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Characterizing Co-movements between Indian and Emerging Asian Equity Markets through Wavelet Multi-Scale Analysis*

Aasif Shah**
Department of Commerce (SOM) Pondicherry Central University
shah_aasifpu@redifffmail.com

Malabika Deo
Department of Commerce (SOM) Pondicherry Central University
deo_malavika@yahoo.co.in

Wayne King
Software Engineer at MathWorks
wmkingty@gmail.com

Multi-scale representations are effective in characterising the time-frequency characteristics of financial return series. They have the capability to reveal the properties not evident with typical time domain analysis. Given the aforesaid, this study derives crucial insights from multi scale analysis to investigate the co-movements between Indian and emerging Asian equity markets using wavelet correlation and wavelet coherence measures. It is reported that the Indian equity market is strongly integrated with Asian equity markets at lower frequency scales and relatively less blended at higher frequencies. On the other hand the results from cross correlations suggest that the lead-lag relationship becomes substantial as we turn to lower frequency scales and finally, wavelet coherence demonstrates that this correlation eventually grows strong in the interim of the crises period at lower frequency scales. Overall the findings are relevant and have strong policy and practical implications.

Keywords: Asian Markets, Time Domain, Frequency Domain, Wavelets, Multi-Scale Analysis
JEL Classification: F36, G11, G15

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** Corresponding Author

I. INTRODUCTION

With significant reforms in the financial sector in India initiated in 1991, Foreign Institutional Investors (FIIs) and Non Resident Indians (NRIs) gained access to Indian stock markets. Additionally, beginning in 1993, the Indian corporate sector also could seek channels of financing and investment in the global markets with the help of Global Depository Receipts (GDR), American Depository Receipts (ADR) and Foreign Currency Convertible Bonds (FCCB). All these financial opportunities contributed to strong improvements in market capitalization, liquidity and the efficiency of the Indian capital market. In addition, there has been a significant increase in its cross-border flows (capital as well as financial) and as a result, India is currently witnessing an unprecedented level of economic interdependence with both developed and developing nations. The study of economic and market interdependence hold important implications for the theory of financial economics which posits that portfolio risk can be reduced through international portfolio diversification provided that the returns in different markets are weakly or negatively correlated (Markowitz, 1952). A major argument regarding stock market interdependence was laid by (Stulz, 1999) who asserted that increased market integration leads to international risk sharing resulting in lower cost of equity capital. Since the first empirical work on the advantages of internationally well-diversified portfolio (Grubel, 1968), there has been a substantial debate in international finance on the linkages between stock markets and their effects on diversification. Since then, a number of studies have emerged on the co-movements among international equity markets (Levy and Sarnat, 1970; Shiller, 1989; Kasa, 1992; Richards, 1995; Forbes and Rigobon, 2002; Johnson and Soenen, 2003; Brooks and Del Negro, 2004; Syriopoulos, 2007). Initially the investigations on stock market linkages were pursued through simple correlation (Granger and Morgenstern, 1970; Brooks and Del Negro 2004; Mukherjee, 2007). Recently more advanced tools like rolling window correlation (Brooks and Del Negro, 2004), switching regimes (Hassler, 1995) and cointegration methods (Arshanapalli and Doukas, 1993; Voronkova, 2004) have also been used. In Asian markets, empirical works based on co-integration of equity markets have examined the extent to which such markets in the region are correlated, in order to scrutinize the diversification opportunities (Mills and Mills, 1991; Huang et al., 2000; Masih and Masih, 2001; Ratanapakorn and Sharma, 2002). Other studies like (Corhay et al., 1993; Chung and Liu, 1994; Islam, 2014) incorporated vector auto-regression, vector error correction model, impulse response analysis, forecast error variance decomposition and granger causality techniques. Additionally, bivariate GARCH models have been used to investigate the degree of market integration (Kang and Yoon, 2011). The idea was to bring different kinds of tools so as to capture an unambiguous linkage between the underlying markets. However, the methodological experimentations led the authors to two different schools of thoughts. Some propounded that there is essentially a long run relationship, while others argued that the relationship is exclusively short-term. But the fact remains that the authors have overlooked the fact that the problems hinged on co-integration, error correction techniques and the like. For instance, these models have been constructed to deal with not more than two time frequencies.

After the significant policy shifts in the beginning of the 1990's, the Indian equity market is swiftly integrating with the rest of the world markets. India is active in various bilateral trade agreements with several countries and regional groups across Asia and Europe. The interdependence and integration of its market is clearly reflected in the rising volatility from spillover turmoil emerging from international markets. For example, in September 2008, national stock markets around the world declined precipitously in the wake of the Lehman Brothers collapse. The Indian stock market crashed from a high of 20,000 to a low of around 8,000 points during the year 2008-2009 (Parul and Gupta, 2010). Economists realized that it is important for nations to keep an eye on the interdependence of their financial and equity markets for framing appropriate policies. Over the years several studies have been carried out to investigate stock market linkages of India with both developed as well as developing markets. For example, although reporting strong correlation between Indian and Hong Kong, Singapore, Thailand, Taiwan and Korean markets by using the cointegration and Granger-causality tests, the study by (Bose and Mukherjee, 2006) inferred that the Indian market offers only short term scope for reaping benefits of portfolio diversification. Moreover, they reported weak correlations with US and Japanese returns. The findings of this study however, contradicts (Raj and Dhal, 2008) who, based on multivariate co-integration analysis, concluded that India's dependence on the global markets like US & UK was considerably higher relative to regional markets like Singapore and Hong Kong. He further argued that the Indian market would be influenced by the diversification objective of foreign investors only in the short run. Additionally (Tripathi and Sethi, 2010) showed that Indian market is integrated with the US stock market but not with Japan, UK and China and suggested that the long term benefits can be derived from portfolio diversification. Equity market participants comprise a diverse group that include investors, speculators, intraday traders, hedging strategists, portfolio managers, commercial banks, large multinational corporations and so on. It is notable that these market participants operate on different time scales depending upon their requirements and thus the true dynamic structure of the relationship between variables might vary over different time scales. Viewing this phenomenon from a portfolio diversification perspective, this means that market participants with short-term investment horizons are active at higher frequencies while those with longer-term investment horizons operate on longer scales. Therefore it is imperative to gauge co-movements in stock markets on multiple scales. Wavelet techniques naturally provide a multi-scale analysis of data. This new approach is able to characterize the multi-scale aspects of a return time series to serve as a protocol for various traders, who view the market with different time horizons. In India, using wavelets to examine the beta for Indian stocks (Deo and Shah, 2012b) argue that beta has a tendency to vary depending on the time horizon of the investors. Thus given the diverse horizons, wavelets can provide an easy vehicle with which to study the multi-scale properties of financial return series. With regard to co-moments of return series (Lee, 2004; Fernandez, 2005; Rua and Nunes, 2009; Raghavan et al., 2010) examined wavelet correlation and concluded that benefits of diversification could be exploited at higher frequency intervals. Recently, (Tiwari et al., 2013) adopted wavelet multiple correlation of (Fernandez, 2012) and suggested that diversification opportunities can be grabbed at higher frequencies in Asian Markets. In this paper, we examine to what extent Asian equity markets both in the East Asia region including (China, Japan, Hong Kong, South Korea & Taiwan) and Southeast Asia region comprising of (Singapore, Philippines, Malaysia, Indonesia and Thailand) are integrated over multiple scales with the Indian equity market. The findings suggest that the integration of the Indian market with the emerging Asian markets increase monotonically with the increase in the wavelet scale. This in turn implies time varying diversification opportunities for Indian investors. It was also observed that there exists a lead-lag relationship between India and sample markets. The price change in Asian markets can drive or pull the Indian market at low frequency intervals. Furthermore, with the financial crises, the integration of the Indian market with those of Asian markets rises initially but grows strong as time passes. This implies that investors have some time in the beginning for portfolio diversification even in a crises period. Thus, investors, fund managers and regulators can use our insights to formulate effective portfolio diversification strategies.

The remainder of the paper is organized as follows. Section II gives a narrative description of Asian Markets. Section III explains the wavelet multi-scale analysis decomposition. Section IV describes the data, sample structure and discussion of results and finally Section V brings together the key findings and makes some concluding remarks.

II. ASIAN MARKETS: AN OVERVIEW

In the recent past, the economic growth as well as industrialization of many Asian countries has been phenomenal, by any measure of performance (Bakker and Chapple, 2003). In the beginning, it was Japan that took the lead and attained high economic growth in the 1960's followed by newly industrialized economies like Korea, Singapore, Taiwan and Hong Kong in the 1980's. In addition, China, India and Vietnam have experienced remarkable and rapid development since the 1990's (Page, 1994). According to the (World Bank, 2013), East Asia and the Pacific remained the world's growth engine in 2013. In fact, the term Asian Tigers is used in reference to four East Asian economies of South Korea, Singapore, Hong Kong and Taiwan (Krueger, 2009). During the period 1990-94, large volumes of foreign capital surged into those East Asian economies that were pursuing deregulation and openness with respect to their money and capital markets. Besides, Southeast Asia also occupied a significant place in the global economy. India has established strong trade relations with both Southeast Asian nations as well as with the individual countries from East Asia. In fact, both these regions consider India as an emerging power in Asia and thus are keen to develop relations with it. (Mukul, 2007) documented that the relationship would be constructive for countries within East Asia and Association of South East Asian Nations (ASEAN) and for the regions as a whole. In turn, India also acknowledges and understands that the east and southeast regions of Asia comprise both developed and emerging economies which have achieved significant progress over the past two decades. It is therefore in the interest of both sides to establish strong economic linkages so as to develop key partnerships.

In early 1997, cracks began to appear, particularly among East and Southeast Asian countries due to financial crises. However, India was able to protect itself from turmoil to a large extent (Dua and Sinha, 2007). Relatively tighter controls in the capital account shielded Pakistan and India from being drawn into the crisis at that time (Josef, 1999). Both regions have come a long way after the 1997 financial crises. Their achievements in negotiating the crisis and then returning to sustained growth are impressive. In the early 1990's, the level of India's interaction and integration with the economies of two regions was low, even after the initiation of the "Look East Policy" in 1992. However, things have changed after the major initiatives taken by India which included a free trade agreement (FTA) with Thailand, an extensive economic partnership agreement with Singapore and Korea and a broad economic partnership agreement (CEPA) with Korea and Japan. As a result, the country is witnessing an exceptional level of capital interdependence and cross-border economic, financial, and business integration with both developed and developing markets in Asia. The current trade of India with East and Southeast Asia represents about a quarter of its total trade; surpassing that with the United States and European Union. The bilateral annual trade between India and South Korea is about USD 16 billion. The share of South Korea in FDI equity inflows to the Indian market from 2000 to 2014 is 0.65% with US$ 1.39 billion. Whereas, the share of Taiwan, China, Hong Kong and Japan amounts to 0.04%, 0.19%, 0.54% and 7.42% respectively. On the other hand the share of Southeast Asian countries like Singapore, Malaysia, Indonesia, Thailand and Philippines comprise 12.35%, 0.31%, 0.26%, 0.08% and 0.05% respectively (FDI Statistics 2014). Table 1 presents an overall glimpse of foreign direct investments inflows (equity) to India from East and Southeast Asian markets for a better understanding on the flow of funds. It is clearly evident that Singapore, Japan and Korea are the major trading partners of India contributing 0.12, 0.06 and 0.07 percent of total equity inflows to the Indian market. Overall the table highlights the strong economic linkages between India and these two important regions of Asia. These linkages however have generated considerable interest among, individual investors, international fund managers and academicians. Essentially, the degree of interdependence among markets has strong implications for international portfolio diversification and financial stability of India. A large body of literature reveals that economic integration increases economic welfare

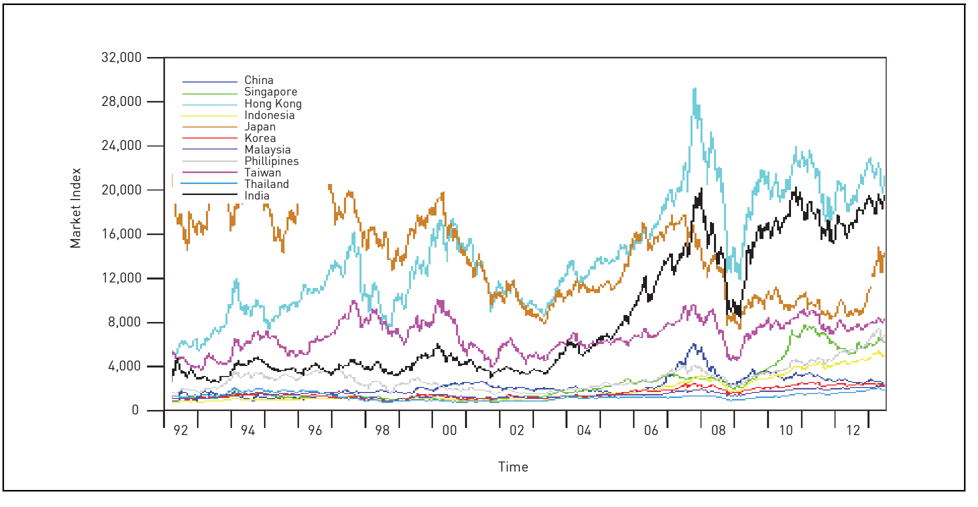
(Bekaert and Harvey 1995). Recently, (Guidi, 2010) assessed the links in terms of cointegration and interdependence between the Indian Stock market and developed Asian markets like Hong Kong, Japan and China. He found time varying conditional correlation relationship among markets which increased during the crisis but returned to its initial levels after crisis. (Tripathi and Sethi, 2010) found that the Indian stock market is integrated with the US stock market, but not with that of Japan, UK & China. On the other hand (Rajwani and Jaydeep, 2013) concluded that the Indian stock market is not integrated with any of the Asian markets either individually or collectively. We study a simultaneous time and frequency content of the return series and demonstrate which frequency essentially captures the greater proportion of benefits from market integration for Indian Investors. The analysis will in turn be instrumental for International investors from sample countries so that they can plan accordingly regarding their investments in the Indian market. Figure 1 depicts weekly Price fluctuations of Asian stock markets during the period starting from 1992-2013. These fluctuations are evident because the individual stocks that make up the stock market fluctuates based on supply and demand. If stock markets are efficient, the prices must evolve randomly. The graph demonstrates that both Asian financial crises of 1997 as well as US subprime mortgage crises of 2008-09 caused a sharp decline in Asian stock markets. According to (IMF, 2009) on the slowdown of economic growth, GDP growth rates declined in all major Asian economies including: Singapore decreased from (7.8 to 1.1); Hong Kong (6.4 to 2.5); Malaysia (6.3 to 4.6); Korea (5.1 to 2.2); (Philippines); (7.2 to 4.6); (China 13.0 to 9.0); Indonesia (6.3 to 6.1); Thailand (4.9 to 2.6) and (India 9.3 to 7.3). The spontaneous reaction of markets to external shocks carry significant implications for both policymakers and market participants. For policymakers, these elements are important in assessing potential costs from financial contagion and policy coordination. For market participants, they may imply reductions in the benefit of portfolio diversification.

Table 1. FDI Equity inflows to India since Jan, 2000 to November, 2014

Rank	Country	2000-2011	During 2012	During 2013	During 2014	Cumulative Total (From Jan, 2000 to November, 2014)		
		FDI Million (Rs.)	FDI Million (Rs.)	FDI Million (Rs.)	FDI Million (Rs.)	FDI Million (Rs.)	FDI Million (US$.)	% with total
2	Singapore	713,175.23	152,421.76	222,116.31	397,378.1	1,485,091.40	29,193.6	0.12
4	Japan	567,762.89	103,644.23	82,344.24	134,023.9	887,775.28	17,636.9	0.06
14	South Korea	39,302.10	18,043.57	9,973.74	8,280.00	75,599.41	1,517.5	0.07
15	Hong Kong	38,101.44	9,153.95	10,144.47	5,175.53	62,575.39	1,283.2	0.00
22	Malaysia	14,208.59	11,553.46	6,423.45	5,554.05	37,739.55	724.92	0.00
24	Indonesia	28,003.30	251.15	69.48	611.84	28,935.77	621.73	0.00
28	China	4,935.38	7,314.44	4,170.17	8,639.47	25,059.46	453.39	0.00
35	Thailand	4,130.99	602.82	3,674.62	1,211.96	9,620.40	184.33	0.00
40	Philippines	142.66	1,365.06	266.56	4,591.81	6,366.09	108.59	0.00
43	Taiwan	2,592.95	501.77	49.36	1,327.39	4,471.47	89.57	0.00

Source: Compiled from FDI statistics Issued by Department of Industrial Policy & Promotion India

Figure 1. Weekly Price Fluctuations of Asian Equity Markets Since 1992-13



1. Why do Markets Move Together?

This is perhaps one of the central questions, particularly from the view point of stock investors and fund managers. Bekaert and Harvey (1995) infers that part of the move towards greater integration is driven by the deregulation across most of the developing countries. Literary works on market integration suggest that as a result of trade globalization, relaxed market restrictions, low transaction costs and the progress in technology and communication, integration among markets has been increased. One of the fundamental reasons for stock market co-movements however, could be that the stock markets of two countries are highly correlated so that financial shocks to the larger country spread to the smaller one via assets-trading. An example of such a spillover is the integration among the capital markets of Argentina and Uruguay. As a consequence of Argentina's 2001-2002 stiff crises and subsequent external debt default and currency devaluation, Uruguay was forced to devalue its currency. Second, trading partners and bilateral or multilateral trade agreements also elevate the transmission of shocks internationally. For instance, when the currency of a country depreciates, imports from its trading partners go down, and the trade balance of the country whose currency is devalued become worse. For example, the Brazilian devaluation of 1999 placed great pressure on its major trading partner, Argentina. The third reason (Chua, 1993) emphasizes the role of technological factors on economic growth. Technological spillovers among nearest countries tend to occur as a result of flow of ideas and capital which are faster and easier across neighbouring countries rather than across distant countries. The fourth reason states that spillovers or contagion crises may occur for institutional reasons according to the theories of (Calvo and Reinhart, 1996).

Therefore it is imperative for both investors as well as fund managers to be well acquainted with stock market co-movements. Similarly, policy-makers need to understand the driving forces behind these linkages. Such an understanding will not only provide a better grasp of the functioning of the underlying stock markets but also allow investors and policy makers to derive significant benefits from such economic integration including lower costs of trading financial assets, diversified portfolios, and more stable consumption patterns mostly during periods when the level of economic activity fluctuates widely. Thus a study on stock market integration, either theoretical or empirical, carries a great significance for various stakeholders.

2. Correlation, Risk and Diversification

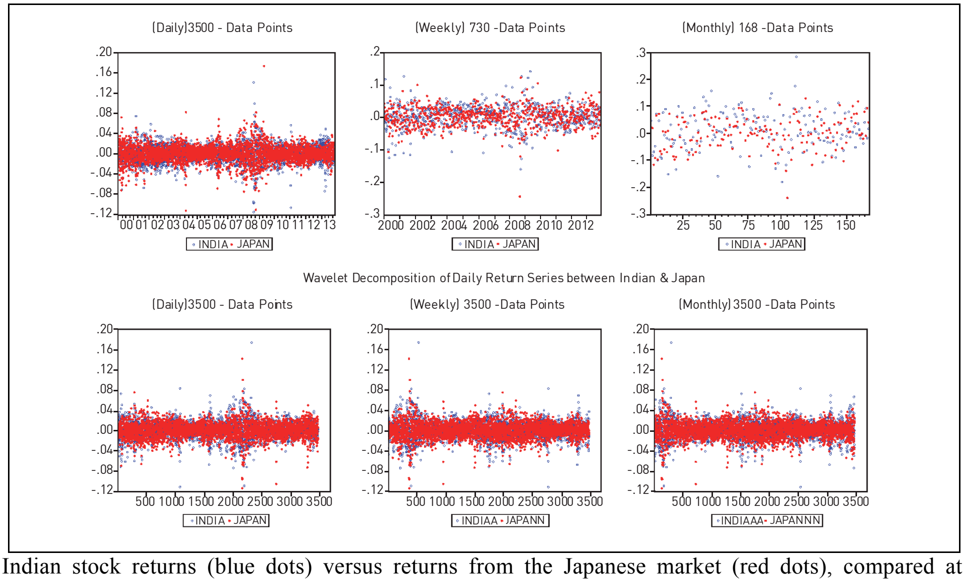
The decision to diversify globally is part of a firm's overall investment strategy. Markowitz (1952) went on to show analytically how the benefits of diversification depend on correlation. The roots of international portfolio diversification depend on the correlation coefficient across markets, the risk of each market, and the returns in each market. To illustrate how the correlation among individual security returns affects portfolio risk, consider investing in two risky stocks X and Y. Let us presume that the risk of a stock is measured by its standard deviation of return, which for assets X and Y is denoted by σ_x and σ_y respectively. Let a be the fraction invested in stock X and b be the fraction invested in stock Y. When the returns on stocks within a portfolio are perfectly positively correlated, the portfolio risk is the weighted average of the risks of the stocks in the portfolio. The more interesting case is when the assets are not perfectly correlated; there is a nonlinear relationship between portfolio risk and the risks of the underlying assets. In this case, at least some of the risk from one stock will be offset by the other stock, so the standard deviation of the portfolio P is always less than the weighted average of σ_x & σ_y. Thus, the risk of a portfolio is less than the average risk of the underlying stocks. The benefits of international diversification truly materialize when the returns of stock markets in a particular region, say (Asia), are not perfectly positively correlated because there exists different industrial structures in different markets, and because all economies do not follow the same business cycle. Investors therefore expect smaller return correlations between investments in different countries than between investments within a given country. Lessard (1973) argues that a significant part of the risk that cannot be diversified within a single country can be diversified internationally. It is believed that an internationally diversified portfolio has a lower beta. This implies that if the market becomes integrated, it reduces the scope for reduction of beta in international diversification.

III. WAVELET MULTI-SCALE DECOMPOSITION

The typical time domain method aims at studying the elemental properties of an economic variable whose realizations are recorded at a predetermined frequency. However, this approach does not produce any clue in relation to the frequency domains of an underlying variable. Accordingly, it makes the pretended assumption that the relevant frequency to study the behaviour of the underlying variable matches its sampling frequency. However, an issue arises if the variable realizations depend, in a much complicated manner, on several frequency components. The concept of wavelets was initially introduced by (Ramsey and

Lampart, 1998a; Ramsey and Lampart, 1998b) into the analysis of economic and financial relationships between income and expenditure followed by (Gencay et al., 2002) who examined the relationship between money growth and inflation. They also extended the Wavelets to estimate the relationship between risk and return. To be precise, wavelet methods deconstruct return series into different time-frequency scales. To illustrate the effect of different time intervals on market integration, we choose Indian and Japanese stock market returns and compared them under both conventional as well as wavelet decomposition scales. The plots in Figure 2 depict the comparison results, if retrieved through conventional decomposition, could lead to biased estimations due to loss of data points when return interval is changed from daily to weekly to monthly.

Figure 2. Conventional Decomposition of Daily Return Series between Indian and Japan



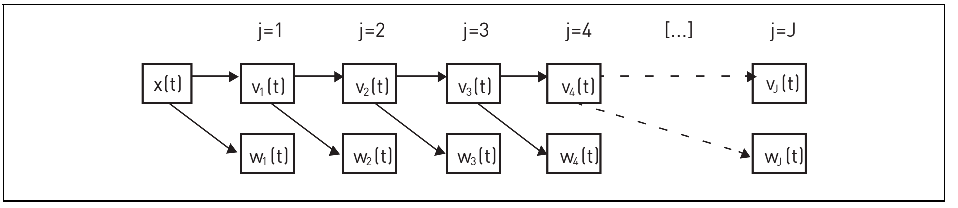
Indian stock returns (blue dots) versus returns from the Japanese market (red dots), compared at different time periods. It can be seen noticed that when the comparison interval is reduced or decomposed from daily to weekly to monthly under conventional decomposition, the number of sample points decreases from 3500 to 730 to168 respectively which results in loss of information. However if the same return series is decomposed from daily to weekly to monthly under wavelet transformation, the sample or data points remains the same and hence does not result in loss of information.

Until recent times the integration of equity markets has generally been reviewed following typical time-domain approach without taking notice on frequency domains. Nevertheless, an obvious possibility is there that the relationship might show a different tune at different frequencies in view of diverse trading nature of market participants. The promising linkage amidst equity markets can therefore be different across frequencies and the underlying relationship can change over time. Given its ability to deconstruct the return series into different time scales and address market heterogeneity, the wavelet method is quite persuasive. The wavelet and scaling coefficients at the first level of decomposition are obtained by convolution of the data series with the father wavelets $\varphi(t)$ and mother wavelet $\psi(t)$

$$\int \varphi(t)dt = 1 \qquad \int \psi(t)dt = 0, \tag{1}$$

The father wavelets are meant for the low frequency components of a return series and the mother wavelets are meant for the high-frequency components. In other words, father wavelet deals with the trend components and mother wavelet characterizes all the variations from the trend. This in turn means that a series of mother wavelets are used to represent a function while only one father wavelet is accounted to represent a function. To continue the deconstruction of the return series into frequency components, one needs to resort to pyramid algorithm (see Figure 3). Let $x(t)$ represent an original stock return series say (weekly). $w_1(t)$ denotes first level wavelet decomposition scale that captures (2~4) weeks stock return fluctuation in the market and $v_1(t)$ denotes a smooth scale. Furthermore, in order to capture (4-8) weeks stock return fluctuation, smooth series, that is, ($v_1(t)$) require decomposition which in turn will produce $w_2(t)$ & $v_2(t)$. Here $v_2(t)$ denotes smooth series for further decomposition and $w_2(t)$ is associated up to eight week stock return fluctuations.

Figure 3. Flowchart of the pyramid algorithm



The algorithm depicts that a time series, say $x(t)$, can be deconstructed by the wavelet transformation as under:

$$x(t) = \sum s_{j,k}\emptyset_{s,k}(t) + \sum d_{s,k}\varphi_{s,k}(t) + \sum_k d_{j-1,k}\varphi_{j-1,k}(t) + \ldots\ldots + \sum_k d_{1,k}\varphi_{1,k}(t) \tag{2}$$

Where J specifies the number of multi-scale levels and k ranges from one to the number of coefficients in each level and $s_{J,k}$, $d_{J,k}$,….., $d_{1,k}$ represent the wavelet transform coefficients and $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ denote the approximating wavelets functions. The wavelet decompositions can be expressed as

$$s_{J,k} = \int \phi_{J,k}(t) f(t) dt \tag{3}$$

$$d_{j,k} = \int \psi_{j,k}(t) f(t) dt \text{, for j=1,2,……}J. \tag{4}$$

J is the maximum integer such that 2^J takes a value less than the number of observations.

The detail coefficients, $d_{J,k}$,….., $d_{1,k}$, represents increasing finer scale deviation from the smooth trend and $s_{J,k}$, which represent the smooth coefficient, capture the trend. Hence, the wavelet series approximation of the original series $f(t)$ can be expressed follows:

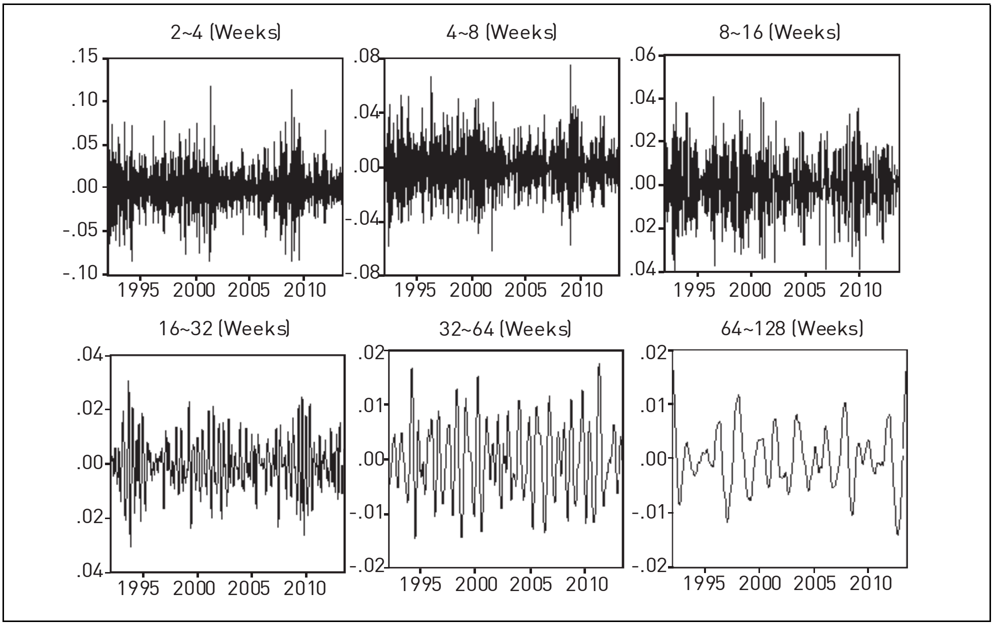
$$f(t) = S_{J,k}(t) + D_{J,k}(t) + D_{J-1,k}(t) + ... + D_1(t). \tag{5}$$

where $S_{J,k}$ is the smooth signal and $D_{J,k}$, $D_{J-1,k}$, $D_{J-2,k}$ .... $D_{1,k}$ are detailed signals. These smooth and detailed signals are expressed as follows:

$$\mathrm{S}_{j,k} = \sum_k S_{j,k} \emptyset_{j,k}(t),$$
$$D_{j,k} = \sum_k d_{j,k}\varphi_{j,k}(t), \& D_{1.k} = \sum_k d_{1,k}\varphi_{1,k}(t), J = 1,2, \dots, J-1 \tag{6}$$

The $S_{J,k}$, $D_{J,k}$, $D_{J-1,k}$, $D_{J-2,k}$ .... $D_{1,k}$ are listed in increasing order of the finer scale components. Figure 4 depicts the behaviour of original return series of the Indian market over different time frequency intervals. As is evident from the plot that the wavelet scale is increasing, the wavelet coefficients become thicker, hence analyzing such patterns become a critical part of the investment.

Figure 4. Multi-Scale Decomposition of Equity Returns From Indian Market



1. Wavelet Correlation and Cross Correlation

The measurement of wavelet correlation involves the computation of variances of $\{x_t, y_t\}$ and co-variances $\{x_t\}$ and $\{y_t\}$ at contrasting wavelet scales. Wavelet variance basically describes the substitution of variability against certain scales. For stochastic process, say x, it is estimated using the maximal overlap discrete wavelet transform (MODWT henceforth) coefficients for scale $\tau_j = 2^{j-1}$ through:

$$\hat{\sigma}_x^2(\tau_j) = \frac{1}{\hat{N}_j} \sum_{k=L_j-1}^{N-1} (\hat{W}_{j,k})^2$$

where $\hat{W}_{j,k}$ denotes the coefficient of MODWT wavelet variable x at scale and $\hat{N}_j$ is the number of coefficients unaffected by boundary, and L_j is the length of the scale τ_j wavelet filter. The wavelet covariance deconstructs the covariance between two stochastic processes at each scale. Given the wavelet covariance for $\{x_t, y_t\}$ and wavelet variances for $\{x_t\}$ and $\{y_t\}$, the wavelet correlation can be put across as follows:

$$\hat{\rho}_{xy}(\tau_j) = \frac{Cov_{xy}(\tau_j)}{\hat{\sigma}_x^2(\tau_j)\hat{\sigma}_y^2(\tau_j)}$$

The cross correlation is a more powerful tool for examining the relationship between two time series. The cross correlation function considers the two series not only simultaneously (at lag 0), but also with a time shift. It reveals causal relationships and information flow structures in the sense of Granger causality. If two time series x and y are generated on the basis of a synchronous information flow, they would end up in symmetric lagged correlation function. The wavelet cross-correlation deconstructs the cross-correlation between x and y on a scale-by-scale basis. Thus it is possible to see as how the relation between two time series changes with time horizons. (Geneçy et al., 2002) characterized the wavelet cross-correlation as:

$$\hat{\rho}_{x,k}(\tau_j) = \frac{\gamma_{x,k}(\tau_j)}{\hat{\sigma}_1(\tau_j)\hat{\sigma}_2^2(\tau_j)}$$

where $\sigma^2_{x,k}(\tau_j), \sigma^2(\tau_j)$ denotes the wavelet variances for $X_{1,t}$ and $X_{2,t}$ associated with scale τ_j and $\gamma_{x,k}(\tau_j)$, and the wavelet covariance between $x_{1,t}$ and $x_{2,t-k}$ associated with scale τ_j.

2. Wavelet Coherence (Power Spectrum)

In addition to wavelet correlation and cross correlation, we introduce bi-variate wavelet technique called wavelet coherence. First we define the cross wavelet power of two return series $x(t)$ and $y(t)$ as $|W_{xy}(u,j)| = W_x(u,s)\overline{W}_y(u,j),$ where $W_x(u,s)$ and $W_y(u,j)$ denote the continuous wavelet transformations of time series $x(t)$ and $y(t)$ respectively. The bar, on the other hand, denotes a complex conjugate. Parameter u allocates a time position whereas parameter j denotes the scale parameter. The cross wavelet power uncovers areas in time-frequency space where the time series show a high common power. However, in the co-movement analysis, we search for areas where the two time series in time-frequency space co-move, but does not necessarily have high power. Useful wavelet technique for finding these co-movements is the wavelet coherence. Following (Torrence and Webster, 1998), we characterize the wavelet coherence of two time series as

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)},$$

Where S represents a smoothing operator. It could be seen that this definition closely resembles that of a conventional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in time frequency space. We write the smoothing operator S as $S(W) = S_{scale}(S_{time}(W_n(s))$ Where S scale denotes smoothing along the wavelet scale axis and S time smoothing in time.

IV. DATA, RESULTS AND DISCUSSION

Our data set consists of weekly stock indices of eleven (11) emerging Asian equity markets including the Indian capital market between January 1, 1992 and June 30, 2013. The representative market indices[1] of each country were retrieved from the Bloomberg data base. In order to check the stationarity of underlying variables, Augmented Dickey Fuller and Phillip Pheron tests were carried out followed by basic descriptive statistics. Each return series were found to be stationary at first difference. To assess the distributional properties of return series of emerging markets, we begin with descriptive statistics[2]. The average daily returns of emerging stock markets are found to be positive and ranges between 0.001% and 0.003%. However, high level of standard deviation was observed ranging from 0.030 (Japan) to 0.040 (South Korea) during the sample period. Furthermore, except Malaysia, Taiwan and Thailand, all other stock returns are negatively skewed meaning that huge negative stock returns are more obvious than huge positive returns. While Kurtosis statistics illustrated that all return series are leptokurtic with a large positive kurtosis value, the Jarque–Bera statistics on the other hand, strongly disapproves the null hypothesis that the Gaussian distribution of returns is normal.

In order to estimate the wavelet correlation of the Indian equity market with the rest of the Asian equity markets, we further proceed with deconstructing all return series in time frequency localization using MODWT. This localization property makes wavelets useful because it allows for handling a nonstationary time series that may change quickly over time (Deo and Shah, 2012a). We preferred MODWT to the discrete wavelet transform (DWT henceforth) because of important reasons as mentioned by (Percival and Walden, 2000), such as MODWT of level J being well-defined by any sample size N, and MODWT wavelet variance estimator is asymptotically more efficient than the same estimator based on DWT. Given the sample of 1124 observations or roughly 22 years of data, the maximum decomposition possibility is given by [log2(T)]. However, for higher level

1 Bombay Stock Exchange/SENSEX (India), Hang Sang Index/HIS (Hong Kong), Shanghai Stock Exchange Composite Index/SHCOMP (China), Bursa (Malaysia), Jakarta Stock exchange composite/JCI (Indonesia) , Strait time Index/STI(Singapore), Philippines Stock exchange Index (PSEi), Set Index/SET (Thailand), Korean Stock Exchange/KOSPI (South Korea), Taiwan Stock Exchange weighted Index/TWSE(Taiwan)

2 To prevent the space, we did not report unit root and descriptive statistical coefficients of sample return series. Nevertheless, it would be available on request to corresponding author.

decompositions, there is significant possibility that feasible wavelet coefficients become smaller and boundary conditions are violated. A boundary is simply a character string indicating the boundary method used in the decomposition by assuming it as either ‘Periodic’ or a ‘Reflection’. According to (Gencay et al., 2002), the most natural technique for dealing with the boundary is to assume the length N series as periodic and grab observations from the other end to finish the computations. Thus based on the periodic assumption, we choose to restrict the decomposition of time series of stock returns into six details (wi 1 to wi6) and one (vi6) smooth component. The wavelet scales are such that scale 1 is associated with a 2-4 week period, scale 2 with a 4-8 week period, scale 3= 8-16 week period, scale 4=16-32 weeks period, scale 5=32-64 weeks period, scale 6= 64-128 weeks period and the last scale represents smooth decomposition. Overall we generated 66 return series from 11 original raw return series (11*6) without losing any data point or informational content. For several reasons, we do not report results for smooth series since it captures a long term fluctuation where predetermined frequency component is not known. After decomposing the given series into details and smooths, we proceed with wavelet correlation and cross correlation. Table 2 presents both Pearson as well as wavelet correlation coefficients between India and emerging Asian equity markets with upper and lower bounds of 95 percent confidence intervals.

Table 2. Wavelet Correlations between Indian and Asian Equity Markets

Countries	P. Correlation	D1	D2	D3	D4	D5	D6	Mean
China	0.24	0.16	0.22	0.26	0.35	0.44	0.51	0.35
Hong Kong	0.32	0.28	0.31	0.33	0.48	0.60	0.68	0.45
Indonesia	0.27	0.23	0.25	0.28	0.32	0.60	0.70	0.40
Japan	0.28	0.25	0.30	0.34	0.38	0.37	0.55	0.37
Korea	0.30	0.29	0.30	0.29	0.32	0.53	0.59	0.39
Malaysia	0.20	0.15	0.20	0.25	0.28	0.50	0.61	0.33
Philippines	0.25	0.17	0.21	0.28	0.40	0.65	0.70	0.40
Singapore	0.24	0.21	0.29	0.33	0.45	0.52	0.61	0.40
Taiwan	0.24	0.15	0.28	0.30	0.35	0.53	0.58	0.37
Thailand	0.26	0.20	0.25	0.32	0.34	0.55	0.57	0.37

Note: P. Correlation denotes Pearson Correlation and D1 to D6 denotes wavelet decomposition scales

The Pearson Correlation demonstrates less than 30% association between the Indian equity market and other Asian equity markets, while the wavelet correlation reveals that this particular degree of relationship could be realistic for shorter intervals only. In other words, it infers that lower frequency domains are essentially associated with strong linkages among markets which require attention of investors, fund managers and policy makers. The average wavelet correlation of Indian equity market with those of sample markets comprise about 35% which is still greater than the Pearson statistical measure. Overall, the integration of the Indian equity market with rest of the Asian markets ranges from (15% to 70%) over (D1 to D6) scale. This implies that the investors with short term investment horizons can enjoy international portfolio diversification and also asset allocations. While portfolio diversification would help them in reducing the business risk, asset allocation would facilitate stabilization of returns particularly over extended periods when markets are relatively integrated. The results also suggest that higher frequencies (shorter intervals) are attractive for risk-averse investors. However as the investment interval is increased from four weeks (D1) to eight weeks (D2) to sixteen weeks (D3) and so on, the diversification opportunities are monotonically reduced. These findings infer that the investors as well as fund managers must rebalance their portfolio with respect to different asset classes. The strong correlations over lower frequency intervals imply that Indian investors will seek reduced information asymmetry by demanding better governance, larger quantity and superior information disclosure through security regulations and financial reports. This will in turn lead to the reduction of cost of capital. However, such integration could also affect their expected returns or cost of capital. For example; volatilities of stock market returns of developing markets like India are generally higher than those of developed markets like Japan and Korea. As a result, to keep the variance and covariance constant, the prices of market index should increase and expected returns should decrease. When the Indian market becomes more integrated with say, Japan and Korea, the sensitivity of its market return increases and so does the co-variances of its market with Japan and Korea. When the increase in covariance is smaller than the increase in local stock variances, the prices are typically higher. Errunza and Miller (2000) describes the cost of capital or expected return of any security in the integrated market to be lower because those traded on segmented markets are mostly held by local investors and their expected return depends on the local price risk and national covariance risk. Next we proceed with wavelet cross correlation[3] function as a measure of similarity of two waveforms and a function of a time-lag applied to one of them. It is obtained by allowing 15 lags between observed and fitted values from the same linear combination at each of the wavelet scales. In particular, we studied whether there exists any pulling effect between the Indian equity market and the rest of the Asian equity markets i.e., whether at a given time the return value of one market (such as Japan) influences that of another market (India) at contrasting time lags. Table 3 summarizes the cross wavelet coefficients between Indian and Asian equity markets. It is observed that up to level 3, that is, sixteen (16) weeks, there exists no lead lag effect between Indian and Asian equity markets. However as the wavelet scale is increased to level 4, the lead lag effect between Indian and Asian markets become evident at lag (-10 & +10). The interesting thing to be observed is that from prior ten weeks (-10) to lag 0, Indian market is negatively correlated but the interaction turned out to be positive for most of the markets except for Taiwan, Philippines and Japan during the next ten weeks (+10). The coefficients at level 5 which is associated with (32-64) weeks exhibit the negative lead lag effect prior to (-15) weeks and also during subsequent (15) weeks following the original lag. The positive cross correlation is detected during (-5 to +5) time lag. Finally some unique results are observed at level 6, capturing stock return fluctuations for (64-128) weeks. During this period, the Indian market is positively and extensively correlated at all studied lags. Figure 5 shows the cross correlation plot between Indian and Japanese equity returns. The existence of a lead lag relationship is clearly apparent at lower frequencies but not at higher frequencies. It implies that the price change in the Indian market appears later in time followed by the changes in the Japanese market. Hence, it is inferred that the Japanese market is able to pull the Indian market in the lower frequency scales. Similar findings with more or less deviation are apparent with other markets. Therefore we argue that the unexpected changes in Asian equity markets could provide a clue to Indian investors (holding investment approximately up to 3 years) regarding the effect of that change on the Indian equity market so that they have enough time to manage and rebalance their investment portfolios.

3 Again to preserve space, we do not provide plots for wavelet cross correlation. However, we report one cross correlation plot between stock returns of India and Japan to help out the readers as to how the plotting estimation was carried out. Nevertheless, remaining plots are available upon request.

Table 3. Wavelet Cross Correlation between Indian and Asian Equity Markets

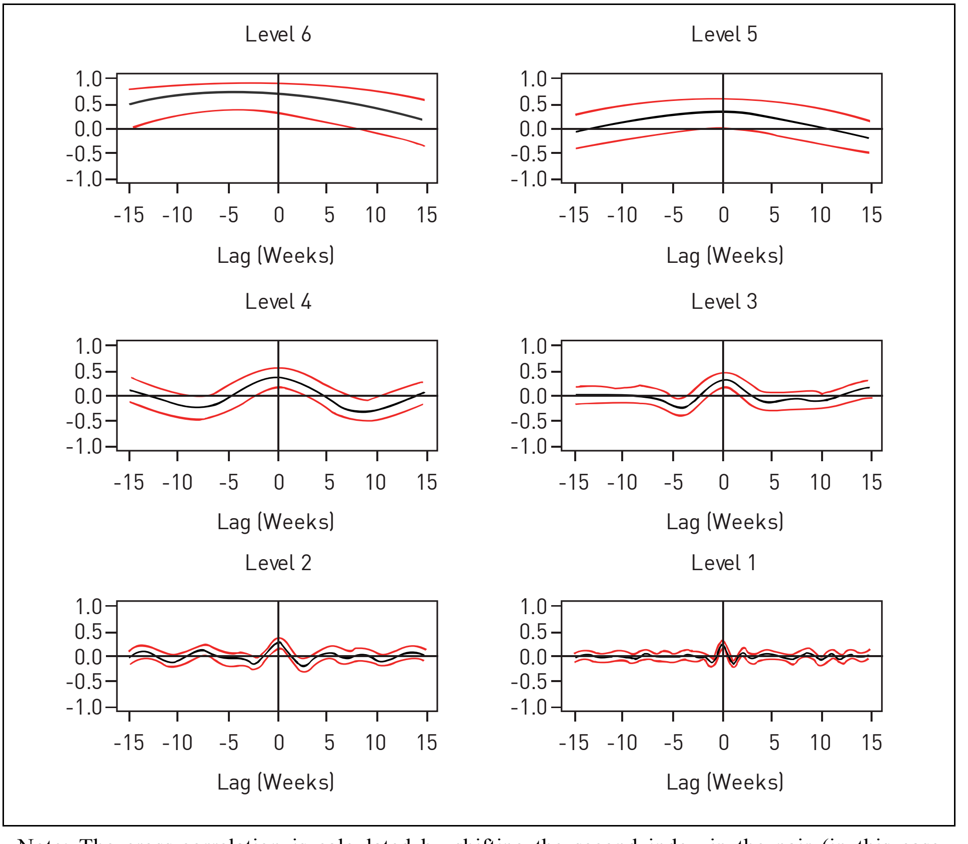
	Level 1							Level 2						
Lags →	-15	-10	-5	0	5	10	15	-15	-10	-5	0	5	10	15
China	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0	0.22	0.00	0.00	0.00
Hong Kong	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.00	0.00	0	0.31	0.00	0.00	0.00
Indonesia	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0	0.25	0.00	0.00	0.00
Japan	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0	0.30	0.00	0.00	0.00
Korea	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0	0.30	0.00	0.00	0.00
Malaysia	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0	0.20	0.00	0.00	0.00
Philippines	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0	0.21	0.00	0.00	0.00
Singapore	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.00	0	0.29	0.00	0.00	0.00
Taiwan	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0	0.28	0.00	0.00	0.00
Thailand	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0	0.25	0.00	0.00	0.00

	Level 3							Level 4						
Lags →	-15	-10	-5	0	5	10	15	15	-10	-5	0	5	10	15
China	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00	-0.30	0.00	0.35	0	0.20	0.00
Hong Kong	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	-0.25	0.00	0.48	0	0.20	0.00
Indonesia	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.00	-0.25	0.00	0.32	0	0.00	0.00
Japan	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.00	-0.20	0.00	0.38	0	-0.25	0.00
Korea	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	-0.30	0.00	0.32	0	0.25	0.00
Malaysia	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	-0.35	0.00	0.28	0	0.00	0.00
Philippines	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.00	-0.10	0.00	0.40	0	-0.10	0.00
Singapore	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	-0.25	0.00	0.45	0	0.25	0.00
Taiwan	0.00	0.00	0.00	0.30	0.00	0.00	0.00	0.00	-0.20	0.00	0.35	0	-0.20	0.00
Thailand	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	-0.20	0.00	0.34	0	0.00	0.00

	Level 5							Level 6						
Lags →	-15	-10	-5	0	5	10	15	-15	-10	-5	0	5	10	15
China	-0.20	-0.1	0.30	0.44	0.35	0.3	-0.2	0.30	0.35	0.40	0.51	0.55	0.5	0.3
Hong Kong	-0.25	-0.1	0.20	0.60	0.50	0.3	-0.1	0.25	0.40	0.50	0.68	0.50	0.4	0.35
Indonesia	-0.20	0.0	0.25	0.60	0.40	0.1	-0.2	0.00	0.30	0.40	0.70	0.60	0.5	0.50
Japan	0.00	0.1	0.25	0.37	0.25	0.0	0.0	0.50	0.55	0.60	0.55	0.50	0.3	0.10
Korea	-0.25	0.0	0.25	0.53	0.40	0.2	-0.1	0.25	0.40	0.50	0.59	0.60	0.5	0.45
Malaysia	-0.10	0.0	0.40	0.50	0.50	0.0	-0.1	0.00	0.45	0.55	0.61	0.55	0.5	0.40
Philippines	-0.40	0.0	0.40	0.65	0.40	0.2	-0.2	0.00	0.20	0.45	0.71	0.55	0.5	0.45
Singapore	-0.30	0.0	0.35	0.52	0.40	0.2	-0.1	0.00	0.30	0.40	0.61	0.60	0.5	0.40
Taiwan	-0.10	0.0	0.25	0.53	0.25	0.0	-0.2	0.50	0.60	0.65	0.58	0.50	0.4	0.20
Thailand	-0.35	-0.2	0.20	0.55	0.50	0.3	0.0	0.20	0.45	0.60	0.57	0.57	0.5	0.40

Note: Level 1 to Level 6 denotes wavelet decomposition scales capturing market return fluctuations over multiple time frequency scales ranging from 4 weeks to 128 weeks for the sample countries.

Figure 5. Wavelet Cross Correlation between Return Series of India and Japan using Daubechies least asymmetric (LA) wavelet filter of length 4.



Note: The cross-correlation is calculated by shifting the second index in the pair (in this case Japan). The 95% confidence intervals are drawn with a dotted line. The red lines denote upper and lower bounds of the 95% confidence interval. The black line shows the cross correlation at different lags. Level 1=2~4 weeks, Level 2= 4~8 weeks, Level 3= 8~16 weeks, Level 4= 16~32 weeks, Level 5= 32~64 weeks and Level 6= 64~128 weeks.

It is important to mention here that Wavelet correlation is plagued with several issues. For instance; if the study period is 2000-2014, the methodology would produce an average relationship between two markets over different time and frequency scales. However, an issue arises when instead of just the average, the market participants become interested in knowing the abovementioned relationship in time frequency localization at each year so as to be able to identify the real relationship during crises and non crises periods. Islam (2014) documents that ‘the most significant economic crisis in recent history, the Global Financial Crisis (GFC) of 2007-2008, warrants much investigation. Thus, taking this vital concern into consideration, we make use of wavelet coherence (Power Spectrum) to overcome the limitations related to wavelet correlation and to provide evidence of potentially intresting structures like dominant scales of variation in data. Figure 6 demonstrates the individual wavelet coherance plots between Indian and Asian equity markets. Time is recorded on the horizontal and vertical axes, giving us the periods and corresponding scales. The spectrum of colours shows the strength of the relationship between the Indian equity market and rest of the Asian markets. The red shade represents the correlation of about 80%. While the blue shade represents acorrelation of about 20% and the yellow shade illustrates a correlation of about 60%. The black bounded lines describes the confidence band at 95% level. Year 1997-98 and 2008-09 denotes crisis periods for the Asian and United States respectively.

It can be seen that there are some markets like Indonesia, Malaysia, Hong Kong, Singapore and Philippines that reveals strong integration with the Indian equity market during 1997 and 2008 crises period at lower frequency components. While observing the wavelet coherence plots of these markets, it is clearly evident from the red colour that integration of the Indian equity market tends to start after four weeks after the crisis of 2008 occurred and with the passage of time, this integration grows stronger. These results contradict (Forbes and Rigobon, 2002) who suggested that the impact of a crisis on correlation will often be short-term and result in short-lived spikes in correlation. But our findings are backed by (Markwat et al., 2009) who revealed that global contagion events can be a relatively long and drawn-out process as they are often preceded by a series of local regional crashes. Identical results were also documented by (Bertero and Mayer, 1990; Sheng and Tu, 2000; Manning, 2002; Ng, 2002; Dunis and Shannon, 2005) on the impact of Asian crises on market integration with the exception of (Ibrahim, 2006).

Figure 6. Wavelet Coherence Plots (Power Spectrum) between Indian & Asian Equity Markets

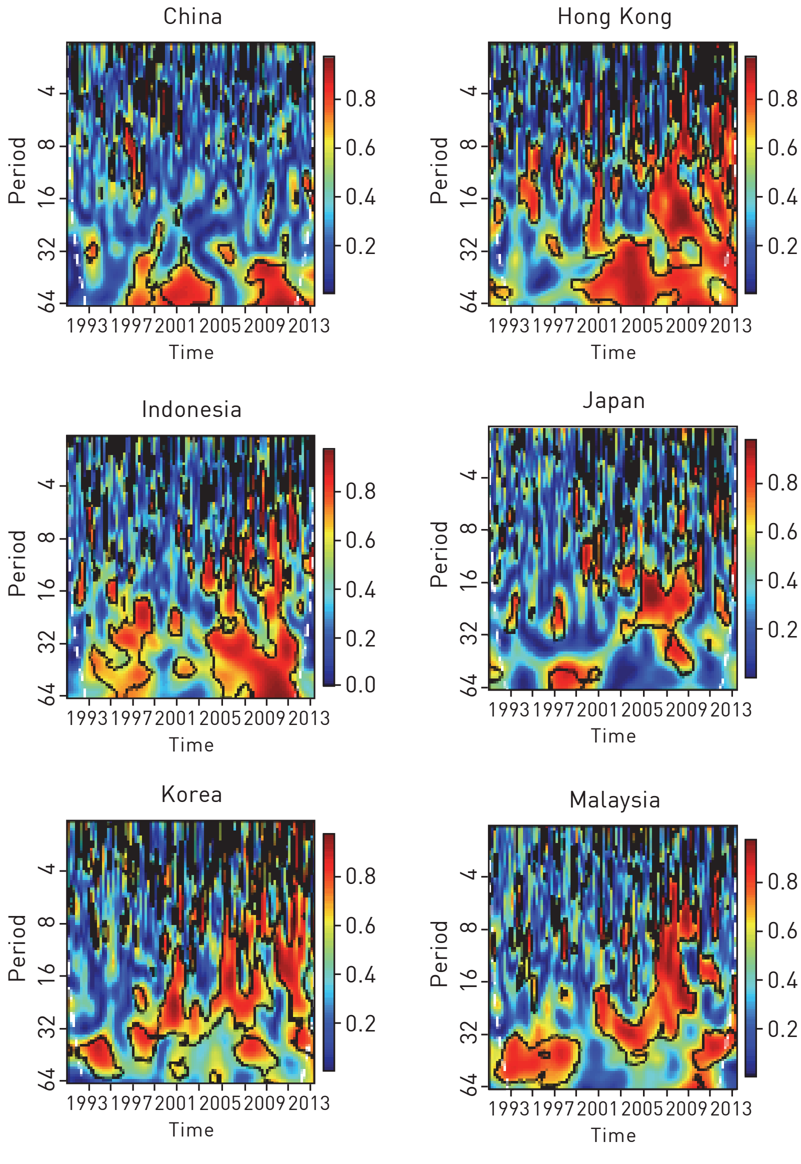
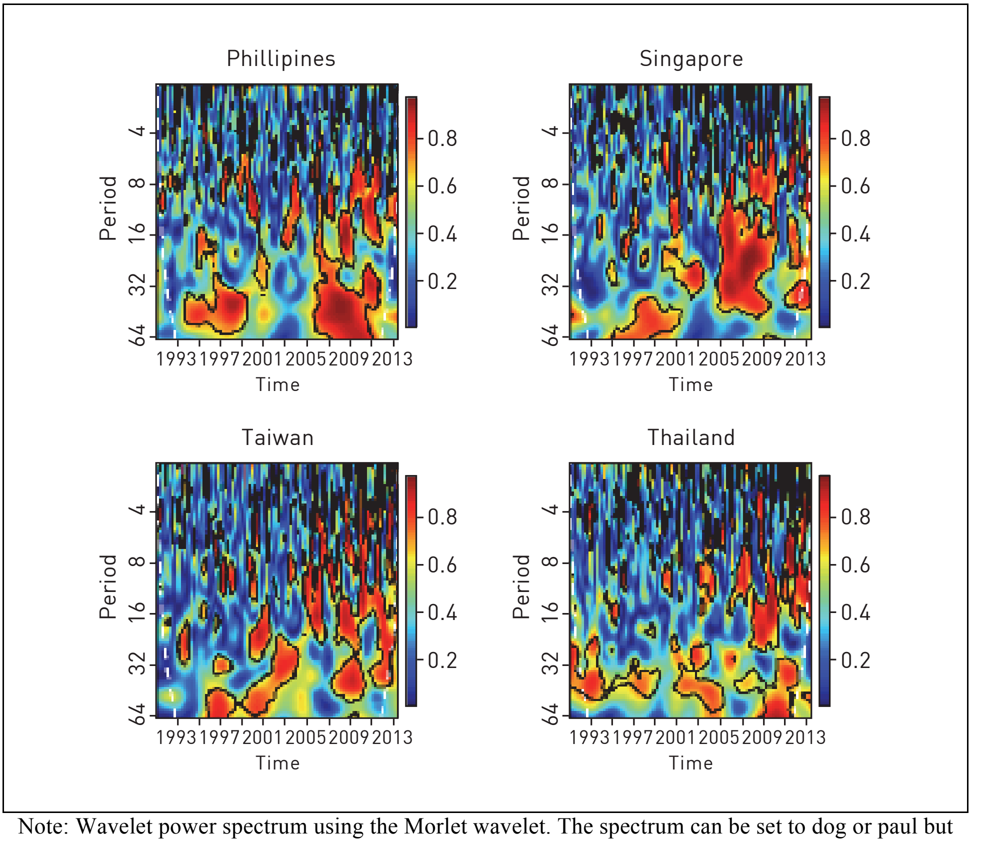


Figure 6. Continued



Note: Wavelet power spectrum using the Morlet wavelet. The spectrum can be set to dog or paul but significance test is available for Morlet wavelet only.

V. CONCLUSION AND POLICY IMPLICATIONS

The degree of capital market integrations are important issues for both policymakers and market participants. For policymakers, these are important elements in assessing potential costs from financial contagion and also for policy coordination. For market participants, these elements may imply reductions in the benefit of portfolio diversification. Markowitz (1952) and Tobin (1959) agreed that the expected returns and risk of a portfolio largely depends upon the correlation among stock returns. If correlation does not exist among stock returns, portfolio diversification can reduce risk. If market correlations are weak, then international diversification can be really and indisputably beneficial (Forbes and Rigobon, 2002). Therefore correlation has to be considered as a decisive factor in risk estimation of financial and real portfolios (Smith et al., 2007). With this background, our paper focused on the simultaneous time-frequency localization to provide additional insights into dynamic linkages of the Indian equity market with those of emerging Asian Markets, and we believe that the analysis can contribute to the risk diversification process both for Indian as well as investors from sample countries. In particular, the study tried to bring out the wavelet transformation method as a new analytic approach to review the scope of risk and portfolio diversification in view of the diverse investment horizons. The wavelet correlation shows that the Indian market is correlated with Asian equity markets largely on lower frequencies, implying that diversification opportunities for investors are more likely at higher frequencies of returns. The results also suggest that higher frequencies (shorter intervals) are attractive for risk-averse investors. Additionally, high frequency intervals offer diversification opportunities also during crisis periods. However, as the investment interval is increased from two weeks to four weeks to eight weeks and so on, the diversification opportunities are monotonically reduced. This monotonic increase in correlations could lead to efficiency gains from domestic Indian firms because they have to compete directly with foreign rivals and this competition according to (Kose et al., 2006) could lead to better corporate governance. The results of cross correlation suggest that Indian investors can make projections on their own market from the sudden changes in other Asian markets at lower frequency scales. But the investment of market participants could be more vulnerable to economic crises at lower frequencies. The possible reasons may be the Contagion Effect as discussed by (Roll, 1988; King and Wadhwani, 1990). Such findings are largely absent from previous empirical research on diversification and dependence in international markets.

Thus an important implication of our findings suggest that the degree of Indian market integration with those of Asian markets tends to change over time and because of the time-varying nature of correlations, benefits of diversification are also time-varying. These findings are consistent with (Bekaert and Harvey, 1995; Goetzmann et al., 2005). There are also evidences that inter-asset correlations generally increase during financial crises. Such findings are consistent with (Longin and Solnik, 2001; Ang and Bekaert, 2002). Overall, the results are plausible for Indian investors and fund managers with respect to making decisions on when to increase/decrease participation in any specific Asian stock market. It also provides information for foreign Investors as to when they ought to participate in the Indian Market.

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About the Author

Aasif Shah is Ph.D student at Department of Commerce, School of Management Pondicherry Central University India. His research interest includes Capital Market Efficiency, Risk Management and Time Series analysis He has published many papers in reputed Journals like international Journal of Business and Society, Asia-Pacific Journal of Management Research and Innovation, Journal of Economic Integration, Journal of South Asian Global Business Research, Business & Management Quarterly Review etc. Besides, he has presented his work in many reputed conferences at IIT Kharagepur, IIM Indore & IICM Mumbai. He has several outstanding paper awards to his credit.

Prof. Malabika Deo is currently holding the position of Professor at Department of Commerce, School of Management Pondicherry University. She is the member of several academic associations and decision making bodies. Her research interest includes Capital markets, derivative market, portfolio Management, Behavioural finance & Islamic finance. She has more than 130 papers to her credit including many reputed International publications. Her work appeared in Asia-Pacific Business Review, Asia-Pacific Journal of Management Research and Innovation, European Journal of Finance, Economic and Business Administration, International Review of Applied Financial Issues & Economics etc. She is two times recipient of Gold Medal award for producing an excellent research in capital & derivative markets. In addition, she has many best paper awards to her credit.

Dr. King is currently a software engineer at MathWorks. He holds his Ph.D degree in signal and array processing. His specialty is statistical signal processing including the application of multi-scale techniques to stochastic processes. Wayne has published papers in Nature, Journal of Time Series Analysis, Journal of the Acoustical Society of America, Cerebral Cortex, and Ear and Hearing.

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