represented by the interest rates, is not a major determinant of the equities. Scenario (3) in Table 2 shows that the Nikkei225 is an important determinant of the S&P500. In other words, a sluggish S&P500 could likely in part be explained by the poor performance of the Nikkei500. This result is consistent with the trend and phenomena pointed out previously (Hamao *et al* 1991, and Lin *et al* 1991). Finally, as far as equity volatility spillovers are concerned, no evidence is provided supporting their existence in either direction. This result is in contrast to Hamao *et al* (1990). While many factors could be considered to explain this discrepancy, including the different sample period and model specification, the use of the Student-*t* distribution would lead us to reject the existence of volatility spillover.[6] It thus underlines the importance of the non-normality assumption when estimating the equity returns.

4.2. Spillover effects between industrialized and emerging economies

[6] Our GARCH(1, 1) results, which are not presented here, confirm the absence of volatility spillover from New York to Tokyo during 1985:4:1 to 1988:3:31 when the assumption of the Student-t distribution is used. In contrast, our data support volatility spillover during the same period when the normality assumption is employed, which is consistent with Hamao *et al* (1990).

Using the volatility data for the Nikkei225 and S&P500 estimated under scenario (1), this sub-section studies the existence of spillover effects between industrialized and emerging economies (Korea, the Philippines, and Hong Kong). The relevant results are presented in Tables 3 and 4, which demonstrate that the model specifications are appropriate in terms of the diagnostic tests, and parameter size and statistical significance of the ARCH, GARCH, and the degrees of freedom terms. It is interesting to note that equity indices of emerging markets do not seem to have a long memory process since the differencing term, *d*, is insignificant (Table 3). One exception is the Philippines' composite that has a long memory ($d \in (0, 0.5)$). The Philippines' equity seems to behave somewhat differently compared with the other emerging markets. While further research is required, this finding may be due to the relatively small and shallow financial market where the impact of news is likely to be more persistent. In short, it could be argued thus that the Philippine market is most distant from the EMH concept.

Tables 3 and 4 show that there is strong evidence of price spillover effects between the industrialized and emerging markets. Price spillover is found from Tokyo and New York to the three emerging economies (Table 3). Similarly, some evidence of the existence of price spillover effects have been reported from emerging markets to industrialized countries (Table 4). While only the Hang Seng composite has affected the S&P500 during our sample period, our data show that the Tokyo market has been affected by price changes in other Asian markets. Indeed, the KOSPI, and the Philippines' and Hang Seng composites are all found to be significant in the mean equations for the Nikkei225. The Hang Seng composite remains in the S&P500 equation perhaps due to its close economic links to the US through its currency being pegged to the US dollar. Overall, our data suggest that unidirectional spillover effects exist from New York to the Korean and Philippine markets, but that there is no unique causality between Tokyo and other Asian markets.

Furthermore, Japanese and US interest rates are found to be irrelevant to the movements of the indices of the three emerging markets. On the contrary, the interest rates of Korea and Hong Kong are significant in explaining their own equity prices. Consistent with economic theory, the parameters of these interest rates are negative, confirming that a decline in interest rates was associated with an increase in equity indices.

Finally, while the ARCH and GARCH terms are statistically significant, there is no evidence to support the existence of volatility spillover in either direction (Tables 3 and 4). It seems that this channel was absent during our sample period.

4.4 Spillover effects among emerging economies

This sub-section extends the analysis of the previous sections and examines spillover effects among emerging markets. Study of spillover among Asian emerging markets is rare, and Wei *et al* (1995) is one exception analyzing volatility spillover between Hong Kong and Taiwan. In order to carry out this study, the interest rates and equity data of Japan and the US are excluded from our models since they were found to be statistically insignificant in previous sections.[7] However, the volatility estimates of the Nikkei225 and the S&P500 remain in the models in addition to those of Asian equities.

The mean equations in Table 5 show evidence of price spillover effects among the three countries. However, there is no spillover in only one direction among emerging

[7] The exclusion of these variables from our models facilitates the model conversion.

economies with the one exception of the KOPSI that affected the Philippines' composite, but not vice-versa. This result is in sharp contrast to previous studies that used samples of "large" and "small" countries (see the introductory section). But our result is somewhat to be expected since most of these financial markets have developed along with their economic growth, and the current institutional and legal frameworks are relatively more comparable with those of industrialized countries.

With respect to volatility spillover, we did not obtain any evidence to support its existence among Asian countries, which is consistent with the result obtained in our previous section.

Finally, this table also confirms our previous finding that the Philippine market is less efficient compared with financial markets of other Asian emerging economies. Its return data exhibit evidence for the long memory since its differencing terms, *d*, alone are statistically significant.

5. Conclusion

This paper revisited the issue of spillover effects across countries using post-Asian crisis data of Hong Kong, Japan, Korea, the Philippines, and the US. Applying the ARFIMA-GARCH method, most Asian equity return data do not exhibit a long memory process. One notable exception is Philippines' equity that shows some evidence of a slow decay of the autocorrelation functions (i.e., long memory). The divergent behavior of the Philippine data would seem to be due to the relatively small and shallow financial market there.

Furthermore, our results have confirmed price spillover effects, particularly among Asian markets: equity returns are often significantly and positively correlated, and mutually affect one another. However, unidirectional spillover has not been generally found except for the US to Korea and the Philippines, and from Korea to the Philippines. Similarly, no evidence is obtained of volatility spillover effects. In addition, our specification has included interest rates, but did not support a strong relationship between the interest rates of industrialized countries and Asian equity movements.

These findings have some policy implications. There is no doubt that the financial markets of Korea, the Philippines, and Hong Kong are integrated with those of the rest of the world, and poor performance in industrialized countries' indices has a devastating effect on the equity indices of the three countries. However, Japanese and US interest rates do not seem to be important determinants of either their own equity indices or those of emerging markets. During periods of low inflation and interest rates in industrialized countries, our study suggests that equity changes in emerging markets tend to be more responsive to other factors (maybe domestic factors) that affect equity prices.

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Table 1. Statistical Description of Equity Indices

	Nikkei225	S&P500	KOSPI	Phil Comp	HK Comp
Data description					
Mean	-0.079	-0.048	-0.028	-0.074	-0.055
SD	1.597	1.137	2.379	1.547	1.670
Skewness	0.078	0.033	-0.498	3.176	-0.591
Normality test Chi^2(2)=	71.157 **	47.628 **	93.451 **	380.180 **	117.810 **
Correlation matrix					
Nikkei225	1.000	--	--	--	--
S&P500	0.196	1.000	--	--	--
KOSPI	0.447	0.193	1.000	--	--
Phil Comp	0.127	0.031	0.107	1.000	--
HK Comp	0.485	0.221	0.549	0.100	1.000
ADF unit root test					
with constant					
Lag-6	-9.584 **	-10.170 **	-9.546 **	-9.211 **	-9.961 **
lag-5	-10.870 **	-10.800 **	-10.380 **	-10.010 **	-10.590 **
lag-4	-11.060 **	-11.750 **	-11.520 **	-11.270 **	-10.980 **
lag-3	-12.970 **	-12.610 **	-12.310 **	-12.590 **	-11.200 **
lag-2	-14.780 **	-15.670 **	-14.830 **	-14.750 **	-13.510 **
lag-1	-18.580 **	-19.370 **	-17.930 **	-17.200 **	-17.760 **
lag-0	-25.200 **	-24.760 **	-24.420 **	-22.160 **	-24.390 **
with constant & trend					
Lag-6	-9.606 **	-10.160 **	-9.781 **	-9.341 **	-9.956 **
lag-5	-10.890 **	-10.790 **	-10.600 **	-10.130 **	-10.590 **
lag-4	-11.080 **	-11.740 **	-11.720 **	-11.380 **	-10.970 **
lag-3	-12.990 **	-12.600 **	-12.490 **	-12.690 **	-11.200 **
lag-2	-14.790 **	-15.660 **	-15.000 **	-14.850 **	-13.500 **
lag-1	-18.590 **	-19.360 **	-18.070 **	-17.270 **	-17.750 **
lag-0	-25.200 **	-24.740 **	-24.540 **	-22.220 **	-24.370 **

Note: The SD stands for standard deviation. Skewness of y_t is $\sqrt{sk} = \mu_3 / \mu_2^{3/2}$ where $\mu_i = E[y_t - \mu]^i$. A normal variate has $\sqrt{sk} = 0$. The normality test is that of Jarque and Bara (1987); the autocorrelation test is the modified Box-Pierce.

The unit root test is that of Dickey and Fuller.

Table 2. ARFIMA-GARCH Estimates of The Nikkei225 and S&P500

	(1)		(2)		(3)	
	Nikkei225	S&P500	Nikkei225	S&P500	Nikkei225	S&P500
			Mean equation			
Cst	-0.095 [0.047] *	-0.040 [0.031]	-0.071 [0.035] *	-0.043 [0.031]	-0.092 [0.046] *	-0.021 [0.021]
Nikkei225	--	--	--	--	--	0.158 [0.032] **
S&P (-1)	--	--	0.403 [0.044] **	--	--	--
Int (Japan)	--	--	0.855 [2.354]	--	0.062 [2.650]	-0.384 [2.498]
Int (US)	--	--	--	-0.632 [0.664]	--	-0.657 [0.653]
Int (US) (-1)	--	--	1.179 [0.666]	--	--	--
d	-0.036 [0.033]	-0.068 [0.035] †	-0.073 [0.032] *	-0.066 [0.035] †	-0.039 [0.033]	-0.129 [0.037] **
			Variance equation			
Cst	0.129 [0.071] †	0.075 [0.044] †	0.119 [0.064] †	0.083 [0.049] †	0.132 [0.073] †	0.100 [0.050] *
Nikkei225V	--	--	--	--	--	-0.019 [0.018]
S&P500V (-1)	--	--	-0.007 [0.032]	--	--	--
GARCH	0.903 [0.038] **	0.888 [0.041] **	0.894 [0.036] **	0.880 [0.044] **	0.902 [0.039] **	0.888 [0.036] **
ARCH	0.047 [0.020] *	0.069 [0.025] **	0.058 [0.020] **	0.073 [0.027] **	0.047 [0.020] *	0.078 [0.025] **
DF	6.260 [1.619] **	6.945 [1.882] **	6.829 [1.859] **	6.864 [1.860] **	6.388 [1.667] **	7.139 [2.106] **
			Residual tests			
Q(5) 1/ =	1.299 (0.935)	4.555 (0.473)	6.801 (0.744)	5.604 (0.847)	1.675 (0.892)	3.004 (0.699)
Q(5) 2/ =	6.433 (0.092) †	0.610 (0.894)	16.549 (0.035) *	3.667 (0.886)	6.481 (0.090) †	2.441 (0.486)
			Sign bias tests			
Sign bias t test	0.013 (0.989)	0.407 (0.684)	0.705 (0.481)	0.838 (0.402)	0.052 (0.958)	0.495 (0.620)
Negative size bias t test	1.398 (0.162)	0.735 (0.462)	1.257 (0.209)	0.344 (0.731)	1.356 (0.175)	0.893 (0.372)
Positive size bias t test	1.625 (0.104)	1.230 (0.219)	1.092 (0.275)	1.132 (0.258)	1.688 (0.092) †	1.258 (0.208)

Note:

1/ standardized residuals ($v_t = \varepsilon_t / \sqrt{\sigma_t^2}$)

2/ squared standardized residuals

The sign bias tests are based on Engle and Ng (1993). The sign bias (1), negative size bias (2), and positive sign bias test (3) can be expressed as follows: (1) $v_t^2 = a + bS_{t-1}^- + \vartheta w_t + e_t$, (2) $v_t^2 = a + bS_{t-1}^- \varepsilon_{t-1} + \beta w_t + e_t$, and (3) $v_t^2 = a + bS_{t-1}^+ \varepsilon_{t-1} + \beta w_t + e_t$, where $w_t = [1, h_{t-1}, \varepsilon_{t-1}^2]'$ and $S_{t-1}^- = 1$ if $\varepsilon_{t-1} < 0$ and $S_{t-1}^- = 0$ otherwise, and $S_{t-1}^+ = 1 - S_{t-1}^-$.

The Cst is the constant, and DF stands for the degree of freedom.

Table 3. Spillover Effects from Industrialized Countries to Emerging Markets.

	KOSPI	Phil Comp	Hang Seng Comp	KOSPI	Phil Comp	Hang Seng Comp	KOSPI	Phil Comp	Hang Seng Comp
Mean equation									
Cst	0.084 [0.062]	-0.109 [0.072]	-0.000 [0.040]	0.083 [0.062]	-0.109 [0.072]	-0.000 [0.040]	0.076 [0.061]	-0.110 [0.072]	-0.005 [0.040]
Nikkei225	0.469 [0.051] **	0.091 [0.028] **	0.326 [0.035] **	0.471 [0.051] **	0.090 [0.028] **	0.326 [0.035] **	0.470 [0.051] **	0.091 [0.028] **	0.328 [0.035] **
S&P500(-1)	0.427 [0.065] **	0.142 [0.035] **	0.470 [0.044] **	0.428 [0.065] **	0.142 [0.035] **	0.470 [0.044] **	0.425 [0.064] **	0.141 [0.035] **	0.468 [0.044] **
Int	-2.858 [1.417] *	0.576 [0.349] †	-1.984 [0.517] **	-2.865 [1.416] *	0.577 [0.349] †	-1.984 [0.517] **	-2.763 [1.415] †	0.575 [0.349] †	-1.960 [0.518] **
Int(Japan)	--	--	--	-2.848 [3.927]	0.452 [3.321]	-0.626 [2.745]	--	--	--
Int(US)(-1)	--	--	--	--	--	--	-0.923 [0.910]	-0.118 [0.510]	-0.716 [0.657]
d	-0.034 [0.032]	0.094 [0.034] **	-0.037 [0.036]	-0.033 [0.032]	0.094 [0.034] **	-0.037 [0.036]	-0.036 [0.032]	0.095 [0.034] **	-0.037 [0.035]
Variance equation									
Cst	0.484 [0.262] †	0.088 [0.174]	0.080 [0.046] †	0.476 [0.260] †	0.089 [0.173]	0.080 [0.046] †	0.496 [0.267] †	0.086 [0.174]	0.082 [0.047] †
Nikkei225V	-0.102 [0.069]	-0.036 [0.070]	-0.017 [0.018]	-0.099 [0.069]	-0.036 [0.070]	-0.017 [0.017]	-0.103 [0.069]	-0.034 [0.070]	-0.017 [0.018]
S&P500V(-1)	0.064 [0.096]	0.231 [0.117] *	0.010 [0.030]	0.062 [0.096]	0.230 [0.117] *	0.010 [0.030]	0.063 [0.096]	0.231 [0.118] *	0.011 [0.030]
GARCH	0.813 [0.075] **	0.622 [0.086] **	0.905 [0.037] **	0.813 [0.075] **	0.623 [0.086] **	0.905 [0.037] **	0.808 [0.076] **	0.622 [0.086] **	0.902 [0.038] **
ARCH	0.101 [0.041] *	0.196 [0.076] *	0.060 [0.022] **	0.102 [0.041] *	0.196 [0.076] *	0.060 [0.022] **	0.103 [0.042] *	0.196 [0.076] *	0.062 [0.022] **
DF	9.335 [3.088] **	3.491 [0.540] **	10.721 [3.802] **	9.435 [3.148] **	3.493 [0.541] **	10.720 [3.802] **	9.444 [3.157] **	3.484 [0.540] **	10.722 [3.792] **
Residual tests									
Q(5) 1/ =	2.601 (0.761)	7.998 (0.156)	2.956 (0.707)	2.767 (0.736)	8.003 (0.156)	2.951 (0.708)	2.906 (0.714)	7.995 (0.157)	3.234 (0.664)
Q(5) 2/ =	0.896 (0.826)	2.630 (0.452)	2.051 (0.562)	0.737 (0.865)	2.661 (0.447)	2.050 (0.598)	0.873 (0.832)	2.629 (0.452)	1.851 (0.604)
Sign bias tests									
Sign bias t test	0.498 (0.619)	1.059 (0.290)	1.260 (0.208)	0.538 (0.591)	1.054 (0.292)	1.258 (0.209)	0.756 (0.449)	1.062 (0.288)	0.952 (0.341)
Negative size bias t test	0.208 (0.836)	0.226 (0.821)	0.965 (0.335)	0.199 (0.843)	0.246 (0.805)	0.963 (0.336)	0.026 (0.979)	0.225 (0.822)	0.804 (0.422)
Positive size bias t test	0.449 (0.653)	0.914 (0.361)	0.979 (0.327)	0.419 (0.675)	0.920 (0.358)	0.981 (0.327)	0.323 (0.746)	0.913 (0.361)	1.101 (0.271)

Table 4. Spillover Effects from Emerging Markets to Industrialized Countries.

	Nikkei225			S&P500		
Mean equation						
Cst	-0.080 [0.033] *	-0.077 [0.038] *	-0.076 [0.035] *	-0.024 [0.021]	-0.021 [0.021]	-0.022 [0.018]
Nikkei225	--	--	--	0.144 [0.035] **	0.157 [0.032] **	0.122 [0.035] **
S&P500(-1)	0.244 [0.044] **	0.392 [0.046] **	0.188 [0.047] **	--	--	--
KOSPI	0.227 [0.024] *	--	--	0.023 [0.023]	--	--
Phil Comp	--	0.082 [0.037] *	--	--	0.010 [0.031]	--
Hang Seng Comp	--	--	0.358 [0.038] **	--	--	0.094 [0.038] *
Int (Korea)	0.609 [0.883]	--	--	0.313 [0.884]	--	--
Int (Phil)	--	0.185 [0.173]	--	--	-0.013 [0.157]	--
Int (Hong Kong)	--	--	0.447 [0.474]	--	--	0.483 [0.473]
Int(Japan)	2.775 [2.456]	0.942 [2.540]	0.692 [2.287]	-0.288 [2.534]	-0.438 [2.521]	-0.429 [2.502]
Int(US)	--	--	--	0.609 [0.654]	-0.633 [0.658]	-0.592 [0.671]
Int(US)(-1)	1.263 [0.639] *	1.161 [0.676] †	1.016 [0.634]	--	--	--
d	-0.079 [0.033] *	-0.066 [0.033] *	-0.069 [0.034] *	-0.136 [0.038] **	-0.131 [0.037] **	-0.164 [0.040] **
Variance equation						
Cst	0.162 [0.076] *	0.139 [0.066] *	0.132 [0.073] †	0.065 [0.072]	0.103 [0.052] *	-0.000 [0.105]
Nikkei225V	--	--	--	-0.011 [0.024]	-0.020 [0.019]	0.008 [0.040]
S&P500V(-1)	0.002 [0.031]	0.001 [0.034]	0.030 [0.045]	--	--	--
KOSPIV	-0.013 [0.011]	--	--	0.009 [0.014]	--	--
Phil CompV	--	-0.009 [0.005] †	--	--	-0.002 [0.008]	--
Hang Seng CompV	--	--	-0.033 [0.033]	--	--	0.118 [0.094]
GARCH	0.891 [0.039] **	0.892 [0.036] **	0.882 [0.049] **	0.875 [0.051] **	0.891 [0.035] **	0.778 [0.104] **
ARCH	0.052 [0.022] *	0.053 [0.019] **	0.051 [0.021] *	0.078 [0.027] **	0.078 [0.025] **	0.083 [0.032] *
DF	6.639 [1.910] **	7.627 [2.290] **	8.872 [3.158] **	2.578 [2.409] **	7.185 [2.140] **	8.592 [3.017] **
Residual tests						
Q(5) 1/ =	1.962 (0.854)	1.550 (0.907)	2.996 (0.701)	2.657 (0.753)	2.937 (0.710)	1.659 (0.894)
Q(5) 2/ =	6.935 (0.074) †	10.444 (0.015) *	6.316 (0.097) †	1.737 (0.629)	2.321 (0.508)	1.250 (0.741)
Sign bias tests						
Sign bias t test	1.899 (0.058)	1.163 (0.245)	0.492 (0.623)	0.662 (0.508)	0.530 (0.596)	0.688 (0.492)
Negative size bias t test	1.718 (0.089)	1.614 (0.107)	1.118 (0.264)	0.719 (0.472)	0.870 (0.384)	0.451 (0.652)
Positive size bias t test	0.101 (0.920)	0.810 (0.418)	1.235 (0.217)	1.211 (0.226)	1.254 (0.210)	1.307 (0.191)

Table 5. Spillover Effects between Emerging Markets

	KOSPI	KOSPI	Phil Comp	Phil Comp	HK Comp	HK Comp
			Mean equation			
Cst	0.088 [0.058]	0.078 [0.059]	-0.113 [0.069]	-0.112 [0.070]	-0.026 [0.038]	-0.002 [0.037]
Nikkei	0.463 [0.051] **	0.308 [0.051] **	0.076 [0.030] *	0.075 [0.031] *	0.244 [0.035] **	0.316 [0.035] **
S&P(-1)	0.419 [0.065] **	0.185 [0.066] **	0.127 [0.036] **	0.123 [0.037] **	0.377 [0.044] **	0.458 [0.044] **
KOSPI	--	--	0.037 [0.021] †	--	0.192 [0.026] **	--
Phil Comp	0.090 [0.057]	--	--	--	--	0.079 [0.033] **
HS Comp	--	0.489 [0.057] **	--	0.051 [0.034] †	--	--
Int (Korea)	-2.875 [1.419] *	-2.176 [1.350]	--	--	--	--
Int (Phil)	--	--	0.542 [0.350]	0.611 [0.341]	--	--
Int (Hong Kong)	--	--	--	--	-1.606 [0.487] **	-2.008 [0.513] **
d	-0.043 [0.033]	-0.035 [0.032]	0.085 [0.035] *	0.090 [0.034] **	-0.039 [0.036]	-0.044 [0.035]
			Variance equation			
Cst	0.453 [0.279]	0.652 [0.358] †	-0.089 [0.244]	-0.096 [0.212]	0.056 [0.051]	0.838 [0.040] *
NikkeiV	-0.096 [0.068]	-0.110 [0.069]	-0.005 [0.080]	0.012 [0.076]	-0.010 [0.016]	-0.021 [0.015]
S&PV(-1)	0.058 [0.095]	0.000 [0.105]	0.244 [0.127] †	0.158 [0.121]	0.011 [0.026]	0.018 [0.026]
KOSPIV	--	--	0.037 [0.042]	--	0.000 [0.009]	--
Phil CompV	0.009 [0.032]	--	--	--	--	-0.009 [0.003] **
HS CompV	--	0.055 [0.138]	--	0.144 [0.112]	--	--
GARCH	0.820 [0.094] **	0.776 [0.108] **	0.595 [0.098] **	0.608 [0.095] **	0.916 [0.042] **	0.919 [0.029] **
ARCH	0.095 [0.045] *	0.089 [0.045] †	0.175 [0.074] *	0.179 [0.075] *	0.049 [0.020] *	0.051 [0.019] **
DF	9.467 [3.254] **	9.359 [3.457] **	3.527 [0.552] **	3.497 [0.543] **	15.208 [8.457] †	10.646 [3.834] **
			Residual tests			
Q(5) 1/ =	2.723 (0.742)	4.268 (0.511)	8.0235 (0.144)	8.296 (0.141)	4.259 (0.513)	3.116 (0.682)
Q(5) 2/ =	0.886 (0.829)	2.280 (0.516)	3.184 (0.365)	2.504 (0.475)	0.807 (0.848)	1.368 (0.713)
			Sign bias tests			
Sign bias t test	0.960 (0.337)	0.597 (0.550)	0.981 (0.327)	0.957 (0.338)	1.358 (0.175)	1.644 (0.100)
Negative size bias t test	0.056 (0.956)	0.838 (0.402)	0.287 (0.774)	1.279 (0.201)	0.484 (0.628)	0.915 (0.360)
Positive size bias t test	0.208 (0.835)	0.665 (0.506)	0.842 (0.400)	0.170 (0.867)	1.915 (0.055) †	0.629 (0.529)