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Transmission Of Equity Returns And Volatility In Asian Developed And Emerging Markets: A Multivariate Garch Analysis

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ABSTRACT

This paper examines the transmission of equity returns and volatility among Asian equity markets and investigates the differences that exist in this regard between the developed and emerging markets. Three developed markets (Hong Kong, Japan and Singapore) and six emerging markets (Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand) are included in the analysis. A multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) model is used to identify the source and magnitude of spillovers. The results generally indicate the presence of large and predominantly positive mean and volatility spillovers. Nevertheless, mean spillovers from the developed to the emerging markets are not homogenous across the emerging markets, and own-volatility spillovers are generally higher than cross-volatility spillovers for all markets, but especially for the emerging markets.

1. INTRODUCTION

Following the massive devaluation of the Thai baht in July 1997, most East Asian and South-East Asian financial markets, particularly in Korea, Malaysia, Indonesia and the Philippines, experienced similarly dramatic devaluations in exchange rates. In these markets managed currencies were allowed to move in a wider band or abandoned altogether, capital control measures were introduced, bank and sovereign ratings were downgraded, and inflationary expectations revised upward along with unemployment (Baig and Goldfajn, 1998; Zhang, 2001; Park and Song, 2001). As the crises intensified, foreign exchange and stock market turmoil spread across Asia. News of economic and political distress, particularly bank and corporate fragility, became commonplace, and modest recoveries in some markets were repeatedly assailed by deteriorating conditions in others. Only by mid 1999 was Asian recovery becoming a reality, and only after extensive microeconomic reform, fiscal contraction and international financial assistance (Boorman, *et al*., 2000).

Quite apart from the posited macroeconomic, structural and policy origins of the Asian economic, currency and financial crises, the manner in which these crises reverberated across national stock markets has created considerable interest in the study of the transmission of returns and volatility among emerging capital markets (Bekaert and Harvey, 1997; Bekaert and Harvey, 2000). Most early studies of market interdependencies and contagion effects have generally relied upon Granger-causality testing of market indices. However, while these studies suggest "…uni-directional (mean return) spillovers from the larger to smaller markets, [they have also generally failed] …to capture the autoregressive second moment of the distribution of stock returns (i.e. the feature that the conditional variance of stock returns is time varying) which results in inconsistent estimates of the ordinary least squares estimation of mean spillovers" (Gallagher and Twomey, 1998: 342).

Accordingly, more recent work has availed itself of the sizeable advances in autoregressive conditional heteroskedastic (ARCH) and generalised autoregressive conditional

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heteroskedastic (GARCH) models to study the conditional volatility of stock markets and ascertain the predictability of future stock return volatility conditional on past volatilities and return shocks [see, for instance, Tse and Zuo (1996), Aggarwal *et al*. (1999), Adrangi *et al*. (1999) and Huang and Yang (2000)]. A few studies have even extended these to the multivariate case [see, for example, Tse (2000), Tay and Zhu (2000) and Scheicher (2001)]. However, relatively few studies have adopted an exclusively Asian regional perspective. And even where Asian markets are examined in a broader multilateral context (that is, along with North American and European markets) there is generally an emphasis on the more developed Asian economies. As far as the authors are aware, no study to date has examined the transmission of returns and volatility across the broad spectrum of Asian emerging and developed markets within the context of the multivariate generalised autoregressive conditional heteroskedastic (MGARCH) model as employed in this analysis.

The paper itself is divided into four main areas. The second section briefly discusses the data to be employed in the analysis. The econometric method used to estimate the mean and volatility spillovers is outlined in the third section. The results are dealt with in the fourth section. The paper ends with some brief concluding remarks.

2. DATA AND SUMMARY STATISTICS

The data employed in the study is drawn from value-weighted equity market indices for nine major Asian markets: namely, Hong Kong (*HON*), Japan (*JAP*), Singapore (*SNG*), Indonesia (*IND*), Korea (*KOR*), Malaysia (*MAL*), the Philippines (*PHI*), Taiwan (*TAI*) and Thailand (*THA*). All data is obtained from Morgan Stanley Capital International (MSCI) and encompasses the period 15 January 1988 to 6 October 2000. Under the MSCI taxonomy, Hong Kong, Japan and Singapore are categorised as 'developed' markets, with the remainder classified as 'emerging' markets. MSCI indices are widely employed in the literature on equity market comovements and volatility transmission on the basis of the degree of comparability and avoidance of dual listing [see, for instance, Meric and Meric (1997), Yuhn (1997), Roca (1999) and Cheung and Lai (1999)].

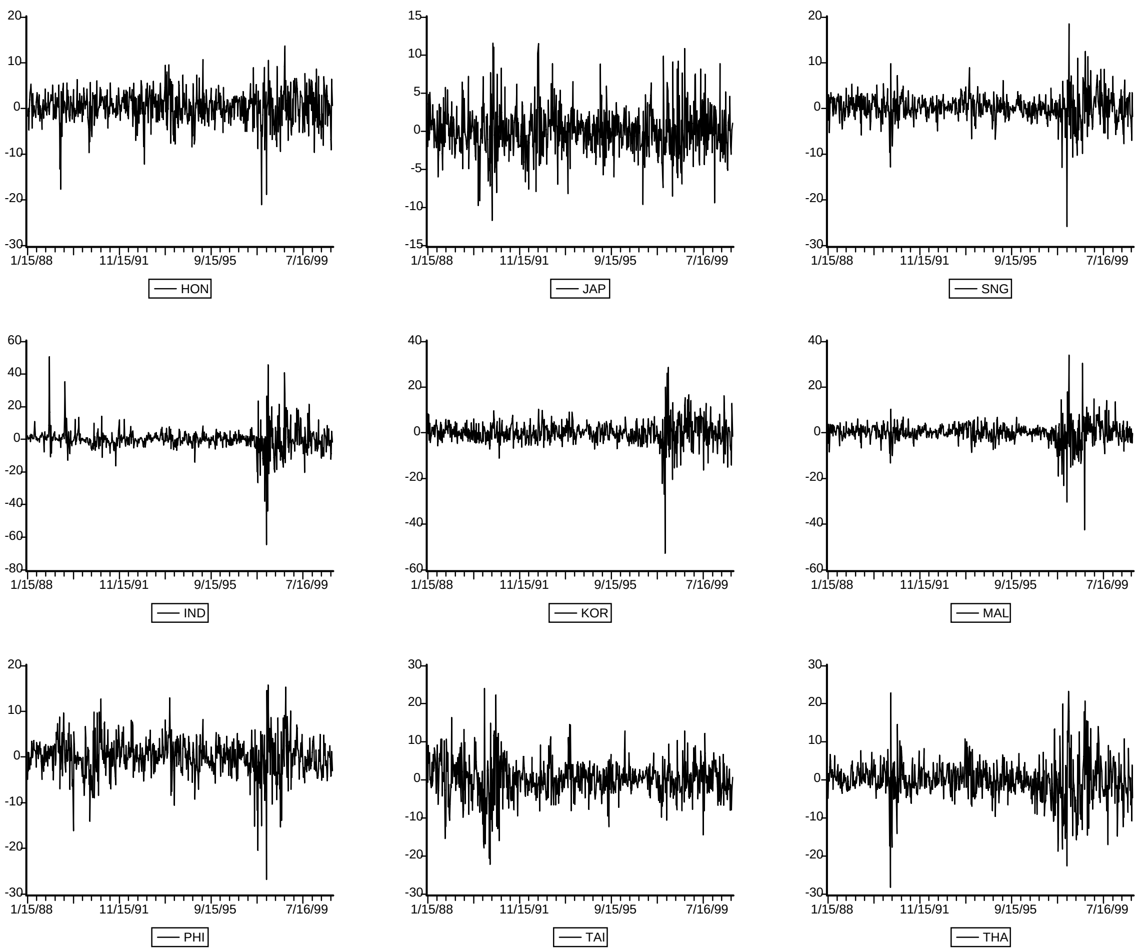
Table 1. Summary statistics of weekly returns for nine Asian markets

	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera statistic	*p*-value
HON	0.2266	0.3459	13.6544	-21.0565	3.7158	-0.7285	6.4835	395.04	0.0000
JAP	0.0024	-0.0769	11.5805	-11.6959	3.2476	0.2925	4.2833	55.11	0.0000
SNG	0.1486	0.2210	18.5059	-25.7944	3.1879	-0.6646	12.4917	2545.26	0.0000
All developed	0.1259	0.1460	18.5059	-25.7944	3.3916	-0.4089	7.4987	1737.87	0.0000
IND	-0.0071	-0.0438	50.6979	-64.4974	7.4889	-0.1234	21.1184	9097.62	0.0000
KOR	0.0037	-0.0172	28.5862	-52.7127	5.3379	-1.2725	20.6453	8806.58	0.0000
MAL	0.0666	0.3651	34.0006	-42.5217	4.8607	-0.8616	20.7008	8763.84	0.0000
PHI	0.0388	0.0831	15.7171	-26.7969	4.1822	-0.6506	7.7071	660.83	0.0000
TAI	0.1360	0.1945	24.0581	-22.1608	5.1860	-0.0166	5.3880	158.04	0.0000
THA	-0.1106	-0.1740	23.3176	-28.1769	5.4166	-0.1537	6.8479	412.88	0.0000
All emerging	0.0212	0.0498	50.6979	-64.4974	5.5035	-0.4222	19.3729	44685.55	0.0000

Weekly data is specified. On one hand, it has been argued "daily return data is preferred to the lower frequency data such as weekly and monthly returns because longer horizon returns can obscure transient responses to innovations which may last for a few days only" (Elyasiani *et al*., 1998: 94). However, Roca (1999: 505), amongst others, has countered "…daily data are deemed to contain 'too much noise' and is affected by the day-of-the-week effect while monthly data are also affected by the month of the year effect". Ramchand and Susmel (1998), Aggarwal *et al*. (1999), and Tay and Zhu (2000) are among the large number of studies that have employed weekly data instead of monthly data in order to provide a sufficient number of observations required to estimate the GARCH or MGARCH models without the noise of daily data. The weekly return in the market i is represented by the continuously compounded return or log return of the index (in US dollar terms) at time t such that $\Delta p_{it} = \log(p_{it}/p_{it-1}) \times 100$ where Δp_{it} denotes the rate of change of p_{it}.

Table 1 presents descriptive statistics for each return series for the period 1988 to 2000. Samples means, medians, maximums, minimums, standard deviations, skewness, kurtosis and the Jacque-Bera statistic and p-value are reported for the weekly dollar returns. The highest mean returns are in Hong Kong (0.2266%) and Singapore (0.1486%) while the lowest are in Indonesia (–0.0071%) and Thailand (-0.1106%). Weekly returns are also higher across the three developed markets (0.1259%) than in the six emerging markets (0.0212%).

Figure 1. Asian developed and emerging markets weekly returns, January 1988 to October 2000



As anticipated, volatility (as measured by standard deviation) is also higher in the emerging markets as against the developed markets. The three developed markets display similar levels of volatility ranging from 3.19 (Singapore) to 3.72 (Hong Kong). The volatility across the three developed markets is 3.39 percent. The standard deviations for the emerging markets on the other hand range from 4.18 (Philippines) to 7.49 (Indonesia). Of the emerging markets, Malaysia and the Philippines are the least volatile, while Indonesia and Thailand are the most volatile. The volatility across the six emerging markets is 5.5 percent. A visual perspective on the volatility of returns can be gained from the plots of weekly returns for each series in Figure 1. These findings are in accordance with the recent international analysis of equity returns and volatility by Erb *et al.* (1996).

The distributional properties of the return series generally appear to be non-normal. All of the emerging markets have negative skewness, while in contrast among the developed markets Hong Kong and Singapore are negatively skewed while Japan is positively skewed. Huang and Yang (2000) and Tay and Zhu (2000), amongst others, have documented positive and/or negative skewness in Asian equity returns. The kurtosis, or degree of excess, in all markets, both developed and emerging, exceeds three, indicating a leptokurtic distribution. Excess kurtosis in equity returns has been well documented by a number of other studies including Bekaert and Harvey (1997). The final statistic in Table 1 is the calculated Jarque-Bera statistic and corresponding p-value used to test the null hypotheses that the weekly distribution of returns are normally distributed. With all p-values equal to zero at four decimal places, we reject the null hypothesis that returns for developed and emerging Asian markets are well approximated by the normal distribution.

3. MULTIVARIATE GARCH MODEL

Autoregressive conditional heteroscedasticity (ARCH) and generalised ARCH (GARCH) models that take into account the time-varying variances of univariate economic time series data have been widely employed. Suitable surveys of ARCH modeling in general and its widespread use in finance applications may be found in Bera and Higgins (1993) and Bollerslev *et al*. (1992) respectively. Pagan (1996) also contains discussion of recent developments in this expanding literature.

More recently, the univariate GARCH model has been extended to the multivariate GARCH (MGARCH) case, with the recognition that MGARCH models are potentially useful developments regarding the parameterization of conditional cross-moments. For example, Bollerslev (1990) used a MGARCH approach to examine the coherence in short-run nominal exchange rates, while Karolyi (1995) employed a similar model to examine the international transmission of stock returns between the United States and Canada. Dunne (1999) also employed a MGARCH model, though in the context of accommodating time variation in the systematic market-risk of the traditional capital asset pricing model (CAPM). And Kearney and Patton (2000) used a series of 3-, 4- and 5- variable MGARCH models to study the transmission of exchange rate volatility across European Monetary System (EMS) currencies prior to the introduction of the single currency. However, while the popularity of models such as these has increased in recent years, "…the number of reported studies of multivariate GARCH models remains small relative to the number of univariate studies" (Kearney and Patton, 2000: 34).

The following MGARCH model is developed to examine the joint processes relating the weekly rates of return for nine Asian equity markets from 15/1/1988 to 6/10/2000. The sample period is chosen on the basis that it represents the longest common time period over which data for most of the major emerging Asian markets is available. The nine countries examined are: Hong Kong (*HON*), Japan (*JAP*), Singapore (*SNG*), Indonesia (*IND*), Korea (*KOR*), Malaysia (*MAL*), the Philippines (*PHI*), Taiwan (*TAI*) and Thailand (*THA*). Of these, three are generally regarded as developed markets (*HON*, *JAP* and *SNG*) with the remainder defined as emerging markets. The following conditional expected return equation accommodates each market's own returns and the returns of other markets lagged one period.

$$R_t = \alpha + AR_{t-1} + \varepsilon_t \quad (1)$$

where R_t is an $n \times 1$ vector of weekly returns at time t for each market and $\varepsilon_t | I_{t-1} \sim N(0, H_t)$. The $n \times 1$ vector of random errors, ε_t is the innovation for each market at time t with its corresponding $n \times n$ conditional variance-covariance matrix, H_t. The market information available at time t - 1 is represented by the information set I_{t-1}. The $n \times 1$ vector, α, represent long-term drift coefficients. The estimates of the elements of the matrix, A, can provide measures of the significance of the own and cross-mean spillovers. This multivariate structure then enables the measurement of the effects of the innovations in the mean stock returns of one series on its own lagged returns and those of the lagged returns of other markets.

Engle and Kroner (1995) present various MGARCH models with variations to the conditional variance-covariance matrix of equations. For the purposes of the following analysis, the BEKK (Baba, Engle, Kraft and Kroner) model is employed, whereby the variance-covariance matrix of equations depends on the squares and cross products of innovation ε_t and volatility H_t for each market lagged one period. One important feature of this specification is that it builds in sufficient generality, allowing the conditional variances and covariances of the stock markets to influence each other, and, at the same time, does not require the estimation of a large number of parameters (Karolyi 1995). The model also ensures the condition of a positive semi-definite conditional variance-covariance matrix in the optimisation process, and is a necessary condition for the estimated variances to be zero or positive. The BEKK parameterisation for the MGARCH model is written as:

$$H_t = B'B + C'\varepsilon_t \varepsilon_{t-1} C + G'H_{t-1}G \quad (2)$$

where b_{ij} are elements of an $n \times n$ symmetric matrix of constants B, the elements c_{ij} of the symmetric $n \times n$ matrix C measure the degree of innovation from market i to market j, and the elements g_{ij} of the symmetric $n \times n$ matrix G indicate the persistence in conditional volatility between market i and market j.

The BHHH (Berndt, Hall, Hall and Hausman) algorithm is used to produce the maximum likelihood parameter estimates and their corresponding asymptotic standard errors. Overall, the proposed model has eighty-one parameters in the mean equations, excluding the nine constant (intercept) parameters, and forty-five intercept, forty-five white noise and forty-five volatility parameters in the estimation of the covariance process, giving two hundred and twenty-five parameters in total. Finally, the Ljung-Box Q statistic is used to test for randomness in the noise terms, ε_t, for the estimated MGARCH model and is asymptotically distributed as χ^2 with (p - k) degrees of freedom and k is the number of explanatory variables. The Q test statistic is used to test the null hypothesis that the model is correctly specified, or equivalently, that the noise terms are random.

4. EMPIRICAL RESULTS

The estimated coefficients and standard errors for the conditional mean return equations are presented in Table 2. Three Asian markets, namely Hong Kong, Indonesia and Korea, exhibit significant mean-spillovers from Japanese returns. The Hong Kong mean return is significantly influenced in future periods of one week by the present return shocks of the Japanese market. The three significant Japanese mean spillovers that exist range from -0.0387 (Indonesia) to 0.0658 (Hong Kong). The mean return for the Thai market is influenced by the lagged returns of the markets in Hong Kong, Singapore, Indonesia, Korea, and the Philippines, whereas the Singaporean and Taiwanese markets are not influenced by the returns of other Asian markets. Of the nine Asian markets, the lagged returns of Japan, Korea and Thailand have the greatest overall influence.

Table 2. Estimated coefficients for conditional mean return equations

	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
	HON (i = 1)		JAP (i = 2)		SNG (i = 3)	
α	0.2130	0.1703	0.0231	0.1412	0.1195	0.1440
a_{i1}	0.0439	0.0636	0.0376	0.0589	-0.0154	0.0923
a_{i2}	*0.0707	0.0479	-0.0626	0.0552	-0.0272	0.0717
a_{i3}	*0.0658	0.0488	0.0226	0.0534	-0.1008	0.0792
a_{i4}	0.1515	0.1331	0.1094	0.1313	-0.0987	0.1691
a_{i5}	0.0116	0.0765	**0.1407	0.0702	-0.0817	0.1262
a_{i6}	0.0743	0.0790	-0.0616	0.0799	-0.0591	0.1123
a_{i7}	***0.1613	0.0635	0.0018	0.0665	-0.0024	0.1103
a_{i8}	0.0762	0.0798	-0.0152	0.0761	-0.0317	0.1107
a_{i9}	*0.1018	0.0731	0.0242	0.0899	-0.0445	0.1319
	IND (i = 4)		KOR (i = 5)		MAL (i = 6)	
α	-0.0998	0.3503	0.0085	0.2255	0.0527	0.2306
a_{i1}	0.0010	0.0324	0.0374	0.0405	-0.0472	0.0421
a_{i2}	*-0.0387	0.0251	**0.0588	0.0328	-0.0558	0.0476
a_{i3}	0.0205	0.0279	0.0383	0.0331	-0.0377	0.0367
a_{i4}	-0.0022	0.0695	0.0866	0.0910	***-0.2693	0.0865
a_{i5}	-0.0447	0.0457	**-0.1204	0.0597	-0.0428	0.0645
a_{i6}	-0.0015	0.0450	*0.0736	0.0506	-0.0393	0.0750
a_{i7}	-0.0306	0.0352	0.0020	0.0436	-0.0350	0.0553
a_{i8}	-0.0068	0.0461	0.0385	0.0549	-0.0330	0.0631
a_{i9}	-0.0324	0.0425	-0.0123	0.0542	*-0.1098	0.0815
	PHI (i = 7)		TAI (i = 8)		THA(i = 9)	
α	-0.0483	0.1859	0.1668	0.2259	-0.1830	0.2527
a_{i1}	0.0085	0.0530	0.0055	0.0338	*0.0595	0.0411
a_{i2}	0.0220	0.0446	-0.0224	0.0272	-0.0210	0.0343
a_{i3}	0.0583	0.0472	0.0259	0.0287	**0.0587	0.0350
a_{i4}	0.0246	0.1159	0.0751	0.0737	**0.1885	0.0883
a_{i5}	0.0170	0.0697	0.0262	0.0454	***0.1537	0.0566
a_{i6}	0.0160	0.0673	0.0356	0.0475	0.0497	0.0483
a_{i7}	0.0191	0.0619	0.0326	0.0350	***0.1129	0.0426
a_{i8}	***0.2150	0.0673	0.0105	0.0546	-0.0416	0.0596
a_{i9}	***0.1934	0.0759	-0.0167	0.0531	0.0601	0.0631

Notes: Asterisks indicate significance at the * - .10, ** - .05 and *** - .001 level.

Importantly, the mean spillovers from the developed markets to the emerging markets are not homogeneous across the six emerging markets. For example, only Korea and Indonesia exhibit a significant mean spillover from Japan, and only Thailand from Hong Kong and Singapore. Equally important, the significant mean spillovers that do exist from developed to emerging markets are generally small. For example, a one percent increase in the Hong Kong market will only Granger-cause the Thai market to increase by 0.06 percent over the following week.

Similarly, a one percent increase in the Japanese market is also only associated with a 0.06 percent increase in the Korean market. By way of contrast, the mean spillovers within Asian emerging markets are associated with larger magnitudes of change in the Granger-caused markets. For instance, a one percent increase in the Taiwanese and Thai markets Granger-causes a 0.21 and 0.19 percent increase respectively in the Phillipines market. And the magnitudes of causation for the Thai market are overwhelmingly larger for the merging markets than for the developed markets: to be exact, Indonesia (0.188), Korea (0.153) and the Philippines (0.1129) as against Hong Kong (0.059) and Singapore (0.058). Nonetheless, the conditional mean equations only partly support earlier findings that Asian emerging markets lag behind Asian developed markets. While innovations from some of the developed markets do get incorporated into certain emerging markets with a lag, for most of the emerging markets there are relatively few own and mean-spillover effects at play. Exceptions include Thailand that has two significant and positive spillovers from developed markets (Hong Kong and Singapore) and three from other emerging markets (Indonesia, Korea and the Philippines), and Taiwan, which has no significant, own and cross mean-spillover effects.

The conditional variance covariance equations incorporated in the current paper's multivariate GARCH methodology effectively capture the volatility and cross volatility spillovers among Asian emerging markets. These have not generally been considered by previous studies. Table 3 presents the estimated coefficients for the variance covariance matrix of equations. These quantify the effects of the lagged own and cross innovations and lagged own and cross volatility persistence on the present own and cross volatility of the nine Asian markets. And consistent with several other studies, the coefficients of the variance covariance equations are significant for own and cross innovations and volatility spillovers to the individual returns for all Asian markets, indicating the presence of ARCH and GARCH effects.

Own-volatility spillovers in all markets are large and significant indicating the presence of strong ARCH effects. The own-volatility spillover effects range from 0.0824 (Korea) to 0.0969 (Phillipines). With the exception of Hong Kong, own-volatility spillover effects are generally higher for the emerging markets than for the developed markets. In terms of cross-volatility effects in the emerging markets, past innovations in Japan have the greatest effect on future volatility in Indonesia from among past innovations in other developed market returns. This condition also holds for Korea, the Philippines and Thailand. However, in the case of Malaysia and Taiwan past innovations in Singapore have the greatest influence on future volatility. Importantly, while innovations in all nine Asian markets influence the volatility of all other markets, the own-volatility spillovers are generally larger than the cross-volatility spillovers. This would suggest that past volatility shocks in individual developed and emerging markets have a greater effect on future volatility than past volatility shocks in other markets.

In the GARCH set of parameters, all of the estimated coefficients are significant. For Hong Kong the lagged volatility persistence range from 0.79 for Indonesia to 0.85 for Taiwan. This means that the past volatility shocks in Taiwan have a greater effect on the future Hong Kong volatility over time than the past volatility shocks in other Asian returns. Conversely, in Thailand the post volatility shocks range from 0.81 for Malaysia to 0.84 for Korea. In terms of cross-volatility persistence in Asia, the most influential market would appear to be Taiwan. That is, past volatility shocks in Taiwan in combination with the volatility persistence in two developed markets and three emerging markets, has the greatest effect on the future volatility in these markets. As a general rule, the average emerging cross-volatility persistence is greater for developed markets than in the emerging markets.

Table 3. Estimated coefficients for variance covariance equations

	HON ($i = 1$)		JAP ($i = 2$)		SNG ($i = 3$)		IND ($i = 4$)		KOR ($i = 5$)		MAL ($i = 6$)		PHI ($i = 7$)		TAI ($i = 8$)		THA ($i = 9$)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
b_{i1}	1.2281	0.4639	0.2668	0.1907	0.4667	0.1514	0.7355	0.4934	0.3226	0.2280	0.4626	0.2586	0.4448	0.2181	0.2743	0.1582	0.5856	0.1582
b_{i2}	0.2668	0.1907	0.9596	0.3899	0.2793	0.1410	0.1605	0.2631	0.4145	0.2749	0.2648	0.1795	0.1854	0.1398	0.2455	0.1872	0.3576	0.2206
b_{i3}	0.4667	0.1514	0.2793	0.1410	0.6471	0.1757	0.6669	0.2799	0.2971	0.1649	0.5613	0.1754	0.4305	0.1523	0.3400	0.1540	0.6942	0.1953
b_{i4}	0.7355	0.4934	0.1605	0.2631	0.6669	0.2799	4.0176	0.9810	0.4857	0.3835	0.8443	0.4842	0.7983	0.3386	0.0985	0.2749	0.8772	0.4785
b_{i5}	0.3226	0.2280	0.4145	0.2749	0.2971	0.1649	0.4857	0.3835	1.9041	0.7638	0.3105	0.2646	0.2504	0.2032	0.1582	0.2398	0.5867	0.2996
b_{i6}	0.4626	0.2586	0.2648	0.1795	0.5613	0.1754	0.8443	0.4842	0.3105	0.2646	1.5155	0.4747	0.5630	0.2589	0.3566	0.2777	0.8607	0.3806
b_{i7}	0.4448	0.2181	0.1854	0.1398	0.4305	0.1523	0.7983	0.3386	0.2504	0.2032	0.5630	0.2589	1.3966	0.5640	0.3771	0.2382	0.7967	0.2750
b_{i8}	0.2743	0.1582	0.2455	0.1872	0.3400	0.1540	0.0985	0.2749	0.1582	0.2398	0.3566	0.2777	0.3771	0.2382	1.9264	0.6680	0.5654	0.2736
b_{i9}	0.5856	0.1582	0.3576	0.2206	0.6942	0.1953	0.8772	0.4785	0.5867	0.2996	0.8607	0.3806	0.7967	0.2750	0.5654	0.2736	2.2681	0.6763
c_{i1}	0.0936	0.0251	0.0779	0.0308	0.0797	0.0209	0.0885	0.0421	0.0783	0.0315	0.0846	0.0290	0.0841	0.0295	0.0784	0.0273	0.0799	0.0215
c_{i2}	0.0779	0.0308	0.0825	0.0245	0.0841	0.0217	0.0920	0.0341	0.0833	0.0348	0.0702	0.0319	0.0911	0.0324	0.0756	0.0292	0.0860	0.0229
c_{i3}	0.0797	0.0209	0.0841	0.0217	0.0825	0.0220	0.0893	0.0189	0.0721	0.0245	0.0808	0.0265	0.0835	0.0217	0.0900	0.0261	0.0851	0.0184
c_{i4}	0.0885	0.0421	0.0920	0.0341	0.0893	0.0189	0.0934	0.0273	0.0865	0.0248	0.0851	0.0330	0.0880	0.0258	0.0681	0.0359	0.0826	0.0283
c_{i5}	0.0783	0.0315	0.0833	0.0348	0.0721	0.0245	0.0865	0.0248	0.0824	0.0266	0.0710	0.0376	0.0790	0.0318	0.0621	0.0405	0.0727	0.0237
c_{i6}	0.0846	0.0290	0.0702	0.0319	0.0808	0.0265	0.0851	0.0330	0.0710	0.0376	0.0900	0.0297	0.0921	0.0285	0.0854	0.0383	0.0935	0.0277
c_{i7}	0.0841	0.0295	0.0911	0.0324	0.0835	0.0217	0.0880	0.0258	0.0790	0.0318	0.0921	0.0285	0.0969	0.0345	0.0862	0.0238	0.0865	0.0197
c_{i8}	0.0784	0.0273	0.0756	0.0292	0.0900	0.0261	0.0681	0.0359	0.0621	0.0405	0.0854	0.0383	0.0862	0.0238	0.0875	0.0256	0.0817	0.0282
c_{i9}	0.0799	0.0215	0.0860	0.0229	0.0851	0.0184	0.0826	0.0283	0.0727	0.0237	0.0935	0.0277	0.0865	0.0197	0.0817	0.0282	0.0892	0.0221
g_{i1}	0.8063	0.0543	0.8186	0.0894	0.8371	0.0394	0.7932	0.0921	0.8364	0.0675	0.8352	0.0622	0.8276	0.0576	0.8495	0.0509	0.8323	0.0426
g_{i2}	0.8186	0.0894	0.8163	0.0572	0.8238	0.0553	0.8004	0.0790	0.7966	0.0872	0.8582	0.0649	0.8113	0.0650	0.8430	0.0702	0.8183	0.0543
g_{i3}	0.8371	0.0394	0.8238	0.0553	0.8417	0.0339	0.8150	0.0385	0.8474	0.0493	0.8414	0.0389	0.8322	0.0409	0.8260	0.0530	0.8284	0.0320
g_{i4}	0.7932	0.0921	0.8004	0.0790	0.8150	0.0385	0.8178	0.0402	0.8357	0.0530	0.8170	0.0587	0.8236	0.0461	0.8507	0.0846	0.8321	0.0481
g_{i5}	0.8364	0.0675	0.7966	0.0872	0.8474	0.0493	0.8357	0.0530	0.8345	0.0512	0.8340	0.0932	0.8266	0.0702	0.8483	0.1066	0.8426	0.0526
g_{i6}	0.8352	0.0622	0.8582	0.0649	0.8414	0.0389	0.8170	0.0587	0.8340	0.0932	0.8281	0.0427	0.8193	0.0595	0.8456	0.0750	0.8093	0.0597
g_{i7}	0.8276	0.0576	0.8113	0.0650	0.8322	0.0409	0.8236	0.0461	0.8266	0.0702	0.8193	0.0595	0.8148	0.0597	0.8302	0.0607	0.8165	0.0414
g_{i8}	0.8495	0.0509	0.8430	0.0702	0.8260	0.0530	0.8507	0.0846	0.8483	0.1066	0.8456	0.0750	0.8302	0.0607	0.8344	0.0455	0.8269	0.0542
g_{i9}	0.8323	0.0426	0.8183	0.0543	0.8284	0.0320	0.8321	0.0481	0.8426	0.0526	0.8093	0.0597	0.8165	0.0414	0.8269	0.0542	0.8181	0.0401

An examination of the diagonal values, or the own-volatility persistence, for the GARCH effects indicates that overall persistence of stock market volatility is highest for Singapore (0.84) and lowest for Hong Kong (0.81). On average the own volatility persistence for the developed countries are lower (0.8214) than that of the emerging countries (0.8246). This would suggest that developed markets in Asia derive relatively more of their volatility persistence from outside the domestic market, whereas emerging markets derive relatively more of their volatility persistence from within the domestic market. That is, emerging markets are relatively less susceptible to conditions within the region, so far as volatility is concerned, than the developed markets.

Table 4. Tests for standardized residuals

	HON	JAP	SNG	IND	KOR	MAL	PHI	TAI	THA
L-B statistic	13.5800	14.8000	18.4900	14.9900	12.7400	24.7700	15.3900	16.6400	13.5800
p-value	0.3281	0.2525	0.1017	0.2419	0.3880	0.0160	0.2207	0.1638	0.3286

Finally, the Ljung-Box *Q* statistics in Table 4 show no evidence of autocorrelation in the standardised residuals (all of the *p*-values are greater than .05) with the exception of Malaysia (a *p*-value of 0.016). Given that eight of the nine conditional expected return equations provide an adequate description of the data, we can conclude that the conditional mean return equations are correctly specified.

5. CONCLUDING REMARKS

This paper examines the transmission of equity returns and volatility among nine Asian equity markets during the period 1988 to 2000. Three of these markets are regarded as developed (Hong Kong, Japan and Singapore) while the majority is categorised as emerging (namely, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand). A multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) model is used to identify the source and magnitude of spillovers. The estimated coefficients from the conditional mean return equations indicate, as expected, that all Asian equity markets are highly integrated. Nevertheless, mean spillovers from the developed to the emerging markets are not homogenous across the emerging markets, suggesting that some markets may be more useful in forecasting equity returns in emerging markets than others. Own-volatility spillovers are also generally higher than cross-volatility spillovers for all markets, but especially for the emerging markets. This would indicate that changes in volatility in emerging markets from domestic conditions are relatively more important than those usually found in developed markets, at least in the Asian context.

This analysis could be extended in a number of ways. One approach would be to estimate a system of non-symmetrical conditional variance equations for an identical set of data. This would allow the analysis of cross volatility innovations and persistence to vary according to the direction of the information flow. Unfortunately, strict computing requirements did not permit the application of this model with the broad set of developed and emerging markets specified in the analysis. With time, the set of Asian emerging markets included in the analysis could also be extended. For instance, MSCI equity indices have recently been calculated for Sri Lanka, India, Pakistan, Vietnam and China. This would permit greater empirical certainly on the nature and significance of mean and volatility spillovers among Asian emerging markets.

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