

Causality Analysis of USA Stock Market over Indian Stock Market

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Abstract: Since last few decades there have been a number of observations indicating the possibility that the behaviour of American stock exchange may have a significant influence on the behaviour of Indian stock market. The present work is an effort in this direction and the purpose of the present work is to measure connectedness of prime stock exchange indices of India viz. SENSEX and NIFTY separately with the prime American stock exchange index viz. DOW JONES. To analyze connectedness, we have used Correlation of Probability of Recurrence (CPR) method which is based on Recurrence Plot. We have examined CPR for 150 points, 250 points and 350 points window and we have compared the results with Pearson's cross-correlation coefficient ρ . It has been observed that the markets move in and move out of periods of strong connectivity instead of moving monotonously towards increasing global connectivity as deduced by ρ . We have also performed Granger Causality Analysis of SENSEX and NIFTY separately with DOW JONES and also separately with some other emerging Asian Stock exchanges like HANG-SENG, NIKKEI, FTSE ALL SHARE, STRAIGHT TIMES INDEX, KOSPI COMPOSITE INDEX and TSEC WEIGHTED INDEX. It has been observed that DOW JONES Granger causes both SENSEX and NIFTY more than any other prime Asian Stock Market Indices and effect of Granger causality increases in the windows where both the time series are strongly connected.

Keywords: Correlation of Probability of Recurrence, Recurrence plot, Cross-Correlation coefficient, Granger Causality Analysis.

1. Introduction

Stock market is a complex dynamical system involving large number of heterogeneous factors. An important area of study is to measure interrelation between different stock indices worldwide. Commonly Pearson's cross-correlation coefficient ρ has been used frequently as a measure of connectedness¹⁻¹⁸. In recent times many alternative approaches has been suggested for measuring connectedness, like Recurrence Plot (RP), Cross Recurrence Plot (CPR) and Joint Recurrence Plot(JRP)¹⁹. In our study, we have used idea of recurrence to analyze connectedness between different financial time series. It is an advance technique used in nonlinear data analysis. We have used correlation of probability of recurrence (CPR) which is based on recurrence plot. It is used to quantify phase synchronization between non-phase-coherent and non-stationary time series¹⁹⁻²⁰. As synchronization is related to connectedness and co-movements, it is expected that CPR too is a measure of connectedness.

Recurrence is being used in several areas of applied sciences e.g. for measuring heart rate²¹⁻²², for identifying Memory Components in Single-Trial EEGs²³, in brain signal analysis²⁴, wrist pulse analysis²⁵, in correlation analysis among currencies²⁶, identification in nature of crashes²⁷, in estimation of initial time of a bubble²⁸, in quantifying the behavior of global stock markets during financial crisis²⁹ and synchronicity and convergence of the GDP among countries under Euro region³⁰.

The Granger causality test is a statistical hypothesis test for determining whether a time series is useful to forecast another time series³¹. According to this test, if a series A "Granger-causes" (or "G-causes") another series B, then past values of A should contain useful information to predict B above and beyond the information contained in past values of B alone. It is based on linear regression modeling of stochastic processes. This test is applied in various areas of neuroscience in last few years³²⁻³⁹. It is reasonable to believe that if two series is connected, then one series may Granger cause another. We will check this assumption.

In the present paper, we have tried to measure connectedness of prime stock exchanges of India viz. SENSEX and NIFTY separately with prime American stock exchange viz. DOW JONES. To serve this purpose, we have used a Recurrence Plot based technique, Correlation of Probability of

Recurrence (CPR). We have examined CPR for 150 points, 250 points and 350 points window and we have compared the results with Pearson's cross-correlation coefficient ρ which is a well established form of connectedness.

We have also analyzed Granger Causality of SENSEX and NIFTY separately with DOW JONES and also separately with some other prime and emerging Asian Stock exchanges like HANG-SENG, NIKKEI, FTSE ALL SHARE, STRAIGHT TIMES INDEX, KOSPI COMPOSITE INDEX and TSEC WEIGHTED INDEX to understand the influence of American stock market over Indian stock market compared to the prime Asian stock market indices.

2. Theory

2.1. Recurrence Plots:

A Recurrence Plot (RP) is a visual way to see the recurrence pattern of a dynamical system⁴⁰. A recurrence is defined as the return of the trajectory in its earlier state. A recurrence is said to occur when the system returns to the neighborhood of an earlier point in the phase space. If a point $\vec{x}_i \in R^m$ in a trajectory $\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n$, the recurrence matrix R is estimated as:

$$(2.1) \quad R_{i,j}(\varepsilon) = \Theta(\varepsilon - \|\vec{x}_i - \vec{x}_j\|), \quad i, j = 1, 2 \dots n,$$

where n is the number of points in the trajectory, ε is the appropriate threshold distance, $\Theta(\cdot)$ is the Heaviside function (i.e., $\Theta(a) = 0$ if $a < 0$ and $\Theta(a) = 1$ if $a \geq 0$) and $\|\cdot\|$ is an appropriate norm. So, R is a matrix with elements 0 and 1 only and a Recurrence Plot is a graphical representation of R obtained by marking a black dot for every 1 and white dot for every 0.

2.2. Probability of Recurrence:

The Probability of Recurrence ($p(\tau)$), also called τ -recurrence rate, is the recurrence rate of a diagonal line situated at τ steps from the main diagonal, i.e., $R_{i,i+\tau} \quad \forall i=1, 2, \dots, n-\tau$ (N. Marwan, M. C. Romano, M. Thiel, and J. Kurths¹⁹). It measures the probability of a $(i+\tau)^{th}$ point falling in the ε -neighborhood of i^{th} point:

$$(2.2) \quad p(\tau) = \frac{1}{n-\tau} \sum_{i=1}^{n-\tau} R_{i,i+\tau}.$$

It can be viewed as a generalized form of an autocorrelation function that statistically reflects the time scales of the system in which it tends to return to a previous value.

2.3. Correlation of Probability of Recurrence (CPR):

The Correlation of Probability of Recurrence (CPR) is defined as the cross-correlation coefficient between the probabilities of recurrence of 2 trajectories¹⁹⁻²⁰ $\bar{x}$ and $\bar{y}$

$$(2.3) \quad CPR = \langle \rho_{\bar{x}}(\tau) \rho_{\bar{y}}(\tau) \rangle,$$

where $\langle . \rangle$ is the expected value and $\bar{x}$ is the normalized series x with mean 0 and standard deviation 1.

CPR characterized the degree of phase synchronization between two time series. $CPR \approx 1$ implies that the two time series are phase synchronized¹⁹. More generally it gives a measure the level to which two trajectories $\bar{x}$ and $\bar{y}$ has similar time scale of recurrence. So, two time series with high CPR tend to occur at similar times, suggesting some similarity between them.

2.4. Pearson Correlation:

Pearson correlation coefficient ρ is the expectation value of the product of two normalized time series. It is commonly used to measure the relation between two time series.

$$(2.4) \quad \rho_{\bar{x}, \bar{y}} = \langle \bar{x} \bar{y} \rangle.$$

If $|\rho| \approx 1$, then there is maximum chance that two time series have linear relationship and if $|\rho| \approx 0$, then this chance is minimum. More the value of $|\rho|$ toward 1, more will be the chance that both the time series have good relationship.

2.5. Significance Testing and Twin Surrogates:

In our experiment, CPR alone may not correctly interpret the connectivity as the parameters in time series analysis cannot be changed or controlled. Moreover, the dynamics of the system is also unknown. So, in

such case, it is crucial to generate surrogate time series and check for the statistical significance of the observed CPR against the distribution of CPR obtained from surrogate data sets. This is done by the method of testing of hypothesis.

The Twin Surrogates (TS) algorithm is a recurrence based algorithm to generate surrogate time series⁴¹. A pair of points $\vec{x}_i$ and $\vec{x}_j$ of a trajectory $\vec{x}$ of length n are called twins if $R_{k,i} = R_{k,j}$ for $k=1,2,...,n$. This implies that $\vec{x}_i$ and $\vec{x}_j$ have same neighborhood in phase space. The iterative algorithm of TS method is described below:

1. Identifying twins from recurrence plot of the trajectory $\vec{x}$.
2. Taking any arbitrary point $\vec{x}_k \in \vec{x}$ as the initial point of surrogate trajectory $\vec{s}$.
3. If $\vec{x}_i \in \vec{s}$ is the previous point of $\vec{s}$ and $\vec{x}_i$ has no twin, then the next point of $\vec{s}$ is $\vec{x}_{i+1}$; otherwise if $\vec{x}_i$ is $m-1$ twins, then the next point of $\vec{s}$ is any one of that the particular set of m twins, chosen with equal probability.

We use TS to generate a test distribution using which we test the significance of the observed measure M (which can be either CPR or ρ). The null hypothesis for the significance test is that each surrogate is independent trajectory of the same dynamical system from which observed time series is generated. In other words, our null hypothesis is that value of M is similar in case of original time series and its surrogate. This process is done by following steps:

1. The value of M between two time series A and B are estimated. Let it be M_0
2. TS are generated from the series B .
3. M_0 is calculated between each TS generated in step-2 and the series A . This yields the test distribution of M . Our assumption is this distribution is roughly normal distribution as each TS corresponds to a separate trajectory of series B starting from an independent initial condition.
4. The mean μ and standard deviation σ are estimated from this test distribution.

5. The test statistic Z is then given by

$$(2.5) \quad Z = \frac{M_0 - \mu}{\sigma},$$

where Z is a standard normal variate.

The pre-chosen probability is decided below which M is said to be significantly different from the test distribution and the pre-chosen probability is called significance level of the test. The probability value, commonly known as p -value is the probability with which the value of the test statistic would be as or more inconsistent with the null hypothesis as the value of the test statistic we calculated from our data, if the null hypothesis were true. p -value represents the probability that null hypothesis cannot be rejected. In our work, p -value represents the probability that M might actually from test distribution.

2.6. Granger Causality Analysis:

Granger causality test involves using F -tests to test whether lagged information on a variable Y provides any statistically significant information about a variable X in the presence of lagged X . If not, then "Y does not Granger-cause X ", otherwise "Y Granger-cause X "³¹. If a time series is stationary process, the test is performed using the level values of two variables. If the variables are non-stationary, the test is performed using the first or higher differences. There are many ways in which to implement a test of Granger causality between two time series X and Y . One of the most efficient and simple approach uses the autoregressive specification of a bivariate vector auto regression. We assume a particular autoregressive lag length p , and estimate the following unrestricted equation by ordinary least squares (OLS):

$$(2.6) \quad x_t = c_1 + \sum_{i=1}^p a_i x_{t-i} + \sum_{i=1}^p b_i y_{t-i} + u_t,$$

$$H_0 : b_1 = b_2 = \dots = b_p = 0.$$

We conduct an F -test of the null hypothesis by estimating the following restricted equation also by OLS:

$$(2.7) \quad x_t = c_t + \sum_{i=1}^p d_i x_{t-i} + e_t.$$

Then we compare their respective sum of squared residuals.

$$(2.8) \quad RSS_1 = \sum_{t=1}^T u_t^2 \quad \text{and} \quad RSS_0 = \sum_{t=1}^T e_t^2.$$

If the test statistic

$$(2.9) \quad S_1 = \frac{(RSS_0 - RSS_1) / p}{RSS_1 / (T - 2p - 1)} F_{p, T-2p-1}$$

is greater than the specified critical value, then reject the null hypothesis that Y does not Granger-cause X .

RESULT

3.1. Data Set:

For the present connectivity analysis, we have taken 3 stock market indices: SENSEX, NIFTY and DOW JONES. For Granger causality analysis, six more stock exchange indices from Asian market have been included: HANG-SENG, Nikkei, FTSE All Share, Straights Times Index, KOSPI Composite Index and TSEC Weighted Index. For all these nine indices the time intervals for computation are taken from 3rd July, 1990 up to 31st December, 2012.

The data sets have unequal length as the holidays are different in different countries. To make uniform analysis of CPR, we have deleted mismatched dates and corresponding closed values from SENSEX, NIFTY and DOW JONES indices. We have obtained 4952 data points.

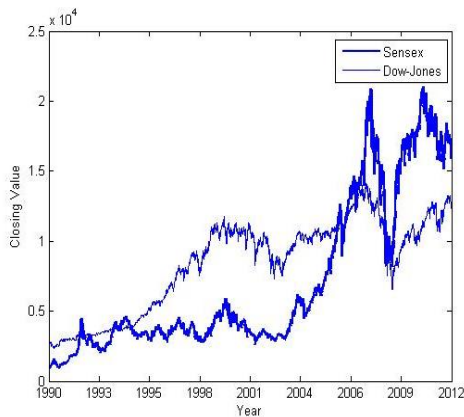


Figure 1(a)

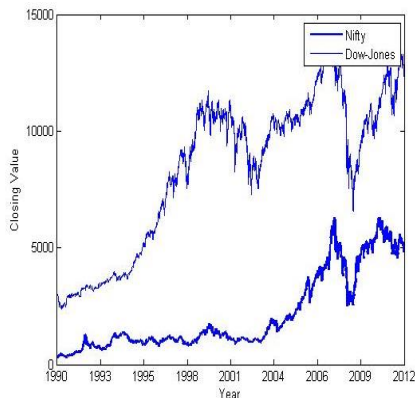


Figure 1(b)

Figure 1: (a) Daily Closed Values for SENSEX & DOW JONES
(b) NIFTY & DOW JONES

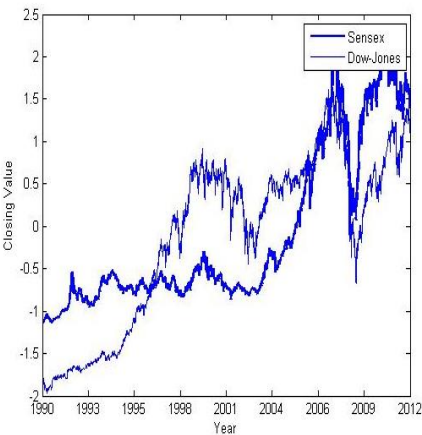


Figure 2(a)

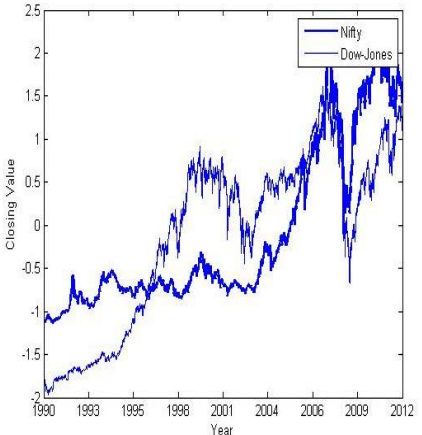


Figure 2(b)

Figure 2: Normalization of Daily closed values for:
(a) SENSEX & DOW JONES; (b) NIFTY & DOW JONES

As the index values of different indices are arbitrary (Figure 1), we have normalized data sets to mean zero and standard deviation one (Figure 2) to make quantitative analysis better. This helps us to compare scaled time series with same value of parameters.

3.1. Selection of Parameters:

3.1.1. Widow Size:

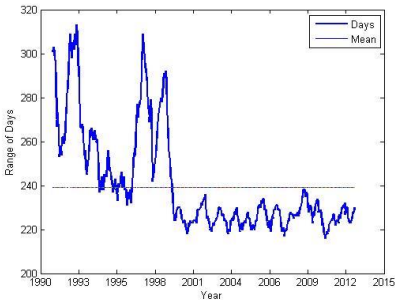


Figure 3(a)

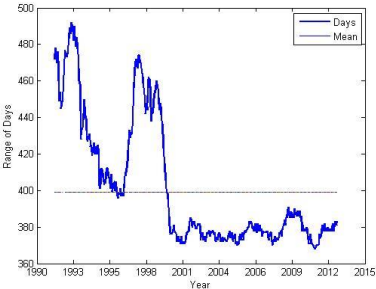


Figure 3(b)

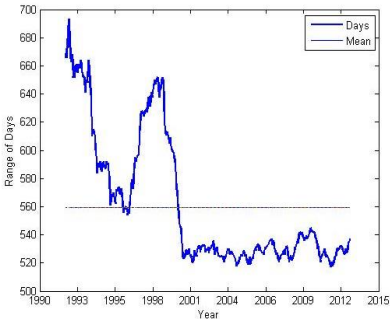


Figure 3(c)

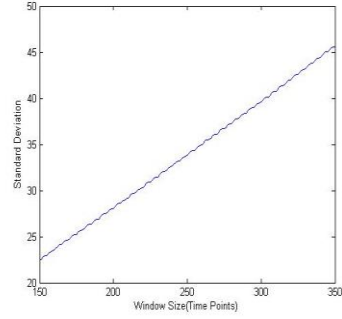


Figure 3(d)

Figure 3, Selection of Window Size (a)-(c) The range of days contained in windows of sizes 150, 250 & 350 time points with steps of 10 time points. The horizontal lines represent the mean of days; (d) The standard distribution of the distribution of range of days contained in the windows sized between 150 and 350 time points.

We slide a window of fixed length along the data set and estimate CPR or ρ . As we have deleted unmatched dates among indices, the actual range of days in a window size is actually greater than window size. Also the range varies as window moves along the time series (Figure 3(a)-(c)).

We have also varied window size from 150 time points to 350 time points and measure standard deviation of the range of days contained in each window and interestingly found that standard deviation increased almost monotonically with increased window size. As standard deviation is a measure of dispersion, ideally the window with least size would give most accurate estimate, but it also reduces effectiveness of RP parameters. So, we have used all three time points.

3.1.2. RP Parameters:

There are several ways to construct RP from time series data¹⁹. We have used a fixed threshold ε . There is no fixed value of ε . It depends on the aim of the study and nature of the data set. The choice of ε should be such that recurrence matrix R should represent the dynamics of whole time series. It should be neither be too small (to avoid excluding crucial references) nor be too large (to avoid counting micro level recurrences). One rule of thumb is that ε should not exceed 10% of the maximum distance between the points in the time series⁴².

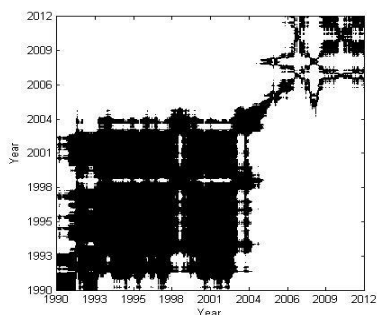


Figure 4(a)

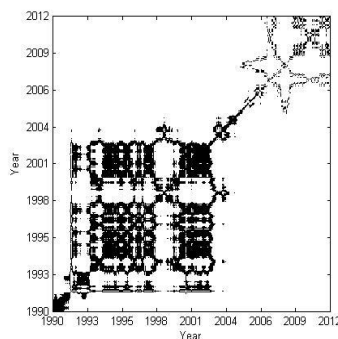


Figure 4(b)

Figure 4: Recurrence plots for different threshold values (a) RP for SENSEX, $\varepsilon = 10\%$ of maximum distance; (b) RP after normalizing the data in (a) and $\varepsilon = 0.1$, which is around 2% of maximum distance.

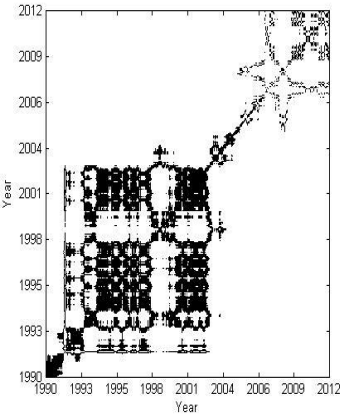


Figure 5(a)

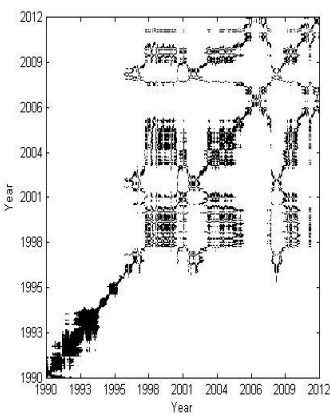


Figure 5(b)

Figure 5: Recurrence plots for normalized data of (a) NIFTY, $\varepsilon = 0.1$; (b) DOW JONES, $\varepsilon = 0.1$

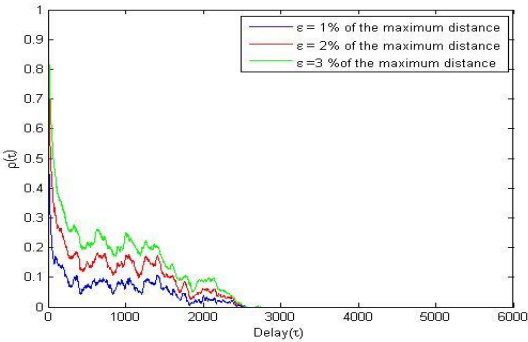


Figure 6: $p(\tau)$ curves for SENSEX with $\varepsilon = 1\%, 2\%$ & 3% & of the maximum distance.

In our study, if we have kept $\varepsilon \approx 10\%$ of the maximum distance and got a dense RP (Figure-4(a)). So, to capture finer structure maintaining sufficient statistics in CPR, we have taken $\varepsilon = 0.1$ for all RPs and normalize time series before any recurrence based calculation. This effectively have reduced the recurrence threshold to around 2% of maximum distance and given the clearer scenario of recurrence plot (Figure-4(b)). RPs for NIFY and DOW JONES is given in Figure-5.

We have also found that qualitative nature of recurrence is flexible with this choice of ε . In Figure-6, $p(\tau)$ curves for SENSEX data obtained from its RP (Figure-4(b)) are shown for $\varepsilon = 1\%, 2\%$ & 3% of maximum distance. It has been observed that though magnitude of recurrences has increased with increasing ε , the qualitative nature of the graphs remain almost same.

3.2. Analyzing Connectivity Trends:

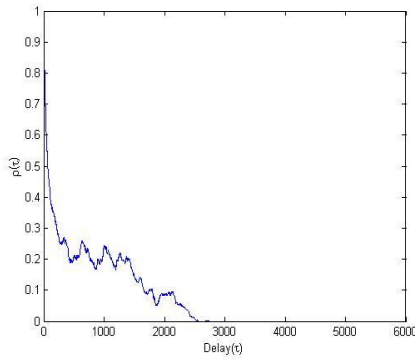


Figure 7(a)

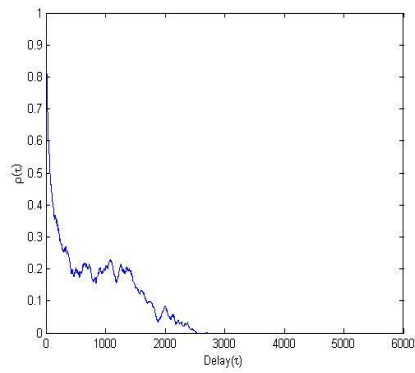


Figure 7(b)

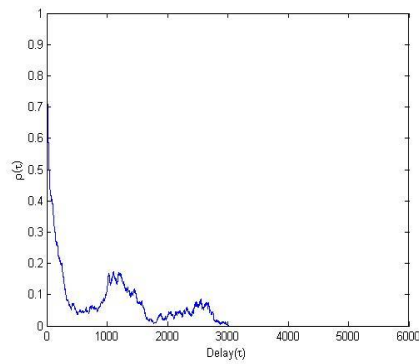


Figure 7(c)

Figure 7: $p(\tau)$ curves for (a) SENSEX; (b) NIFTY & (c) DOW JONES with $\varepsilon = 0.1$.

Firstly, $p(\tau)$ are calculated for SENSEX, NIFTY & DOW JONES and is represented in Figure-7.

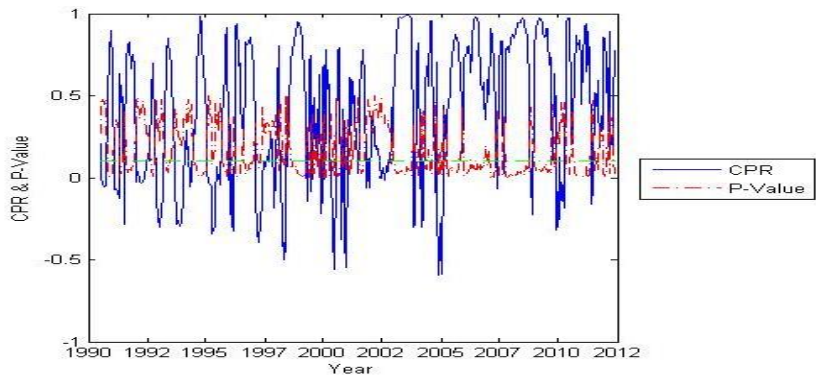


Figure 8(a)

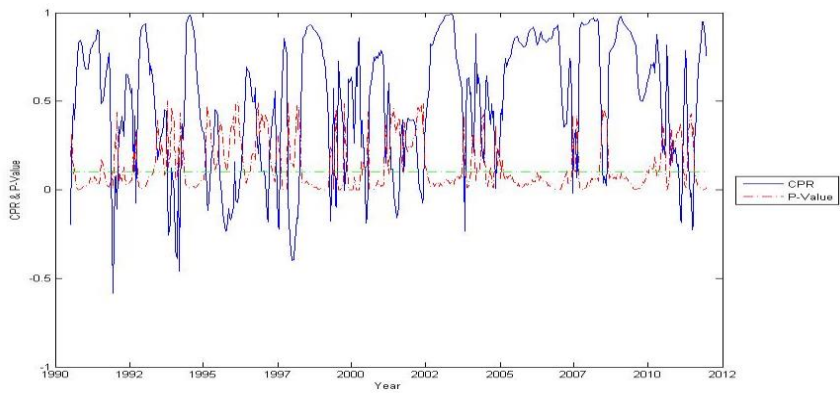


Figure 8(b)

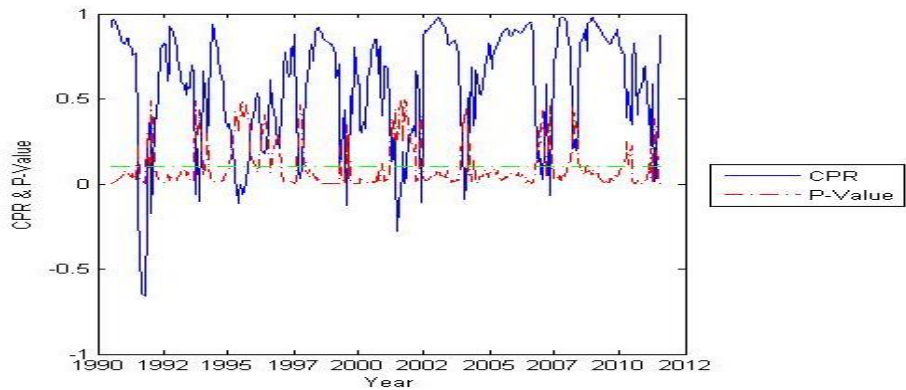


Figure 8(c)

Figure 8: Trends in CPR. CPR & corresponding p-values for SENSEX-DOW JONES pair with window size (a) 150 time points; (b) 250 time points & (c) 350 time points. The horizontal dotted line denotes the test significance level, $p=0.1$.

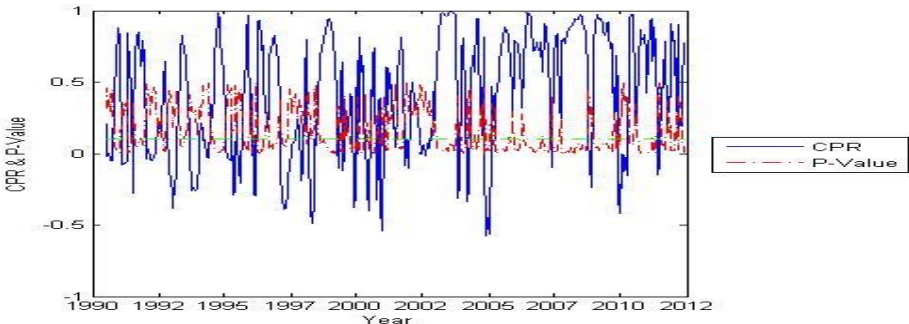


Figure 9(a)

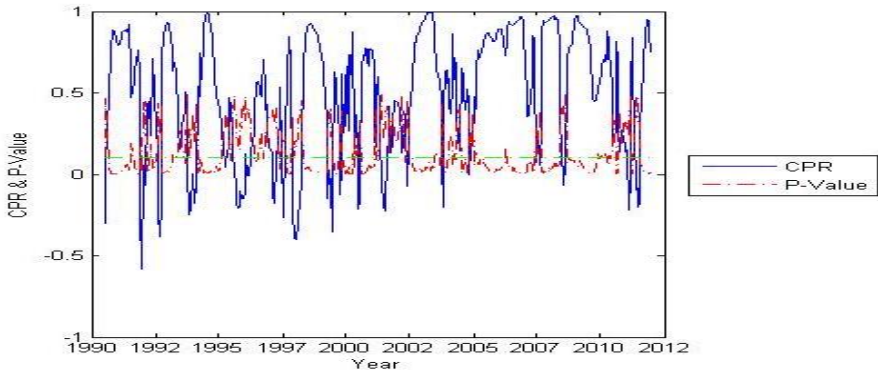


Figure 9(b)

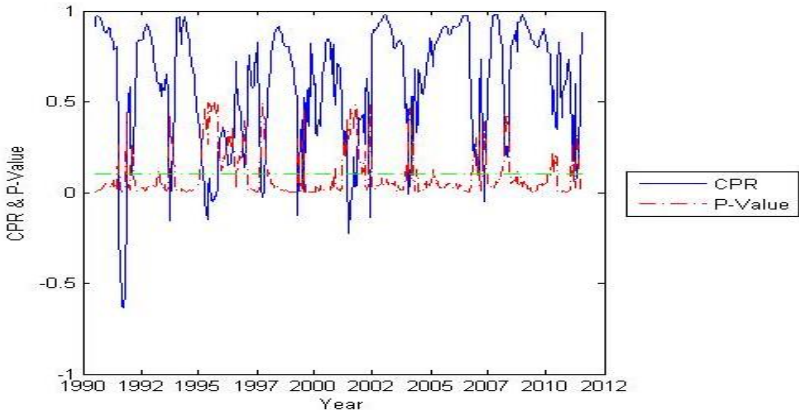


Figure 9(c)

Figure 9: Trends in CPR. CPR & corresponding p-values for NIFTY-DOW JONES pair with window size (a) 150 time points; (b) 250 time points & (c) 350 time points. The horizontal dotted line denotes the test significance level, $p=0.1$.

Then CPR and ρ values have been estimated for two pairs of data, namely, (i) SENSEX-DOW JONES and (ii) NIFTY-DOW JONES varying window size as 150 times points, 250 time points and 350 time points and steps of 10 time points. The result is given in Figure-8 for first pair and in Figure-9 in second pair. At every step, CPR (or ρ) values is tested for significance with 100 Twin surrogates at 10% level of significance.

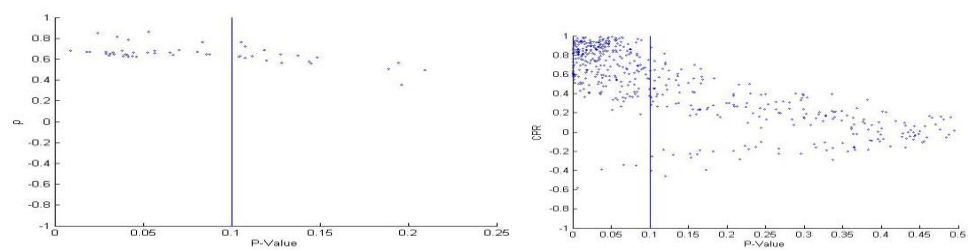


Figure-11 (a) Figure-11(b)
Figure 11: Distribution of (a) ρ & (b) CPR against p-value.

Then we have analyzed and compared distribution of CPR and ρ against p – value which is given in Figure-11.

3.3. Granger Causality Analysis:

Next we have analyzed Granger causality of SENSEX and NIFTY separately with DOW JONES (USA) and six emerging stock market indices in Asia viz. HANG-SENG (Hong Kong), NIKKEI (Japan), FTSE ALL SHARE (Singapore), STRAIGHT TIMES INDEX (Singapore), KOSPI COMPOSITE INDEX (South Korea) and TSEC WEIGHTED INDEX (Taiwan). We have taken window size of 250 time points and steps of 10 time points. We have measured Granger causality separately for the cases where CPR between two time series is greater than 0.8 and where CPR between two time series is greater than 0.5. The result is summarized in Table-1 given below:

Table 1: Granger Causality Analysis between different stock market indices

A	B	No. of Data Points	No. of Wind-ows of sizes 250 time points	A Granger Cause B with 95% level of significance	CPR between A and B grea	A Granger Cause B and CPR greater than 0.5	CPR between A and B grea	A Granger Cause B and CPR greater than 0.8

					t er than 0.5		ter than 0.8	
DOW JONES	Sense x	5100	486	372(76.54%)	272	225(82.72%)	142	127(89.44%)
DOW JONES	Nifty	5100	486	370(76.13%)	271	221(81.55%)	142	125(88.03%)
Hang -Seng	Sense x	5059	481	288(59.88%)	326	215(65.95%)	217	140(64.16%)
Hang -Seng	Nifty	5059	481	308(64.03%)	282	209(74.11%)	153	126(82.35%)
Nikkei	Sense x	4952	471	209(44.37%)	257	115(44.75%)	126	47(37.30%)
Nikkei	Nifty	4952	471	208(44.16%)	248	111(44.76%)	128	55(42.97%)
FTSE All Share	Sense x	5138	489	315(64.42%)	295	224(75.93%)	152	128(84.21%)
FTSE All Share	Nifty	5138	489	316(64.62%)	291	217(74.57%)	151	123(81.46%)
Straight Times Index	Sense x	5110	487	222(45.58%)	345	165(47.83%)	213	96(45.07%)
Straight Times Index	Nifty	5110	487	235(48.25%)	344	173(50.29%)	219	100(45.66%)
KOSPI Composite Index	Sense x	3582	334	149(44.61%)	234	103(44.02%)	168	68(40.48%)
KOSPI Composite Index	Nifty	3582	334	144(43.11%)	233	103(44.21%)	161	64(39.75%)
TSEC Weighted Index	Sense x	3570	333	116(34.83%)	220	82(37.27%)	106	42(39.62%)
TSEC Weighted Index	Nifty	3570	333	113(33.93%)	212	75(35.38%)	100	40(40.00%)

4. Discussion And Conclusion

In the present work, we have measured the connectivity between stock markets by estimating CPR. From Figure-8 & Figure-9, it is evident that the graph of CPR is not monotonically increasing; rather it oscillates between smaller period of low CPR and broader period of high CPR. So, CPR does

not change monotonically with time, it moves in and out with different time periods. Also, it is clear from the graphs that the regions with higher CPR values have lower p values and vice versa which implies that higher ranges of CPR seem to be more statistically significant than lower ranges of CPR. This pattern is same for both the pair of SENSEX-DOW JONES & NIFTY-DOW JONES and for all window size of 150, 250 and 350 time points.

So, if CPR is a measure of similarity and hence connectedness, it may be no wrong to say that Indian stock markets are not moving towards a greater connectivity with USA, rather it is oscillating between long periods of strong connectedness and short period of weaker connectedness. They come close to each other, stay close for a longer time and again move apart for a relatively shorter time.

The trend in Pearson's correlation coefficient ρ is quite different from CPR as we see from Figure-10. It is almost a monotonically increasing function in contrast to CPR which is oscillating. So, correlation coefficient shows an overall movement towards higher values as time progresses. So, two measures of connectivity are quite different. While CPR measures the tendency of time series values to return to its earlier values at similar time scales, ρ measures the tendency of time series to move together in same (or opposite) directions. As both the methods are different, it is expected that the results would be different. While CPR, being a recurrence-based method, highlights essential features of the dynamical system, ρ signify the co-evolution of states. So, as number of data increases, the tendency of ρ is expected to be high, but it is not necessarily true in case of CPR. This is already reflected in our result. CPR also has lower p -values than ρ as we seen from Figure-11. Most CPR values are grouped close to $p=0$ axes whether ρ has broader spread. This implies that probability of rejecting the null hypothesis is lower in case of CPR than ρ .

Lastly, we have performed Granger causality analysis among different pairs of data. We may say from Table 1 that DOW JONES Granger cause both SENSEX and NIFTY at 95% level of significance as in almost 77% of the windows, the result is true. For other indices, we cannot say that as the percentage of the windows where separately they Granger cause SENSEX or NIFTY is really low (varies from 33% to 65%). Also we have measured Granger causality separately for the windows where CPR is more than 0.8 and CPR more than 0.5. It is evident that in case of SENSEX-DOW JONES pair, at almost 89% of windows where CPR is more than 0.8, DOW JONES Granger cause SENSEX and for NIFTY-DOW JONES pair, it is almost 88%. We have also performed the test where CPR is greater than 0.5. In that

case percentage drops little bit to almost 83% for SENSEX-DOW JONES pair and 82% for NIFTY-DOW JONES pair. Thus, from these statistics, we may say that the probability that a time series may Granger cause another is more when CPR between two time series more or in other words, two time series are strongly connected. So in fine we can conclude that DOW JONES Granger cause both SENSEX and NIFTY more than any other Asian Stock Market Indices and effect of Granger causality increases in the windows where both the time series are strongly connected. As Granger causality is associated with forecasting, DOW JONES may be considered as an important factor to forecast the behaviour of Indian stock market.

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