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Analyzing On Effect Of U.S. Sub-Prime Crises On Five Major Stock Markets Of Different Countries Using Hybrid Wavelet And Neural Network Model.

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ABSTRACT

The correlation of stock returns across different markets has been widely applied to evaluate the spill over effects across stock markets. The impacts of U.S. subprime crisis of 2007 have been an important issue in academic literature during and shortly after crisis period because of its very severe effects on financial markets and reel economy in all over the world. In this paper, we investigate degree of correlation or co-movement of 5 major stock markets of 5 countries: India(Nifty), China(SHCOMP), Germany(DAX), United Kingdom(FTSE 100) and Japan (NKY) in relation to U.S. stock market(*NASDAQ*) independently using a hybrid wavelet and neural network model. We use a simple Multi-layer Perceptron Neural Network (MLPNN) based wavelet decomposition to analyse the relationship between these stock markets. The study indicate that the hybrid model can provide a valuable alternative to the existing conventional methodologies in testing financial contagions and better untangle the relationships between financial institutions.

JEL Classification: C49, E43, E44, E47.

Keywords :-Subprime crises, artificial neural networks, wavelets, wavelet neural networks, Wavenets.

I. INTRODUCTION

The subprime crises that began in the summer of 2007 initially manifested itself as a problem for U.S. financial institutions. At first, the crises was simmering within the United States, but subsequently it boiled over and set off vortices and currents not only in the U.S. financial markets, but also in the global markets. As a result of this tremendous financial turmoil, dramatic changes have taken place in the financial landscape and the global financial markets have been seriously affected[1]. It created financial turmoil had significant effect on both the daily returns and the volatility of stock prices in almost major stock markets of the world. Europe was the first affected, thereafter its contagion spread to the rest of the world. East Asia did not escape. The nature of the current global financial crisis is unprecedented in terms of the scale of the problems in the financial sector, particularly in the United States and Europe, the depth and speed of the worldwide contagion and the severity of the recession , particularly in emerging market economies, small countries, and East Asia[7]. This crisis affected real economies as well as financial markets, resulting, in drops in productivity growth, increases in unemployment rate, and a decrease in international trade and so on.

The correlation of stock returns across different markets has been widely applied to evaluate the spillover effects across stock markets. [2] shows that the cross-country correlations in the stock markets remain large and significant. By identifying potential channels for financial market spillovers in twelve transition economies, [3] demonstrated that a visible increase in stock market correlations during the 1994-99 period, points to increased financial market integration. [4] uses extreme value theory to uncover nonlinear relationships and analyze contagion in financial markets, found that contagion is higher for negative returns than for positive returns.

There is ample factual evidence that national markets have become more inter-connected with one another with respect to cross-border trade and capital flows during the past few decades[5]. It seems reasonable to assume that these cross-border market linkages have increased the likelihood for shocks in an economically and financially important country to be transmitted internationally. This would particularly be the case as regards a country like the United States. One would hence expect sizable spillovers from the recent and severe U.S. financial crisis to other countries given the overall importance of the United States for the world's economy and financial markets [6]. The most recent financial crisis in the United States, the worst since the Great Depression, provides a good opportunity to reassess the degree to which any interdependencies among stock market returns in different countries that existed may have changed over time, and especially prior to, during, and after various events characterizing the crisis[5].

The impacts of subprime crisis have been an important issue in academic literature during and shortly after crisis period because of its very severe effects on financial markets and reel economy in all over the world. Therefore, there are many studies that have attempted to investigate the impacts of crisis especially in terms of the impact of volatility on stock return behaviors[8]. We summarize few of them here. [9] employed the VAR framework and variance decomposition methods to detect the cointegration of stock markets and explored empirically the effects of the subprime crisis by using daily data of five selected stock markets for the period February 15, 2006, to December 31, 2008. The results showed the increased level of correlations between the markets during the subprime crisis. The study revealed the increasing effect of major financial markets on emerging markets. [10] used GARCH models to investigate the impact of the 2008 financial crisis on the Istanbul Stock Exchange. It revealed that unconditional volatility of the Istanbul Stock Exchange increased between 2007 and 2010. The impact the 2008 subprime crisis and the last European debt crisis had on the Asian stock market was investigated in [11]. The study revealed that all stock market returns exhibited volatility clustering, volatility persistence, asymmetry and leverage effects. The study in [12] found that the US subprime crisis significantly impacted volatility clustering and induced the increment of leverage effects in major international financial markets and that the GARCH (1,1) model is sufficient for modeling conditional volatility. The GARCH-M model is employed in [13] to capture the relation between returns and volatility, and they used the Chow breakpoint to examine the beginning and ending dates of the crash and to detect structural changes in parameters. The findings indicate that the crisis negatively affected all stock returns and that the time-varying trend in the volatility increased during crisis periods. Event study methodology, in [14] point out the differences of effects of shocks originated from US subprime and European debt crisis on emerging markets and indicate that subprime crisis have a consistently negative impact on the equity and bond markets in emerging markets. In another study in [15], the DCC-GARCH approach find that subprime crisis have permanent impact on conditional correlation relationships between U.S, Europe and BRICS countries.

Our study is based on an examination of the degree of correlation or co-movement of 5 major stock markets of 5 countries: India(Nifty), China(SHCOMP), Germany(DAX), United Kingdom(FTSE 100) and Japan (NKY) in relation with U.S. stock market(*NASDAQ*) using a hybrid wavelet and neural network model.

II. WAVELETS

Wavelets theory is based on Fourier analysis, in which any function can be represented as the sum of sine and cosine functions. A wavelet ψ(t) is simply a function of time t that obeys a basic rule, known as the wavelet admissibility condition[16]:

$$C_\psi = \int_0^\infty \frac{|\psi(f)|}{f} df < \infty \qquad \text{---------- (1)}$$

where ψ(f) is the Fourier transform, a function of frequency f, of ψ(t). Depending on normalization rules, there are two types of wavelets within a given function/family where **(2a)** represents father wavelet and **(2b)** represents mother wavelet with j =1,……, *J* and *J*-level wavelet decomposition [18]:

$$\phi_{j,k} = 2^{-j/2}\phi\left(t - 2^j k / 2^j\right) \qquad \text{--- (2a)}$$

$$\psi_{j,k} = 2^{-j/2}\psi\left(t - 2^j k / 2^j\right) \qquad \text{---- (2b)}$$

Based on the length of data there are two types of wavelet transforms namely continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Since most of the time series have finite number of values, discrete version of wavelet transform is used in finance and economics applications and in most of the natural sciences. Discrete wavelets are defined as [17]:

$$\phi_{j,k} = 2^{j/2}\phi\left(2^j t - k\right)$$

----- **(3a)**

$$\psi_{j,k} = 2^{j/2}\psi\left(2^j t - k\right)$$

----- **(3b)**

Where ϕ and ψ satisfying as follows:

$$\phi(t) = \sum_k h(k)\phi_{1,k}$$

-----**(4a)**

$$\psi(t) = \sqrt{2}\sum_k (-1)^k h(-k+1)\phi(2t-k) = \sqrt{2}\sum_k g(k)\phi(2t-k)$$

------**(4b)**

In practice the DWT is implemented via pyramid algorithm. For each iteration of pyramid algorithm three objects are required as the data vector x, the wavelet filter h_i and the scaling filter g_i. At the first level, j =1, DWT wavelet coefficients $\psi_{i,t}$ and scaling coefficients $v_{i,t}$ as follows:

$$v_{l,t} = \sum_{l-0}^{L-1} g_l x_{2t+1-l \bmod N}$$

---- **(5a)**

$$\psi_{l,t} = \sum_{l-0}^{L-1} h_l x_{2t+1-l \bmod N}$$

---- **(5b)**

Wavelet analysis has shown a tremendous performance in the area of financial time series analysis as it provides an important tool for extracting information from financial data with applications ranging from short term prediction to the testing of market models due to its flexibility to handle very irregular data series. Wavelets possess ability to locate precisely time regime shifts and discontinuities by decomposing financial time series on a variety of time scales simultaneously so that relationships between economic variables may well differ across time scales. They have been successfully used in forecasting stock market prices, crude oil prices, GDP growth, trading prices, exchange rates, expenditure and income, money growth and inflation, volatility in foreign exchange markets, price fluctuations, sales etc from the last decade[17-22].

III. ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s).

Figure 1: Artificial Neuron and Multilayered artificial neuron network

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons are represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm

The basic architecture consists of three types of neurons layers: input, hidden and output. The way that individual artificial neurons are interconnected is called topology, architecture or graph of an artificial neural network. The fact that interconnection can be done innumerous ways results in numerous possible topologies that are divided into two basic classes: Feed-forward and Recurrent topology.

Figure 2: Feed Forward Topology

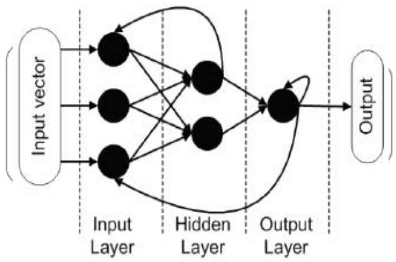
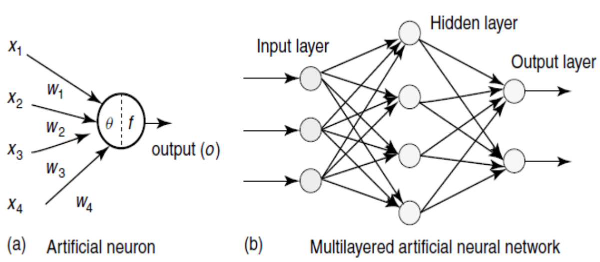


Figure 3: Recurrent Topology

In a simple feed forward topology (acyclic graph), information flows from inputs to outputs in only one direction and in a simple recurrent topology (semi-cyclic graph), some of the information flows not only in one direction from input to output but also in opposite direction [23-25]. In this study we use Multi-layer Perceptron (MLP) model which is composed of several layers nodes. The first or the lowest layer is an input layer where the external information is received. The



last or the highest layer is an output layer where the problem solution is obtained. These two layers are separated by one or more intermediate nodes called the hidden layer. The nodes in adjacent layers adjacent are usually connected by acyclic arcs from a lower layer to a higher layer.

ANNs have drawn considerable attention in financial engineering in the recent years because of their interesting learning abilities. Recent studies have revealed the predictive power of the ANNs in approximating discontinuous functions as they have the ability to formalize unclassified information and more importantly, to forecast financial time series. Another important advantage of ANN is that they can approximate any nonlinear function without having any prior assumption about the properties of the data series unlike the traditional forecasting methods which assumes a linear relationship between inputs and outputs. In recent years, AAN have successfully been applied for the forecasting of financial time series such as stock market indexes, exchange rates, crude oil prices, inflation and gold prices[26-33].

IV. WAVELET NEURAL NETWORKS

The combination of wavelet theory and neural networks has lead to the development of wavelet neural networks. A wavelet neural network generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family. The structure of wavelet neural network is depicted in figure 4.

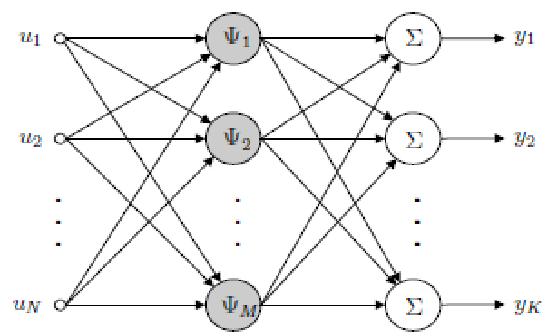


Figure 4. Structure of wavelet neural network

There are two main approaches to creating wavelet neural networks[34].

In the first the wavelet and the neural network processing are performed separately. The input signal is first decomposed using some wavelet basis by the neurons in the hidden layer. The wavelet coefficients are then output to one or more summers whose input weights are modified in accordance with some learning algorithm. In this approach, only dyadic dilations and translations of the mother wavelet form the wavelet basis. This type of wavelet neural network is usually referred to as a *wavenet*.

The second type combines the two theories. In this case the translation and dilation of the wavelets along with the summer weights are modified in accordance with some learning algorithm. This is usually referred to as wavelet network .

The origin of wavelet networks can be traced back to the work of Daugman in 1988, which uses Gabor wavelet and neural network for the classification of images and became popular after the pioneer work of Zhang, Benveniste and Szu in early 1990's. Wavelet neural networks are suitable for forecasting the financial time series because wavelets can decompose the financial time series into their time-scale components and unravel the non-linear relationship between economic variables. In recent years, economists have shown a considerable interest for forecasting financial time series using hybrid models.

Wavelet neural network have been widely-used for forecasting oil prices [35], stock index [36], electricity demand [37], [38,39] and other time series. But there are not many applications of wavelet neural network for exchange rate forecasting. [39] is an example, in this study, the author proposes a hybrid model which combines Wavelet Neural Network and Genetic Algorithm for forecasting exchange rates. The experimental results show that the proposed method provides satisfactory performance for different forecasting horizons and, strangely the author claims that the accuracy of forecasting does not decline when the forecasting horizon increases. The result of empirical study shows that Wavelet Neural Network model give better results for time series forecasting than other models . The comparison study of forecast accuracy show that the first procedure (with stepwise) of non-stationary time series yields the best forecast compared to ARIMA, MAR and WNN models by using other procedures. It's showed by the smallest RMSE at testing data[40].

The back-propagation neural network (BPNN) model and the wavelet neural network (WNN) model were compared by the crisis forecasting accuracy and in-sample and out-of-sample test. The results showed that WNN model could be applied to the currency crises could effectively capture the economic variables associated with the currency crises, and might be to provide a more powerful tool for macroeconomic time series data [41]. A method based on the wavelet analysis and the artificial intelligence was used to predict the A300 index in China and NASDAQ index in the USA. Comparing with wavelet-ARIMA model and simple BP neural network, the combined model of wavelet and neural network demonstrate superiority in predicting power [42].An integrated system is presented in [43] where wavelet transforms and recurrent neural network (RNN) based on artificial bee colony (abc) algorithm (called ABC-RNN) are combined for stock price forecasting. The study was based on the simulation results of several international stock markets, including the Dow Jones Industrial Average Index (DJIA), London FTSE-100 Index (FTSE), Tokyo Nikkei-225 Index (Nikkei), and Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and demonstrated that proposed hybrid system was highly promising and could be implemented in a real-time trading system for forecasting stock prices and maximizing profits. A methodology that combines artificial intelligence modeling techniques with wavelet multiresolution methodology for forecasting of daily spot foreign exchange rates of major internationally traded currencies is proposed in [44].Results of the empirical study indicate superior performance of the proposed technique as compared to the traditional exchange rate forecasting models.

The traditional prediction model is not able to achieve a satisfying prediction effect in the problem of a nonlinear system and non-stationary financial signal. The wavelet neural network has overcome the deficiency of traditional prediction model which is limited to linear system when predicting. The returns in Shanghai stock market from January 10th, 2006 to July 18th, 2008 was used to compare simulation error of stock market returns between BP network and wavelet neural network. The results show that the simulation result of wavelet neural network is more accurate than that of BP network, and wavelet neural network constructed can forecast stock market returns more accurately [45]. An integrated wavelet transform, recurrent neural network and artificial bee colony algorithm used in [46] to forecast Taiwan Stock Exchange Capitalization Weighted Stock Index(TAIEX) in which Haar wavelet family is used to decompose the stock price time series . The artificial bee colony algorithm is used to optimize the recurrent neural network weights and baises. It was observed that this approach outperformed previous methods found in the literature to predict TAIEX. A discrete wavelet transform and back propagation neural network is proposed in [47] to predict monthly closing price of the Shanghai Composite Index. Low frequency signals were fed to neural networks to predict the future value of stock index. It was observed that wavelet signals improve the accuracy of neural networks in comparison with previous studies. A wavelet neural network model (neuro-wavelet) for the short-term forecast of stock returns from high-frequency financial data is proposed in [48]. The proposed hybrid model combines the inherent capability of wavelets and artificial neural networks to capture non-stationary and non-linear attributes embedded in financial time series. The hybrid model achieved accurate results, even though it did not need to have a predefined specific parametric model to initiate a simulation process. In particular, the proposed neuro-wavelet network showed superior modeling and forecasting performance when compared against two parametric methods. In [49], the GMDH neural network model was used for forecasting the price of crude oil, while assuming the price series have time varying variance. A wavelet transform was employed as a tool for pre processing the oil price data sets before inputting it into the GMDH neural network. The best performance results are obtained in the case where both smoothed and non-smoothed data sets are used to calculate the moving average and the time varying variance. Hence by smoothing data sets, the authors claim that they are able to obtain a more than 40% improvement in the prediction accuracy by using this hybrid model. A new method called improved wavelet neural network is proposed in [50] in which a Genetic Algorithm is used to optimize the initial weights, stretching parameters and movement parameters. The application of this improved method to stock market prediction to Shanghai index data show that this method is effective and this model has good prediction performance.

V. EMPIRICAL STUDY

A. Data

We use the weekly data from major national stock market indices of six countries: United States, India, China, Germany, United Kingdom and Japan. Comparison of stock exchange indexes encompasses the period of Feb, 1999 to October, 2013. The whole data is divided into three periods: Pre-Crises, Crises and Post-Crises. For our analysis, we study the weekly stock price returns which was calculated as the natural logarithmic differences of the weekly stock prices and represented as follows:

$$r_t = \log(p_t) - \log(p_{t-1}) \times 100 \quad (1)$$

Where P_t and P_{t-1} represent the stock price index at time t and t − 1, respectively.

Summary statistics for weekly stock price returns for these three periods for these six countries is respectively presented in Table 1, 2 and 3.In our study, the Pre-crises period is taken from February 1999 to June, 2007, Crises period is taken from July, 2007 to December, 2009 and Post-Crises period is taken from January, 2010 to October,2013. The time series plots of six countries for these three periods are depicted in Fig 1, 2 and 3. The actual weekly stock price returns in these figures are 100 times the values shown in these figures.

We briefly describe the national indices in this paragraph. *NASDAQ* is an American stock exchange. It is the second-largest exchange in the U.S. and world by market capitalization and trading volume. It trades more *U.S.* equities than any other *U.S.* exchange. It is renowned for its high performance INET technology and has proven reliability with 99.99 % uptime. Firms count on *NASDAQ* for unsurpassed speed and tested capacity to execute trades quickly and efficiently. In addition, its value-added products and services provide the complete package for U.S. equity trading. *Nifty*, also called *CNX Nifty* is National Stock Exchange of India's benchmark stock market index for Indian equity market. Nifty is owned and managed by India Index Services and Products(IISL), which is a wholly owned subsidiary of the NSE Strategic Investment Corporation Limited. The CNX Nifty covers 22 sectors of the Indian economy and offers investment managers exposure to the Indian market in one portfolio. *SHCOMP*, The Shanghai SE Composite is a major stock market index which tracks the performance of all A-shares and B-shares listed on the Shanghai Stock Exchange, in China. It is a capitalization-weighted index. The total number of companies on the composite index is 872. *DAX*, the German stock index is a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange. It measures the performance of the Prime Standard's 30 largest German companies in terms of order book volume and market capitalization. The performance index is the more commonly quoted, however the price index is more similar to commonly quoted indexes in other countries .*FTSE 100* is a share index of the 100 companies listed on theLondon Stock Exchange with the highest market capitalization. It is one of the most widely-used stock indices and is seen as a gauge of prosperity for businesses regulated by UK company law. *NKY or Nikkei 225* is a stock market index for theTokyo Stock Exchange(TSE). Currently, the *Nikkei* is the most widely quoted average of Japanese equities, similar to the Dow Jones Industrial Average, the Nikkei index is calculated on a price weighted basis of the 225 largest Japanese stocks on the Tokyo stock exchange.

Table 1. Pre-Crises Period (Feb.1999 to June, 2007)

Country Index	US NASDAQ	India Nifty	China SHCOMP	Germany DAX	UK FTSE 100	Japan NKY
Max	2.94	**2.71**	**2.28**	**3.38**	**2.29**	**3.20**
Min	-3.33	-2.36	-3.46	-5.30	-3.24	-6.07
Mean	0.12	0.04	-0.08	0.09	0.05	0.07
S.D.	0.86	0.91	0.95	1.05	0.81	1.11
Skewness	4.49	3.19	3.64	7.75	5.10	7.55
Kurtosis	-0.61	-0.20	-0.37	-1.02	-0.70	-1.03
Jarque-Bera	31.22*	1.67	7.95	208.5*	53.30*	208.4*

Table 2. Crises Period (July, 2007 to December, 2009)

Country Index	US NASDAQ	India Nifty	China SHCOMP	Germany DAX	UK FTSE 100	Japan NKY
Max	2.71	7.11	5.72	2.48	3.16	4.61
Min	-6.58	-6.43	-5.58	-6.02	-5.11	-7.72
Mean	-0.05	0.06	-0.08	-0.10	-0.07	-0.18
S.D.	1.40	1.96	2.01	1.46	1.24	1.55
Skewness	6.18	4.42	2.86	4.91	4.50	6.69
Kurtosis	-1.13	-0.13	-0.20	-0.97	-0.68	-0.57
Jarque-Bera	**82.33***	**11.26***	**0.99***	**40.27***	**22.22***	**80.82***

Table 3. Post-Crises Period (January, 2010 to October, 2013)

Country Index	US NASDAQ	India Nifty	China SHCOMP	Germany DAX	UK FTSE 100	Japan NKY
Max	**4.15**	**3.23**	**5.24**	**5.11**	**3.84**	**4.12**
Min	**-4.99**	**-4.96**	**-3.83**	**-5.90**	**-3.30**	**-2.73**
Mean	**0.02**	**0.15**	**0.09**	**0.03**	**0.01**	**0.04**
S.D.	**1.17**	**1.19**	**1.17**	**1.23**	**0.78**	**1.04**
Skewness	**5.25**	**4.69**	**4.60**	**6.49**	**7.13**	**3.46**
Kurtosis	**-0.16**	**-0.91**	**0.33**	**-0.53**	**-0.21**	**-0.09**
Jarque-Bera	**85.93**	**67.57**	**89.84**	**169.88**	**184.50**	**12.67**

Note : *The Jarque-Bera test statistic is larger than the critical value at 1% significance level, which indicates rejection of the null hypothesis, and hence series fails in normality test.

B. Methodology

Wavelets can be used to decompose a given function or continuous- time signal into components of different scales. Wavelet transforms represent time series that have discontinuities and sharp peaks. Wavelets can accurately deconstruct and reconstruct time series that is finite, non-stationary and non periodic or both. There are two types of wavelet transform, i.e., Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT). In CWT, the analyzing wavelet is shifted smoothly over the full domain of the analyzed function during its computation. It is rather difficult to analyse the data when we calculate wavelet coefficients at every possible scale. The analysis can be more accurate and faster by choosing the scales by the power of two. In this study, we have used only DWT. There are numerous types of wavelets available for analyzing time series for the reduction of noise. In our study, we observed that Daubechies (db) wavelet have better performance than other wavelets. The reconstructed time series is later fed as an input to the neural network for training. We restrict ourselves to studying the effect of de-noising by wavelets and the reconstructed de-noised signal is then fed into the artificial neural network (ANN). The framework of our model is depicted in Figure 5.

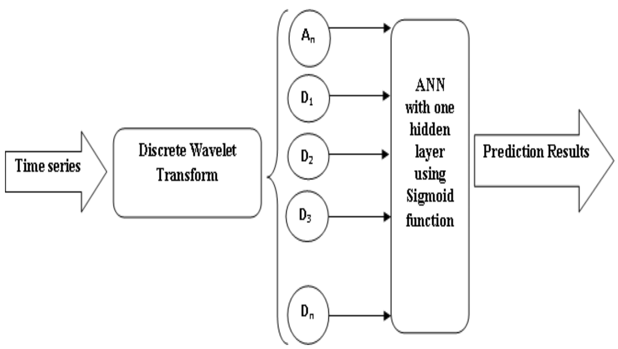


Figure 5. Framework of the Model

The Wavelet GUI Toolbox of Matlab software was used for this purpose that includes automatic thresholding. The de-noising procedure proceeds in three steps:

1. Decomposition by any wavelet such as Haar, Daubechies, Symlets, Coiflets etc.
2. Thresholding detail coefficients. These different wavelets are analysed for different levels and scales, fixed form threshold is chosen and soft thresholding is applied to detail coefficients. The wavelet at particular level and scale with better performance is chosen in our case.
3. Reconstruction. In our case the reconstructed series is obtained with that particular wavelet.

This wavelet decomposed and reconstructed series is fed to a simple Multi-layer Perceptron Neural Network (MLPNN) model and the observations are recorded for the forecasted values. The model was trained in a process called supervised learning. In supervised learning, the input and output are repeatedly fed into the neural network. With each presentation of input data, the model output is matched with the given target output and an error is calculated. This error is back propagated through the network to adjust the weights with the goal of minimizing the error and achieving simulation closer and closer to the desired target output. The Levenberg–Marquardt algorithm (LMA) is used in the current study to train the network because of its simplicity. It is an iterative algorithm that locates the minimum function value which is expressed as sum of squares of nonlinear functions. The optimum number of neurons in the single hidden layer is determined using trial and error procedure.

C. RESULTS AND DISCUSSION

A preliminary investigation of summary statistics of weekly stock price returns for all these six countries indicate higher variability during the crises period as there is increase in the standard deviation of the values when compared to their respective values during Pre-Crises and Post-Crises periods. We can also see that the China (SHCOMP) market shows the highest variability as measured by the standard deviation of the weekly stock price returns during the Crises period.

Jarque-Bera normality test rejects normality of all series at 1% level of significance during the crises period which indicates volatility in markets during that period in all the countries under study. It also indicates that there is volatility in stock markets in all the countries except India and China during the post-crises period also.

We also see that there is increase in the skewness of the values for two markets namely US (NASDAQ) and Japan (NKY) which indicates more lack of symmetry and that data is skewed right in these two markets which means that the right tail is long relative to the left tail in the Crises period. Japan (NKY) market has highest skewness in the crises period which indicates frequent small negative outcomes, and extremely bad scenarios are not as likely in the market. We also observe that this market has more skewness in the Post-Crises period also.

We also see that US (NASDAQ)market has got lowest kurtosis value in the Crises period which indicates that returns have a larger degree of variance i.e., more fluctuations than other markets truly indicative of Crises period in the US market. India(Nifty) has got highest kurtosis value which indicates lesser degree of variance i.e. less fluctuations in the Crises period than other markets.

The main objective of this study is to observe the effect of US Sub-Prime Crises of 2007 on five major stock markets of different countries: India(Nifty),China(SHCOMP),Germany(DAX), UK(FTSE-100) and Japan(NKY) using the hybrid Wavelet Multilayer Perceptron Neural Network (MLPNN) technique. In this regard an attempt is made to correlate these five major stock markets with US(NASDAQ) stock market. The results of our model are compared with artificial neural network model to guage its performance.

At first, data pre-processing was performed by approximating the weekly stock price returns for these three periods under study i.e, Pre-Crises, Crises and Post-Crises periods by 5 different discrete wavelets namely Haar, Daubechies, Symlets , Coiflets and Discrete Meyer with different subclasses(or wavelet functions) in each case with different levels of decomposition. It was observed that the best results were obtained with Daubechies wavelet with wavelet function db4 at different levels of decomposition. The performance measure used was root mean square error (RMSE).The best approximation results obtained for these three periods under study by wavelet function db4 of Daubechies wavelet is depicted in Table 4, 5, and 6 respectively for these three periods under study.

The wavelet approximated Weekly Stock Price Returns obtained for US(NASDAQ) stock market are taken as input to the artificial neural network (ANN) for each three periods(Pre-Crises, Crises and Post-Crises) under study. These approximations are depicted in figure 6, 7 and 8 respectively for three periods under study. The wavelet approximated Weekly Stock Price Returns obtained for five other stock markets .i.e., India(Nifty), China(SHCOMP), Germany(DAX), UK(FTSE-100) and Japan(NKY) at best decomposition level obtained with db4 subclass of the Daubechies wavelet are taken as the target (output) separately for these three periods under study.

The network was trained in the single hidden layer. The ANN model is trained between 5 to 20 number of neurons in the hidden layer and the values are taken in trial and error fashion for number of hidden neurons in which minimum RMSE value is obtained for the number of neurons in the hidden layer in the said range. The model is trained up to maximum of 1000 epochs reached. Sigmoid function was used for the neurons of the hidden and output layers to process their respective inputs for the simple MLPNN model. The training of the network was considered to be completed when the network performance determined by the validation/testing was satisfactory. The network was re-trained, if it failed to perform satisfactory during testing phase. All the models were trained using 431 sample values in Pre-Crises period, 130 sample values in Crises period and 201 sample values in Post-Crises periods respectively. The sample values were distributed randomly and it was observed that all the models unarguably performed optimally under conditions when the samples were divided for Training (65%), Validation (15%) and Testing (20 %). The objective of this study is limited to evaluating effect of US(NASDAQ) stock market on other five stock markets of five different counties by using wavelet approximated neural network model. The performance measures are compared as shown in Table 8 and depicted graphically in figure 9 for three periods under study for US stock market vs. Stock markets of five other countries. All the calculations were performed using Wavelet Tool box and Neural Network Financial Tool box in MATLAB R2010a.

The performance measures used are Root Mean Squared Error (RMSE) and Pearson's Correlation Coefficient (R) and Coefficient of Determination (R2). The results of two models are compared in table 7 and table 8. Lower values of RMSE indicate better fit. In our case Model 2 has got lower RMSE values than Model 1. In general, the higher the R-Squared , the better the model fits the data. In our case model 2 has got higher R-Squared values than model 1. Hence better results are obtained with hybrid model.

VI. CONCLUSIONS

This paper investigates the interdependence between the US stock market and India, China, Germany, UK and Japan market using the hybrid Wavelet Multilayer Perceptron Neural Network (MLPNN) model during Pre-Crises, Crises and Post-Crises control periods. The financial crises that took place during 2007-09 disclosed several drawbacks in which the global stock market underwent significant losses and US stock market was its epicenter. The empirical results shown in Table 8 and depicted by figure 9 reveal the following conclusions:

-In the Pre-Crises period, there is least R value between US and China and highest RMSE between these two markets in this period. This is shown in Table 8 and depicted graphically in figure 9. It suggests that there was least interconnection between US and China markets in the Pre-Crises period followed by Indian stock market which indicates least co-movement with regard to US market. While Germany has got highest R value which suggests highest interconnection and hence more dependency on US stock market in the Pre-Crises period followed by UK stock market. Since there is least

RMSE with the UK market, it suggests that this market follows closer co-movement with regard to US market.

(Performance Measure: RMSE) Decomposition by Daubechies Wavelet with sub class db4 at different Levels								
Country	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
US	**0.008**	0.010	0.011	0.011	0.012	0.012	0.012	0.012
India	**0.007**	0.009	0.011	0.011	0.011	0.012	0.012	0.012
China	**0.007**	0.009	0.010	0.011	0.011	0.011	0.011	0.012
Germany	**0.008**	0.010	0.011	0.012	0.012	0.012	0.012	0.012
UK	**0.005**	0.007	0.007	0.008	0.008	0.008	0.008	0.008
Japan	**0.006**	0.009	0.010	0.010	0.010	0.010	0.010	0.010

- In the Crises Period, we observe that Germany has again got highest R value which again suggests highest interconnection between US and German stock markets in the Crises period and also indicates that German market got most affected during the US crises of 2007-09 than other markets under study. Since Japan market has got second highest R value in the crises period which indicates that this market also got affected by greater extent in this crises period. It further reveals that contagion effects display their influence on Germany and Japan markets significantly in this period and the markets of India and China and UK were less affected. One interesting observation is that UK market remained most robust during the Crises period. This is evident by the fact that this market has got minimum R value and although least RMSE values indicate closer co-movement between UK and US markets in this crises period. There is a decreasing trend in the R and RMSE values for the two markets namely India and UK from Pre-Crises to Crises period which indicates decrease in interconnection of these markets with US market during the transition period but increase in their co-movements which in turn indicates more sustainability of these markets during the Crises period. Since there is maximum RMSE with the China market, it indicates least co-movement with regard to US market in this period also.

- In the Post-Crises period, India has got the least R value which indicates that the decreasing trend in interconnection between US and India markets continues from Crises to Post-Crises period also. There is also decrease in RMSE value which indicates increase in the co-movement of Indian market with US market which suggests less dependency on US market than other markets followed by China after the crises period. There is an interesting fact that Japan market has got highest RMSE which indicates decrease in co-movements between two markets and hence lesser dependency after Crises period. Since UK has got highest R value which indicates highest interconnection, and increase in RMSE suggests decrease in co-movements after the Crises period.

The present study has successfully demonstrated that the hybrid wavelet MLPNN model can provide a valuable alternative to the existing conventional methodologies in testing financial contagions.

Table 4 : Pre-crises Data(431 samples)

Country	**1**	**2**	**3**	**4**	**5**	**6**	**7**
US	**0.49e-05**	1.79e-05	7.90e-05	7.92e-05	11.7e-05	8.8e-05	37.3e-05
India	**0.69e-04**	0.96e-04	2.61e-04	1.67e-04	1.13e-04	5.6e-04	4.35e-04
China	**0.074e-04**	0.41e-04	1.14e-04	1.49e-04	1.93e-04	4.88e-04	4.60e-04
Germany	**0.356e-05**	2.48e-05	6.75e-05	5.95e-05	7.80e-05	16.4e-05	9.00e-05
UK	**0.67e-18**	1.00e-18	1.56e-18	1.07e-18	1.60e-18	1.7e-18	1.27e-18
Japan	**0.35e-05**	3.45e-05	2.59e-05	0.393e-05	12.8e-05	6.3e-05	0.464e-05

Table 5 : Crises Data(130 samples)

Country	**1**	**2**	**3**	**4**	**5**	**6**	**7**
US	**0.46e-05**	1.74e-05	2.02e-05	3.56e-05	0.74e-05	2.08e-05	1.56e-05
India	**0.01e-05**	0.66e-05	0.08e-05	1.84e-05	7.86e-05	29.38e-05	55.09e-05
China	**0.02e-05**	2.29e-05	4.9e-05	14.83e-05	20.16e-05	25.39e-05	46.86e-05
Germany	**0.36e-05**	1.84e-05	1.80e-05	1.78e-05	0.25e-05	4.21e-05	1.945e-05
UK	**0.43e-05**	2.03e-05	2.87e-05	3.19e-05	4.94e-05	11.41e-05	18.67e-05
Japan	**0.68e-05**	1.33e-05	2.02e-05	3.69e-05	1.99e-05	9.62e-05	21.61e-05

Table 6 : Post-Crises Data(201 samples)

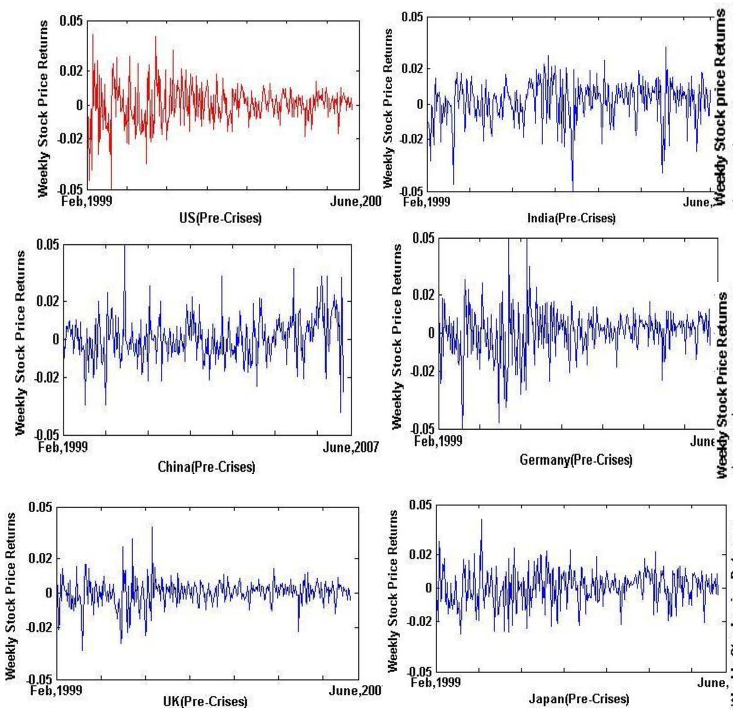


Figure 6. Approximations of Pre-Crises data by Daubechies wavelet

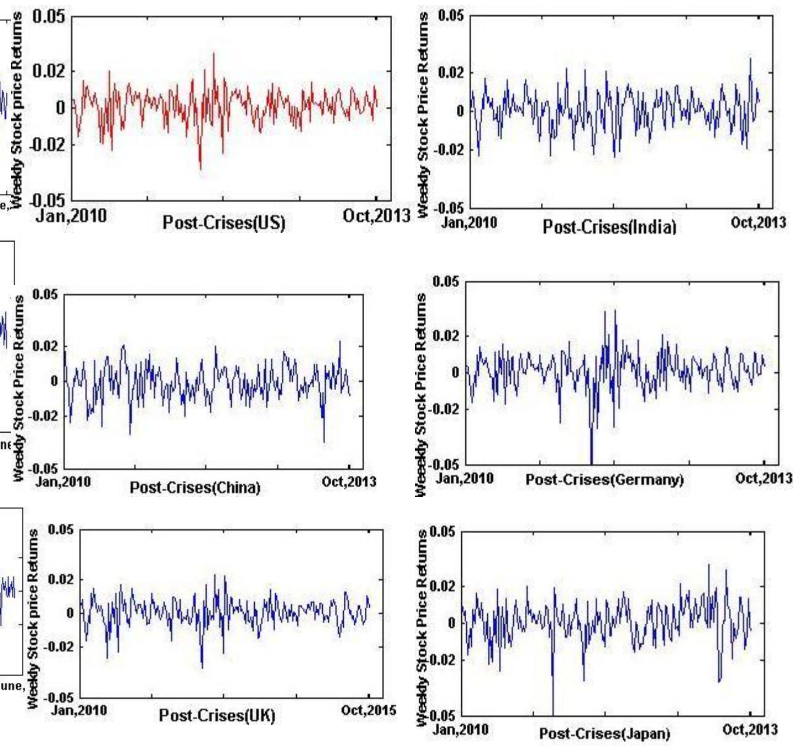


Figure 8. Approximations of Post- Crises data by Daubechies wavelet

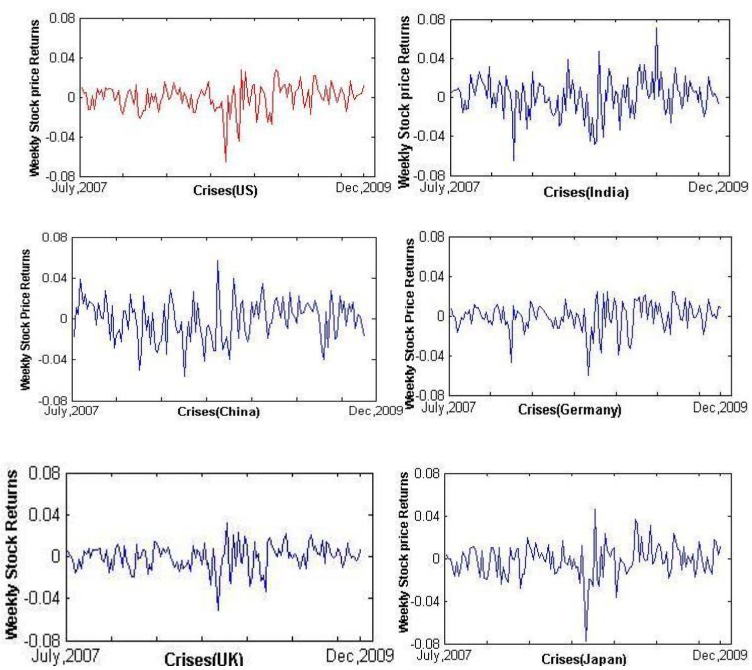


Figure 7. Approximations of Crises data by Daubechies wavelet

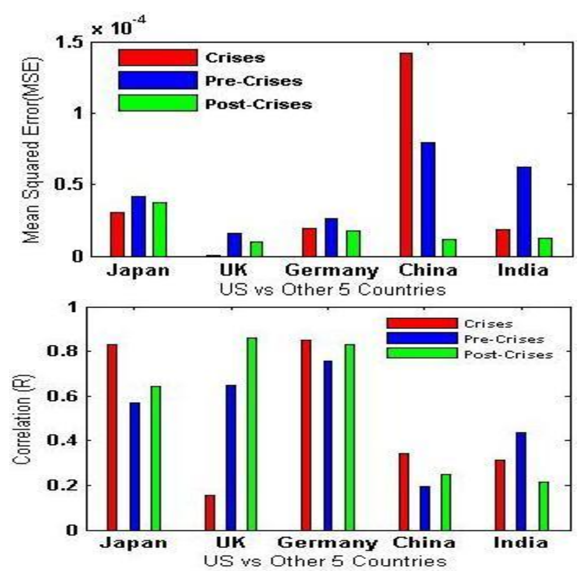


Figure 9.

Wavelet Decomposed Regression Analysis Results obtained with ANN US vs. Other 5 Countries Model:2									
	Pre-Crises			Crises			Post-Crises		
Country	RMSE	R	R^2	RMSE	R	R^2	RMSE	R	R^2
India	**7.56E-03**	0.1782	0.422	4.33E-03	0.2310	0.481	3.51E-03	0.2151	0.464
China	6.93E-03	0.1943	0.441	**11.9E-03**	0.3506	0.592	3.42E-03	0.2508	0.501
Germany	5.10E-03	**0.7864**	0.887	4.40E-03	**0.8717**	**0.934**	4.22E-03	0.8324	0.912
UK	3.96E-03	0.6804	0.825	0.50E-03	0.8644	0.930	3.10E-03	**0.8582**	**0.926**
Japan	6.43E-03	0.5704	0.755	6.43E-03	0.8280	0.910	**6.08E-03**	0.6408	0.800

Table 7 : ANN Model

Regression Analysis Results obtained with ANN (US vs. Other 5 Countries) Model:1									
	Pre-Crises			Crises			Post-Crises		
Country	RMSE	R	R^2	RMSE	R	R^2	RMSE	R	R^2
India	**8.87E-03**	0.13585	0.369	13.2E-03	0.2017	0.449	8.43E-03	0.2014	0.449
China	7.62E-03	0.12695	0.356	**13.5E-03**	0.3283	0.573	7.62E-03	0.2353	0.485
Germany	6.90E-03	**0.74436**	0.863	5.66E-03	**0.8474**	**0.921**	4.80E-03	0.8179	0.904
UK	4.24E-03	0.65885	0.812	1.56E-03	0.8447	0.919	4.24E-03	**0.8392**	**0.916**
Japan	8.66E-03	0.52356	0.724	7.94E-03	0.7932	0.891	**9.00E-03**	0.6199	0.787

Table 8 : Hybrid Model

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