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State Dependent Correlation and Lead-Lag Relation when Volatility of Markets is Large: Evidence from the US and Asian Emerging Markets

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By using the filtered probability calculated from the SWARCH model (Hamilton and Susmel (1994)), this paper examines the state of volatility of the equity markets. More specifically, we explore the nature of correlation coefficients and lead-lag relations between the US and the emerging economies. Such relations and correlation are found to have intensified during the Asian financial crisis. In the case when the volatility was great, US stock prices clearly led the emerging markets. Furthermore, stock prices of Japan, Hong Kong and Singapore also led the Asian emerging markets.

I. Introduction

The flow of portfolio investments to emerging financial markets experienced a significant increase from $6.2 billion in 1987 to $37.2 billion in 1992 (Gooptu (1994)). Although debt instruments - bonds, certificates of deposit and commercial paper - are still the main components of such flows, portfolio investors have shown increasing interest in equities of developing countries. For example, Claessens and Gooptu (1994) estimate that the flow of foreign capital to the equity markets of emerging economies almost doubled from $7.6 billion in 1991 to $13.1 billion in 1992. Needless to say, the revival of emerging financial markets after the debt crisis of the early 1980s represents a new challenge to researchers. However, the recent turmoil in Asian markets has cast a dark cloud over the stability of international portfolio investment, especially in the presence of large volatility. Since July of 1997, the ‘Asian Flu’ spread out rapidly to Hong Kong, South Korea and Japan. On October 27, the Hang Seng index plummeted 1438 points as a result of sky rocketing short term interest rate in an effort to prevent the Hong Kong dollar from depreciating. Triggered by the free fall of the Hang Seng index, the Dow Jones Industrial Average (DJIA) suffered a 554.26 point loss. As shown in Table 1, all nine major Asian stock markets experienced serious set backs, ranging from 13.4%

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in Thailand to 40.3% in Indonesia. It is to be pointed out that average rate of return in the Asian markets is higher than that of developed nations, so is their volatility.[1] Admittedly, low correlation between the emerging and the developed equity markets is of particular interest to portfolio managers who use international diversification to reduce risk. Nonetheless, major events like the so-called 'Asian Flu' would undoubtedly add profound volatility to the markets. As such a question often raised is whether the international correlation (or interdependence) increases in period of high turbulence. The presence of volatility in markets is precisely the culprit when the benefit of risk diversification is needed most. It is therefore to the disadvantage of international portfolio managers if large volatility accompanies high correlation.

Table 1 A Comparison of Daily Stock Prices and Exchange Rates Between July 1 and November 14, 1997

stock index	HKN	IND	JPN	KOA	MAL	PHI	SIG	THA	TWN
11/14/97	9957.33	436.84	15082.52	520.01	677.47	1844.95	425.89	456.87	7482.92
7/1/97	15196.79	731.61	20175.52	758.03	1078.90	2815.54	494.00	527.28	9030.28
% Change	-34.48%	-40.29%	-25.24%	-31.40%	-37.21%	-34.47%	-13.79%	-13.35%	-17.14%

Note: HKN = Hong Kong, IND = Indonesia, JPN = Japan, KOA = Korea, MAL = Malaysia, PHI = Philippines, SIG = Singapore, THA = Thailand, TWN = Taiwan. All prices are based on daily market close; all exchange rates are expressed as number of local currencies per US dollar.

Prior studies largely fall into two categories. First, like many others, Ratner (1992) claims that the international correlations remain relatively constant over the period of 1973-89. Hence a set of constant correlation coefficients is indicative of stable interaction among equity markets. Second, the correlation relation is found to be evolving through time. For example, employing daily data for the eight markets over the three years (1972, 1980 and 1987), Koch and Koch (1991) conclude from a simple Chow test that international markets have recently grown more interdependent. Moreover, Longin and Solnik (1995) discover via a multivariate GARCH model that the correlation is increasing in periods of high market volatility. The phenomenon is reinforced by Solnik *et al.* (1996). Similar results may be found in King and Wadhwani (1990), King, Sentana and Wadhwani (1994) and Karolya and Stulz (1996), Erb, Harvey, and Viskanta (1994). In particular, their findings demonstrate that correlations are higher in bear markets and during recession. One stylized fact found in Bekaert and Harvey (1997) reveals again that the correlation between markets rises in the periods when the volatility of markets is large. It seems that the international correlation increases when global factors dominate domestic ones and affect all financial markets. The dominance of global factors tends to be associated with major events (e.g., the oil crises, the Gulf war etc.). Viewed in this perspective, we expect a stronger correlation (interaction) among various national stock markets during the period of high volatility than in a period of low volatility.

Generally speaking, previous analyses consider primarily unconditional correlation computed over different subperiods. In this paper, we propose an explicit model that

1. See Bekaert and Harvey (1997).

provides conditional correlation coefficients in different states of volatility. Beyond that, we apply the Granger-causality model to analyze the interaction between different states (low and high volatility) among various national stock markets. Low coefficients are found to exist between most of the Asian emerging markets and the US in terms of unconditional correlation. However, after taking different states into consideration via the filtered probability of the Markov-switching model, asymmetrical state-dependent correlation coefficients begin to surface. This is to say, while in state one (low volatility), the correlation between the US and the Asian emerging markets is low, becoming stronger and significant in state two (high volatility). Applying the Granger-causality test, we find stronger interactions in a high volatility period, but only weak interdependence when the volatility is low. The result is in general agreement with Bekaert and Harvey (1995). The next section discusses the Markov Switching model (MS); Section III provides a description of data and results from the MS model; Section IV presents (i) the state-dependent correlation coefficients conditional on the probabilities estimated from the MS model and (ii) the Granger-causality results. Section V illustrates that cumulative abnormal profit in state 1 is generally positive but becomes negative in state 2. A conclusion is given in the last section.

II. Switching ARCH (SWARCH) Model[2]

Consider an AR(p)-GARCH(p,q) process for variable y_t:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t ;\quad \varepsilon_t \sim N(0, h_t), \tag{1}$$

$$\varepsilon_t = \sqrt{h_t}\, w_t,$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \gamma_j h_{t-j}, \tag{2}$$

where w_t is assumed to be i.i.d. and N(0,1). This model has found a wide variety of applications in the finance literature and its appeal lies in the ability to capture the time varying nature of volatility. Notwithstanding its strength, such a model, however, fails to capture structural shifts in the data caused by low probability events (e.g., the crash of 1987, recession or recent Asian financial crisis). Diebold (1986), as well as Lamoreux and Lastrapes (1990) argues that the persistence frequently found in the ARCH models is due to the presence of structural breaks. Cai (1994), Brunner (1991) and Hamilton and Susmel (1994) modify the ARCH specification to account for such structural changes in data and propose a switching ARCH (SWARCH) model where the variance Equation (2) is revised to be:

$$\varepsilon_t = \sqrt{g_{s_t}} \cdot u_t,$$

2. The model is primarily based on Hamilton and Lin (1996).

$$u_t = \sqrt{h_t} \cdot w_t, \tag{3}$$
$$h_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-1}^2 .$$

Note w_t is assumed to be i.i.d. and N(0,1),[3] ; s_t is an unobserved latent variable that represents the volatility phases of a stock market. In absence of such phases, the parameter g_{s_1} would simply equal unity for all t. In that case Equation (3) describes stock returns with an autoregression whose residual ε_t follows a pth-order ARCH process.

More generally, for g_{s_1} not identically equal to unity, the latent ARCH process u_t is multiplied by a scale factor $\sqrt{g_{s_1}}$. It represents the current phase s_t which in turn characterizes overall stock volatility. Hamilton and Susmel (1994) normalize $g_1 = 1$, in that case g_2 has the interpretation as the ratio of the average variance of stock returns when $s_t = 2$ to that when $s_t = 1$. To coefficients of Equation (3) may be estimated via a maximum likelihood approach.

As a byproduct of the maximum likelihood approach, Hamilton (1989) shows that we can make inferences about a particular state of the stock return at any date. The filter probability, $p(s_t, s_{t-1} \mid y_t, y_{t-1}, \cdots)$, denotes the conditional probability with the state at date t being represented by s_t and that at date $t-1$ by s_{t-1}. The smooth probabilities, $p(s_t \mid y_T, y_{t-1}, \cdots)$, on the other hand are inferences about the state at date t based on data available through some future date T (end of sample). Smooth probabilities reflect ex post evaluation as they encompass entire sample period. On the other hand, the filter probability evaluates the likelihood at time t whether the rate of change in stock returns belong to state 1 (small volatility) or state 2 (large volatility).

III. Data and Results of the SWARCH Model

Eight Asian along with the US stock markets are included in the present study. Stock prices taken from Datastream Data Bank span from Jan. 3 1986 to Jan. 5 1998 (3132 observations in total) for the following markets: Hong Kong (HKN), Japan (JPN), South Korea (KOA), Malaysia (MAL), Philippines (PHI), Singapore (SIG), Thailand (THA), and Taiwan (TWN).[4] To start the analysis, we first define the rate of change of stock prices as

$$y_t = (\log Y_t - \log Y_{t-1}) \times 100 \tag{4}$$

in which Y_t is stock prices in each markets at time t. The estimation results based on Equation (4) are represented in Table 2.

3. To better estimate the model parameters in the presence of profound leptokurtic return distributions in the Asian markets, we replace the normality assumption with a student t distribution.

4. We are very grateful for the generosity extended by the economics department of the University of California, San Diego, in providing the data.

Table 2 Estimates of the SWARCH Model for the Nine Asian and the US Stock Markets

	HKN	JPN	KOA	MAL	PHI	SIG	THA	TWN	USA
β_0	0.0984 0.0185[a]	0.0630 0.0160	0.0123 0.0392	0.0459 0.0146	0.0284 0.0219	0.0235 0.0123	0.0751 0.0177	0.0937 0.0244	0.0726 0.0127
β_1	0.0846 0.0190[a]	0.0033 0.0182	0.0675 0.0214	0.1771 0.0187	0.2066 0.0187	0.1619 0.0193	0.1750 0.0192	0.0523 0.0181	0.0144 0.0139
α_0	0.9486 0.0562[a]	0.4433 0.0362	1.1634 0.0712	0.5409 0.0516	0.8269 0.0854	0.3783 0.0303	0.6542 0.0536	1.2479 0.0930	0.4809 0.0345
α_1	0.1218 0.0300[a]	0.1033 0.0296	0.0854 0.0344	0.2407 0.0423	0.2033 0.0424	0.2217 0.0465	0.1822 0.0338	0.0777 0.0266	0.0527 0.0186
α_2	0.0844 0.0268[a]	0.1515 0.0339	0.0772 0.0438	0.1890 0.0397	0.1295 0.0366	0.1025 0.0402	0.2084 0.0380	0.2221 0.0415	0.0321 0.0192
g_2	5.6558 0.6639[a]	4.9928 0.4063	5.8094 0.8746	3.7135 0.4292	5.1863 0.5630	4.4844 0.7660	5.0400 0.5149	5.4489 0.5239	2.6529 0.2041
v	2.9708 0.4576[a]	3.5913 0.5924	5.4927 1.2004	1.8710 0.3085	2.1905 0.4006	2.3114 0.4136	2.8650 0.4846	2.7664 0.4962	2.1662 0.3367
p_{11} p_{22}	0.9965 0.9842	0.9915 0.9914	0.9913 0.9401	0.9963 0.9955	0.9867 0.9830	0.9925 0.9692	0.9936 0.9885	0.9948 0.9920	0.9984 0.9982
$(1-p_{11})^{-1}$ $(1-p_{22})^{-1}$	285.71 63.29	117.65 116.28	114.94 16.69	270.27 222.22	75.19 58.82	133.33 32.47	156.25 86.96	192.31 125.00	625.00 555.56
π_1 π_2	0.8170 0.1830	0.5011 0.4989	0.8729 0.1271	0.5487 0.4513	0.5607 0.4393	0.8033 0.1967	0.6416 0.3584	0.6060 0.3940	0.5220 0.4780
log L	-5029.04	-4756.27	-5291.35	-4659.49	-5603.96	-3671.37	-5145.43	-6188.37	-3801.41

Note: HKN = Hong Kong, JPN = Japan, KOA = South Korea, MAL = Malaysia, PHI = Philippines, SIG = Singapore, THA = Thailand, TWN = Taiwan. The estimates are based on the SWARCH model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + e_t \quad e_t \sim t_v(0, h_t) \quad e_t = \sqrt{g_{s_t}} \cdot u_t \quad u_t = \sqrt{h_t} \cdot w_t \quad h_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i e_{t-i}^2$$

where v = the degrees of freedom of the t distribution; g_2 = average variance of state 2 (high volatility) with g_1 = 1 by design; p_{11} and p_{22} are transition probability from state 1 (2) to state 1 (2); π is average ergodic probability; logL = likelihood function value; rows with superscript a denote standard errors of the estimates. a = estimated standard error.

As indicated in Table 2, significant coefficients of AR(1) except in the markets of the US and Japan are manifestly present especially in the markets of Malaysia, the Philippines, Singapore and Thailand where the coefficients exceed 18%. As Harvey (1995) points out, the AR(1) coefficients are generally greater than 10% for emerging stock markets. As such it represents a noticeable portion of predictability in their future prices. The estimation based on ARCH(2) is found to be statistically significant for all the markets indicating the existence of clustering phenomenon of stock returns. Note that the index of persistence $(\alpha_1 + \alpha_2)$ from the SWARCH after considering Markov-switching process is significantly below 1. This is very much in agreement with what Lamoureux and Lastrapes (1990) have warned: “The extent to which persistence in variance may be overstated is because of the existence of, and failure to take account of, deterministic structural shift in the model.”

Are the two states justified in analyzing the stock returns?[5] An examination of Table 2 provides an affirmative answer. As the size of variance in state 1 is set at unity, the average value of variance in state 2 or g_2 throws some light on the structural change on the stock markets. In the US market, for instance, the variance in state 2 is 2.67 times as large as that of state 1; 5.55 times as large as in the Hong Kong market indicating a significant difference. Bekaert and Harvey (1995) find greater volatility in emerging markets than in developed markets. However, we discover that the developed Asian markets such as Hong Kong, Japan and Singapore have no less volatility than that of the emerging markets. As our sample period encompasses the Asian Flu period, it indicates the volatile nature even for developed markets in the presence of major events.

As a result of the leptokurtic return distributions, ν values (the degrees of freedom from the t distributions) are found to be significant, ranging from the smallest ν value of 3.90 (Malaysia) to the largest one of 8.73 (South Korea). Also reported in Table 2 are both transition probability and ergodic probability. Transition probability measures the magnitude of persistency observed in which data stay in one state; that is, higher values suggest length of stay is more likely to be longer. The length of stay can be calculated as $(1-p_{ii})^{-1}$ $i=1$ or 2. Ergodic probability reflects the proportion of time (probability) the sample data stay in a particular state. For instance, the ergodic probabilities are less than 20% for the Hong Kong, South Korea and Singapore markets to stay in state 2 (high volatility). In contrast, the Japanese stock market experienced the high volatility state in half of the sample period. The average length of stay in state 1 (low volatility) is longest (625 days) for the US, but lasted only 75 days in the Philippines market. Similarly, the average length of stay in state 2 is 556 days for the US market with the shortest one of 17 days in South Korea. These estimates from the Markov switching technique provide valuable pieces of information and as such are instrumental in deciphering the lead-lag relations discussed in the next section.

IV. State Dependency and Granger-Causality Between the US and the Asian Stock Markets

Previous studies have successfully identified large correlation coefficients and stronger intermarket dynamics (integration) during the periods of greater volatility (e.g., Bekaert and Harvey (1995, 1997)). However, the segmentation of sample periods was entirely event-based. For example, 'Black Monday' is used as a demarcation date. While convenient, it ignores the information of small volatility during the period of great volatility and vice versa. Hence a statistical approach to determining the state of volatility in terms of the filtered probability may be considered appropriate. We first calculate the correlation coefficients between states and test the Granger-causality among different national stock indices.

5. Hamilton and Lin (1996) suggest that the parsimony in estimating parameters of the SWARCH model is important. Besides, it does not seem necessary to have more than two states in the present paper, and hence, we use two states.

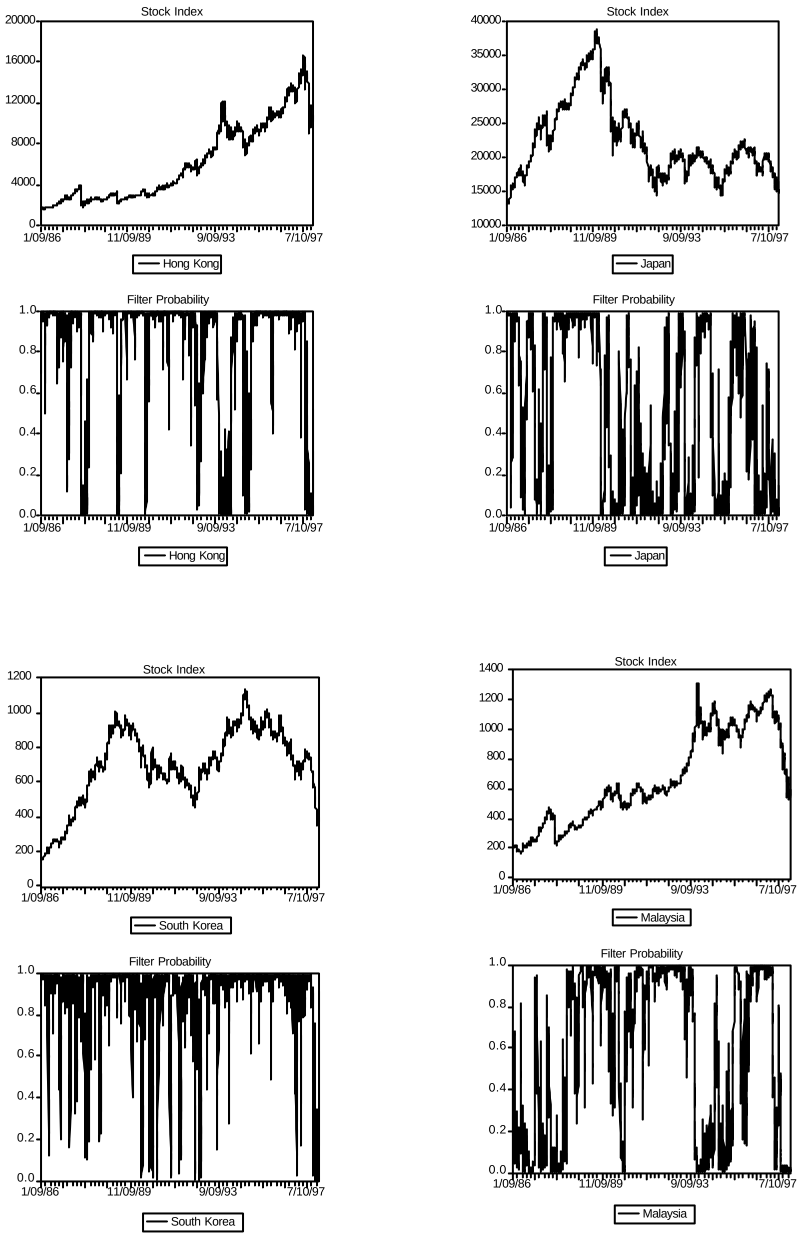


Figure 1-1 Stock Price Trend and the Filter Probability of the Nine National Stock Markets

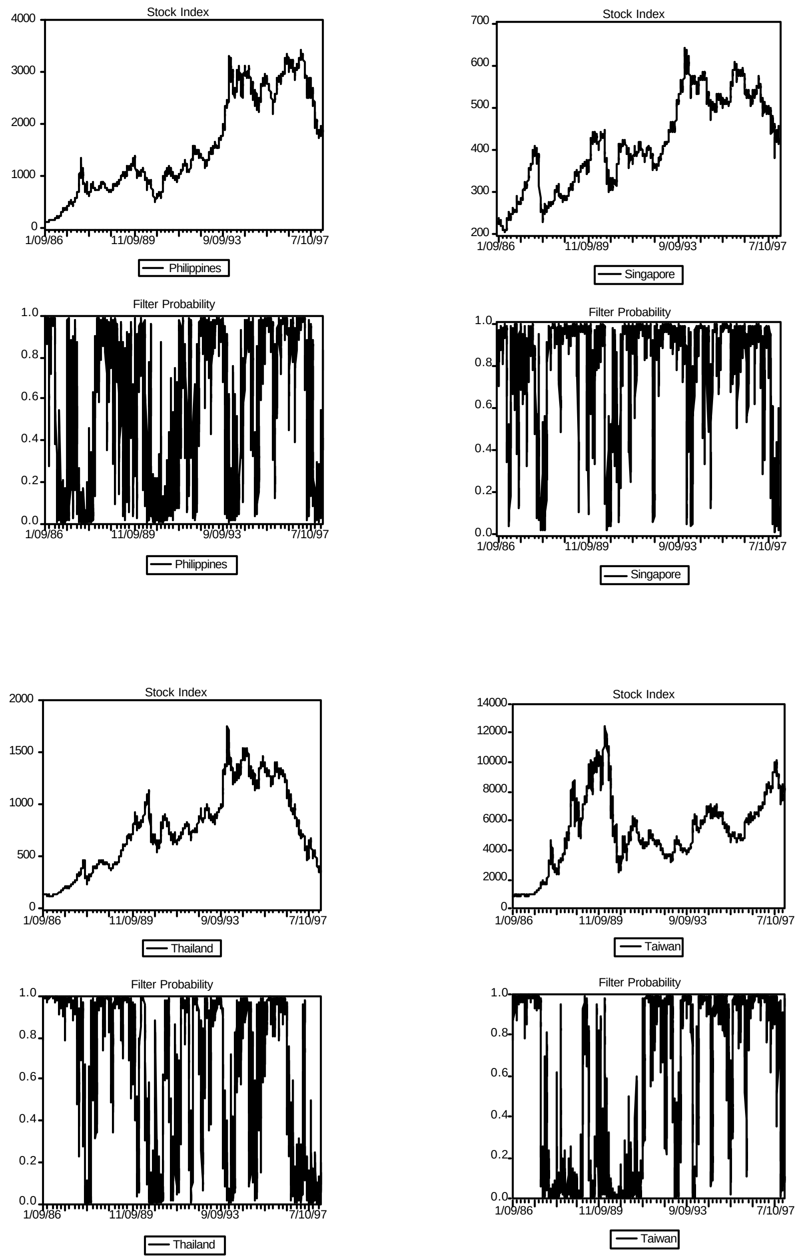


Figure 1-2 Stock Price Trend and the Filter Probability of the Nine National Stock Markets

Figure 1-3 Stock Price Trend and the Filter Probability of the Nine National Stock Markets

Stock price trends and filter probabilities from the SWARCH model (Figure 1) reveal several interesting phenomena. First, the Asian stock markets exhibited a great deal of volatility in response to the US market crash of 1987. Its persistence was not long except for the markets of Philippines, Taiwan and Malaysia. During the recent Asian financial crisis, the magnitude of volatility increases noticeably as mirrored by the filter probability (less than 0.5) shown on the right hand side of graphs in Figure 1.

Table 3 Correlation Coefficients of Nine Stock Indices Under Two Different Volatility States

Panel A	HKN	JPN	KOA	MAL	PHI	SIG	THA	TWN	USA
HKN	1.0000								
JPN	0.2401	1.0000							
KOA	0.0710	0.0558	1.0000						
MAL	0.3943	0.2683	0.1090	1.0000					
PHI	0.1811	0.0991	0.0403	0.1987	1.0000				
SIG	0.3995	0.2701	0.1201	0.6300	0.1695	1.0000			
THA	0.2494	0.1529	0.1209	0.3225	0.1780	0.3187	1.0000		
TWN	0.0824	0.1245	0.0845	0.1133	0.0831	0.1348	0.1489	1.0000	
USA	0.1808	0.1018	0.0287	0.1182	-0.0217	0.1714	0.0225	-0.0291	1.0000

Table 3 (Continued)

Panel B	HKN	JPN	KOA	MAL	PHI	SIG	THA	TWN	USA
HKN	1.0000								
JPN	0.2062	1.0000							
KOA	0.0514	0.0136	1.0000						
MAL	0.3343	0.1946	0.0423	1.0000					
PHI	0.1224	0.0048	0.0411	0.0917	1.0000				
SIG	0.2974	0.1669	0.0357	0.6424	0.1969	1.0000			
THA	0.2204	0.1292	0.0531	0.2888	0.1022	0.2374	1.0000		
TWN	0.0647	0.0141	0.0528	0.0360	0.0148	0.0361	0.0564	1.0000	
USA	0.0655	0.0870	0.0252	0.0118	0.0799	0.0444	0.0031	0.0187	1.0000

Panel C	HKN	JPN	KOA	MAL	PHI	SIG	THA	TWN	USA
HKN	1.0000								
JPN	0.3656	1.0000							
KOA	0.2008	0.1185	1.0000						
MAL	0.5111	0.3580	0.3684	1.0000					
PHI	0.3489	0.1953	0.1460	0.2251	1.0000				
SIG	0.5431	0.4475	0.3541	0.6912	0.2161	1.0000			
THA	0.3628	0.2129	0.3599	0.4281	0.2815	0.4494	1.0000		
TWN	0.1035	0.2427	0.2707	0.1842	0.1061	0.2770	0.2987	1.0000	
USA	0.3048	0.1147	0.0886	0.1504	-0.0592	0.3152	0.0291	-0.0327	1.0000

Note: Panel A, B and C represent the correlation coefficients for the entire sample period (01/03/1986 ~ 01/05/1998), state 1 (low volatility) and state 2 (high volatility), respectively.

Reported in the first part of Table 3 are correlation coefficients for the entire sample period for the nine national stock markets. These low coefficients with respect to the US market are consistent with the results from prior studies. The strongest correlation is found in the Hong Kong market (0.18), followed by Singapore, Malaysia and Japan. In contrast, Taiwan and the Philippines markets witnessed negative correlation with the US market. Insignificant but positive coefficients are found for the markets of South Korea and Thailand. Of the emerging markets, the Malaysia market has the strongest correlation with the US market.[6] It appears that Hong Kong and Japan exert positive correlation with the rest of markets while Taiwan and the Philippines exhibit negative correlation with the other markets. As is well-known in econometric estimations, lumping together observation of inherently different states can leave out important information, and lead to inaccurate conclusion. For this reason, we partition the sample period into low and high volatility periods to obtain better estimates of the nine national stock indices. During the low volatility period, insignificant correlation coefficients between the Asian and the US markets suggest that investment in the Asian markets could well reduce the risk in international portfolio. The greatest one is found between the US

6. By using monthly data from 1976 through 1992, Harvey (1995) found a strong correlation coefficient (0.53) between the markets of Malaysia and the US.

and Japan (0.087) and the smallest one is between the US and Thailand (0.0031) during the low volatility period. The correlation coefficients among the Asian stock markets are also found to be less than those for the entire sample period. On the contrary, the correlation coefficients between the US and the Asian markets are greater than those for the entire sample period with the largest correlation coefficients (0.3152) between the US and Singapore and the smallest coefficient (0.0291) between the US and Thailand during the high volatility period. In addition, markets of Taiwan and the Philippines had negative correlation with the US market. Similar results are found as well within the Asian markets: greater correlation coefficients during the high volatility period. For instance, the correlation coefficients between the Hong Kong and other Asian markets during the high volatility period are two or three times as great as those during the low volatility period. The fact that correlation coefficients are relatively high during the high volatility period implies that risk-reduction via international diversification may hold true only in low volatility period.

On one hand, recent studies have provided some evidence highlighting the positive correlation between correlation and integration of capital markets. On the other hand, as Harvey (1995b, p.809) puts it: "… However, there is no necessary link between correlation and integration. A country can have zero correlation with the world market and be perfectly integrated into world capital markets. The low correlation could be caused by the weighted average of the firm betas …" But, market integration is too important a topic for analyzing risk to be ignored. As both the single-factor and the multiple-factor CAPMs represent some measures of risk, the specification of CAPMs is of utmost importance in the statistical estimations. Needless to say, integration relations become stronger if some foreign explanatory variables can better explain the regression structure especially in the era of high volatility.

Strictly speaking, the strength of the Granger-causality does not lie in the causality per se. Rather, it can be used in improving predictive power via using historical data of the explanatory variables. A significant Granger-causality in international equity markets implies intensified integration of the markets. The Granger-causality model can be formulated as shown below:

$$\begin{aligned} \Delta y_{1t} &= \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} \Delta y_{1t-i} + \sum_{i=1}^{k} \alpha_{2i} \Delta y_{2t-i} + \varepsilon_{1t}, \\ \Delta y_{2t} &= \beta_0 + \sum_{i=1}^{k} \beta_{1i} \Delta y_{1t-i} + \sum_{i=1}^{k} \beta_{2i} \Delta y_{2t-i} + \varepsilon_{2t}, \end{aligned} \tag{5}$$

in which y_{1t} and y_{2t} represent stock prices of country 1 and 2 at time t. Failure to reject the $H_0: \alpha_{21} = \alpha_{22} = \cdots = \alpha_{2k} = 0$ implies that the stock price of nation 2 does not Granger cause that of nation 1. Likewise, failure to reject $H_0: \beta_{11} = \beta_{12} = \cdots = \beta_{1k} = 0$ suggests that the stock price of nation 1 does not Granger cause that of nation 2. Before applying the causality test based on Equation (5), one must examine the time series properties of these variables. That is, should the bivariate-VAR model (first difference) or that with the error correction term (VAR-VECM) be employed. This common procedure is first to apply a unit root test before conducting cointegration analysis. After that, one may perform the Granger-causality test. In our analysis, we adopt the Phillips and Perron approach (1988) that can handle the serial correlation problem in testing unit roots of national stock indices. There exist noticeable time trends in these indices as shown in Figure 1. As a result, we use the Phillips and Perron's z_{τ} test statistics for the hypothesis test (Table 4).[7]

Table 4 Unit Root Test of the Nine National Stock Indices

	y	Δy
HKN	-2.5755	-57.2188*
JPN	-2.8500	-56.2788*
KOA	-1.5862	-52.6301*
MAL	-0.2025	-47.3484*
PHI	-2.4897	-47.4762*
SIG	-1.7954	-48.3632*
THA	-2.3422	-46.9511*
TWN	-2.0974	-51.7245*
USA	-2.2262	-55.1771*

Note the Phillips-Perron or PP test is adopted with the null of a unit root. $\Delta y = \log y_t - \log y_{t-1}$ and y are logarithmic stock price indices. We employ the PP test with time trend or z_{τ} test. * = 1% significant level.

An examination of Table 4 indicates that we cannot reject the mull hypothesis (unit root) for logarithmic stock price indices of the nine nations. However, we are able to reject the mull hypothesis easily using the first difference. According to the interpretation of the Engle-Granger cointegration technique, the linear combination of national stock indices - which are I(1) - could be I(0). To test the cointegration, we apply the two-stage Engle-Granger model.[8] First, we perform the following regression analysis:

$$y_{1t} = \alpha + bt + y_{2t} + \varepsilon_t. \tag{6}$$

To test whether ε_t is of I(1), we then make use of the Phillips and Perron test (or as an alternative, one could apply augmented Dickey Fuller test).

7. Readers are referred to Hamilton (1994, pp.506-515) for details about the Phillips and Perron unit root test.
8. One could also use the Johansen's maximum likelihood model, but the residual-based approach is convenient to apply.

Table 5 Pairwise Cointegration Test Results

x	y	x on y	y on x	x	y	x on y	y on x
HKN	JPN	-2.8312	-2.8949	KOA	THA	-3.1380	-2.0688
HKN	KOA	-2.4711	-1.3422	KOA	TWN	-1.4041	-1.6836
HKN	MAL	-2.7468	-0.2605	KOA	USA	-3.0134	-3.2128
HKN	PHI	-3.0498	-3.1754	MAL	PHI	-2.4135	-3.0934
HKN	SIG	-2.7020	-1.9139	MAL	SIG	-2.1291	-3.1232
HKN	THA	-2.5789	0.3409	MAL	THA	-2.6907	-2.9903
HKN	TWN	-2.9314	-2.4285	MAL	TWN	-0.1447	-1.8156
HKN	USA	-2.3044	-1.9126	MAL	USA	-1.0633	-2.8153
JPN	KOA	-2.5997	-1.7086	PHI	SIG	-3.9827**	-3.3030
JPN	MAL	-2.9833	-0.5195	PHI	THA	-3.1065	-1.1208
JPN	PHI	-2.4251	-2.2185	PHI	TWN	-2.1323	-1.6334
JPN	SIG	-2.9436	-1.8621	PHI	USA	-2.8531	-2.5259
JPN	THA	-2.6577	0.0913	SIG	THA	-2.9333	-1.8160
JPN	TWN	-3.7485**	-3.3348	SIG	TWN	-1.7409	-1.9863
JPN	USA	-2.7454	-2.1328	SIG	USA	-1.9916	-2.3997
KOA	MAL	-3.4331**	-1.9648	THA	TWN	0.7760	-1.4201
KOA	PHI	-2.3930	-3.0041	THA	USA	-2.6258	-3.8107**
KOA	SIG	-2.6236	-2.5303	TWN	USA	-2.1678	-2.2804

The two-stage residual-based test by Engle and Granger is applied. With the Phillips-Perron (1988) model used in the second stage. Failure to reject the null hypothesis implies a lack of cointegration between the variables. ** = 5% significant level.

An inspection of Table 5 suggests that we cannot reject the null hypothesis for 36 pairwise cointegration relations between national stock indices. That is, there exists no cointegration relations and as such Equation (5) is sufficient for the Granger-causality test. The Granger-causality results during different volatility states (panel A and B) are reported in Table 6.

Table 6 The Granger Causality Test Results under Two Different States

Panel A	HKN	JPN	KOA	MAL	PHI	SIG	THA	TWN	USA
HKN		0.34	0.02	1.39	3.91**	5.30**	5.35**	0.82	0.05
JPN	0.67		2.63***	0.01	0.91	0.17	0.03	0.53	1.85
KOA	0.28	0.79		0.38	0.77	3.02***	0.66	1.61	0.00
MAL	5.28**	1.21	5.69**		3.58**	0.09	0.38	0.34	0.08
PHI	0.00	0.04	0.88	1.54		3.69**	0.21	1.10	0.03
SIG	0.01	1.12	3.93**	4.00**	5.57*		5.57**	1.94	3.17***
THA	0.48	0.17	0.62	1.06	0.88	1.27		6.53**	4.02**
TWN	0.73	1.32	0.52	0.42	0.91	0.44	1.60		0.00
USA	197.39*	38.63*	0.69	141.94*	23.10*	208.00*	69.36*	6.65*	

Table 6 (Continued)

Panel B	HKN	JPN	KOA	MAL	PHI	SIG	THA	TWN	USA
HKN		3.18**	0.00	0.20	4.76**	0.53	8.78*	8.15*	6.83**
JPN	1.51		0.98	1.00	13.15*	5.39*	9.52*	6.05**	14.90*
KOA	0.00	0.70		4.22**	3.40***	0.91	2.77***	3.08***	0.01
MAL	12.46*	2.17	1.65		28.01*	1.44	35.58*	8.98*	3.68***
PHI	0.03	9.19*	0.00	3.01***		1.62	5.37**	0.38	2.20
SIG	13.13*	22.21*	0.01	22.15*	33.11*		34.70*	18.46*	0.21
THA	1.15	0.00	0.79	0.19	6.09**	0.02		5.68**	0.38
TWN	7.57	1.63	0.00	1.91	2.75***	0.00	3.31**		0.40
USA	29.34*	180.81*	10.17*	137.50*	63.91*	14.75*	70.91*	27.31*	

Note: The numbers in Panel A and B represents F statistics of the Granger-causality tests under state 1 (low volatility) and state 2 (high volatility) respectively. *, **, *** are significance level at α = 1%, 5% and 10% respectively. The Granger-causality model is based on the following:

$$\Delta y_{1t} = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} \Delta y_{1t-i} + \sum_{i=1}^{k} \alpha_{2i} \Delta y_{2t-i} + \varepsilon_{1t},$$

$$\Delta y_{2t} = \beta_0 + \sum_{i=1}^{k} \beta_{1i} \Delta y_{1t-i} + \sum_{i=1}^{k} \beta_{2i} \Delta y_{2t-i} + \varepsilon_{2t},$$

in which y_{1t} and y_{2t} represent stock prices of nation 1 and 2 respectively. Failure to reject the $H_0: \alpha_{21} = \alpha_{22} = \cdots = \alpha_{2k} = 0$ implies that change in stock price of nation 2 (column) does not Granger-cause that of nation 1 (row). Likewise, failure to reject $H_0: \beta_{11} = \beta_{12} = \cdots = \beta_{1k} = 0$ suggests that change in stock price of nation 1 (row) does not Granger-cause that of nation 2 (column).

Note that the first column lists the national stock indices that lead the price movement (rate of change in stock prices) while the first row provides the national stock indices that lag behind in price movement. For example, the numbers in the third row of Panel A in Table 4 represent F statistics for the null hypothesis of Japanese stock price movement does not Granger cause that of the other eight markets. On the contrary, the numbers in the third column reports the F statistics for the null hypothesis that price movements of the other eight stock markets do not Granger-cause that in the market of Japan. During the state 1 of low volatility (Panel A of Table 4), there exist 23 significant F statistics for at least α=10%. This is to say we reject the non-existence of the Granger-causality among the nine national stock indices. Interestingly enough, such significant F's increase to 40 in state 2 of high volatility. The result is consistent with prior studies in that degree of market interaction and integration intensifies during the period of high volatility. It is well known in the literature (e.g., Wei *et al*. (1995) and Hu *et al.* (1998)) that the US exerts a far greater impact on the Asian emerging markets than does Japan. From Table 4, it is found that the US market leads all other Asian markets in both states. Furthermore, the market of Japan is found to lead the South Korea market in the state of low volatility with α=10%. In the state of high volatility Japanese stock prices (past) can be used to improve the predictive power of the stock prices in current period of the market of the Philippines, Taiwan, Thailand and Singapore.

Beyond that, price movements of Hong Kong and Singapore are beneficial in forecasting that of other markets (see Panel B of Table 4). It is to be pointed out that the US market basically assumes the leader's role especially over the markets of Taiwan and Thailand during the low volatility period. However, all the markets except Philippines are found to lead the Taiwan and the Thailand markets during the high volatility period. As shown in Panel B of Table 4, there exist some feedback relations among the US, Japan, Hong Kong and Malaysia markets with a strong Japan-Hong Kong feedback relation (α < 5%). This finding is significant: while there is no feedback relation from the Asian markets to the US in the low volatility period, there indeed exists a feedback relationship from the Asian markets to the US in the high volatility period. Little wonder that such a feedback relation was borne out in the recent Asian financial crisis.

V. Event Study

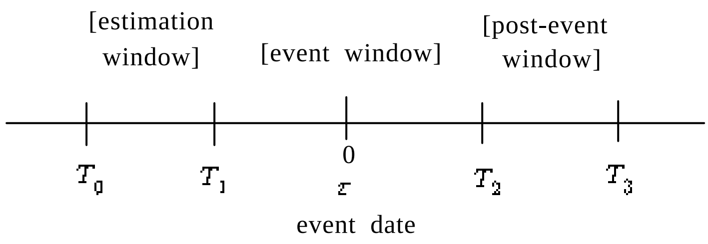
Section IV indicates that lead-lag and correlation relations are relatively weak in state I (low volatility), and as a practical matter, one may like to examine the abnormal returns in each state. To do so, we employ the event-study approach for the 12-year sample period. The major events are (i) the market crash on October 19, 1987 in which DJIA plummeted nearly 500 points (event 1); (ii) the great depreciation of the Thai baht on July 2, 1998 triggered the financial debacle in Asia (event 2); and (iii) the Hang Seng index suffered a major landslide drop (1438 points) on October 27, 1997 through raising the short term interest rates substantially in order to peg its currency value to the US dollar (event 3). Event 3 in turn triggered a 544.26-point decrease in DJIA[9] in the US. Now we define the abnormal return as follows:

$$\varepsilon^{*}_{jt} = R_{jt} - E[R_{jt} \mid X_t], \tag{7}$$

where ε^{*}_{jt}, R_{jt} and $E[R_{jt}]$ denote abnormal, real, and normal returns respectively. Two models are typically used to estimate normal returns: constant-mean-return model and market model. In the case of constant mean model, X_t is a constant; it becomes market returns in the market model. Since we are more interested in market volatility, the market model is used to estimate normal returns.

As in these event analyses, an estimation window is needed before the event took place. One can then calculate normal and abnormal profits based on Equation (7). Figure 2 illustrates the process.

9. Other events could also be important; however, we choose these three events for their major impacts on national stock markets.



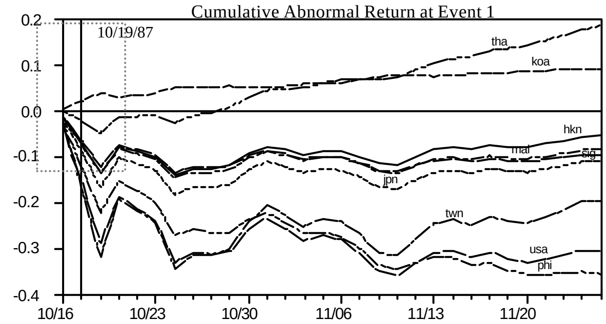
Source: Campbell, Lo and Mackinlay (1997, p.157)

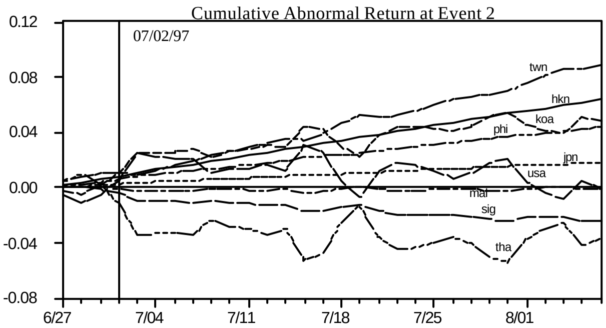
Figure 2 Time Line for an Event Study

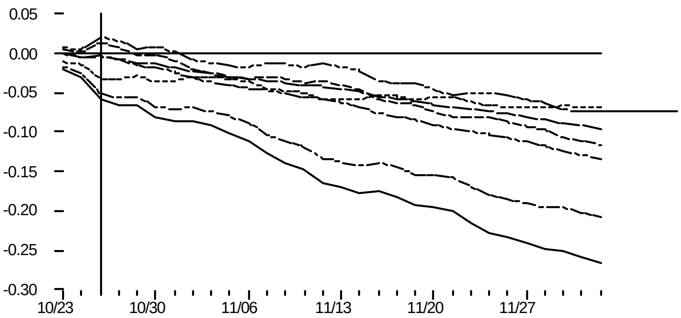
In the case of three different events, the relationship among cumulative abnormal returns of the national stock markets is depicted in Figure 3.

A perusal of Figure 3 points out that only Thailand and South Korea have positive cumulative abnormal market returns during event-1 period. Within 19 days of event 1, the abnormal returns are lowest for the US; followed by the Philippines, Taiwan, Japan, Singapore, Malaysia and Hong Kong. Beyond that period, the abnormal returns are lowest in the Philippines market. In terms of the filter probability of the SWARCH model (Table 7), all the markets except South Korea, had switched from state 1 to state 2 (e.g., Hong Kong, Japan, Singapore). From Figure 3, it can be seen that only Thailand's cumulative abnormal return was positive in state 2. In state 1, however, all the cumulative abnormal returns were negative except in the Korean market.

In the period of event 2 (Table 7), the markets of the US, Thailand, Japan were in state 2; markets of Hong Kong, South Korea, Singapore and Taiwan stayed in state 1; and those of Malaysia and the Philippines were in transition state (from state 1 to 2). In terms of cumulative abnormal returns, markets of Taiwan, Hong Kong, South Korea, the Philippines and Japan experienced positive returns while those of Singapore and Thailand were negative. The cumulative abnormal returns hovered around zero for the US and Malaysian market, with greater volatility for the US market. In general, the cumulative abnormal returns were less significant during event-2 period than those of event-1. In a similar vein, we could see positive cumulative abnormal returns during state 1 (lower volatility) but negative ones during state 2 (greater volatility). In the period of event 3, when the 'Asian flu' exerted its influence on the world financial markets, we can readily identify negative cumulative abnormal returns (Figure 2), with the lowest cumulative abnormal returns in the markets of Hong Kong, followed by Malaysia, Taiwan, the Philippines, South Korea, Singapore, Japan, Thailand and the US. The result is consistent with the filter probability approach in which all nine markets are in high volatility state.







Note: hkn = Hong Kong, jpn = Japan, koa = South Korea, mal = Malaysia, phi = Philippines, sig = Singapore, the = Thailand, twn = Taiwan

Figure 3 Path of Cumulative Abnormal Returns of the Nine Stock Markets (3 Events)

Table 7 Changes of the Filter Probability of the Nine National Stock Indices

		[illegible]								

In a nutshell, there seems to exist a tendency that greater volatility corresponds to negative cumulative abnormal returns while lower volatility matches with the positive returns. In the transition period (from state 1 to 2), the abnormal returns can go either way or even become zero.

VI. Conclusion

Stock price movements mirror the impact of information arrivals; larger movements reflect stronger momentum of the information content. Arbitrary segmentation of sample period (e.g., the 1987 Black Monday stock crash) can mask important interaction effects and hence lead to inaccurate results. To circumvent this problem, we make use of the SWARCH model developed by Hamilton and Susmel (1994) to determine the state of volatility via the filter probability. It is found that even mature markets such as Hong Kong exhibit a great deal of volatility during the recent Asian financial turmoil. From the calculated state-dependent correlation coefficient via the filter probability, we have found noticeable asymmetry between the two states: The correlation is much higher during the period of high volatility. As such international portfolio diversification may not be satisfactorily achieved from investing in the Asian market.

Also discovered is the increased integration among the national markets in the high volatility period. The existence of a strong integration is important in model specification (e.g., CAPM). It also provides the possibility of using prices of foreign markets to better predict the domestic stock price movements. In terms of the Granger-causality test, such causality effect becomes much stronger during the high volatility period. In addition to the existing knowledge that the US market frequently leads the Asian emerging markets, we have found that other mature markets in Asia such as Hong Kong, Japan and Singapore can play a leader's role as well during the high volatility period.

In addition, via the event analysis, there seemed to be a connection between (i) greater volatility and negative cumulative abnormal returns and (ii) lower volatility and positive cumulative abnormal returns. To a multinational portfolio manager, risk diversion and high cumulative abnormal returns are nearly mutually exclusive in the period of great market volatility. As such, forecasting market volatility plays a pivotal role in order to minimize investment losses.

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