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Wavelet perspective of time varying dynamic of Chinese, Indian and other major markets

Abstract

This study examines the bilateral relationship of stock markets of two emerging economies, the Sensex and Nifty Index from India and the Shenzhen and Shanghai Stock Exchange Index from China as compared to other developed markets. A high-frequency data-set covering a period of 9 years using Haar wavelet methodology is utilized to the time varying dynamics of both Indian and Chinese markets. Results indicated that correlation between the markets varies over time. All the emerging markets behaved differently owing to the restriction imposed and the liberalization in these markets. The Indian markets seem to be highly correlated with major developed markets much earlier when compared with the Chinese markets. However, by the end of 2008, all these Asian markets studied showed signs of weaker correlation against the Dow Jones. This was evidenced resulting from the drastic downward movement of the Dow Jones Index.

Keywords: market diversification, wavelet analysis.

JEL Classification: G15.

Introduction

International stock markets have been becoming more integrated in recent years. This is due to the progressive removal of restrictions and the relaxation of controls over capital movements, which has allowed free flow of funds across markets.

Recognizing these benefits of international diversification, numerous studies in finance literature have concentrated on the measuring of international correlations and linkages of national stock markets across developed and emerging markets. However, the extent to which portfolio managers can practically implement risk reduction not only depends on the intertemporal stability of (expected) stock market returns, but also on (expected) correlations, which measure the amount of similarity in the movement of financial markets.

These integrated markets are likely to be correlated which could erode the idea of international risk diversification in the long run. However, this international risk diversification may have been somewhat overstated too. This is because the risk protection brought by diversifying assets across markets is likely to be reduced when it is needed most, namely in periods of high volatility or, worse, extreme negative price movements. These are best referred to as periods of correlation breakdowns which are important in macroeconomic policies and strategies towards liberalizations.

Since 1998, the number of listed companies in China rose from twelve to nearly fourteen hundred, investors in Chinese exchanges rose from four hundred thousand to just under sixty-seven million by the end of 2005. In September 2006, the two exchanges (Shanghai and Shenzhen) had 1,377 listed

companies, with total market capitalization of US\$400 billion. However, by the end of 2008 the market capitalization has increased close to 7 folds to US\$2,658.2 billion. In terms of foreign investment in these two markets, after the December reforms, foreign investors are now allowed (with limitations) to trade in A shares under the Qualified Foreign Institutional Investor program (QFII). Currently, a total of 79 foreign institutional investors have been approved to buy and sell A shares under the QFII program. In contrast, the Indian market has much liberty towards foreign investors where foreign investments can apply to all companies in the securities market, including bourses, depositories and clearing corporations for investment purposes. During the period from 1992-93 to 1998-99 out of the total capital inflow to India of about US\$ 28.6 billion, a little more than US\$ 15 billion or nearly 54 per cent of the total, was at the expense of foreign portfolio investments. Portfolio investments brought in by Foreign Investments (FIIs) have been the most dynamic source of capital to emerging markets in 1990s.

With economic liberalization reforms undertaken by two newly emerging economies, those of China and India, openness to trade has led to greater capital flows within the markets to further enhance growth. During the last decade, China's economy as measured by GDP¹ has grown at an average of 10 per cent per annum while India's at 7 per cent per annum. During this period, the trade volume, capital flows and mutual economic agreements with other markets have also increased rapidly. The market capitalization of China's share market was approximately \$2.3 trillion in May, 2007, the second largest in Asia after Japan (\$4.7 trillion). Market analysts

¹ GDP is calculated as the value of the total final output of all goods and services produced in a single year within a country's boundaries.

projected the Chinese capital market to be the second largest share market after USA by 2020¹. At the same time, equity market in India, which was nearly 90 percent of GDP, was considerably ahead of many emerging economies². However, the question of whether both the markets of these two countries are integrated with other stock markets is a major concern raised by many investors.

Applying Haar wavelet algorithms for better resolution and smooth changes in time series, this paper investigates how both the Indian and Chinese markets correlate in comparison with four other major international markets to observe the dynamic structural change in correlation since 2001 to 2008. The rest of the paper is organized as follows: Section 1 reviews the empirical studies on this issue. The wavelet methodology is discussed in section 2, while section 3 provides a discussion of the data as well as the empirical results. Finally, the last section offers concluding remarks.

1. Literature review

Numerous studies have been done to investigate stock market correlation, linkages, integration or interdependence. Stock markets are said to be integrated when correlation exists between markets. Although the results of these studies are mixed, inconsistent and sometimes contradict each other, the ultimate motivation behind the studies is the benefit of diversification. If evidence of stock market linkage was found, it would imply that there is a common force that brings these markets together. Hence, the benefit of diversification would be limited.

Apart from analyzing only the interdependencies of stock markets, many researchers also focused on the impact of major events such as market crises, market liberalization, and such like the stock market linkages since the early 1990s. Most of this research on international stock market linkages concentrated on the mature and emerging markets.

Studies by Hilliard (1997) and Efthymios and Tsionas (2002) investigated the interrelationship between daily returns generated by major stock exchanges. Evidence was found that strong interdependence exists between the daily returns generated by Dow Jones Industrial Index and other selected world indices. Aggarwal et al. (2003) in another paper examined time-varying integration of European equity markets from the period of 1985 to 2002 using daily data for the main EU countries.

Utilizing traditional co-integration and dynamic eigenvalue analysis in their study, they revealed evidence of integration in European countries only after the establishment of EMU and the ECB during 1997-98 period.

Similarly, due to the substantial increase of capital flows from developing markets to emerging markets of the Asian countries, considerable attention has also focused on possible linkages and interdependencies in major Asian countries. The general consensus is that correlations between emerging and developed stock markets are generally on the increase (Siklos and Ng, 2001; Tan and Tse, 2002; Click and Plummer, 2005; Lim, 2007; Choudhry et al., 2007; Royfaizal et al., 2007 and Abbas et al., 2008).

Although there are numerous writings on financial or stock market integration, only a small number of studies concentrated on the relationship between two major emerging markets, i.e. China and India with other major developed stock markets in the world. Sharma and Kennedy (1977) examine the price behavior of the Indian market with the US and UK markets and conclude that the behavior of the Indian market is statistically indistinguishable from that of the US and UK markets and find no evidence of systematic cyclical component or periodicity for these markets. On the other hand works done by Wong et al. (2005) using the BSE 200 data found that the Indian stock market is integrated with other developed markets of the World. Similarly, Chen et al. (2006) examine the bilateral relations between three pairs of stock markets, namely India-U.S., India-China and China-U.S. Chen used weekly stock index of Bombay Stocks Exchange National Index for India, Shanghai Stock Exchange for China, and the S&P 500 index for U.S. market from 1991 to 2004 to detect the co-movement of these pairs of stock markets. Chen's result shows that the three markets are fractionally co-integrated with each other. It also suggests that the two emerging markets appear to be more closely linked to each other relative to the U.S.

In another related work, Rashid (2004) studied the indicators that are associated with the increasing stock market return volatility initiating crises in emerging markets of Mexico, Korea, South Africa, Turkey and Malaysia. Using a backward multiple regressions the study revealed that volume of stock trading and currency exchange represents the highest positive correlation for the volatility in stock price of emerging markets.

In a more recent work, Janak and Sarat (2008) investigated the financial integration of India's stock market with global and major regional mar-

¹ China Share Market", <http://www.economywatch.com/market/share-market/world/china.html>, March 2008.

² Mund Asuncion Jennifer, "India's Capital Markets: Unlocking the Door to Future Growth", www.db.com/spain/content/downloads/DB_Research_Current_Issues_070214.pdf, February 14th 2007

kets. They use six stock price indices: the 200-scrip index of BSE of India to represent domestic market, stock price indices of Singapore and Hong Kong to represent the regional markets and three stock price indices of U.S., U.K., and Japan to represent the global markets. Both daily and weekly data from end-March 2003 to end-January 2008 were applied. The results suggest that Indian market's dependence on global markets, such as U.S. and U.K., is substantially higher than on regional markets such as Singapore and Hong Kong while Japanese market exerts a weak influence on Indian market.

Even with the above studies of Indian and Chinese markets, no major work has been done with a longer time horizon, covering the time segment prior to the liberalization of the Chinese markets with a varying time structure. Time varying here refers to correlations estimation by using a specific window of time. Traditional approach using time varying gives equal importance to all observations within the total time period; however, the advantage of Haar wavelet transformation is that it uses rectangular windows to sample the time series and this transformation window doubles at each step until it encompasses the entire time series.

Wavelets here are referred to as 'small waves' that grow and decay in a limited time period and are expressed as a function of the time position (translation parameter) and the scale (dilation parameter), which is related with the frequency (Kaiser, 1994). Generally, wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. A complete description of the methodology is as follows.

2. Wavelet methodology

Wavelet theory was born in the mid-1980s (Grossmann & Morlet, 1984; Goupplaud et al., 1984). After the 1990s, the literature rapidly expanded and wavelet analysis was used extensively in physics, geophysics, astronomy, epidemiology, signal processing etc., but this technique was rarely used either in the field of finance or economic. Ramsey and Lampart (1998) and Ramsey (1999) reveal the strong preference of wavelet transformation from the traditional econometric methods, since then its usage has spiralled.

Financial markets generate large quantities of high-frequency data which are quantified and then decisions are made. However, due to the market efficiency and the intensity of the data, a lot of information tends to be present and if wrongly treated would suggest spurious findings. Through wavelet analysis, the data set undergoes a pre-process

through de-noising and is then segmented into various time scales.

2.1. Haar wavelet transformations. Wavelet Transformation (WT) provides a way of analyzing local behavior of functions. It possesses the ability to filter the polynomial behavior to some predefined degree which represents the correct characterization of time series in non-stationary global trends.

Conceptually, wavelet transformation is an inner product of the time series with the scaled and translated wavelet $\varphi(x)$ usually an n th derivative of a smoothing kernel $\theta(x)$. The scaling and translation actions are performed by two parameters; the scale parameter s 'adapts' the width of the wavelet to the *microscopic resolution* required, thus changing its frequency contents and the location of the analyzing wavelet is determined by the parameter b :

$$Wf(s,b) = \langle f, \varphi \rangle (s,b) = \frac{1}{s} \int_s dx f(x) \varphi\left(\frac{x-b}{s}\right), \quad (1)$$

where $s, b \in R$ and $s > 0$ for the continuous version (CWT) or are taken on a discrete, usually hierarchical grid of value s_i, b_j for discrete version (DWT).

Ω is the support of the $f(x)$ or the length of the time series. The choice of smoothing kernel $\theta(x)$ and related wavelet $\varphi(x)$ depends on the application and on the desired properties of the wavelet transform. In this paper, a simple block smoothing function was carried out to have the optimal localization both in frequency and positions of the related wavelets.

$$\theta(x) = \begin{cases} 1 & \text{for } 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}. \quad (2)$$

The wavelets obtained from this kernel are defined on finite support and are referred to as Haar:

$$\theta(x) = \begin{cases} 1 & \text{for } 0 \leq x \leq \frac{1}{2}, \\ -1 & \text{for } \frac{1}{2} \leq x \leq 1. \\ 0 & \text{otherwise} \end{cases}. \quad (3)$$

For a particular choice of rescaling and position shift parameters (dyadic pyramidal scheme), the Haar system constitutes an orthonormal basis:

$$\varphi_{m,n}(x) = 2^{-m} \varphi(2^{-m} x - n), \quad m > 0, \quad n = 0 \dots 2^m. \quad (4)$$

Assume an arbitrary time series $f = \{f_i\}$, $i = 1 \dots 2^N$ on the normalized support $\Omega(f) = [0,1]$. Using the orthonormal basis just described, the function f can be represented with the linear combination of Haar wavelets:

$$f = f^0 + \sum_{m=0}^N \sum_{l=0}^{2^m} c_{m,l} \varphi_{m,l}, \tag{5}$$

where f_0 is the most coarse approximation of the time series $f^0 = \langle f, \theta \rangle$, and each coefficient $c_{m,l}$ of the representation can be obtained as $c_{m,l} = \langle f, \varphi_{m,l} \rangle$. The f^j of the time series f with the smoothing kernel $\theta_{j,k}$ form a ladder of multi-resolution approximations:

$$f^{j-1} = f^j + \sum_{k=0}^{2^j} \langle f, \varphi_{j,k} \rangle \varphi_{j,k}, \tag{6}$$

where $f^j = \langle f, \theta_{j,k} \rangle$ and $\theta_{j,k} = 2^{-j} \theta(2^{-j}x - k)$.

It is then possible to move from one approximation level $j-1$ to another level j by simply adding the detail contained in the corresponding wavelet coefficient $c_{j,k}, k = 0 \dots 2^j$.

Next the measure of the correlation between components $c_g^{i,j}$ and $c_f^{k,j}$ of two respective time series f and g can be put as:

$$C(f, g) = \sum_{\{i,j,k,l\}=0}^{m,n} \omega_i c_f^{i,j} \omega_k c_g^{k,l} \delta_{i,j,k,l}, \tag{7}$$

where $\delta_{i,j,k,l} = 1$ when $i=k$, and $j=l$.

And the weights ω_i and ω_k depend on their respective scales i and k . From experience, the orthogonality of the coefficients is best employed without weighting. Normalization is then necessary in order to arrive at the correlation product between $[0,1]$ and will simply take the form of

$$C_{normalized}(f, g) = \frac{C(f, g)}{\sqrt{C(f, f)C(g, g)}}. \tag{8}$$

The distance of the two representations is then obtained as follows:

$$\text{Distance}(f, g) = -\log(|C_{normalized}(f, g)|). \tag{9}$$

2.2. Data. Data used in this study were market indices from the Bombay Stock Exchange (BSE) represented by the Sensex 30 Index, and National Stock Exchange (NSE) represented by the S&P CNX Nifty Index and from the Shanghai Stock Exchange Composite Index and Shenzhen Composite Index. Along with the Indian and Chinese market data, data for four major markets being the Dow Jones Industrial Average (DJIA), FTSE-100, Nikkei-225 and Hang Seng Index of Hong Kong were also used.

This study uses daily closing price for each index from February 2001 to December 2008, representing a total of 2,048 observations. The daily closing price data of the eight indices are obtained from Bloomberg database. The data took into consideration only those days on which markets were open in all the markets. All of the indices are expressed in terms of local currencies to avoid problems associated with transformation due to fluctuations in exchange rates and also to avoid the restrictive assumption the relative purchasing power parity holds. In addition, the preference for local currencies is focused on the domestic causes of stock market interdependence. According to Leong and Felmingham (2001), by converting these indices to a common currency there is a possibility that the impact of local economic conditions and domestic economic policy may be distorted. In addition, earlier studies have found similar results if the price indices were measured in local currencies or were converted into a common currency, usually into dollars.

The wavelet decomposition of the data was carried out using wavelet toolkit on a Matlab platform while the description was tabulated via Eviews 5.1.

3. Data description

Table 1 below presents the descriptive statistics on daily returns of each of the eight markets. The sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis and the Jarque-Bera statistics along the p -value are reported on the hourly returns.

Table 1. Summary of descriptive statistics of daily returns

	Observation	Mean	Variance	Standard deviation	Kurtosis	Skewness	Jarque Bera p-value
DOW JONES	2048	0.799	0.736	0.858	21.261	3.339	0.000
FTSE	2048	0.824	0.769	0.877	18.972	3.025	0.000
NIKKEI	2048	1.058	1.078	1.038	15.557	2.596	0.000
HAN SENG	2048	1.123	1.676	1.294	28.790	3.676	0.000
Average of developed market		0.951	1.065	1.017	21.145	3.159	
SENSEX	2048	1.175	1.280	1.131	11.511	2.283	0.000
NIFTY	2048	1.166	1.299	1.140	13.393	2.438	0.000
Average of Indian market		1.170	1.289	1.135	12.452	2.361	

Table 1 (cont.). Summary of descriptive statistics of daily returns

	Observation	Mean	Variance	Standard deviation	Kurtosis	Skewness	Jarque Bera p-value
SZCOMP	2048	1.168	1.654	1.286	11.984	2.520	0.000
SHCOMP	2048	1.265	1.876	1.370	11.091	2.424	0.000
Average of Chinese market		1.217	1.765	1.328	11.537	2.472	

Table 1 above reports the summary statistics of the daily market returns of all the eight markets. It is noted that higher average returns are associated to both the Indian and Chinese markets, with the highest perceived in the Shanghai Composite Index of China. Both the Dow Jones and FTSE returns indicated the lowest market return. Similar results are also seen in the standard deviation figures with both the Dow Jones and FTSE index being the least while the Chinese markets indicating higher values. This would mean that the higher the returns shown

in a market, the higher will be the risk (standard deviation) associated with the similar market. The kurtosis being the degree of excess in all markets exceeds the value of three, indicating leptokurtic distribution and it is likely to be present when dealing with opening market values. Similar results were also documented in Bekaert and Harvey (1997). Next, the visual perspective on the volatility of market absolute returns is graphed to see the extent to which each market changed over the study period.

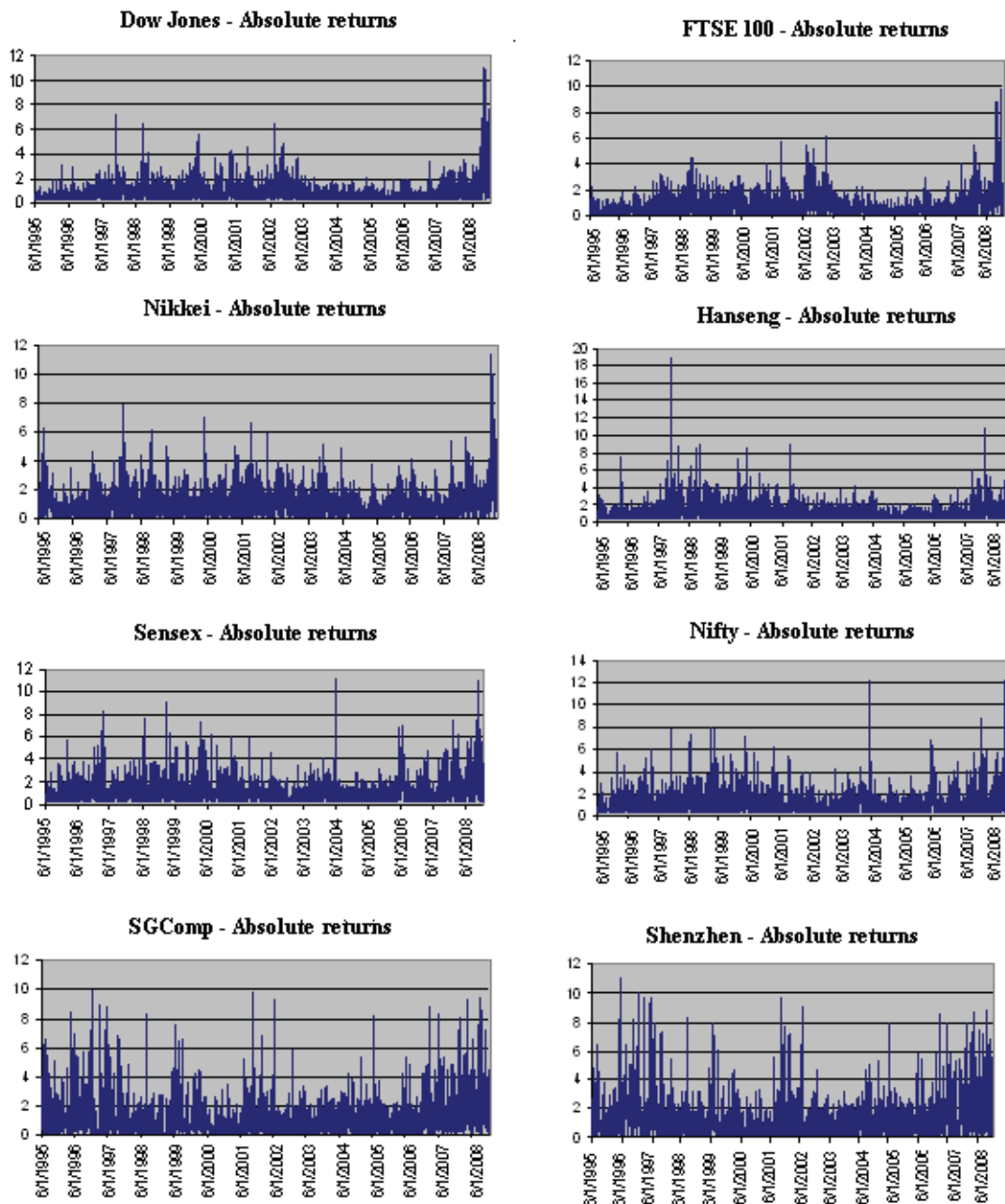


Fig. 1. Absolute market returns of emerging and developed markets

From Figure 1 above, the trend and volatility of market returns in all developed markets (Dow Jones, FTSE, Nikkei and Hang Seng) show a similar pattern over the analysis period. The other developing markets also showed a similar trend, but the volatility differs for both the Chinese markets, showing a much higher percentage level of absolute market returns change throughout the analysis period. However, this situation was not that prevailing in both the Indian markets which had similar pattern of the developed markets. As for the time varying structure of the absolute returns

it is analyzed, correlated and discussed in the following section.

3.1. Empirical results. In investigating the time varying change of each market returns, the Haar wavelet transformation was applied (refer to section 2.1 above). The correlation between each of the developed market returns against each of Indian and Chinese market returns was made. This time varying is being compiled until level 11 of the Haar wavelet transformation. The results are presented in Table 2 below.

Table 2. Market time varying correlation of Dow Jones returns

Scale	DW_FT	DW_NK	DW_HS	DW_SE	DW_NF	DW_SG	DW_SH
d1	0.188	-0.132	0.011	0.036	0.056	-0.020	-0.024
d2	0.281	0.114	0.180	0.031	0.040	0.003	0.024
d3	0.362	0.141	0.208	0.021	0.027	0.090	0.085
d4	0.513	0.237	0.234	0.117	0.099	0.059	0.075
d5	0.741	0.497	0.450	0.351	0.308	0.015	0.023
d6	0.878	0.800	0.809	0.567	0.523	0.157	0.044
d7	0.901	0.834	0.815	0.514	0.471	0.057	-0.049
d8	0.921	0.800	0.785	0.512	0.467	-0.079	-0.156
d9	0.951	0.825	0.814	0.535	0.444	0.409	0.338
d10	0.974	0.976	0.894	0.829	0.782	0.740	0.717
d11	0.998	0.987	0.735	0.718	0.633	0.573	0.574

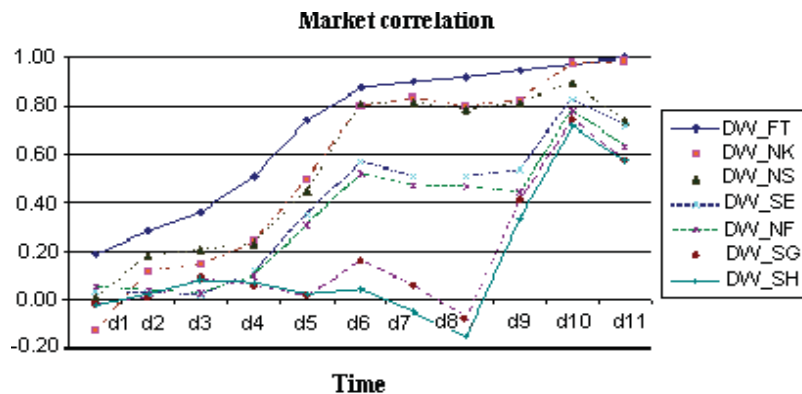


Fig. 2. Market time varying correlation of Dow Jones returns

From Table 2 above, the correlations of each market returns are tabulated against the Dow Jones market returns in eleven different time varying scales which envelope the total analysis period (Figure 1). Almost all the markets showed sign of close correlation. However, after d10 time scale (12/29/08), only FTSE indicated close correlation with Dow Jones. The rest of the Asian markets showed a much lower sign of correlation.

The Indian and Chinese markets behaved differently during the whole analysis period. Initially, from D1 (2/2/2001) to D4 (15/3/2001) both the Indian and Chinese markets were hardly correlated as compared to FTSE, NIKKEI and Hang Seng with the Dow Jones Index. However, the correlation figures for Indian markets saw an improvement after 2001 (D4) and these were in agreement with the other major markets in Asia (NIKKEI and Hang Seng). There was a period where there was hardly any

change in terms of correlation in both the Indian markets (D6 to D9). This was mainly due to panic selling and political controversy in India, compounded by a price fixing scandal in the Sensex market. It resulted in touching an eight-year low, falling eleven percent in a day trading on September 21st, 2003. This security concern and investors jitteriness continued into 2003. The situation reversed after 2007 (D9) when both the Sensex and Nifty were again seen highly correlated with the Dow Jones Index.

On the other hand, due to the closely regulated Chinese markets, only one third of the stocks were allowed to be traded by public investors¹. This saw a period of poor correlation between the Chinese markets and other developed markets up to D8

¹ Prior to 2005, trading was not allowed in nearly two-third of the stocks because the government did not want these companies to be held publicly.

(2005). Only after the capital market reform in China there was an improvement in market correlation which represented an approximately 80 percent correlation with the Dow Jones.

An interesting observation was present by the end of 2008: there was a decline in market correlation in both

the Indian and Chinese markets, the NIKKEI and the Han Seng against the Dow Jones returns. Theoretically, this would signify a diversification opportunity. However, from the computation of the change in the market correlation, there was a significant reduction over time (see Figure 3 below).

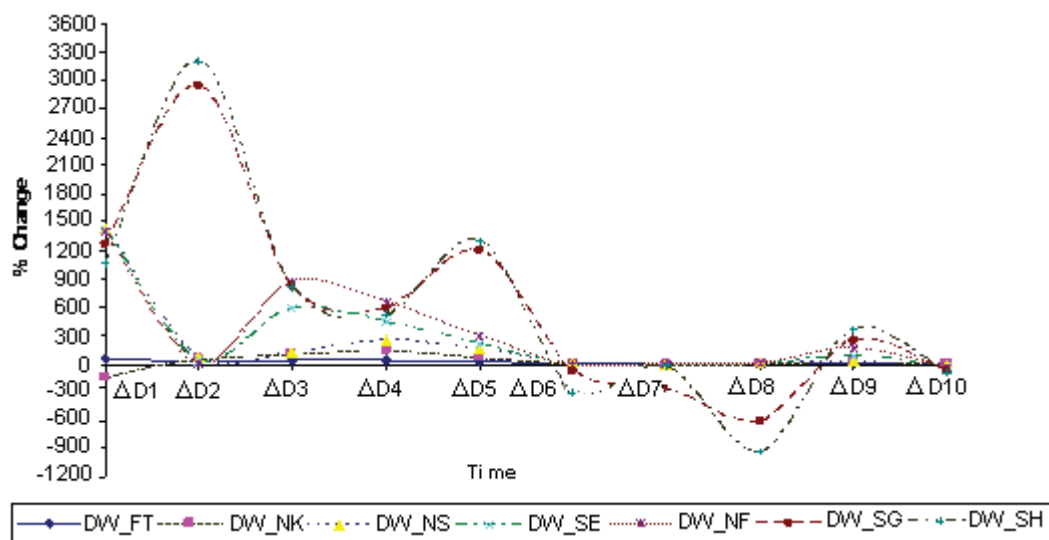


Fig. 3. Correlation change over time varying

Figure 3 above represents the change with regard to return of market correlation since 2001. All developed markets (FTSE, NIKKEI and Han Seng) showed the least diversification opportunity available among these markets. As for the emerging markets (Indian and Chinese markets), there were signs indicating the possibility of diversification; however, the regulatory restrictions in the respective markets made this the least possible. Among all the markets studied, the Chinese markets show the greatest sign of change in terms of its correlation with other major markets. The Chinese Capital Market performance is guided by China Securities Regulatory Commission. Large companies are the major players in the capital market at the Shanghai Stock Exchange. This equity market consisted of two types of shares – tradeable and non-tradeable. The tradeable shares were of two types: ‘A’ shares and ‘B’ shares. ‘A’ shares were priced in the local currency, while ‘B’ shares were quoted in the U.S. dollars. Meanwhile the Shenzhen Stock Exchange consisted of the companies in which the Government of China maintained major stake and this, therefore, reduced investor’s diversification possibility.

As can be seen from the observation above, when markets become more integrated, as a result of liberalization or deregulation, this also indirectly implies a reduction in benefits from international diversification as it is observed in both the Chinese markets.

Conclusion

This study observed the correlation of both Indian (SENSEX and NIFTY) and Chinese (SHENZHEN and SGCOMP) markets as against other major de-

veloped markets, namely the DOW JONES, FTSE, NIKKEI and Han Seng. A Haar wavelet methodology with time varying was utilized based on market returns from February 2001 to December 2008.

The above correlation analysis suggests that correlation among markets varies over time. All the emerging markets behaved differently due to the restriction imposed and the liberalization in these markets. The Indian markets seem to be highly correlated much earlier when compared to the Chinese markets. However, near the end of 2008, all the Asian markets studied showed sign of weaker correlation against the Dow Jones. This is because these markets are relatively well insulated against the global financial crisis resulting from the sub-prime issue.

Since both India and China are viewed as the economic super-powers of the future, diversification opportunities may arise but they are likely to be short-term rather than long-term. Because of the early liberalization of the Indian market, it does have some advantages over the Chinese market. This is because since 2001 the Bombay Sensex market value increased by a factor of three, whereas during the same period, China’s mainland equity markets had lost half of their value. This resulted mainly from the limited shareholding by non-state investors in Chinese markets. Most of the best performers in China prefer to be listed in the Hong Kong market which is better regulated than the traditional Chinese

markets and conforms to international standards and requirements. As a conclusion, the possibility of diversification opportunities that prevail in emerging markets will very much be short-term gain and would depend heavily on the respective market.

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