Economic Factors Contributing to Time-Varying Conditional Correlations in Stock Returns

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Abstract:
This paper attempts to find economic and financial factors contributing to the changing correlations of stock returns. Time-varying correlations were documented in previous studies, but a few attempts have been made to investigate their evolution. Using daily data from the Asia-Pacific region, this paper provides evidence that return correlations are negatively correlated with the distance between the markets. Furthermore, correlations tend to be higher in advanced countries and increase at times of the active trading (e.g., around the Lehman shock). Instead, the level of correlations declines among pairs of countries with less financial integration.

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1. Introduction

International diversification of financial assets is directly linked with welfare gains and losses, and standard economic theories such as the international capital asset pricing model suggest a sound financial portfolio should contain negatively correlated stocks in order to minimize unexpected risks. Therefore, a correlation of equities is an important topic for investors and researchers. Indeed, many studies have conducted empirical investigation into this issue, and can be classified broadly into two groups.[1]

The first type examines the presence of correlation (or interdependence) of financial markets using stock prices and/or return data. Classic studies include Levy and Sarnat (1970) who showed a positive correlation ranging from 0.09 to 0.81 in data from advanced countries from 1951 to 1967. Hamao et al (1990) confirmed this result and furthermore reported a unidirectional causality from New York (NY) to London and London to Tokyo. While evidence of unidirectional causality appears to have become weaker as a result of the development of financial markets worldwide (e.g., Lin et al 1994), correlations between the markets exist even when more recent data are analyzed and country coverage is expanded to include emerging markets (Masih and Masih 1997).

Furthermore, return correlations are apparently time-varying and tend to increase at times of financial crisis. Unstable correlations over time are documented in Makridakis and Wheelwright (1974), and an increase in correlations during crises was found, for example, by King and Wadhwani (1990) who investigated the October 1987 crash (or Black Monday). They reported that correlations between the London and NY stock markets increased from 0.27 to 0.8 during the crisis but dropped to 0.19 after the crash effects ceased and the market returned to normal. Such time-varying correlations are confirmed by a statistical test in data from industrial countries from 1960-1990 (Lognin and Solnik 1995). Similar evidence was obtained for emerging markets too. Liu et al (1998) provide evidence of apparent increases in interdependence in the aftermath of Black Monday among emerging markets. A surge in return correlations is also reported after the 1994 Mexican peso crisis in Calvo and Reinhart (1996) as well as the Asian crisis (Yang 2005). Finally, Bayoumi et al (2007) also showed a similar, increasing trend in correlations during a series of recent financial crises. Therefore, these results lead us to the conclusion that international diversification tends to be rather limited during crisis

[1] See also Yu, Fung and Tam (2010) which provide a comprehensive review

periods.[2]

The second type analyzes which economic and financial factors explain time-dependent correlations, but this line of research is sparse compared with the first group. For example, Roll (1992) pointed to time zone differences as one reason for low return correlations. He shows that European markets have a low correlation (less than 0.3) with the US, but have a high correlation with other European countries (e.g., 0.7 between Germany and Switzerland). Similarly, Flavin et al (2002) and Baker and Loughran (2007) confirmed the importance of difference in location in explaining return correlations. Roll also discusses that a similar industrial structure between countries leads to a high degree of correlation of stock returns. To the extent that neighboring countries share similar endowments, a distance may capture this effect.

In addition, some researchers argued that the country's openness was a critical factor in explaining the development of correlations. In this connection, Chen and Zhang (1997) used monthly data from 1980 to 1990 and empirically emphasized the important role of international trade through which the financial markets are linked. Pretorius (2002) conducted a comprehensive study using a wide range of quarterly data from 1995 to 2000 such as international trade, inflation differentials, interest rate differentials, economic growth, and volatility of the returns. From a panel data regression for 10 emerging markets between 1995 and 2000, the intensity of trades is found to be positively associated with correlations. Moreover, using a dummy variable, markets within the same region are found to have higher correlations than otherwise.

Against this background, we attempt to explain correlations of stock returns among Asian countries. Note that this paper is not meant to focus on the presence of contagious effects which are generally defined as adverse effects from one country to another only during the crisis period, but analyze the overall correlations (or interdependence) of stock returns. While some similar research was done before (Pretorius 2002), our paper is unique in several areas. First, the sample period is updated to contain the period of the Lehman shock of September 15, 2008. A lot of research was conducted using the samples around Black Monday and the 1997 Asian crisis, but relatively less was done around the period of the Lehman shock. Second, we use high frequency data and thus

[2] On the other hand, with the definition of contagion as a significant increase in cross-market linkages, Forbes and Rigobon (2002) argue that there was no contagion rather interdependence between the markets during the Black Monday, 1994 Mexican, and 1997 Asian crises. In addition, Kuper and Lestano (2007) observed that the correlation between Indonesia and Thailand declined during the Asian crisis.

employ different explanatory variables. In particular, we introduce a proxy of capital market openness based on the covered interest parity condition. This concept is not new but has not been used in previous studies. Finally, conditional correlations will be estimated by the Dynamic Conditional Correlation (DCC) Model, which will be explained in the next section.

In short, we provide some explanations of return correlations: they tend to increase when the markets are geographically close, are experiencing active trading, and are advanced ones. In contrast, the low level of capital market integration leads to low correlations.

2. The Dynamic Conditional Correlation Model

Two types of research were summarized in the introduction, but the estimation of time-varying correlations is not straightforward whichever type of the analysis is conducted. There are several statistical methods to obtain time dependent correlations. However, Engle (2002) discussed deficiencies of such methods previously employed by a number of researchers. For example, both rolling correlation and RiskMetrics approaches are based on a particular value of weights attached to past observations, but there is no theoretical guidance to justify these weights in these models.

In this connection, Engle's Dynamic Conditional Correlation (DCC) Model (2002) will be used to calculate them. This model is a breakthrough for practitioners and researchers alike since conditional correlations were often assumed to be constant in multivariate GARCH models due to computational reasons although such an assumption is known to be invalid. Indeed, the conventional multivariate GARCH models often failed to achieve convergence in the estimation process even when analyzing just a couple of stocks.

For a vector of stock returns (r_t), the DCC-GARCH can be expressed as in the next equation.

$$r_t \mid F_{t-1} \sim N(0, H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

where H_t is a covariance matrix and t presents time (t=1,…,T). Furthermore, R_t is a time-varying correlation matrix and is of interest to us, and D_t is diag(sqr(h_{it})) and is a matrix of time-varying standard deviations for country i (i=1,…,N). Since this model becomes the Constant Conditional Correlation (CCC) model (Bollerslev 1990) when R_t=R, the DCC can be viewed as an extension of the CCC.

The unique feature of this model is its ability to treat conditional variances (D) and the correlation matrix (R) separately, which makes the concept of time-dependent correlations operational. With respect to the former, Engle proposed obtaining time-varying standard deviations, diag(sqr(h_{it})), from a univariate GARCH model such as GARCH(1,1).

$$h_{it} = \omega_i + \alpha_i r_{it-1}^2 + \beta_i h_{it-1} \tag{3}$$

The condition $\alpha_i + \beta_i < 1$ ensures non-negativity of variances and the mean-reverting process of the data. Obviously other types of GARCH models can be used to specify conditional covariance, but this paper utilizes this most standard model (i.e., GARCH(1,1)) since it captures reasonably well the data generating process of our statistics.

As regards the correlation matrix, the dynamic correlation is proposed to have the next structure.

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{4}$$

where Q_t is a symmetric positive definite matrix and is assumed to be $Q_t = (1-a-b)\bar{Q} + a(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + bQ_{t-1}$. The $\bar{Q}$ is the unconditional variance of the standardized residual ($\varepsilon_t = D_t^{-1} r_t$ and $\varepsilon_t \sim N(0, R_t)$), and parameters, a and b, are non-negative with $a + b < 1$ for the model to be mean-reverting. In short, there will be $N(N$-1)/2 combinations of conditional correlations.

For the estimation, Engle (2002) proposes a two-step method based on the log-likelihood functions for components of variance (L_v) and correlations (L_c).

$$L(\theta, \vartheta) = L_v(\theta) + L_c(\theta, \vartheta) \tag{5}$$

The first component of (5) for conditional variance is:

$$L_v = -0.5\sum_{t=1}^{T}\sum_{i=1}^{N}(\log(2\pi) + \log(h_{it}) + r_{it}^2 / h_{it}) \tag{6}$$

The second component of (5) for conditional correlations is:

$$L_c = -0.5\sum_{t=1}^{T}(\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t) \tag{7}$$

In the two-step method, parameter θ is estimated by maximizing equation (6) first, and given this estimate, ϑ will be obtained from (7). Engle discusses that these estimates are consistent under regularity conditions.

Yang (2005) and Kuper and Lestano (2007) used the DCC model to analyze the interdependence of stock markets in the 1997 Asian crisis. A general conclusion is that conditional correlations increased around the crisis period. We shall apply the DCC to the period around the Lehman Shock and furthermore investigate the evolution of correlations.

3. Estimates of Conditional Correlations

Given our decision to include China and India which have significantly increased their presence in the world economy in the last decade and have limited historical data, high frequency (daily) data have been chosen in order to have sufficient observations for the statistical analyses. This departs from most previous studies analyzing causes of varying correlations.

More specifically, our data cover the sample period from 2005/10/10 to 2010/10/29 for 9 Asian and Pacific countries: namely; Australia, China, Hong Kong (HK), India, Indonesia, Japan, New Zealand (NZ), (South) Korea, and Taiwan. The beginning of the sample period is determined by the availability of data including those used to explain the evolution of the correlations (See Section 4). The major stock index in each country is chosen for our analysis and is listed on Table 1. Their price and volume data are downloaded from finance.yahoo.com, and stock returns ($Return_{it}$) are calculated as: $(p_{it}-p_{it-1})$*100, where p is a log price with subscripts i for countries (i=1,…,9) and t for time.

Stock returns of each country are plotted in Figure 1, and their basic statistics are summarized in Table 2. In this figure, we can observe radical movements in stock returns in 2008-09 when the Lehman Brothers went bankrupt and adverse effects of the sub-prime loan crisis spread to other countries. Table 2 shows that stock markets in developing countries performed better than those in advanced countries. The average of stock returns is negative for Japan and NZ, implying a declining trend in their prices. In contrast, Chinese and Indonesian stocks performed strongly during our sample period. Furthermore, Chinese stock returns have experienced the highest level of volatility in terms of the standard error, and NZ experienced least volatility during our sample period. These seem to suggest the dynamism of the Chinese economy compared with other Asian countries. Finally, we confirm the significant presence of ARCH effects in all series using Engle's test, and therefore it seems appropriate to employ GARCH-type models.

Table 3 is a matrix of unconditional correlations of stock returns. The lowest correlation of 0.203 is found in stocks between China and NZ, and the highest of 0.677 between Koran and Taiwan. Australia-Japan also exhibited a high correlation of 0.667. Thus generally a pair containing a developing country has a low correlation of stock returns (r).[3] Their correlation coefficients between stocks i and j can be obtained as:

$$\frac{\sum_{t=1}^{T}(r_{it}-\bar{r}_i)(r_{jt}-\bar{r}_j)}{\sqrt{\sum_{t=1}^{T}(r_{it}-\bar{r}_i)^2}\sqrt{\sum_{t=1}^{T}(r_{jt}-\bar{r}_j)^2}}$$

where a bar above variables indicates their average value.

The parameters of conditional variance equations from the DCC are reported in Table 4. As expected, ARCH and GARCH parameters are positive and their sum is below unity confirming the stationary process of our data. The Q test is also conducted to check if there is autocorrelation in each equation, and shows that generally our specification is appropriate although there is one instance that the model suffers from this problem at the standard (i.e., five percent) significance level.

Figure 2 shows our estimates of conditional variance for each country from the DCC model. As expected, they are positive and exhibit a surge in 2008-2009 at the time of the Lehman shock, which was a prevailing phenomenon across countries. Since conditional

3 Following the country classification of the IMF, advanced countries include Australia, HK, Japan, Korea, NZ and Taiwan, and the developing countries are China, India and Indonesia (as of this writing).

variance is interpreted as uncertainty in the financial market, this figure suggests that increased uncertainty from the Lehman shock existed in all of our countries.

Figure 3 shows our estimates of conditional correlations. They do not show any particular trends but seem to follow a stationary process. Furthermore, judging by the figure, it is clear that the assumption of constant correlations is inappropriate. Their value ranges are within theoretical values and are positive all the time, consistent with unconditional correlations reported in Table 3.

Table 5 lists country pairs according to the average size of conditional correlations. Although the order is slightly different from that in Table 3, there is a tendency of pairs of advanced countries to have higher conditional correlations. For example, a high correlation exists in Japan-Korea and Australia-Japan, and a low correlation in China-NZ. Although marginal, there is a stable relationship among pairs of advanced countries since volatility of conditional correlations is lower among these countries.

4. Explanations of Conditional Correlations

Then what changes the level of conditional correlations? For this purpose, we consider the following variables to explain the level of correlations. Our choice of explanatory variables reflects partially our data frequency. Therefore, some variables may not be regarded as so-called economic fundamentals, and for this reason variables like international trade and economic structure are not included in our specification.

Dist	The distance between capitals of countries (km)
Vol	The volume of stocks traded in a day
Devi	The absolute value of deviation from the covered interest parity condition
China	Dummy variable (=1 for China, HK and Taiwan, and =0 otherwise)

The first explanatory variable is the physical distance (*Dist*) between financial markets, which is reported to be negatively associated with stock return correlations. Goldstein (1998) argued that the contagious effects of the 1997 Asian crisis can be partly explained by socio-economic structures which are similar among those adversely affected by the crisis (i.e., the neighbor effect). This data is expected to capture differences in time and location as well as economic structures which were pointed out by previous studies.

Table 6 shows geographical distance between the markets of each country. The longest distance is obtained between India and NZ, and the shortest between Taiwan and China (Shanghai). In addition, HK and Taiwan are located within a similarly short distance. One might expect a high return correlation between China, HK and Taiwan due to the close proximity, but their correlations are around 0.3 to 0.6 and are actually lower than one between two large advanced economies, Australia and Japan (see Table 5).

Another variable, the volume of traded stocks (*Vol*), is the total volume in paired countries. As discussed in the introduction, there is a tendency of reduced diversification of financial portfolios reflecting in a high correlation during periods of chaotic economic and financial conditions. Thus high volume should be positively associated with correlations. This variable may also be related to the herd behavior of investors (Goldstein 1998), according to which a substantial increase in (one direction of) trades during the crisis is triggered by asymmetric information among investors. Investors who possess less information follow the investment decisions of other investors who appear to have more information.

Table 7 shows the average trading volume per day in the two countries. The volume is shown in a full period, and before and after the Lehman Brothers' crisis.[4] The trading volume is shown to have apparently increased since the beginning of the crisis.

In addition to these data, we consider the absolute value of deviations from the covered interest parity (CIP) condition as a proxy for capital market openness. To our knowledge, this is the first study using this data to explain time-dependent correlations. In international finance, such deviations are regarded as an indication of financial market fragmentation. There are several other proxies to measure capital market integration such as the Feldstein-Horioka method as well as the real interest parity, uncovered interest parity (UIP) and CIP conditions. Among them, Frankel (1992) discussed that the CIP is the best approach to measure international capital mobility since this concept hinges least on other economic assumptions. According to his empirical investigation, capital controls and other barriers to prevent free capital movement were generally removed in advanced countries by 1988. Thus given our sample period, we would

[4] The post-Lehman shock period includes effects of the Greek economic crisis (late 2009-early 2010). But the latter effects seem to be relatively limited (see Figures1 and 2).

expect a high level of capital mobility across advanced countries.

There is still a debate in academic literature about what deviations from the CIP capture, but it is generally believed that they reflect the presence of transaction costs, risk premiums, and other barriers to prevent capital movements, among others. The introduction of this variable can be also viewed as consistent with previous studies which used interest rates and/or exchange rates individually. Given our high frequency data, this is probably the best proxy to measure capital market integration. The data (forward and spot exchange rates, and 3-month interest rates) are obtained from DataStream.

Table 8 lists a pair of countries with the order of capital market openness. Our data is the absolute value of deviations, and sizable deviations indicate a high level of financial market fragmentation. This table suggests that, as expected, there are small deviations from the CIP among a pair of advanced countries such as Australia-NZ and HK-Japan. In contrast, there is evidence of large deviations and thus low capital integration among developing countries like China-Indonesia. Given high conditional correlations among advanced countries (Table 5), this proxy should be negatively correlated with conditional correlations.

Finally, we use a dummy variable to capture potential unique features shared by countries. In particular, a dummy (*China*) is introduced to capture effects of the Chinese region (China, HK and Taiwan) where the culture is very similar to each other.[5]

Using these data, a variant of the following equation is statistically estimated, on the basis of the random effects model, using the maximum likelihood estimation method.[6]

$$Return_{ij,t} = \beta_0 + \beta_1 Dist_{ij} + \beta_2 \Delta Vol_{ij,t-1} + \beta_3 CIP_{ij,t-1} + \beta_4 China_i + e_{ij,t} \qquad (6)$$

where $X_{ij,t}$ indicates that a variable X for a pair of countries i and j at time t. Greek letters are parameters of interest to be estimated, and e is the residual. The Δ is the first

[5] We also considered a dummy (*Indust*) in order to capture unique effects among industrial countries. Since these countries generally have more advanced and deregulated financial markets, a higher correlation is expected among themselves than a pair of developing countries. This dummy is found to be positively correlated with conditional correlations, but seems to have a very similar effect to *Devi*. Thus results from this variable are not reported in our study in Table 9.

[6] The fixed effects model is also considered as one way to estimate it, but we often face the multi-collinearity problem since two dummy variables are also considered in our specification. Thus only results from the random effects model are reported here.

difference operator, and for some variables, their lagged values are used in order to deal with a potential endogeneity problem.[7] Thus our model is analogous to the gravity model which is often used to study the pattern of international trade.

The results from a different specification are summarized in Table 9 where, for presentation purposes, the distance is expressed in 1,000 km rather than that presented in Table 3. The general conclusion is that conditional correlations are negatively correlated with the distance but positively with the volume. Furthermore, return correlations are higher among economies whose financial markets are more advanced and deregulated.

The first conclusion regarding distance is consistent with Roll (1992), Flavin et al (2002) and Baker and Loughran (2007). For example, Flavin et al (2002) confirm a positive relationship in data from major financial markets in the world for the period 1991-2001. A similar result is reported by Barker and Loughran (2007) for stocks listed on the US market using a spatial econometric model. Unlike previous studies, our data set covers only Asia-Pacific countries and so geographical distances are rather limited. However, distance still seems to be relevant in explaining time-dependent correlations. Furthermore, our finding suggests that an additional 1,000 km in the distance will reduce the correlation by 1 to 2 percent. Given that there have been developments in financial markets which facilitated in reducing transaction costs, the distance between markets may be better interpreted as the overlapping opening hours of the financial markets. If the markets are open at the same time, the arrival of new information occurs simultaneously and thus increases correlations in these markets.

The positive relationship between correlations and the size of trade volume is also in line with the findings of previous studies. Our result suggests an increase in correlations during the Lehman Shock when the trading became very active, which was observed during other financial crises such as Black Monday, and the Mexican peso and Asian crises. In this connection, we confirmed a difficulty of investors constructing an optimal portfolio since negatively correlated stock indices appear to exist less during the crisis.

Finally, our dummy (*China*) turns out to be negative but statistically insignificant. One might have expected a higher correlation for a pair of similar countries/regions from previous studies (e.g., Pretorius 2002). Our negative sign may be due to the effect of a

[7] We also examine the contemporaneous relationship (i.e, without taking the lag for *Vol* and *CIP*) of equation 6. But the conclusion drawn from such an analysis does not alter the conclusion presented in this paper.

developing country, mainland China, since her correlations are relatively low (see Table 5). Equation D (Table 9) does not include this dummy since it is found to be insignificant.

5. Conclusion

Using advanced econometric methods, we examine return correlations in the Asia-Pacific region. Unlike most previous studies on the analysis of return correlations investigating the causes of their dynamics, time-varying correlations are calculated using the DCC-GARCH and high frequency data, and we obtained the following findings.

Generally, this paper provides evidence that returns correlations are closely associated with other economic and financial factors. For example, they were negatively correlated with the distance between the markets. Furthermore, correlations tend to be higher in advanced countries and increase at the time of an active trading period (e.g., around the Lehman shock)—a result similar to that obtained from other financial and economic crises. Furthermore, a pair of countries with less financial integration tends to have a lower correlation. Therefore, one message to investors willing to diversify their portfolio is to pick stocks from a variety of locations. Then such a portfolio likely contains stocks negatively correlated with other stocks, or at least weakly and positively with others.

As a final remark which would bear further consideration in the future, conditional correlations could be estimated one of the regime switching models. Our conditional correlations are estimated by the most standard multivariate model, but some researchers have incorporated a state-dependent element in GARCH-type models. However, at least by judging from the graph of our estimated correlations, we did not observe clear evidence of the presence of regime-shifts in conditional correlations.

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Tables

Table 1. List of Stock Indices

Country	Stock index	Country	Stock index
Australia	All Ordinaries	Japan	Nikkei225
China	Shanghai Composite	New Zealand	NZSE50
Hong Kong	Hang Seng	Korea	Seoul Composite
India	BSE30	Taiwan	Taiwan Weighted
Indonesia	Jakarta Composite		

Table 2. Basic Statistics

	Mean	Std. Dev	ARCH(5)	ARCH(10)
Australia	0.005	1.289	F(5,1308) = 62.726 **	F(10,1298)=37.786 **
China	0.073	1.958	F(5,1308)=10.992 **	F(10,1298)=8.0763 **
HK	0.033	1.907	F(5,1308)=84.332 **	F(10,1298)= 50.200 **
India	0.065	1.896	F(5,1308)=17.693 **	F(10,1298)= 13.774 **
Indonesia	0.090	1.619	F(5,1308) = 36.131 **	F(10,1298)= 18.562 **
Japan	-0.029	1.746	F(5,1308) = 124.37 **	F(10,1298)= 77.457 **
NZ	-0.002	0.836	F(5,1308)= 129.59**	F(10,1298)= 72.755 **
Korea	0.032	1.568	F(5,1308)= 82.606**	F(10,1298)= 49.681**
Taiwan	0.024	1.442	F(5,1308)= 29.182**	F(10,1298)= 16.533**

Note: The number in parentheses corresponds to the maximum lag length used in the test.

Table 3. Unconditional Correlation among Stock Returns

Full	AUS	CHI	HK	IND	INDO	JAP	NZ	KOR	TAIW
AUS	1.000								
CHI	0.273	1.000							
HK	0.631	0.411	1.000						
IND	0.451	0.231	0.554	1.000					
INDO	0.533	0.251	0.590	0.496	1.000				
JAP	0.667	0.286	0.640	0.416	0.462	1.000			
NZ	0.589	0.203	0.326	0.268	0.348	0.416	1.000		
KOR	0.633	0.321	0.656	0.464	0.532	0.654	0.383	1.000	
TAIW	0.581	0.294	0.575	0.390	0.516	0.541	0.359	0.677	1.000

Note: Full sample.

Table 4.Conditional Variance Estimates in the Dynamic Conditional Correlation Model

	Cost	ARCH(1)	GARCH(1)	Q (5) test
Australia	0.026 [0.012]*	0.117 [0.027]**	0.869 [0.027]**	1.216
China	0.032 [0.018]	0.064 [0.013]**	0.930 [0.015]**	4.032
HK	0.022 [0.039]*	0.095 [0.000]**	0.900 [0.017]**	10.063
India	0.042 [0.018]*	0.121 [0.025]**	0.874 [0.022]**	3.734
Indonesia	0.068 [0.036]	0.100 [0.022]**	0.875 [0.034]**	2.029
Japan	0.044 [0.018]	0.101 [0.000]**	0.883 [0.020]**	1.028
NZ	0.018 [0.008]*	0.091 [0.023]**	0.879 [0.033]**	4.749
Korea	0.026 [0.011]*	0.078 [0.015]**	0.910 [0.017]**	9.423
Taiwan	0.028 [0.014]*	0.075 [0.018]**	0.912 [0.000]**	13.651*
DCC	--	0.032 [0.274]	0.486 [12.029]	

Note: The numbers in brackets are standard errors. The ** and * indicate that statistics are significant at the one and five percent levels respectively.

Table 5. Basic Statistics of Conditional Correlations

Order	Pair	Mean	Std Err	Order	Pair	Mean	Std Err
1	Japan-Korea	0.663	0.023	19	India-Korea	0.426	0.030
2	Australia-Japan	0.648	0.024	20	Australia-India	0.426	0.031
3	Korea-Taiwan	0.647	0.024	21	China-HK	0.397	0.032
4	HK-Korea	0.633	0.023	22	Japan-NZ	0.393	0.031
5	Australia-HK	0.625	0.024	23	India-Japan	0.373	0.033
6	Australia-Korea	0.621	0.024	24	India-Taiwan	0.370	0.030
7	HK-Japan	0.585	0.026	25	NZ-Korea	0.346	0.033
8	HK-Indonesia	0.584	0.025	26	HK-NZ	0.331	0.032
9	HK-Taiwan	0.578	0.026	27	NZ-Taiwan	0.313	0.035
10	Australia-Taiwan	0.555	0.028	28	China-Korea	0.302	0.034
11	Japan-Taiwan	0.555	0.026	29	Indonesia-NZ	0.297	0.032
12	Australia-NZ	0.524	0.026	30	China-Taiwan	0.279	0.036
13	HK-India	0.513	0.028	31	China-Japan	0.260	0.033
14	Australia-Indonesia	0.488	0.028	32	Australia-China	0.258	0.035
15	Indonesia-Korea	0.482	0.029	33	Indonesia-NZ	0.256	0.033
16	India-Indonesia	0.467	0.028	34	China-Indonesia	0.244	0.036
17	Indonesia-Japan	0.446	0.030	35	China-India	0.215	0.034
18	Indonesia-Taiwan	0.444	0.031	36	China-NZ	0.183	0.032

Table 6. Geographical Distance between Financial Markets (km)

	AUS	CHI	HK	IND	INDO	JAP	NZ	KOR	TAIW
AUS	0								
CHI	7889	0							
HK	7394	1225	0						
IND	10440	4250	3755	0					
INDO	5502	4449	3282	5013	0				
JAP	7834	1760	2886	5847	5793	0			
NZ	2228	9727	9433	12569	7726	9248	0		
KOR	8338	867	2091	4690	5303	1160	10003	0	
TAIW	7273	684	816	4396	3832	2100	9180	1481	0

Table 7. Different Combinations of Trade Volumes (Daily average)

Country pair	All	Before	After	Country pair	All	Before	After
AUS-CHI	4.99E+09	4.58E+09	5.53E+09	HK-NZ	1.73E+09	1.43E+09	2.12E+09
AUS-HK	2.68E+09	2.19E+09	3.34E+09	HK-KOR	1.7E+09	1.4E+09	2.09E+09
AUS-IND	9.87E+08	7.9E+08	1.25E+09	HK-TAIW	1.7E+09	1.41E+09	2.09E+09
AUS-INDO	2.49E+09	1.11E+09	4.33E+09	IND-INDO	1.5E+09	3.24E+08	3.08E+09
AUS-JAP	9.87E+08	7.9E+08	1.25E+09	IND-JAP	161653.9	148175.5	179641.1
AUS-NZ	1.02E+09	8.2E+08	1.28E+09	IND-NZ	30913171	30177128	31895431
AUS-KOR	9.87E+08	7.91E+08	1.25E+09	IND-KOR	399400.3	345857.8	470853.5
AUS-TAIW	9.91E+08	7.94E+08	1.25E+09	IND-TAIW	4248292	4214184	4293811
CHI-HK	5.69E+09	5.19E+09	6.36E+09	INDO-JAP	1.5E+09	3.24E+08	3.08E+09
CHI-IND	4E+09	3.79E+09	4.28E+09	INDO-NZ	1.53E+09	3.54E+08	3.11E+09
CHI-INDO	5.5E+09	4.11E+09	7.35E+09	INDO-KOR	1.5E+09	3.25E+08	3.08E+09
CHI-JAP	4E+09	3.79E+09	4.28E+09	INDO-TAIW	1.51E+09	3.28E+08	3.08E+09
CHI-NZ	4.03E+09	3.82E+09	4.31E+09	JAP-NZ	31026595	30286739	32013942
CHI-KOR	4E+09	3.79E+09	4.28E+09	JAP-KOR	512823.6	455469.1	589363.9
CHI-TAIW	4E+09	3.79E+09	4.28E+09	JAP-TAIW	4361716	4323795	4412321
HK-IND	1.7E+09	1.4E+09	2.09E+09	NZ-KOR	31264341	30484421	32305154
HK-INDO	3.2E+09	1.73E+09	5.16E+09	NZ-TAIW	35113233	34352747	36128111
HK-JAP	1.7E+09	1.4E+09	2.09E+09	KOR-TAIW	4599462	4521477	4703533

Note: The average size of the number of traded stocks in two stock markets. The cut-off point is Sept/15/2008.

Table 8. Deviations from the CIP

Order	Pair	Size	Order	Pair	Size
1	Australia-NZ	0.005	19	HK-Taiwan	0.017
2	HK-Japan	0.006	20	Australia-Taiwan	0.018
3	Australia-HK	0.008	21	NZ-Taiwan	0.018
4	HK-NZ	0.009	22	China-Taiwan	0.027
5	Australia-Japan	0.010	23	HK-Indonesia	0.028
6	Japan-NZ	0.011	24	China-Korea	0.030
7	HK-India	0.012	25	Indonesia-NZ	0.030
8	India-Japan	0.012	26	Australia-Indonesia	0.030
9	India-Korea	0.013	27	Indonesia-Japan	0.031
10	Australia-India	0.013	28	China-India	0.033
11	Korea-Taiwan	0.013	29	China-Japan	0.034
12	India-NZ	0.013	30	India-Indonesia	0.035
13	India-Taiwan	0.013	31	China-HK	0.035
14	Japan-Korea	0.015	32	China-NZ	0.036
15	Japan-Taiwan	0.016	33	Indonesia-Korea	0.037
16	NZ-Korea	0.016	34	Australia-China	0.037
17	Australia-Korea	0.016	35	Indonesia-Taiwan	0.040
18	HK-Korea	0.016	36	China-Indonesia	0.045

Note: The average value of deviations. The small size of deviations from the CIP implies non-existence of significant trade barriers.

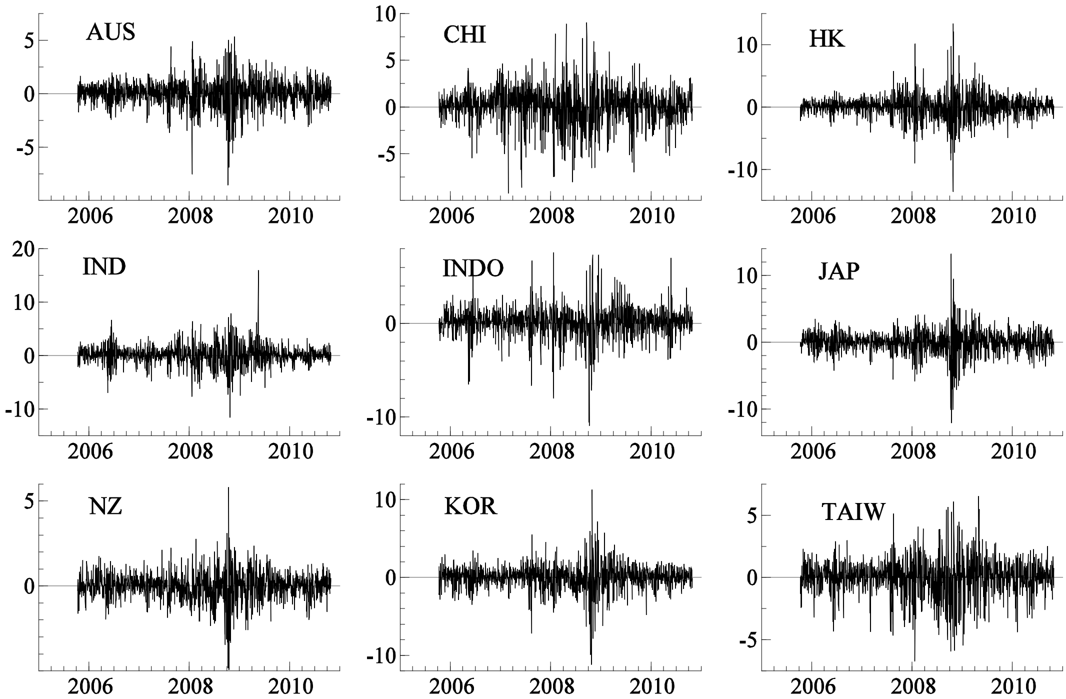
Table 9. Determinants of Conditional Correlation

	Eq. [A]	Eq. [B]	Eq.[C]	Eq.[D]
D.Vol(t-1)		0.001 [0.000]**	0.001 [0.000]**	0.002 [0.000]**
Dist(t)	-0.013 [0.008]+	-0.013 [0.007]+	-0.017 [0.008]*	-0.014 [0.007]*
China(t)	--	--	-0.101 [0.085]	--
Devi(t-1)	--	--	--	-1.492 [0.899]+
Constant	0.507 [0.048]**	0.507 [0.046]**	0.534 [0.054]**	0.543 [0.050]**
Sigma_u	0.134 [0.011]	0.134 [0.013]	0.132 [0.013]	0.127 [0.010]
Sigma_e	0.030 [0.001]	0.030 [0.001]	0.030 [0.001]	0.044 [0.009]
rho	0.953 [0.008]	0.953 [0.009]	0.951 [0.009]	0.893 [0.036]

Note: The numbers in brackets are standard errors obtained via the bootstrap method (1,000 replications). The **, * and + indicate that statistics are significant at the one, five and ten percent levels respectively. The total number of observations is 47,484.

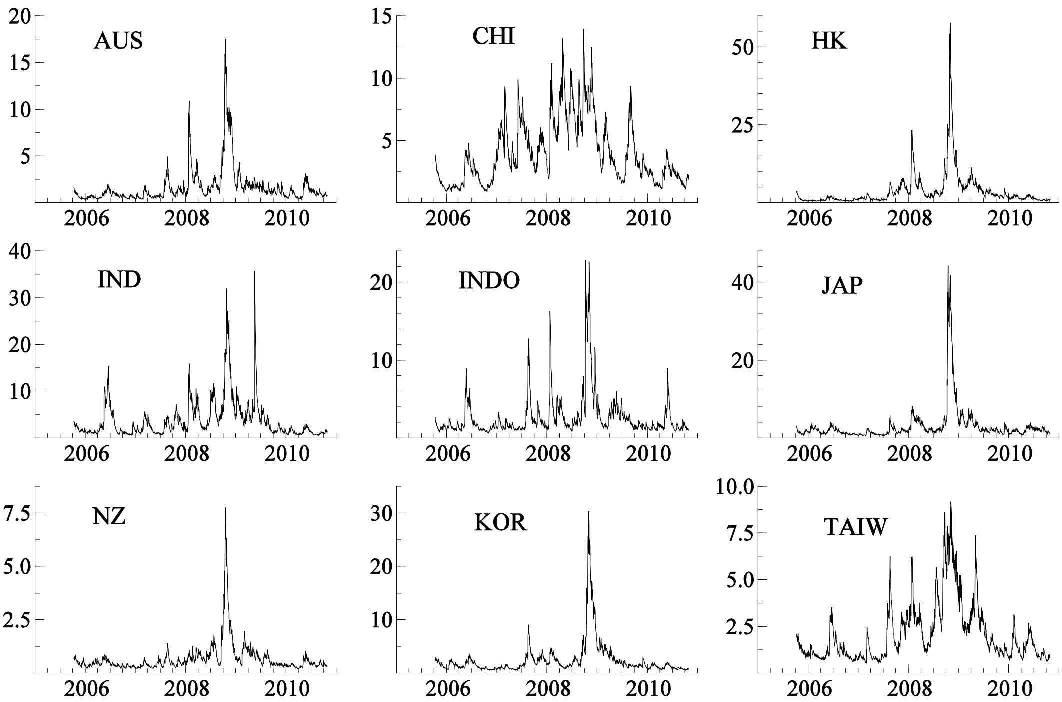
Figures

Figure 1. Stock Returns



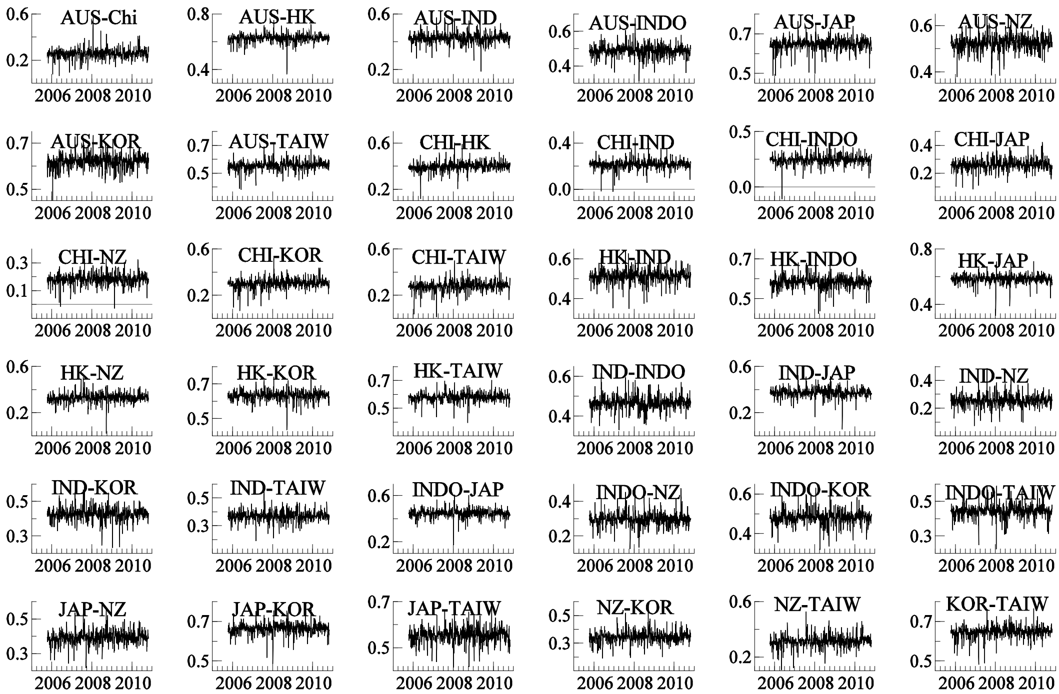
Note: Full sample. Australia (AUS), China (CHI), India (IND), Indonesia (INDO), Japan (JAP), Korea (KOR), and Taiwan (TAIW).

Figure 2. Conditional Variance



Note: Full sample. Australia (AUS), China (CHI), India (IND), Indonesia (INDO), Japan (JAP), Korea (KOR), and Taiwan (TAIW).

Figure 3. Conditional Correlation



Note: Full sample. Australia (AUS), China (CHI), India (IND), Indonesia (INDO), Japan (JAP), Korea (KOR), and Taiwan (TAIW).