Sectoral co-movements in the Indian stock market: A mesoscopic network analysis

Kiran Sharma∗ Shreyansh Shah† Anindya S. Chakrabarti‡ Anirban Chakraborti§

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Abstract

In this article we review several techniques to extract information from stock market data. We discuss recurrence analysis of time series, decomposition of aggregate correlation matrices to study co-movements in financial data, stock level partial correlations with market indices, multi-dimensional scaling and minimum spanning tree. We apply these techniques to daily return time series from the Indian stock market. The analysis allows us to construct networks based on correlation matrices of individual stocks in one hand and on the other, we discuss dynamics of market indices. Thus both micro level and macro level dynamics can be analyzed using such tools. We use the multi-dimensional scaling methods to visualize the sectoral structure of the stock market, and analyze the comovements among the sectoral stocks. Finally, we construct a mesoscopic network based on sectoral indices. Minimum spanning tree technique is seen to be extremely useful in order to separate technologically related sectors and the mapping corresponds to actual production relationship to a reasonable extent.

1 Introduction

In this paper, we present a coherent analysis of the Indian stock market employing several techniques recently proposed in the econophysics literature. Stock market is a fascinating example of a rapidly evolving multi-agent interacting system that generates an enormous amount of very well defined and well documented data. Because of the sheer volume of data, it becomes possible to construct large scale correlation matrices across stocks that contain information about the aggregate market. Thus the loss of information due to aggregation can be minimized to a great extent. Several useful

∗School of Computational and Integrative Sciences, Jawaharlal Nehru University, New Delhi-110067, India. Email: kiran34_sit@jnu.ac.in
†Indian Institute of Technology, Banaras Hindu University, Varanasi-221005, India. Email: shreyansh.shah.mec13@iitbhu.ac.in
‡Economics area, Indian Institute of Management, Vastrapur, Ahmedabad, Gujarat-380015, India, Email: anindyac@iima.ac.in.
§School of Computational and Integrative Sciences, Jawaharlal Nehru University, New Delhi-110067, India, Email: anirban@jnu.ac.in
techniques to analyze such large-scale data have been proposed and there are multiple resources reviewing them. Interested readers can refer to [5] and [6] for excellent and quite extensive textbook expositions.

We present a series of analysis on the Bombay stock exchange, using both macro scale and micro scale data. Even though there are separate attempts in a few other papers that presented analysis on similar data sets, this probably is the first attempt to systematically analyze Indian stock market data in a comprehensive manner. At the beginning of discussion on every technique, we point out the papers that proposed the techniques and subsequent analysis, if any, on Indian or any other emerging market data. India being an emerging market is an interesting example. Several papers (Ref. [10], [2]) have pointed out that there are systematic differences between the dynamic behavior of developed economies and emerging economies.

2 Nonlinear dynamics: recurrence plot analysis

For a very long time it had been conjectured that the stock market indices may have certain features of a highly nonlinear dynamical system. It originated from certain speculations that economic systems in general may show chaotic behavior (see e.g. [7]). [8] considered an idea that the aggregate macro dynamics of an economy may show chaotic behavior. By and large, such theories are no longer considered to be useful descriptions of economic dynamics. However, in recent times there have been some attempts to analyze the stock index behavior by using recurrence analysis based on phase space reconstruction.

In general, the technique’s usefulness comes from the fact that it is non-parametric, does not make any assumptions about the data and can work with non-stationary data. In particular, the technique is useful for detecting sudden large change in a time series. A stock market crash has often been thought of as a phase transition indicating a large abrupt change in the behavior [12]. However, the technique is useful for recovering patterns in potentially highly nonlinear but recursive systems, an assumption that is not satisfied by the stock market. We follow the mode of analysis presented in details in [11] and [10].

Here we describe construction of recurrence plots. It is based on the idea of recurrence within a phase space and the plot exhibits times when a nonlinear system revisits the same phase space during the process of evolution. Consider a time series \( \{ x(i) \}_{i=1}^{N} \) representing an index of a stock market. We know from Takens’ theorem [9] that it is possible to extract information about the phase space from the time series (see also Ref. [10]). We start by embedding \( \{ x \} \) into an \( m \) dimensional space given by,

\[
y(i) = [x(i), x(i + \delta), x(i + 2\delta), ..., x(i + (m - 1)\delta)]
\]

where, \( d \) is the time delay. Together these two parameters constitute the set of embedding parameters. Thus \( y(i) \) is a point in the \( m \) dimensional Euclidean space, representing the evolution of the system in the reconstructed phase space. We collect all such \( y(i) \)'s and present element-by-element
Figure 1: Left panel: Normalized daily return series constructed from BSE index data for five years (6th June, 2011 to 6th June, 2016). Right panel: Recurrence plot constructed from the same data with an embedding dimension equals to 11 and time delay 1.

Figure 2: Distance plots constructed from the BSE index for different values of the embedding dimensions ($m = 2, 5, 11, 21$).
difference with Euclidean norm to create a two dimensional plot. Such a plot exhibits if there is any recurrence as explained below.

Let us define a matrix $R$ such that its $i,j$-th element $(i,j = 1,\ldots,n)$, with $n = N - (m - 1)d$ is expressed as

$$R_{ij}(\epsilon) = \begin{cases} 0 & \text{if } |y(i) - y(j)| > \epsilon \\ 1 & \text{if } |y(i) - y(j)| \leq \epsilon \end{cases}$$

where $\|\cdot\|$ is the Euclidean norm, and $\epsilon$ is the threshold applied which is a positive real number. Recurrence plots are exactly symmetric along the diagonal.

**Inference based on structures:**
In recurrence plots, we see multiple patterns including dots, diagonal as well as vertical and horizontal lines and all possible combinations of them.

- Isolated points exist if states are rare or persistence is low or if they represent high fluctuations.
- Existence of a diagonal line $R_{i+m,j+m} = 1$ (for $m = 1,\ldots,l$ where $l$ is the length of the diagonal line) indicates presence of recurrence i.e. a segment of the time series revisits the same area in the phase space at a lag. If there are lines parallel to the line of identity, it represents the parallel evolution of trajectories.
- Existence of a vertical (horizontal) line $R_{i,j+m} = 1$ (for $m = 1,\ldots,v$ where $v$ is the length of the line) indicates a stage during evolution where the system gets trapped for some time and does not evolve fast. This can be an intermittent behavior.

Now we conduct recurrence quantification analysis (RQA) by studying the structure of the plots numerically. Such an analysis is based essentially on densities of isolated points, diagonal lines as well as vertical lines. We borrow the discussion presented below from [10]. The measures which we have considered are as follows:

- RR: Recurrence rate.
- DET: Fraction of points in the plot forming diagonal lines. This indicates determinism and hence, predictability.
- $\langle L \rangle$: Average lengths of the diagonal lines.
- LMAX: Length of the longest diagonal line (except the line of identity). Its inverse is associated with the divergence of the trajectory in phase-space.
- ENTR: Shannon entropy defined over the distribution of lengths of diagonal lines, indicates diversity of the diagonal lines.
- LAM: Fraction of points forming vertical lines, indicates existence of laminar states in the system.
We have computed the RQA measures for the BSE index under a range of embedding dimension. In each case, we have set the delay equal to 1. In Fig. 1 and 2 we present recurrence analysis on logarithmic return series \( r_\tau = \ln P_\tau - \ln P_{\tau-1} \) constructed from BSE index data. As is apparent, there is no clearly discernible pattern in the data. Next, we follow the standard approach and use the level of the price data upon normalization by the maximum value of the time series \( \tilde{P}_\tau = (P_\tau - P_{\text{min}})/P_{\text{max}} \). Table 1 contains the RQA measures. Most of the prior literature on stock market data consider high values of embedding parameter. It is evident that, in general, recurrence rates are very low and determinism is very high. However, this approach has an inherent problem that it is not particularly good at differentiating non-recursive series from recursive series. In general, we found that when we construct similar measures for standard recursive series, it is not clear from such RQA measures that they can be easily separated from a stochastic series. Thus it does not really shed much light on the problem as the primary focus is to figure out determinism or lack thereof. Ref. [10] discusses a possible application that these measures still retain some usefulness for cross-country analysis. Since in this case we are focusing on one country only, it is not very helpful. So we consider a fully stochastic framework in the rest of the analysis.

3 Empirical study of the correlation structure of the Indian stock market

In this section, we analyze the empirical cross-correlation matrices constructed from the stock market data.

3.1 Data specification, notations, and definitions

In order to study correlations and co-movements in the stock price time series, the popular Pearson correlation coefficient was commonly used. However, with the electronic markets producing data at different frequencies (low to high), it is now known that several factors viz., the statistical uncertainty associated with the finite-size time series, heterogeneity of stocks, heterogeneity of
the average inter-transaction times, and asynchronicity of the transactions may affect the applicability/reliability of this estimator. In this article, we have mainly focused on the daily returns computed from closure prices, for which the Pearson coefficient works well.

3.1.1 Data set

We have used the freely downloadable daily adjusted closure prices from Yahoo finance for $N = 199$ companies in the Bombay Stock Exchange (BSE) SENSEX [14], for five years, over a period spanning from June 6, 2011 to June 6, 2016. Also we have downloaded 199 stock prices of companies chosen randomly from the BSE and 13 sectoral indices of the BSE, for the period May 27, 2011 to May 27, 2016. The lists are given in the appendices I and II.

3.2 Correlation matrices

We construct the correlation matrix from individual stock returns in the following way.

3.2.1 Pearson correlation coefficient

In order to study the equal time cross-correlations between $N$ stocks, we first denote the adjusted closure price of stock $i$ in day $\tau$ by $P_i(\tau)$, and determine the logarithmic return of stock $i$ as $r_i(\tau) = \ln P_i(\tau) - \ln P_i(\tau - 1)$. For the window of $T$ consecutive trading days, these returns form the return vector $r_i$. We use the equal time Pearson correlation coefficients between stocks $i$ and $j$. 

Figure 3: Left panel: Probability density function of the cross-correlation coefficients of 199 BSE stocks. Right panel: Decomposition of the correlation matrix into market mode, group mode and random mode.
Figure 4: Eigenvalue decomposition of the correlation matrix. Left panel: Probability density function of eigenvalues. Inset shows the full distribution. Right panel: Inverse participation ratio with respect to the corresponding eigenvalues.

defined as

$$C_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{[\langle r_i^2 \rangle - \langle r_i \rangle^2][\langle r_j^2 \rangle - \langle r_j \rangle^2]},}$$

(2)

where $\langle ... \rangle$ indicates an average over the window of $T$ successive trading days in the return series. Naturally, such correlation coefficients satisfy the usual condition of $1 \leq C_{ij} \leq 1$ and we can create an $N \times N$ correlation matrix $C$ by collecting all values [15, 16]. By construction, the matrix is symmetric and it serves as the basis of the rest of the present article.

3.3 Decomposition analysis

For the present section, we are following the sequence of methods discussed by Ref. [2] which is one of the first few papers that applied this technique. Suppose we have $N$ return time series of length $T$ that are pairwise uncorrelated. The correlation matrix generated by collecting all pairwise correlations for $N$ such series is called Wishart matrix. In the limit $N \to \infty$ and $T \to \infty$, such that the ratio $Q \equiv T/N > 1$, the eigenvalue distribution of this matrix has a specific distributional form,

$$f(\lambda) = (Q/2\pi)\frac{\sqrt{(\lambda_{max} - \lambda)(\lambda - \lambda_{min})}}{\lambda},$$

(3)

for $\lambda_{min} \leq \lambda \leq \lambda_{max}$ and, 0 otherwise. This distribution is clearly bounded by $\lambda_{max, min} = [1 \pm (1/\sqrt{Q})]^2$. In the BSE data we considered, $Q = 5$. Thus the Wishart matrix should have the
following bounds: $\lambda_{\text{min}} = 0.3056$ and $\lambda_{\text{max}} = 2.0944$. The distribution of eigenvalues unexplained by the Wishart matrix sheds light on the interaction structures and the coevolution process of the stocks in the market.

The largest eigenvalue corresponds to the market mode which captures the aggregate dynamics of the market that is common across all stocks. The eigenvectors associated with the next few eigenvalues (we took the next 5 dominant eigenvalues) describe the sectoral dynamics. The rest of the eigenvectors correspond to the random mode. From such a segregation, it is possible to reconstruct the contributions of different modes to the aggregate correlation matrix.

Following the literature to filter the data to remove market mode and the random noise, we first decompose the aggregate correlation matrix as

$$ C = \sum_{i=0}^{N-1} \lambda_i a_i a_i^T, \quad (4) $$

where $\lambda_i$ are the eigenvalues of the correlation matrix $C$. An easy way to handle the reconstruction of the correlation matrix is to sort the eigenvalues in descending order. Then we rearrange the eigenvectors $a_i$ in corresponding ranks. This allows us the decompose the matrix into three separate components viz. market, group and random:

$$ C = C^M + C^G + C^R, \quad (5) $$

$$ = \lambda_0 a_0 a_0^T + \sum_{i=1}^{N_G} \lambda_i a_i a_i^T + \sum_{i=N_G+1}^{N-1} \lambda_i a_i a_i^T \quad (6) $$

where $N_G$ is taken to be 5 i.e. corresponds to the 5 largest eigenvalues except the first one. It is worth noting that the exact value of $N_G$ is not crucial for the result as long as it is kept within the same ballpark. The decomposition is shown in Fig. 3.

An important finding is that the group mode almost coincides with the random mode whereas the market mode is segregated by a large margin from the rest. Thus the sectoral dynamics are almost absent whereas the market mode is very strong. This is in line with the prior literature (see e.g. [2]).

Following standard procedure (see e.g. Ref. [2]), we also calculate the inverse participation ratio (IPR) to extract information about contribution of different stocks to the eigenvalues. IPR is defined for the $k$-th eigenvector as the sum of fourth power of all individual components of the corresponding eigenvector, $I_k \equiv \sum_{i=1}^{N} [a_{ki}]^4$, where $a_{ki}$ are the components of eigenvector $k$. The result is presented in Fig. 4. Intuitively if a single stock dominates in terms of contribution to any particular eigenvector, then the IPR would go to 1. For example, consider a limiting case of $a_{k1} = 1$ and $a_{ki} = 0$ for $i \neq 1$. On the other hand if all elements were equal to $1/\sqrt{N}$, then we would get $IPR = 1/N$. Thus by considering IPR, we can understand if there is significant contribution coming from specific stocks or a more diversified bundle of stocks.
3.4 Partial correlation analysis

Partial correlation is a newly introduced tool to investigate the effects of third stock on the correlation between a pair of stocks. [13] introduced this analysis for multiple stock markets. In the present paper we apply their technique to the Bombay stock exchange data. To describe its usefulness, consider 3 stocks, \( i \), \( j \) and \( k \), with significant correlation between all three pairs of the stocks. Suppose, we think that the high value of \( C_{ij} \) is the result of their own correlations with \( k \), i.e. part of \( C_{ij} \) might be spurious correlation arising from a third variable effect (in this case \( k \)), we should remove such effects to figure out the actual correlation across \( i \) and \( j \). Then we can recalculate \( C_{ij} \), after controlling for the effect of \( k \). The resultant correlation value is called the partial correlation. The difference between the raw correlation value between a pair of stocks and the corresponding partial correlation tells us how much third-variable effect was there.

For this purpose, we again use the same daily log return \( r_i(t) \). However, we need to adjust for one more factor. From the preceding analysis, we already know that there is a significant market mode. Therefore, that will act a common driving factor. Hence, the market mode should also be controlled for in order to extract the actual correlation values for the exact same reason. In this case, the market mode is given by a market index. Note the difference from the earlier analysis. For constructing the market mode from the eigenvalue analysis, the market mode arise endogenously from the panel data itself whereas in this case, we take the market mode to be given by an exogenous
index time series. Hence, these two types of analysis complement each other.

Following the notation of [13], let $x$, $y$ be two time series and let $M$ be the BSE index for the same time frame. The partial correlation, $(x, y|M)$ is defined as the standard Pearson correlation coefficient (described above) between $x$ and $y$ after controlling for $M$. More technically, this is the correlation between the residuals of $x$ and $y$ which are unexplained by the market index represented by $M$. So first, we need the residuals of the two time series. A simple way is to do it would be to regress both on $M$. Then we can work with the resulting variables. Formally, the correlation is given as

$$C_{x,y|M} = \frac{(C_{x,y} - C_{x,M}C_{y,M})}{\sqrt{(1 - C_{x,M}^2)(1 - C_{y,M}^2)}}$$  \hspace{1cm} (7)

In the same way, when the same two stocks $x$ and $y$ are affected by a common stock $z$, we can control for that effect as well. Given a third stock $z$, the partial correlation between $x$ and $y$ after controlling for both the market factor as well as that third stock $z$, is given by the following formula

$$C_{x,y|M,z} = \frac{C_{x,y|M} - C_{x,z|M}C_{y,z|M}}{\sqrt{(1 - C_{x,z|M}^2)(1 - C_{y,z|M}^2)}}$$  \hspace{1cm} (8)

If it is found that the third stock has an important effect on pairs of stocks, then it is useful to define the ‘Influence Quantity’ (see [13])

$$d(x, y|z) = C_{x,y|M} - C_{x,y|M,z}.$$  \hspace{1cm} (9)

Magnitude of this quantity will reflect how much influence does the third stock influence on a pair of stocks. A natural extension of this idea is to consider the average influence $d(x|z)$ of stock $z$ on the correlations between a given stock $x$ and all other stocks except $x$ itself and $z$. Ref. [13] defined this index as the following

$$d(x|z) = \langle d(x, y|z) \rangle_{y\neq x}.$$  \hspace{1cm} (10)

This quantity captures the average influence from stock $z$ to stock $x$ through the third variable effect after controlling for the market index.

We present all results of our analysis in Fig. 5. Panel (a) shows the correlation coefficients of all stocks after controlling for the market index. Since the bulk of it is below the 45° line, we conclude that the market index has a positive effect on pairwise correlations. This is consistent with the results from the eigenvalue analysis and also with [13]. Similarly, in panel (b) we show the data for the same correlation coefficients after controlling for all possible third variable effects. In panel (d), we present the probability density function of the influence quantity. Again bulk of the distribution is in the positive quadrant implying positive effect on average.

4 Network analysis

In this section, we present network analysis based on the empirical correlation matrix.
4.1 Distance metric

To obtain “distances”, the following transformation

\[ d_{ij} = \sqrt{2(1 - C_{ij})} \]

is used, which clearly satisfies \(2 \geq d_{ij} \geq 0\). Collecting all distances one can form an \(N \times N\) distance matrix \(D\), such that all elements of the matrix are “ultrametric” [17]. The concept of ultrametricity appears in multiple papers. Interested readers can refer to the detailed discussions by Mantegna [18, 19, 20, 15] among others. There are multiple possible ultrametric spaces. We opt for the subdominant ultrametric, as it is simple to work with and its associated topological properties. The choice of the non-linear function is again arbitrary, as long as all the conditions of ultrametricity are met.

4.2 Multidimensional scaling (MDS)

Multidimensional scaling is a method to analyze large scale data that displays the structure of similarity in terms of distances, given by Eq. 11, as a geometrical picture or map, where each stock corresponds to a set of coordinates in a multidimensional space. MDS arranges different stocks in this space according to the strength of the pairwise distances between stocks, – two similar stocks are represented by two set of coordinates that are close to each other, and two stocks behaving differently are placed far apart (see Ref. [21]) in the space. We construct a distance matrix consisting of \(N \times N\) entries from the \(N\) time series available, defined using Eq. 11:

\[
D = \begin{bmatrix}
    d_{11} & d_{12} & \ldots & d_{1N} \\
    d_{21} & d_{22} & \ldots & d_{21} \\
    \vdots & \vdots & \ddots & \vdots \\
    d_{N1} & d_{N2} & \ldots & d_{NN}
\end{bmatrix}
\]

(12)

Given \(D\), the aim of MDS is to generate \(N\) vectors \(x_1, ..., x_N \in \mathbb{R}^D\), such that

\[ \|x_i - x_j\| \approx d_{ij} \quad \forall i, j \in N, \]

(13)

where \(\|\cdot\|\) represents vector norm. We can use the Euclidean distance metric as is done in the classical MDS. Effectively, through MDS we try to find a mathematical embedding of the \(N\) objects into \(\mathbb{R}^D\) by preserving distances. In general, we choose the embedding dimension \(D\) to be 2, so that we are able to plot the vectors \(x_i\) in the form of a map representing \(N\) stocks. It may be noted that \(x_i\) are not necessarily unique under the assumption of the Euclidean metric, as we can arbitrarily translate and rotate them, as long as such transformations leave the distances \(\|x_i - x_j\|\) unaffected. Generally, MDS can be obtained through an optimization problem, where \((x_1, ..., x_N)\)
is the solution of the problem of minimization of a cost function, such as

$$\min_{x_1, \ldots, x_N} \sum_{i<j}(\|x_i - x_j\| - d_{ij})^2.$$  \hspace{1cm} (14)

In order to capture the sectoral behavior of the market visually, we have generated the MDS plot of 199 stocks as described before, for the time window of 250 trading days between May 2015 - May 2016. As before, using the correlation matrix as input, we computed the distance matrix using the transformations (given by Eq. 11). The distance matrix was then used as an input to the inbuilt MDS function in MATLAB [22]. The output of the MDS were the sets of coordinates, which were plotted as the MDS map as shown in Fig. 6.

The coordinates are plotted in a manner such that the centroid of the map coincides with the origin (0, 0). It is interesting to follow the positions of certain sectors: (i) Sugar, (ii) Textiles and (iii) Pharmaceuticals, which will be discussed in details in Section 5.

![Figure 6: Multidimensional scaling of the sample data for the time window May 2015-May 2016.](image)

4.3 Dendrogram

Dendrogram is basically a tree diagram. This is often used to depict the arrangement of multiple nodes through hierarchical clustering. We have used the inbuilt function in MATLAB [23] to generate the hierarchical binary cluster tree (dendrogram) of $N$ stocks connected by many U-shaped lines (as shown in Fig. 7), such that the height of each U represents the distance (given by Eq. 11) between the two data points being connected. Thus, the vertical axis of the tree captures the similarity between different clusters whereas the horizontal axis represents the identity of the objects and clusters. Each joining (fusion) of two clusters is represented on the graph by the splitting of a
vertical line into two vertical lines. The vertical position of the split, shown by the short horizontal bar, gives the distance (similarity) between the two clusters. We set the property “Linkage Type” as “Wards Minimum Variance”, which requires the Distance Method to be Euclidean which results in group formation such that the pooled within-group sum of squares would be minimized. In other words, at every iteration, two clusters in the tree are connected such that it results in the least possible increment in the relevant quantity i.e. pooled within-group sum of squares. Fig. 7 shows the dendrogram of all the 199 stocks clustered in five different colors (by using ‘ColorThreshold’ property in MATLAB). The magenta color represents the cluster of ‘Sugar Industries’.

![Dendrogram of 199 stocks.](image)

**Figure 7: Dendrogram of 199 stocks.**

### 4.4 Minimum spanning tree

A minimum spanning tree is a spanning tree of a connected, undirected graph such that all the $N$ vertices are connected together with the minimal total weighting for its $N - 1$ edges (total distance is minimum). The distance matrix defined by Eq. 11 was used as an input to the inbuilt MST function in MATLAB [24]. See Matlab documentation for all details. Here we state Kruskal and Prim algorithms for the sake of completeness of the present article. Description of the two algorithms (source: see Ref. [24]):

- **Kruskal** – *This algorithm extends the minimum spanning tree by one edge at every discrete time interval by finding an edge which links two separate trees in a spreading forest of growing minimum spanning trees.*

- **Prim** – *This algorithm extends the minimum spanning tree by one edge at every discrete time interval by adding a minimal edge which links a node in the growing minimum spanning tree with one other remaining node.*
Fig. 8 shows the MST for all the 199 stocks. Matlab algorithms set the root node as the first node in the largest connected component, which in our case is node 43.

Figure 8: Minimum spanning tree of the sample data.

5 Sectoral co-movement: mesoscopic network

After quantifying the general cross-correlation structure of the market, we probe deeper into the sectoral co-movements. There are multiple ways to analyze the data. One, we can impose a threshold on the group cross-correlation matrix and construct a network of stocks which move closely. This is the approach that is followed in [2] for example. This approach has some problems. One, the threshold has to be exogenous and hence, basically arbitrary. Two, even with such networks, it is difficult to identify clusters that matches with actual industry classifications. An alternative way is to follow the industry classifications first and then try to see if they form clusters.

To study the sectoral behavior in the market, we have selected stocks from the list of BSE from the industries: (i) Sugar, (ii) Textiles and (iii) Pharmaceuticals. Following the same methodologies as described in the previous sub-sections 4.2, 4.3 and 4.4, we have generated the plots given in Fig.
By looking at the diagram, it becomes clear that the method is partially successful to segregate the market into clusters, but not fully. Therefore, we construct a new network. Rather than working with actual stock returns, we work with sectoral index returns. This marks a prominent departure from the usual mode of analysis. Typically, most studies focus on either an aggregate macro-level market index like S&P 500, or consider collective dynamics of micro-level individual stock returns. Here we consider a *mesoscopic* network to characterize correlations.

Empirically we used the 13 sectoral indices from the BSE (list given in appendix II) for the time window May 2015-May 2016. The resulting multidimensional scaling results have been plotted in Fig. 12, dendogram in Fig. 13 as well as minimum spanning tree in Fig. 14.

The MDS algorithm cannot segregate the markets into clusters in a way that corresponds to the industry classifications. Dendogram produces better results than that. Finally, the minimum spanning tree corresponds to a fairly intuitive market structure. Note that the only information used was sectoral returns’ correlations. The MST shows that the banks and realty sectors are most closely related to the finance sector. Energy sector is most closely associated with oil & gas sector and so on. Thus we see that the sectoral MST approximates the industrial relations in a fairly correct manner.
Figure 10: Plot of dendogram for the sectors.

Figure 11: Plot of MST for the sectors.
Figure 12: Plot of MDS for the indices.

Figure 13: Plot of dendogram for the indices.

Figure 14: Plot of MST of BSE Indices.
6 Summary

In this article we have applied multiple techniques to analyze daily data from Bombay stock exchange. Our analysis covers a large spectrum of tools proposed in the econophysics literature in the last two decades. Using eigendecomposition method, we show that the market cross-correlation structure shows a very prominent market mode. Consistent with the literature, we show that the group mode is not very strong for emerging countries and in fact, is very difficult to differentiate from the random mode. Then we carry out partial correlation analysis, a newly proposed method, on the Indian data. This helps us to explicitly characterize and quantify the average 'third variable' effect in the cross-correlations.

Finally, we turn to network analysis to study the core-periphery structure. We use multidimensional scaling and dendograms to identify clusters. In general, we do not find any significant pattern between such clusters and the industrial classifications. However, a much more intuitive picture emerges when we construct a mesoscopic network with the sectoral indices. We see that minimum spanning tree across the indices clearly segregates nodes according to their industrial classification, by just using the return cross-correlations.

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Table 2: List of all sectoral indices. The first column has the abbreviation, the second column has the full name of the sector, as given in the BSE.

| Abbreviation | Full Name                          |
|--------------|------------------------------------|
| BSESN        | S&P BSE SENSEX                     |
| SENSEX       | S&P BSE SENSEX                     |
| BSE500       | S&P BSE 500                        |
| SI1900       | S&P BSE AUTO                       |
| SIBANK       | S&P BSE BANKEX                     |
| SPBSBMIP     | S&P BSE BASIC MATERIALS            |
| SI0200       | S&P BSE CAPITAL GOODS              |
| SPBSEIP      | S&P BSE ENERGY                     |
| SPBSFIIP     | S&P BSE FINANCE                    |
| SPBSIDIP     | S&P BSE INDUSTRIALS                |
| SI1400       | S&P BSE OIL & GAS                  |
| SIPOWE       | S&P BSE POWER                      |
| SIREAL       | S&P BSE REALTY                     |
| SPBSTLIP     | S&P BSE TELECOM                    |
| SPBSUTIP     | S&P BSE UTILITIES                  |
| SI0800       | S&P BSE HEALTHCARE                 |
9 Appendix II

Table 3: List of all stocks considered for the analysis. The first column has the abbreviation, the second column has the full name and the third column specifies the sector as given in the BSE.

| Abbreviation | Full Name | Sector |
|--------------|-----------|--------|
| ABB          | ABB INDIA LIMITED | Heavy Electrical Equipment |
| ABIRLANUVO   | ADITYA BIRLA NUVO LTD. | Diversified |
| AEGISLOG     | AEGIS LOGISTICS LTD. | Oil Marketing and Distribution |
| AMARAJABAT   | AMARA RAJA BATTERIES LTD. | Auto Parts and Equipment |
| AMBALALSA    | AMBALAL SARABHAI ENTERPRISES LTD. | Pharmaceuticals |
| ANDHRAPET    | ANDHRA PETROCHEMICALS LTD. | Commodity Chemicals |
| ANSALAPI     | ANSAL PROPERTIES and INFRASTRUCTURE LTD. | Realty |
| APPLEFIN     | APPLE FINANCE LTD. | Finance (including NBFCs) |
| ARVIND       | ARVIND LTD. | Textiles |
| ASIANHOTNR   | ASIAN HOTELS (NORTH) LIMITED | Hotels |
| ASSAMCO      | ASSAM COMPANY (INDIA) LIMITED | Tea and Coffee |
| ATFL         | AGRO TECH FOODS LTD. | Other Agricultural Products |
| ATUL         | ATUL LTD. | Agrochemicals |
| ATVPR        | ATV PROJECTS INDIA LTD. | Construction and Engineering |
| AUTOLITIND   | AUTOLITE (INDIA) LTD. | Auto Parts and Equipment |
| AUTORIDFIN   | AUTORIDERS FINANCE LTD. | Finance (including NBFCs) |
| BAJAJELEC    | BAJAJ ELECTRICALS LTD. | Household Appliances |
| BAJAJHIND    | BAJAJ HINDUSTHAN SUGAR LIMITED | Sugar |
| BAJFINANCE   | BAJAJ FINANCE LIMITED | Finance (including NBFCs) |
| BALLARPUR    | BALLARPUR INDUSTRIES LTD. | Paper and Paper Products |
| BALRAMCHIN   | BALRAMPUR CHINI MILLS LTD. | Sugar |
| BANARISUG    | BANNARI AMMAN SUGARS LTD. | Sugar |
| BANCOINDIA   | BANCO PRODUCTS (INDIA) LTD. | Auto Parts and Equipment |
| BASF         | BASF INDIA LTD. | Specialty Chemicals |
| BATAINDIA    | BATA INDIA LTD. | Footwear |
| Code | Company Name                                      | Industry/Department            |
|------|--------------------------------------------------|--------------------------------|
| BEL  | BHARAT ELECTRONICS LTD.                          | Defence                        |
| BEML | BEML LTD.                                        | Commercial Vehicles            |
| BEPL | BHANSALI ENGINEERING POLYMERS LTD.              | Specialty Chemicals            |
| BHIAGGAS | BHAGAWATI GAS LIMITED                           | Industrial Gases               |
| BHEL | BHARAT HEAVY ELECTRICALS LTD.                    | Heavy Electrical Equipment     |
| BHUANSTL | BHUSHAN STEEL LTD.                              | Iron and Steel/Interm.Products |
| BIHSPONG | BIHAR SPONGE IRON LTD.                         | Iron and Steel/Interm.Products |
| BINANIIND | BINANI INDUSTRIES LTD.                      | Holding Companies              |
| BIRLACORPN | BIRLA CORPORATION LIMITED                    | Flagship company               |
| BIRLAERIC | BIRLA ERICSSON OPTICAL LTD.                  | Other Elect.Equip./ Prod.      |
| BLUESTARCO | BLUE STAR LTD.                                | Consumer Electronics           |
| BNKCAP | BNK CAPITAL MARKETS LTD.                        | Other Financial Services        |
| BOMDYEING | BOMBAY DYEING and MFG.CO,LTD.                 | Textiles                       |
| BPL  | BPL LTD.                                         | Consumer Electronics           |
| CAMPHOR | CAMPHOR and ALLIED PRODUCTS LTD.                | Commodity Chemicals            |
| CENTENKA | CENTURY ENKA LTD.                              | Textiles                       |
| CENTEXT | CENTURY EXTRUSIONS LTD.                         | Aluminium                      |
| CENTURYTEX | CENTURY TEXTILES and INDUSTRIES LTD.          | Cement and Cement Products    |
| CESC | CESC LTD.                                        | Electric Utilities             |
| CHAMBLFERT | CHAMBAL FERTILISERS and CHEMICALS LTD.        | Fertilizers                    |
| CHENNPETRO | CHENNAI PETROLEUM CORPORATION LTD.            | Refineries/ Petro-Products     |
| CIPLA | CIPLA LTD.                                       | Pharmaceuticals                |
| CMIFPE | CMI FPE LTD.                                    | Industrial Machinery           |
| CRISIL | CRISIL LTD.                                     | Other Financial Services       |
| CROMPGREAV | CROMPTON GREAVES LTD.                      | Heavy Electrical Equipment     |
| DABUR | DABUR INDIA LTD.                                | Personal Products              |
| DALMIASUG | DALMIA BHARAT SUGAR AND INDUSTRIES LTD         | Sugar                          |
| DCW  | DCW LTD.                                         | Petrochemicals                 |
| DHAMPURSUG | DHAMPUR SUGAR MILLS LTD.                     | Sugar                          |
| Company Name | Description | Industry |
|--------------|-------------|----------|
| DIAMINESQ   | DIAMINES and CHEMICALS LTD. | Commodity Chemicals |
| DICIND      | DIC INDIA LTD. | Specialty Chemicals |
| DISAQ       | DISA INDIA LTD. | Industrial Machinery |
| DRREDDY     | DR.REDDY’S LABORATORIES LTD. | Pharmaceuticals |
| EIDPARRY    | E.I.D.-PARRY (INDIA) LTD. | Sugar |
| ELANTAS     | ELANTAS BECK INDIA LTD. | Commodity Chemicals |
| ELECTCAST   | ELECTROSTEEL CASTINGS LTD. | Construction and Engineering |
| EMPEESUG    | EMPEE SUGARS and CHEMICALS LTD. | Sugar |
| ENVAIREL    | ENVAIR ELECTRODYNE LTD. | Industrial Machinery |
| ESABINDIA   | ESAB INDIA LTD. | Other Industrial Goods |
| ESSLEPRO    | ESSEL PROPAC LTD. | Containers and Packaging |
| ESTER       | ESTER INDUSTRIES LTD. | Commodity Chemicals |
| EXIDEIND    | EXIDE INDUSTRIES LTD. | Auto Parts and Equipment |
| FEDDERLOYD  | FEDDERS LLOYD CORPORATION LTD. | Other Elect.Equip./ Prod. |
| FERROALL    | FERRO ALLOYS CORPORATION LTD. | Iron and Steel/Interm.Products |
| FGP         | FGP LTD. | Finance (including NBFCs) |
| FINCABLES   | FINOLEX CABLES LTD. | Other Elect.Equip./ Prod. |
| FORCENOT    | FORCE MOTORS LTD. | Cars and Utility Vehicles |
| FOSECOIND   | FOSECO INDIA LTD. | Commodity Chemicals |
| GANESHBEE   | GANESH BENZOPLAST LTD. | Commodity Chemicals |
| GARDENSLK   | GARDEN SILK MILLS LTD. | Textiles |
| GHCL        | GHCL LTD. | Commodity Chemicals |
| GLFL        | GUJARAT LEASE FINANCING LTD. | Finance (including NBFCs) |
| GODFRYPHL   | GODFREY PHILLIPS INDIA LTD. | Cigarettes-Tobacco Products |
| GODREJIND   | GODREJ INDUSTRIES LTD. | Commodity Chemicals |
| GOLDENTOBC  | GOLDEN TOBACCO LTD. | Cigarettes-Tobacco Products |
| GOODRICKE   | GOODRICKE GROUP LTD. | Tea and Coffee |
| GOODYEAR    | GOODYEAR INDIA LTD. | Auto Tyres and Rubber Products |
| GRASIM      | GRASIM INDUSTRIES LTD. | Textiles |
| GTL         | GTL LTD. | Other Telecom Services |
| GTNINDS     | GTN INDUSTRIES LTD. | Textiles |
| Company          | Description                                    | Industry                        |
|------------------|------------------------------------------------|---------------------------------|
| GUJFLUORO        | GUJARAT FLUOROCHEMICALS LTD.                   | Industrial Gases                |
| HCC              | HINDUSTAN CONSTRUCTION CO.LTD.                 | Construction and Engineering    |
| HCIL             | HIMADRI CHEMICALS and INDUSTRIES LTD.         | Commodity Chemicals             |
| HDFC             | HOUSING DEVELOPMENT FINANCE CORP.LTD.         | Housing Finance                 |
| HDFCBANK         | HDFC BANK LTD                                  | Banks                           |
| HEIDELBERG       | HEIDELBERGCEMENT INDIA LTD.                    | Cement and Cement Products      |
| HEROMOTOCO       | HERO MOTOCORP LTD.                             | 2/3 Wheelers                    |
| HFCL             | HIMACHAL FUTURISTIC COMMUNICATIONS LTD.        | Telecom Cables                  |
| HINDOILEXP       | HINDUSTAN OIL EXPLORATION CO.LTD.              | Exploration and Production      |
| HINDPETRO        | HINDUSTAN PETROLEUM CORPORATION LTD.           | Refineries/ Petro-Products      |
| HINDUJAVENTEN    | HINDUJA VENTURES LTD.                          | Broadcasting and Cable TV       |
| HINDZINC         | HINDUSTAN ZINC LTD.                            | Zinc                            |
| HMT              | HMT LTD.                                       | Commercial Vehicles             |
| HOTELLEELA       | HOTEL LEELAVENTURE LTD.                        | Hotels                          |
| HSIL             | HSIL LTD.                                      | Containers and Packaging        |
| IDBI             | IDBI BANK LTD.                                 | Banks                           |
| IFCI             | IFCI LTD.                                      | Financial Institutions          |
| IFSL             | INTEGRATED FINANCIAL SERVICES LTD.             | Finance (including NBFCs)       |
| IGPL             | I G PETROCHEMICALS LTD.                        | Commodity Chemicals             |
| INDIAGLYCO       | INDIA GLYCOLS LTD.                             | Commodity Chemicals             |
| INDELETE         | INDIA LEASE DEVELOPMENT LTD.                   | Finance (including NBFCs)       |
| INDORAMA         | INDO RAMA SYNTHETICS (INDIA) LTD.              | Textiles                        |
| INDSUCR          | INDIAN SUCROSE LTD.                            | Beverage Store                  |
| INFY             | INFOSYS LTD.                                   | IT Consulting and Software      |
| INGERRAND        | INGERSOLL-RAND (INDIA) LTD.                    | Industrial Machinery            |
| INSILCO          | INSILCO LTD.                                   | Other Industrial Goods          |
| IONEXCHANG       | ION EXCHANGE (INDIA) LTD.                      | Industrial Machinery            |
| Company        | Description                               |
|---------------|-------------------------------------------|
| ITHL          | INTERNATIONAL TRAVEL HOUSE LTD. Travel Support Services |
| JASCH         | JASCH INDUSTRIES LTD. Textiles             |
| JAYKAY        | JAYKAY ENTERPRISES LTD. Finance (including NBFCs) |
| JCT LTD       | JCT LTD. Textiles                          |
| JINDAL POLY   | JINDAL POLY FILMS LTD. Commodity Chemicals |
| JISLJALEQS    | JAIN IRRIGATION SYSTEMS LTD. Plastic Products |
| JKLAKSHMI     | JK LAKSHMI CEMENT LTD. Cement and Cement Products |
| JSW STEEL     | JSW STEEL LTD. Iron and Steel/Interm.Products |
| KAJARIACER    | KAJARIA CERAMICS LTD. Furniture-Furnishing-Paints |
| KAKATCEM      | KAKATIYA CEMENT SUGAR and INDUSTRIES LTD. Cement and Cement Products |
| KANEL IND     | KANEL INDUSTRIES LTD. Comm.Trading and Distribution |
| KANSAINER     | KANSAI NEROLAC PAINTS LTD. Furniture-Furnishing-Paints |
| KGDENIM       | KG DENIM LTD. Textiles                     |
| KINETIC ENG   | KINETIC ENGINEERING LTD. 2/3 Wheelers      |
| KIRLOSBROS    | KIRLOSKAR BROTHERS LTD. Industrial Machinery |
| KIRLOSID      | KIRLOSKAR INDUSTRIES LTD. Industrial Machinery |
| KOTAK BANK    | KOTAK MAHINDRA BANK LTD. Banks             |
| KSB PUMPS     | KSB PUMPS LTD. Industrial Machinery        |
| KSL           | KALYANI STEELS LTD. Iron and Steel/Interm.Products |
| LAXMIMACH     | LAKSHMI MACHINE WORKS LTD. Industrial Machinery |
| LGBBROS LTD   | L.G.BALAKRISHNAN and BROS.LTD. Auto Parts and Equipment |
| LICHSGFIN     | LIC HOUSING FINANCE LTD. Housing Finance   |
| LML           | LML LTD. 2/3 Wheelers                      |
| LOKHSG        | LOK HOUSING and CONSTRUCTIONS LTD. Realty  |
| LORDSCHLALO   | LORDS CHLORO ALKALI LTD. Commodity Chemicals |
| LUPIN         | LUPIN LTD. Pharmaceuticals                  |
| LYKALABS      | LYKA LABS LTD. Pharmaceuticals              |
| MAFATIND      | MAFATLAL INDUSTRIES LTD. Textiles          |
| MAHSCOOTER    | MAHARASHTRA SCOOTERS LTD. 2/3 Wheelers     |
| Company Name          | Description                        | Industry                                |
|----------------------|-------------------------------------|-----------------------------------------|
| MAHSEAMLES           | MAHARASHTRA SEAMLESS LTD.           | Construction and Engineering            |
| MAJESAUT             | MAJESTIC AUTO LTD.                  | 2/3 Wheelers                            |
| MANALIPETC           | MANALI PETROCHEMICAL LTD.           | Petrochemicals                          |
| MARGOFIN             | MARGO FINANCE LTD.                  | Finance (including NBFCs)               |
| MAVIIND              | MAVI INDUSTRIES LTD.                | Plastic Products                        |
| MERCK                | MERCK LTD.                          | Pharmaceuticals                          |
| METROGLOBL           | METROGLOBAL LTD.                    | Paper and Paper Products                |
| MFSL                 | MAX FINANCIAL SERVICES LTD.         | Life Insurance                          |
| MIDININDIA           | MID INDIA INDUSTRIES LTD.           | Textiles                                |
| MIRCELECTR           | MIRC ELECTRONICS LTD.               | Consumer Electronics                     |
| MOREPENLAB           | MOREPEN LABORATORIES LTD.           | Pharmaceuticals                          |
| MRF                  | MRF LTD.                            | Auto Tyres and Rubber Products          |
| MRPL                 | MANGALORE REFINERY and PETROCHEMICALS LTD. | Refineries/ Petro-Products |
| MTNL                 | MAHANAGAR TELEPHONE NIGAM LTD.      | Telecom Services                        |
| NAHARSPING           | NAHAR SPINNING MILLS LTD.           | Textiles                                |
| NATPEROX             | NATIONAL PEROXIDE LTD.              | Commodity Chemicals                     |
| NCC                  | NCC LTD.                            | Construction and Engineering            |
| NEPCMICON            | NEPC INDIA LTD.                     | Heavy Electrical Equipment              |
| NIITLTD              | NIIT LTD.                           | IT Training Services                    |
| NIRLON               | NIRLON LTD.                         | Misc. Commercial Services               |
| OILCOUNTUB           | OIL COUNTRY TUBULAR LTD.            | Oil                                     |
| ONGC                 | OIL AND NATURAL GAS CORPORATION LTD.| Oil and Gas                             |
| ORIENTBANK           | ORIENTAL BANK OF COMMERCE           | Banks                                   |
| ORIENTHOT            | ORIENTAL HOTELS LTD.                | Hotels                                  |
| OSWALAGRO            | OSWAL AGRO MILLS LTD.               | Real Estate                             |
| PANCM                | PANYAM CEMENTS AND MINERAL INDS.    | Cement and Cement Products              |
| PARRYSUGAR           | PARRYS SUGAR INDUSTRIES LTD.        | Sugar                                   |
| PDUMJEPULP           | PUDUMJEE PULP AND PAPER MILLS LTD.  | Paper and Paper Products                |
| Company   | Description                                      |
|-----------|--------------------------------------------------|
| PEL       | Pharmaceutical                                   |
| PENTAGRAPHP | PENTAMEDIA GRAPHICS LTD.                         |
| PHCAP     | PH CAPITAL LTD.                                  |
| PIDILITIND| PIDILITE INDUSTRIES LTD.                         |
| PILITA     | PIL ITALICA LIFESTYLE LTD.                        |
| PIXTRANS  | PIX TRANSMISSIONS LTD.                           |
| PRAGBOS   | PRAG BOSIMI SYNTHETICS LTD.                      |
| PRIMESECU | PRIME SECURITIES LTD.                            |
| PRISMCEM  | PRISM CEMENT LTD.?                               |
| PUNJCOMMU | PUNJAB COMMUNICATIONS LTD.                       |
| RAIN      | RAIN INDUSTRIES LTD.                             |
| RAJSREESUG| RAJSHREE SUGAR AND CHEMICAL LTD.                 |
| RALLIS    | RALLIS INDIA LIMITED- NITYA AGRO SERVICES        |
| RAMANEWS  | SHREE RAMA NEWSPRINT LTD.                        |
| RAMCOCEM  | THE RAMCO CEMENTS LTD.                            |
| RAYMOND   | RAYMOND GROUP                                    |
| RELCAPITAL| RELIANCE CAPITAL LTD.                            |
| RSWM      | R S W M Ltd.                                     |
| SAIL      | STEEL AUTHORITY OF INDIA LTD.                    |
| SBI       | STATE BANK OF INDIA                              |
| SBIN      | STATE BANK OF INDIA                              |
| SPICEJET  | SPICEJET LTD.                                    |
| SURYAROSNI| SURYA ROSHNI LTD.                                |
| TITAN     | TITAN COMPANY LTD.                               |
| TRENT     | TRENT LTD.                                       |
| UFLEX     | UFLEX LTD.                                       |
| UMANGDAIR | UMANG DAIRIES LTD.                               |
| VEDL      | VEDANTA LTD.                                     |
| WHIRLPOOL | WHIRLPOOL OF INDIA LTD.                          |

*Texts are categorized based on the provided descriptions.*
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