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RETURNS AND VOLATILITY SPILLOVER BETWEEN ASIAN EQUITY MARKETS: A WAVELET APPROACH

ABSTRACT: *We analyse return and volatility spillover across select Asian equity markets using wavelet multiple correlation and cross-correlation. For the purpose of analysis, daily return data is taken from equity markets, viz. Bombay Stock Exchange SENSEX, Tokyo Stock Exchange NIKKEI 225, Hong Kong Shanghai Index (HSI), Amman Equity Index, Korea Composite Stock Price Index (KOSPI), and Singapore Strait Time Index (STI), from 03/01/2000 to 31/12/2013. The results show that the Asian markets are co-integrated in the long run. Further, it is found that a significant part of each market's volatility pattern at intra-week scale can be largely explained by own shocks, but in the long run the volatility dynamics of the market changes as the extent of the spillover increases. From the wavelet multiple cross-correlation values, two developed markets, the STI and the HSI, are identified as potential leaders or followers among the group. From the analysis it is found that the volatility spillover across the studied markets is relatively low at the high frequency, implying that there is possibility of diversification at a daily to intra-week scale. The discrepancies between the markets vanish in the long run; hence a long-term diversification strategy is best avoided.*

KEY WORDS: *Asia, Diversification, Wavelets, Volatility, Spillover, Stock Markets, Risk*

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1. INTRODUCTION

The study of volatility spillover between stock markets is of crucial importance in finance, due to its importance in investment decisions and risk diversification. If there is increased spillover across stock markets there are fewer chances for diversification, whereas segmented stock markets can be used by investors to diversify portfolios. Due to the increasing amount of information flow and the trade and financial liberalization policies followed by many countries in the last two decades, the chances of volatility spillover among equity markets has increased.

The present study analyses the dynamics of volatility spillover across select Asian equity markets. While the developed countries liberalized their equity markets during the 1970s (allowing foreign investors to trade in domestic equity markets), the Asian equity markets were different. Although the Hong Kong equity market was liberalized in 1973, the rest of the Asian equity markets were liberalized in the 1980s and 1990s. In many countries the liberalization of the stock market was carried out in multiple stages. Details of equity market liberalization in major Asian countries are given in Table 1 (Tiwari et.al. 2014).

Country	Liberalization Year
Japan	1985
India	1991
Hong Kong	1973
China	2001
Singapore	1986
South Korea	1991/ 1998
Malaysia	1973/1978/1984
Indonesia	1988/ 1989

It can be seen that the Chinese equity market was liberalized only recently. The Chinese securities market started functioning in 1986 and the Shanghai Stock Exchange (SHSE) began to operate on December 19th, 1990 (Lean 2010). However, China's stock market remained isolated until China's accession to the WTO in 2001.

As the Asian equity markets are relatively young, there is the possibility that investors can diversify risk due to potential information asymmetry. Here we study volatility spillover across select Asian equity markets using a wavelet-based methodology. To this end, we briefly review a few works related to volatility spillover across Asian Equity Markets.

2. LITERATURE REVIEW

There are many studies of volatility spillover across Asian equity markets. We limit ourselves to a number of representative works from the last decade.

Chen and Wong (2003) analyse volatility transmission among the ASEAN countries during the East Asian financial crisis. They follow a two-step method, where in the first stage individual markets are analysed using an APARCH model. In the second stage a CCC GARCH model is employed to study volatility transmission. The results indicate that the nature of the volatility transmission changed significantly during the crisis period.

Employing a BEKK GARCH framework, Worthington and Higgs (2004) study volatility transmission among Asian equity markets. They examine the possibility of developed and developing markets having different patterns by studying the equity markets of Hong Kong, Japan, Singapore, South Korea, Malaysia, the Philippines, Taiwan, and Thailand. They find that all the Asian markets are highly integrated. However, the volatility spillovers were found to be asymmetric in nature. Own volatility spillover was found to be larger than cross-volatility spillover for all the markets, but this phenomenon was predominant in the emerging markets.

Chuang et.al. (2007) examine volatility spillover among the East Asian equity markets using a VAR-BEKK framework. The study takes data from the US, UK, Japan, Hong Kong, Singapore, Korea, Taiwan, and Thailand. Volatility spillover is confirmed, and they find that Japan plays a predominant role in transmitting volatility to other Asian markets.

Another study, by Joshi (2011), examines the nature of volatility spillover among the equity markets of India, Japan, Hong Kong, Indonesia, and South Korea using a BEKK-GARCH framework. The author finds evidence of bidirectional volatility spillover among the markets. The impact of own-volatility spillover is found to be larger than the impact of cross-volatility spillover. Among the studied markets, Japan shows the highest volatility persistence, while China ranks lowest. It is also found that Asian equity markets are weakly co-integrated.

Valiis and Chulia (2011) examine volatility transmission between select Asian markets and the US using daily data from the equity markets of South Korea, Taiwan, Hong Kong, Singapore, Malaysia, Thailand, Indonesia, the Philippines, and China, using a multivariate GARCH framework for their analysis. The study finds that there is excess volatility transmission between the US and Asian equity markets, and that the 2008 crisis did not change the patterns of volatility transmission. It also finds that a country's equity market development is linked to the extent of volatility transmission from the US.

Employing a bivariate DCC framework, Padhi and Lagesh (2012) examine the transmission of volatility between the equity markets of India, the US, Thailand, Malaysia, Indonesia, and Taiwan. They find evidence of volatility transmission among all the participating markets. They also find that Indonesia is the main source of volatility transmission among the studied markets.

Giles and Li (2013) examine volatility spillover between Asian financial markets and the US using a BEKK GARCH framework and data from the US, China, India, Malaysia, the Philippines, Thailand, and Japan. The analysis is split into two periods, the 1997 East Asian crisis and the 2008 crisis. They find that there was strong bidirectional volatility spillover between the US and the Asian markets during the crisis period. They also find that the developed markets are mostly affected by their own past shocks.

Abbas et.al (2013) analyse volatility transmission between Pakistan's equity markets and those of India, China, Japan, Singapore, the UK, the US, and Sri Lanka using a pair-wise GARCH approach. They find that volatility spillover can take place even when the political relationship is hostile, as long as trade and commercial relations exist.

Aloy et.al (2014) study volatility spillover between Asian and US equity markets using the shift volatility model of Filardo. They find that markets such as

Singapore, Japan, and Hong Kong are very much influenced by shocks from the US equity markets, while other markets such as Indonesia, Malaysia, and the Philippines are mostly influenced by regional markets such as Hong Kong and Singapore.

Tiwari et.al (2014) study the co-movement of selected Asian equity markets using wavelet multiple correlation and cross-correlation methods. The results indicate that the Asian markets are co-integrated in the long run.

Lee et.al (2014) employ both parametric and nonparametric methods to examine how a major event would impact return and volatility spillover indices between the Brent oil market and stock markets. The empirical evidence indicates that oil-exporting countries have a significant impact on the returns and volatilities of oil-importing countries. The results also show that the dynamics of both return and volatility spillovers change significantly during major economic events.

Lee et. al. (2014) study the possibility of spillover across North East Asian and European equity markets by employing methods such as DCC GRACH models, the Risk decomposition model, the Generalized Variance model, and the Collective Correlation model. The results indicate that Northeast Asian stock markets are independent of European stock market movements and that European stock markets show an increasing trend of joint integration with Northeast Asian stock markets.

The literature detailed above shows that volatility spillover across Asian markets exists, and that the volatility of an equity market can be largely explained by its own (endogenous) shocks. From a methodological perspective, it shows that volatility spillover has been studied extensively using the multivariate GARCH framework.

However, the methodological constraints associated with time series models means that there is scope for further research. The GARCH and its multivariate extensions can only provide information about volatility spillover at a given frequency. In other words, GARCH measures can only provide an average explanation of market volatility. The markets consist of traders with different risk preferences and different diversification strategies operating at different timescales. Thus, we need to analyse volatility spillover across different timescales, as short-term investors may be interested in short-term fluctuations, medium-term investors in medium-frequency fluctuations, and so on. GARCH models also assume a specific functional form of volatility that is restrictive in nature. The present study addresses these issues, using wavelets for the purpose of analysis.

Wavelets are a filtering method used to decompose a given time series into its various frequencies without losing timescale information. They can be broadly classified into two categories: continuous wavelet transform (CWT) and discreet wavelet transform (DWT). In CWT the given time series are decomposed into continuous timescales, as suggested by the name. However, for many practical purposes such detail is not required, and therefore DWT is applied, which carries out the decomposition in dyadic timescales. However, DWT has serious limitations. The given time series should be dyadic in nature (should be expressed as a power of 2). Further, the decomposed signal is sub-sampled at each level. This has led to the invention of Maximal Overlap Discreet Wavelet Transform (MODWT), which addresses the restrictions of DWT. Here, we use a method based on MODWT.

At an intuitive level we can see why wavelets are useful for analysing financial time series and asset pricing problems. By employing wavelet decomposition methods it is possible to extract information about short-term, medium-term, and long-term investor behaviour and perform analysis on the extracted components. Further, wavelets are preferred over other frequency domain methods such as Fourier transform because they are not affected by the non-stationary nature of the financial time series .

Various studies in financial literature employ wavelet-based methods. Loh (2008) studies volatility spillover across Asian bond markets using wavelets and finds conclusive evidence for spillover across multiple timescales. Kristoufek et.al (2011) study co-integration between European Forex markets using wavelet coherence and find evidence of pair-wise co-movement among the markets. Veiga et. al. (2013) employ wavelet methods to study the spillover mechanism between oil and stock Markets. Naseri and Masik (2014) employ a DCC GARCH model along with pairwise wavelet correlation and wavelet coherence to examine the volatility spillover between developed and emerging Islamic markets. Dajčman and Kavkler (2014) employ wavelet-based regression methods to analyse co-movements between the developed and emerging European markets and finds evidence supporting diversification in the medium term.

We employ a wavelet-based method proposed by Macho (2012) to analyse stock market volatility spillover across selected Asian countries. The wavelet multiple correlation coefficient measure provides the strength of the co-movement between a multivariate time series across different timescales, making it possible to distinguish between short-run, medium-run, and long-run relationships. Wavelet multiple cross-correlation provides a measure to identify a potential group leader that could influence the other variables in the group.

These measures are better than traditional wavelet correlation and cross-correlation measures. Here, if we have 5 markets we have to calculate $nX(n-1)/2=10$ wavelet correlation plots and J (order of wavelet decomposition) times wavelet cross-correlation plots, resulting in a cumbersome process. Further, in a multivariate context, a pair-wise correlation coefficient could be spurious due to possible relationships between variables. The proposed methodology estimates overall correlations and cross-correlation within the multivariate framework across different time scales, making interpretation of the results easier. We will need to plot only two graphs compared to the traditional wavelet correlation measures. A detailed explanation of the methods used is given in the following section.

3. DATA AND METHODOLOGY

We employ daily log returns calculated from the following equity indices: Bombay Stock Exchange (BSE) SENSEX, Tokyo Stock Exchange NIKKEI 225, Hong Kong Shanghai Index (HSI), Amman Equity Index, Korea Composite Stock Price Index (KOSPI), and Singapore Strait Time Index (STI), between 03/01/2000 and 31/12/2013. The methodology consists of two parts. We use the wavelet-based multiple correlation and cross-correlation routines developed by Macho (2012) to study how volatility spillover takes place among these markets across different timescales and to see if we can identify a potential leader among them.

In the first stage, we study the movement of equity returns. Next, we employ absolute returns and squared returns to measure unconditional volatility, and wavelet multiple-correlation and wavelet multiple cross-correlation to analyse the possibility of volatility spillover.

A brief explanation of the method is given in the following paragraphs.

Let $\{X_t\}$ be a multivariate stochastic process and let $\{W_{jt}\}$ be the respective j^{th}-level wavelet coefficients obtained by the application of MODWT. The wavelet multiple correlation (WMC henceforth) $\emptyset x$ (λ_j) can be defined as one single set of multi-scale correlations calculated from X_t as follows.

At each wavelet scale λ_j we calculate the square root of the regression coefficient of determination in that linear combination of variables w_{ijt} , $i=1,2,\ldots n$ for which the coefficient of determination is a maximum. The coefficient of determination corresponding to the regression of a variable Z_i on a set of regressors $\{Z_k, k \neq i\}$ can be obtained as $R_i^2=1-1/\rho^{ii}$, where ρ^{ii} is the i^{th} diagonal element of the inverse of the complete correlation matrix P.

The WMC $\emptyset x$ $(\lambda_{j)})$ is obtained as

$$\phi_X(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\ P_j^{-1}}} \tag{1}$$

where P is the $N\times N$ correlation matrix of W_{jt}, and the *max diag(.)* operator selects the largest element in the diagonal of the argument. Since the R^2_i coefficient can be shown to be equal to the square of the correlation between the observed values of z_i and the fitted values z_i obtained from such a regression, $\emptyset x$ (λj) can also be expressed as:

$$\phi_X(\lambda_j) = Corr(\omega_{ijt}, \widehat{w}_{ijt}) = \frac{Cov(\omega_{ijt}, \widehat{w}_{ijt})}{\sqrt{Var(\omega_{ijt})}\sqrt{Var(\widehat{w}_{ijt})}} \tag{2}$$

where the wavelet variances and covariance are defined as follows:

$$Var(w_{ijt}) = \frac{1}{T_j}\sum_{t=j-1}^{T-1} w_{ijt}^2$$

$$Var(\widehat{w}_{ijt}) = \frac{1}{T_j}\sum_{t=j-1}^{T-1} \widehat{w}_{ijt}^2$$

$$Cov(\omega_{ijt}, \widehat{w}_{ijt}) = \frac{1}{T_j}\sum_{t=L_j-1}^{T-1} \omega_{ijt}\widehat{w}_{ijt}$$

Where w_{ij} on a set of regressors $\{w_{kj}, k \neq i\}$ leads to the maximization of the coefficient of determination, $\widehat{w}_{ij}$ represents the fitted values. The number of wavelet coefficients affected by the boundary associated with a wavelet filter of length L and scale λ_j is calculated as $L_j=(2^j-1)(L-1)+1$. Then the number of wavelet coefficients unaffected by the boundary conditions is obtained as $\tilde{T}_j = T - L_j - 1$.

Allowing a lag τ between the observed and fitted values of the variables selected as the criterion variable at each scale λ_j, we may define the wavelet multiple cross-correlation (WMCC henceforth) as

$$\phi_{X,\tau}(\lambda_j) = Corr(\omega_{ijt}, \widehat{w}_{ijt+\tau}) = \frac{Cov(\omega_{ijt}, \widehat{w}_{ijt+\tau})}{\sqrt{Var(\omega_{ijt})}\sqrt{Var(\widehat{w}_{ijt+\tau})}}$$

For $n=2$ the WMC and WMCC are the same as the standard wavelet correlation and cross-correlation.

Macho (2012) constructs the confidence intervals using Fisher's transformation. Fisher's transformation is defined as *arctanh(r)* where *arctanh(.)* is the inverse hyperbolic tangent function, and it is used to construct the confidence interval for a population correlation, based on the fact that if (X, Y) follows a bivariate normal distribution with $\rho = \mathrm{Corr}(X, Y)$, then the transformed sample correlation coefficient calculated from T independent pairs of observations can be shown to be approximately normally distributed with mean *arctanh(r)* and variance $(T-3)^{-1}$. (Fisher 1921; Johnson et al. 1995). This result is applied to the sample wavelet multiple correlation coefficient $\tilde{\phi}_X(\lambda_j)$ as follows:

Let $X=(X_{1t}, X_2 \ldots\ldots X_T)$ be a realization of multivariate Gaussian stochastic process $X=(x_{1t}, x_2 \ldots\ldots x_t)$ and let $\widetilde{W}_j = (\widetilde{W}_{j0} \ldots \ldots . \widetilde{W}_{j,T-1}) = \{(\widetilde{w}_{1j0} \ldots \ldots . \widetilde{w}_{nj0}), \ldots \ldots \ldots . (\widetilde{w}_{1j,T/2^j-1})\}$, $j=1, 2 \ldots\ldots J$ be vectors of wavelet coefficients obtained by applying a MODWT of order J to each of the univariate time series $(x_{i1}, x_{i2}, \ldots . . x_{iT})$ for $i=1,2 \ldots\ldots . n$. If $\tilde{\phi}_X(\lambda_j)$ is the sample wavelet correlation obtained from equation (1), then

$\tilde{z}_j \sim FN(z_j, (T/2^j-3)^{-1})$, where $z_j = \arctan h(\emptyset_X(\lambda_j))$, $\tilde{z}_j = \arctan h(\tilde{\phi}_X(\lambda_j))$ and FN stands for Folded Normal Distribution. The $100(1-\alpha)\%$ confidence interval for the true value of $\phi_{X,\tau}(\lambda_j)$ is then obtained as $CI_{1-\alpha}\left(\phi_{X,\tau}(\lambda_j)\right) = \tanh(\tilde{z}_j - c_2/\sqrt{T/2^j-3}\ ; \tilde{z}_j + c_1/\sqrt{T/2^j-3})$ where c_1 and c_2 are folded normal critical values

4. ANALYSIS

Prior to the estimation of wavelet-based measures, in Table 1 we present the summary statistics of the return series under analysis.

Variable	Mean	Minimum	Maximum	Std. Dev.	Skewness	Ex. kurtosis
BSE	0.0001715	-0.05129	0.06944	0.00705	-0.1803	6.4278
AMMAN	0.0001222	-0.03731	0.03265	0.00488	-0.482	9.07081
HSI	3.68E-05	-0.05899	0.05823	0.00687	-0.0243	7.91982
KOSPI	8.40E-05	-0.07287	0.06021	0.00741	-0.5812	7.66226
N225	-1.88E-05	-0.0526	0.05748	0.00678	-0.4643	6.34266
STI	2.43E-05	-0.03777	0.04059	0.00547	-0.0767	5.98395

The markets under consideration are a heterogeneous group, with developed markets HSI (Hong Kong), KOSPI (South Korea), N225 (Japan), and STI (Singapore), and emerging markets BSE (India) and AMMAN (Jordan). The primary objective of this paper is to see if there are any common dynamics present among these diverse markets.

From the summary statistics it can be seen than KOSPI and BSE show most fluctuation, as evident in the standard deviation measures. AMMAN is the least fluctuating market. Further, from the skewness and kurtosis values, it is evident that all returns distributions are negatively skewed and exhibit fat tails. Next, we proceed to wavelet multiple correlation and cross-correlation estimates for the return series.

Figures 1 and 2 present the estimated wavelet multiple correlations and cross-correlation coefficients for the return series at different timescales. We estimate wavelet multiple correlation (WMC) using a Daubechies least asymmetric (LA) wavelet filter of length 8, as suggested by Macho (2012). We estimate wavelet details and smooths up to a decomposition level of 6. The corresponding values are given in Tables 2 and 3.

Figure 1. Wavelet Multiple Correlation-Return Series

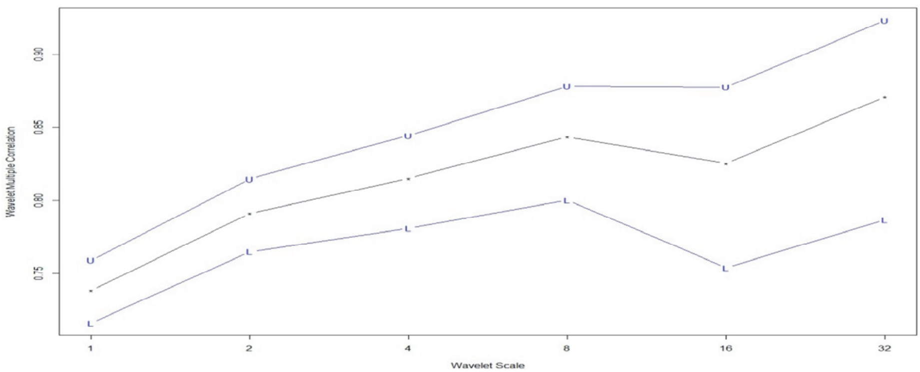
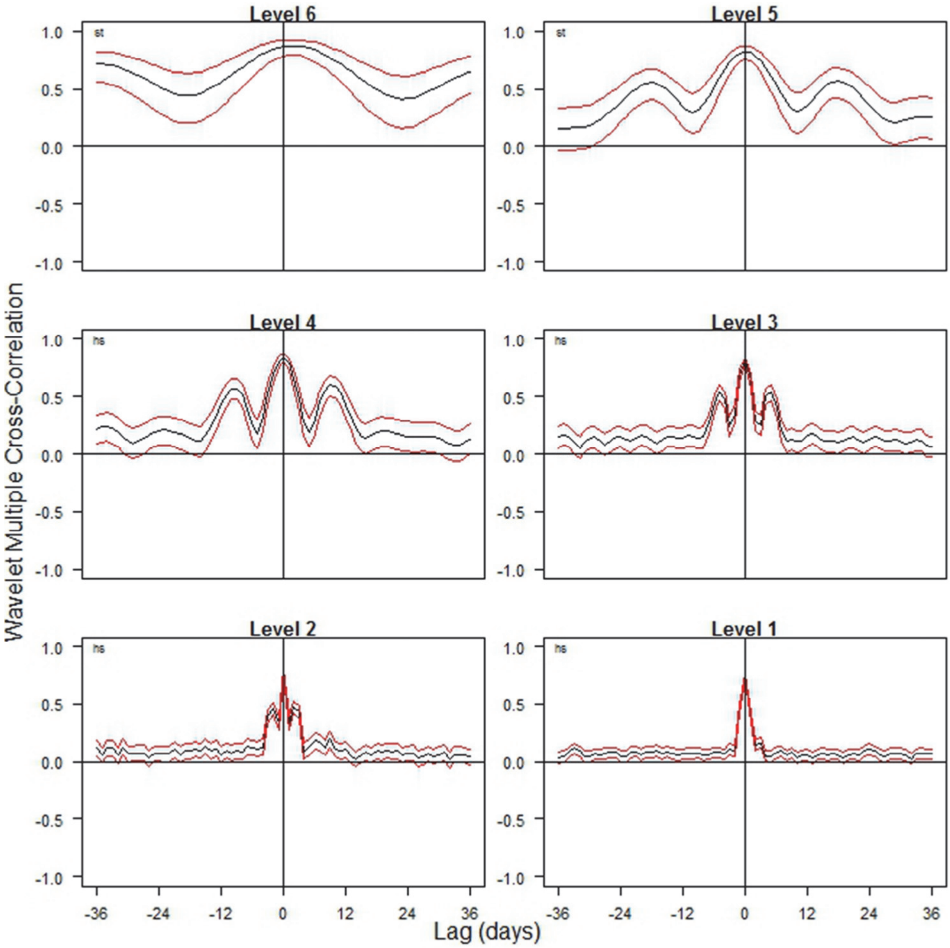


Figure 2. Wavelet Multiple Cross-Correlation-Returns Series



From the wavelet multiple correlation plots we can see that the returns are highly correlated with each other across all the scales. At the daily scale the WMC value is 0.73 at scale 1 (intra-week), and it increases across scales. At scale 6 we can see the possibility of near-perfect co-movement among the return series, as the WMC value is 0.98. Here, the performance of one market can be explained to a large extent by the overall performance of the other markets. The discrepancies between the studied markets vanish around a 32- to 64-day scale. From the multiple correlation values we can say that the return movement of each market is largely influenced by other markets, and there is a possibility of diversification at the intra-week scales.

Next, we analyse the multiple cross-correlation diagram. The market that maximizes the wavelet multiple correlations against the linear combination of other markets at each scale is selected as a potential leader/follower in the group, and is shown in the upper right corner of Figure 2. From scales 1–4, HSI is seen to be maximizing the WMC against others. At scales 5 and 6, STI maximizes WMC against all markets.

However, due to the symmetric nature of the graphs, i.e., the highest values obtained at lag zero, we cannot confirm whether HSI and STI are potential leaders or followers at these scales.

Next, we analyse volatility spillover across the said markets. For this purpose we consider two measures of unconditional volatility: 1) absolute returns and 2) squared returns. The results are shown in Figures 3–6 and the corresponding values are given in Tables 4–7.

Figure 3. Wavelet Multiple Correlation: Absolute Returns

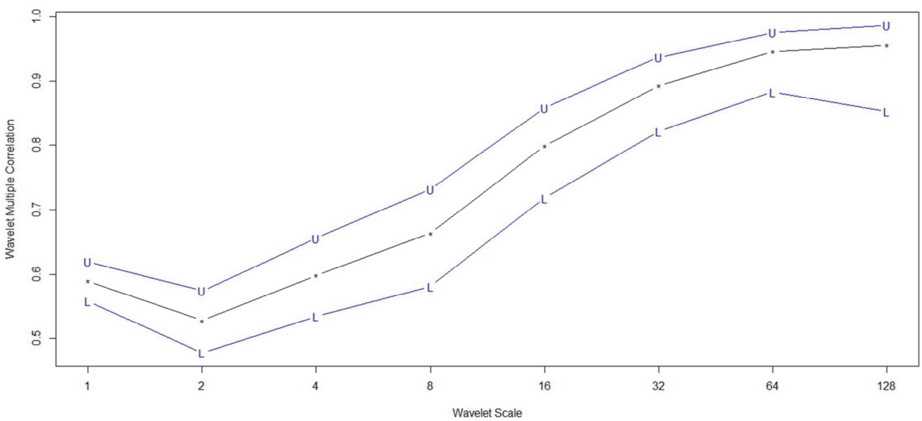
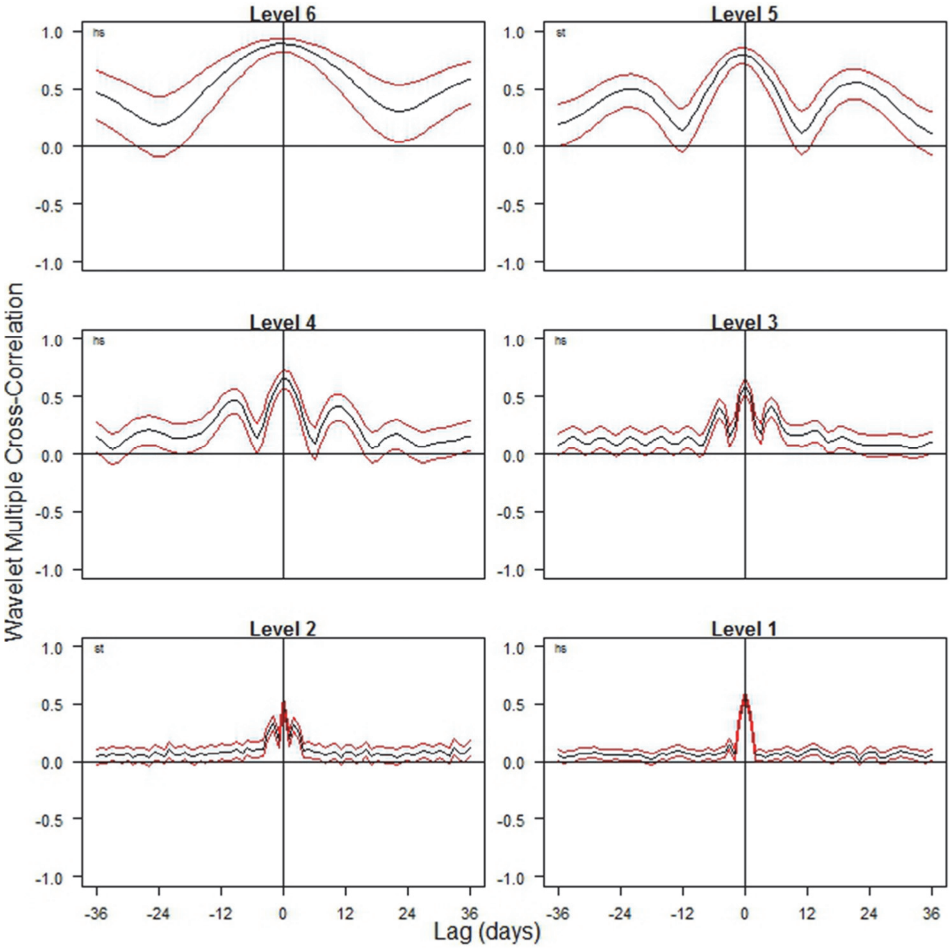


Figure 4. Wavelet Multiple Cross-Correlation: Absolute Returns



Analysing the multiple correlation plots for absolute returns, we can see that the extent of the correlation is significant but less than that of the return series. At scale 1 the volatility spillover is 0.589. Around 58.9% of the volatility in each market can be explained by its own shocks and the rest by spillover from other markets. However, the volatility spillover increases across scales, and at the scale of 32–64 days we can see that the value of the multiple correlation is 0.89, indicating high volatility spillover in the long run. The cross-correlation values are insignificant at scales 1 and 2, but at scales 3–6 the values are significant. Here, HSI is the potential leader/follower at scales 3, 4, and 6, while STI is the potential leader/follower at scale 5. Again, the symmetric nature of the graph prevents us from confirming if these two markets are leaders or followers.

Figure 5. Wavelet Multiple Correlation: Squared Returns

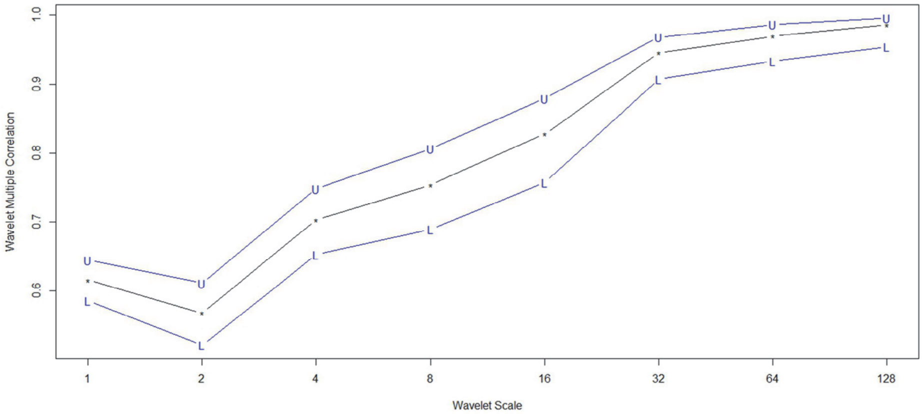
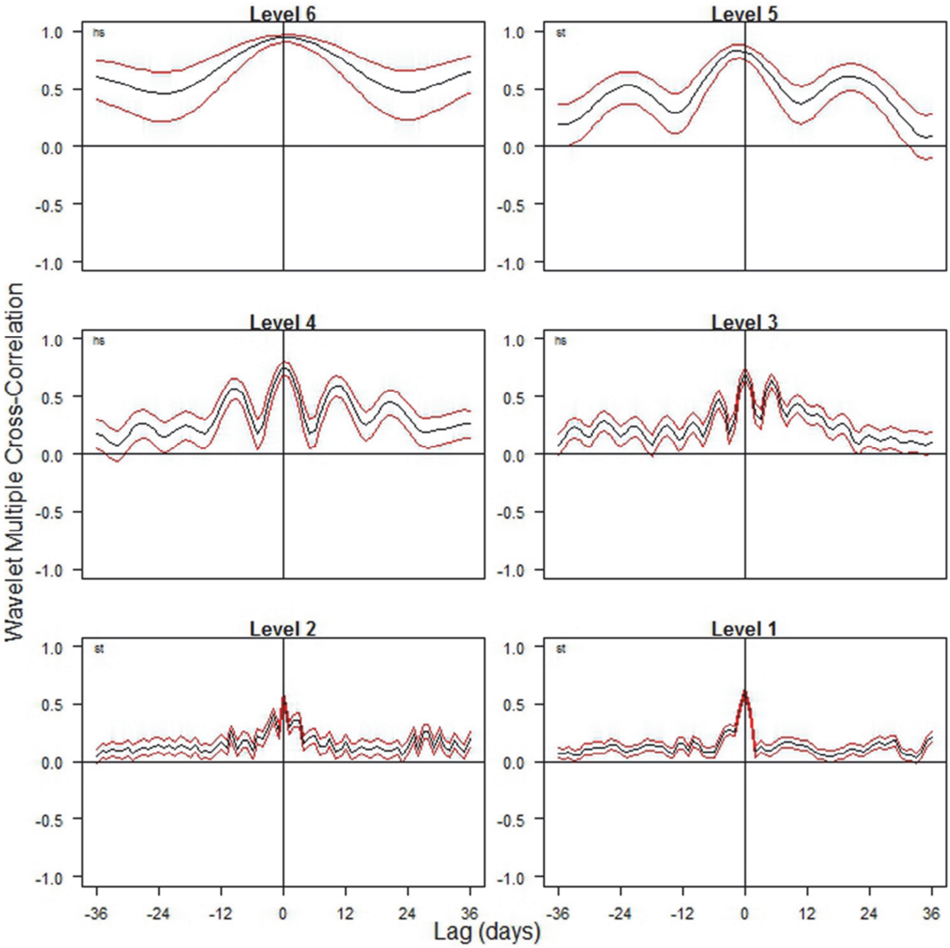


Figure 6. Wavelet Multiple Cross-Correlation: Squared Returns



Examining the multiple correlation plots for the squared returns, we can observe similar behaviour as in the absolute returns. In the multiple cross-correlation plot it can be seen that STI maximizes multiple correlation values against other markets at scales 1, 2, and 5, while HSI maximizes multiple correlation values at scales 3, 4, and 6. Here too, we cannot reach a definite conclusion due to the symmetric nature of the graph.

CONCLUDING REMARKS

In this study, we analyse the return and volatility spillover across select Asian equity markets using a wavelet-based method, namely wavelet multiple correlation and cross-correlation. This exercise provides certain unique insights that are explained below.

First we study the return co-movement by estimating the wavelet multiple correlation coefficients for the return series. We find that the Asian markets move together across multiple timescales and co-integrate in the long run, as evidenced by the high value of the wavelet multiple correlation coefficients (WMC) over increasing scales.

To study the dynamics of volatility spillover we propose a model-free approach, as opposed to the prevailing multivariate GARCH framework. We use two measures of unconditional volatility, namely absolute return and squared return. First we estimate WMC for absolute returns and squared returns to identify any potential spillover. From the value of the WMC coefficients of the absolute and squared return series it is also found that a significant part of the volatility pattern of each market at an intra-week scale can be largely explained by own shocks. However, in the long run the volatility dynamics of the market change as the extent of the spillover increases.

In the next stage of the analysis we try to find the possible lead–lag relationship between the markets. We estimate wavelet multiple cross-correlation (WMCC) values for all three series. From the wavelet multiple cross-correlation values, two developed markets, STI and HSI, are identified as potential leaders or followers among the group. However, due to the symmetric nature of the cross-correlation plots we cannot arrive at a definitive conclusion as to whether these markets lead others.

From the analysis it is found that the volatility spillovers across the studied markets are relatively low at the high frequency, implying that there is a possibility of diversification in the short run, i.e., on a daily to intra-week scale. It can be concluded that there exist diversification opportunities for investors in the short run as the volatility spillover across markets in the short run is moderate. However, as the discrepancies between the markets vanish in the long run, any long-term diversification strategy is best avoided.

REFERENCES

Abbas, Q., Khan, S., & Shah, S. Z. (2013). Volatility transmission in regional Asian stock markets. *Emerging Markets Review*, *16*, 66-77. doi:10.1016/j.ememar.2013.04.004

Baruník, J., Vácha, L. and Krištoufek, L. (2011). Comovement of Central European stock markets using wavelet coherence: Evidence from high-frequency data. Institute of Economic Studies Working Paper 22/2011.

Chen, Y. C., & Wong, K. Y. (2003). Asymmetric Stock-Returns Volatility Transmissions During the Asian Financial Crisis – the case of the ASEAN markets. Retrieved from http://karyiuwong.com/papers/volatility.pdf

Chuang, I., Lu, J., & Tswei, K. (2007). Interdependence of international equity variances: Evidence from East Asian markets. *Emerging Markets Review*, *8*(4), 311-327. doi:10.1016/j.ememar.2007.08.001

Dajčman, S. & Kavkler, A. (2014). Wavelet Analysis of Stock Return Energy Decomposition and Return Comovement – A Case of some Central European and Developed European Stock Markets. *Finance, 52* (1), 104–120.

Dufrénot, G., Jawadi, F., & Louhichi, W. (2014). *Market microstructure and nonlinear dynamics: Keeping financial crisis in context*. Cham: Springer.

Fernández-Macho, J. (2012). Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets. *Physica A: Statistical Mechanics and its Applications*, *391*(4), 1097-1104. doi:10.1016/j.physa.2011.11.002

Fisher, E. A. (1921). On the "probable error" of a coefficient of correlation deduced from a small sample. *Metron*, *11*, 3-32.

Giles, D. E., & Li, Y. (2013). Modelling Volatility Spillover Effects Between Developed Stock Markets and Asian Emerging Stock Markets. *International Journal of Finance & Economics*, *20*(2), 155-177.

Johnson, N. L., Kotz, S., & Balakrishnan, N. (1995). *Continuous univariate distributions: Vol. 2*. New York: Wiley & Sons.

Joshi, P. (2011). Return and Volatility Spillovers Among Asian Stock Markets. *SAGE Open*, *1*(1). doi:10.1177/2158244011413474

Kumar Tiwari, A., Billah Dar, A., Bhanja, N., & Shah, A. (2013). Stock Market Integration in Asian Countries: evidence from Wavelet multiple correlations. *Journal of Economic Integration*, *28*(3), 441-456. doi:10.11130/jei.2013.28.3.441

Lee, G. & Jeong, J. (2014). Global Financial Crisis and Stock Market Integration between Northeast Asia and Europe. *Review of European Studies, 6* (1), 61–75.

Lee, Y-H., Liao, T-H., Huang, Y-L. & Huang, T-L. (2015). Dynamic Spillovers between Oil and Stock Markets: New Approaches at Spillover Index. *International Journal of Financial Research, 6* (2), 178–189.

Loh, L. (2008). Volatility Spillovers in the Asian Bond Market: A Wavelet Analysis. Working paper, EDHEC.

Martín-Barragán, B., Ramos, S. B. & Veiga, H. (2013). Correlations between oil and stock markets: A wavelet-based approach. Universidad Carlos III Working Paper 13-05.

Naseri, M. & Masih, M. (2014). Integration and Comovement of Developed and Emerging Islamic Stock Markets: A Case Study of Malaysia. MPRA Paper No. 5879

Padhi, P., & Lagesh, M. A. (2012). Volatility Spillover and Time Varying Correlation Among the Indian, Asian and US Stock Markets. *Journal of Quantitative Economics*, *10*(2), 77-90.

Valls, N., & Chuliá, H. (2012). Volatility Transmission and Correlation Analysis between the USA and Asia: The Impact of the Global Financial Crisis. *Global Economic Review*, *41*(2), 111-129. doi: 10.1080/1226508x.2012.686476

Worthington, A., & Higgs, H. (2004). Transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis. *Int. J. Fin. Econ*, *9*(1), 71-80. doi:10.1002/ijfe.222

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APPENDIX I. Wavelet Multiple Correlation and Cross-Correlation Tables

Table 2. Wavelet Multiple Correlation: Returns

Level	WMC	Lower CI	Upper CI
1	0.738085	0.715891	0.758789
2	0.790947	0.764633	0.814628
3	0.815037	0.780768	0.844417
4	0.843388	0.79996	0.878027
5	0.82523	0.753811	0.877379
6	0.870809	0.786416	0.923288

Table 3. Wavelet Multiple Cross-Correlations: Returns

Level/Lags	24	-18	-12	-6	0	6	12	18	24
1	0.044488	0.082882	0.065656	0.078835	0.738085	0.081434	0.058546	0.062071	0.11146
2	0.069894	0.091814	0.061902	0.119815	0.790947	0.179678	0.102914	0.092733	0.071053
3	0.152943	0.118391	0.14155	0.438881	0.815037	0.397654	0.160339	0.101142	0.128504
4	0.205382	0.13847	0.439179	0.235072	0.843388	0.298608	0.428484	0.183478	0.155934
5	0.386566	0.551973	0.346921	0.516333	0.82523	0.531509	0.354897	0.567703	0.360688
6	0.520119	0.444894	0.560218	0.751852	0.870809	0.840774	0.689056	0.493394	0.414026

Table 4. Wavelet Multiple Correlation: Absolute Returns

Wave	WMC	Lower CI	Upper CI
1	0.58941	0.557823	0.619292
2	0.527665	0.477873	0.574077
3	0.598056	0.53391	0.655358
4	0.662974	0.580891	0.731709
5	0.798698	0.71811	0.858149
6	0.892717	0.821267	0.936598

Table 5. Wavelet Multiple Cross-Correlations: Absolute Returns

Levels/lags	24	-18	-12	-6	0	6	12	18	24
1	0.056745	0.021951	0.088172	0.053949	0.58941	0.065216	0.090609	0.052772	0.086281
2	0.070086	0.043903	0.088023	0.102057	0.527665	0.086899	0.085813	0.071635	0.072582
3	0.093404	0.109171	0.130859	0.330651	0.598056	0.354568	0.171324	0.14468	0.072275
4	0.191309	0.146924	0.389606	0.19505	0.662974	0.090698	0.382291	0.067769	0.126532
5	0.486104	0.419474	0.148252	0.586778	0.798698	0.487059	0.15918	0.507918	0.520601
6	0.186422	0.355157	0.62036	0.820822	0.892717	0.814991	0.618028	0.388717	0.319484

Table 6. Wavelet Multiple Correlation: Squared Returns

Level	WMC	Lower CI	Upper CI
1	0.58941	0.557823	0.619292
2	0.527665	0.477873	0.574077
3	0.598056	0.53391	0.655358
4	0.662974	0.580891	0.731709
5	0.798698	0.71811	0.858149
6	0.892717	0.821267	0.936598

Table 7. Wavelet Multiple Cross-Correlations: Squared Returns

Level/Lag	24	-18	-12	-6	0	6	12	18	24
1	0.056745	0.021951	0.088172	0.053949	0.58941	0.065216	0.090609	0.052772	0.086281
2	0.070086	0.043903	0.088023	0.102057	0.527665	0.086899	0.085813	0.071635	0.072582
3	0.093404	0.109171	0.130859	0.330651	0.598056	0.354568	0.171324	0.14468	0.072275
4	0.191309	0.146924	0.389606	0.19505	0.662974	0.090698	0.382291	0.067769	0.126532
5	0.486104	0.419474	0.148252	0.586778	0.798698	0.487059	0.15918	0.507918	0.520601
6	0.186422	0.355157	0.62036	0.820822	0.892717	0.814991	0.618028	0.388717	0.319484