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Inner composition alignment networks reveal financial impacts of COVID-19

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We show that inner composition alignment networks derived for financial time-series data, studied in response to worldwide lockdown imposed in response to COVID-19 situation, show distinct patterns before, during and after lockdown phase. It is observed that significant couplings between companies as captured by inner composition alignment between time series, reduced considerably across the globe during lockdown and post-lockdown recovery period. The study of global community structure of the networks show that factions of companies emerge during recovery phase, with strong coupling within the members of the faction group, a trend which was absent before lockdown period. The study of strongly connected components of the networks further show that market has fragmented in response to COVID-19 situation. We find that most central firms as characterized by in-degree, out-degree and betweenness centralities belong to Chinese and Japanese economies, indicating a role played by these organizations in financial information propagation across the globe. We further observe that recovery phase of the lockdown period is strongly influenced by financial sector, which is one of the main result of this study. It is also observed that two different group of companies, which may not be co-moving, emerge across economies during COVID-19. We further notice that many companies in US and European economy tend to shield themselves from local influences.

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1. Introduction

Of the many modern constructs that define human existence in present age, markets form a special niche that facilitate exponentially larger proportions of resource allocation that could ever be achieved by an individual or a central command. Essential to sustain present day life, markets affect each individual in the society, often in subtle invisible ways. Governed by basic principles of diversity, interaction among components (companies and organizations etc.), and regulation, markets form a prime example of complex adaptive systems (CASs) [1–3]. A complex adaptive system viewpoint makes it possible to apply modern scientific tools to study such vast and diverse system as a market, studying which otherwise is a very challenging task. The use of modern scientific methods to study finance is a relatively new approach [4–11] and several such studies have successfully characterized many different aspects of markets at different time scales [12–16].

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COVID-19 and its aftermath has been encountered as one of the most unprecedented situation the world has ever witnessed. It is unclear whether such large scale disruptions in market activities in the form of forced lock-down all across the globe has ever been observed before in times of peace. However catastrophic and painful the COVID-19 situation has been for the average person, it presents researches with a unique paradigm to study finance at a macro-scale [17–19]. While the complete repercussions of the COVID-19 situation may only be clear with passage of time, we wish to present an indicative study of the COVID-19 situation as studied from a complex adaptive systems point of view that may help broaden our understanding in this respect.

Network theory, which can be seen as application of graph theory to real world problems, is one of the most common and widely accepted methodology to model and study markets as complex adaptive systems [20–26]. Networks are empirical representations of a complex system, where the underlying topology is a graph such that the various interactive components of the system can be seen as vertices and the interaction of interest between these components is modeled as edges or arcs (if the direction of interaction is also important). A formal definition for networks can be found in [27]. In the current study we wish to present a network representation of the global, Indian and US market where the vertices represent public companies that trade stocks across various stock exchanges and are connected by directed edges or arcs if the closing stock prices of these companies are co-evolving or significantly coupled as captured by their inner composition alignment [28].

We collected financial time-series data (closing indices of stock prices) of 743 large global corporations which comprises of 286 Global Fortune 500 (other than Indian and US) companies, 408 Fortune 500 US companies and 49 large-scale Indian companies for a total of 150 days, roughly representing a period from 1 January to 15 August, 2020. The 286 Global Fortune 500 companies can be further classified as companies belonging to the European region (including UK) which are 132 in number and 137 companies belonging to Asian economies and rest are from other regions. The collected data was divided into three equal parts of 50 indices each, representing pre-lockdown, lockdown and recovery period for COVID-19. The broad objectives of the current studies are to, (a) identify the factions or groups of companies that have co-evolved over the different periods and (b) identify how coupling between companies has changed during different periods. We further wish to get an insight into factors that help mitigate financial difficulties that arise due to COVID-19 situation.

2. Material and methods

The study of the financial impact of COVID-19 on the market presents a unique challenge from a data science point of view, as the size of time series data available to study financial impacts of worldwide lockdowns due to COVID-19 is very small (as low as 50 indices in our case). Many of the common methods that are traditionally used to convey or establish some type of relational information such as causality or information flow or indicate coupling relationship within and among time series data fail to be effective in case of time series of short lengths. In the following section we present results corresponding to very simple methods based on correlation matrices and establish how these methods are either inapplicable or present a limited understanding of the otherwise complex market.

2.1. Covariance and cross-correlation matrix based methods

Methods based on application of random matrix theory to the covariance matrices of stock movements is known as one of the benchmark methods to study financial time series data [29,30]. In order for the random matrix methods to be applicable on the time series data, it is firstly necessary that we restructure the data such that the results are independent of the scale of measurement. To achieve the same, for a given time series \(X_i(t)\) for the stock corresponding to company \(i\), we calculate the logarithmic price return which is defined as \(R_i(t, \delta t) = \ln(X_i(t + \delta t)) - \ln(X_i(t))\) where \(\delta t\) correspond to one day as daily closing indices of stock data is chosen for the study. The resulting logarithmic returns are normalized by subtracting the mean value of returns and dividing the result by the standard deviation of the returns as given by \(N_i(t, \delta t) = \frac{R_i(t, \delta t)}{\sigma_i}\), where \(\sigma_i\) is the mean values of logarithmic returns and \(\sigma_i\) is the standard deviation. The time series that has undefined entries (one such time series was found in both pre-lockdown and lockdown period) due to zero standard deviation were removed from the study. Once the normalized returns are calculated hence, we arrange the data as a matrix \(W_{N \times (T-1)}\) \((N-1)\) in case when time series was removed as described above, so that \(T\) is the length of time series (corresponding to 50 days in each of the pre-lockdown, lockdown and post-lockdown cases) and \(N\) is the number of components (number of stocks equal to 743 in our case) and the resultant matrix has \(T - 1\) columns because of using log returns for the data. The \((N \times N)\) covariance matrix can now be calculated as \(A = WW^\ast\), where \(W^\ast\) denotes the transpose/Hermitian conjugate of \(W\). It must be noted that the orientation of data is important in computing the covariance matrix. If we interchange the rows and columns and represent the data as a \((T \times N)\) matrix, then the covariance matrix would be calculated as \(A = W^\ast W\), which is again a \((N \times N)\) matrix.

There are two cases of interest here. The Wishart and anti-Wishart cases describe the situations where length of the time series \(T\) and the number of time series \(N\) either obey the relation \(T \geq N\) (Wishart) case or the relation \(N > T\) (anti-Wishart) case [31–33]. For uncorrelated time series, the resultant random covariance matrix, with \(N \to \infty\), \(T \to \infty\), such that \(Q = T/N \geq 1\), i.e., the Wishart case has eigenvalue distributed according to the Marchenko–Pastur distribution.

\[
P(\lambda) = \frac{1}{2\pi} \frac{\sqrt{\lambda_{\text{max}} - \lambda \lambda_{\text{min}}}}{\lambda_{\text{max}} - \lambda_{\text{min}}},
\]
This distribution is bounded by the maximum eigenvalue \( \lambda_{\text{max}} \), given by \( \lambda_{\text{max}} = [1 + \frac{1}{\sqrt{Q}}]^2 \) and the minimum eigenvalue \( \lambda_{\text{min}} \), given by \( \lambda_{\text{min}} = [1 - \frac{1}{\sqrt{Q}}]^2 \) [34]. Typically, the Wishart case refers to the truly random \((N \times N)\) matrices where \( T \geq N \) and all the \( N \) eigenvalues are positive. In the anti-Wishart case \((T < N)\), the matrices (again of dimension \( N \times N \)) carry some redundant information. To apply the Marchenko–Pastur distribution of eigenvalues when \( T < N \), it is necessary to replace \( Q \) by \( Q' \) with respect to the original Marchenko–Pastur definition, such that \( Q' = N/T \). In this situation, the covariance matrix spectrum comprises of \( T \) positive eigenvalues and the remaining \((N - T) \) eigenvalues are identically zero.

It may be mentioned here that there exist some ambiguity in the literature about the naming convention of the Wishart and anti-Wishart cases. For example, the anti-Wishart nomenclature is sometimes attributed to the \((T \times T)\) matrices when \( T < N \) [32,33]. However, in the present work, the anti-Wishart format refers to the \((N \times N)\) matrices when \( T < N \).

In the present study, the closing stock prices corresponding to 150 days for 743 companies is divided into three equal parts and subsequently log-returns of data are calculated and then normalized. Thus effectively for calculating \( Q' \) we use the value \( T - 1 \) (which in our case becomes equal to 49) while \( N \) remains 743. However as discussed earlier, for pre-lockdown and lockdown period data for companies that contained undefined values upon normalization as a result of zero standard deviation in the data following the calculation of logarithmic returns (one such company found in both pre-lockdown and lockdown period) was removed from the study and thus \( N \) effectively becomes 742 in these two cases. Using \( Q' = N/(T - 1) \), we obtain \( Q' = 15.16 \) (a slightly different value of 15.14 in other two cases). Thus the largest and the smallest eigenvalue as predicted by random matrix theory (RMT) in our case becomes equal to 1.5796 and 0.5523 respectively (slightly different values equal 1.5800 and 0.5521 in the pre-lockdown and lockdown cases). For proper application of random matrix theory formalism, bulk of the eigenvalues of the covariance matrix should lie within the upper and the lower bounds as predicted by the Marchenko–Pastur distribution i.e. between \( \lambda_{\text{max}} \) and \( \lambda_{\text{min}} \). It is observed that the non-trivial eigenvalues for the three periods viz pre-lockdown, lockdown and post-lockdown period, mostly lie beyond the range predicted by RMT. The few deviations from the bulk behavior provides important insights about the underlying system. For the present dataset considering the anti-Wishart case, it is observed that while the \((N - T + 1)\) eigenvalues are typically zero \((N - T - 2\) in other cases), the non-trivial eigenvalues still showed deviation in large numbers from the bulk predicted by the random matrix theory, thereby indicating high correlation in the data. It is thus not possible to apply RMT framework in the present case due to the time series being very small and the resultant data thus being highly correlated.

We can further use a distance metric based on the cross-correlation matrix \( C \) given by \( d_{ij} = \sqrt{2(1 - C_{ij})} \) to construct minimum spanning tree corresponding to the cross-correlation matrix such that for the \( n - 1 \) edges (where \( n \) is the order of the network i.e., number of stocks used in the study) in the tree, the sum of distance \( \Sigma d_{ij} \) is minimum for any choice of edges possible in the tree. Minimum spanning tree method is known to present a good graphical representation of co-moving stocks that cluster together [29]. The same is observed in our case where we observe clusters of co-moving stocks forming for the pre-lockdown, lockdown and post-lockdown phase with the help of minimum spanning trees for these periods. These results can be accessed as figures presented in the supplementary material.

It must however be noted that the minimum spanning tree method presents a very limited view of the whole wide market system where an array of possible interactions (as represented by a large number of edges or directed arcs in a network as against \( n - 1 \) edges) add to the complexity of the system. Thus in order to thoroughly analyze the market we need to implement a different approach that is applicable on time series of small size.

In a typical study based on financial time series data such as the one undertaken here, we try to unravel the fundamental driving mechanisms that produce the stochastic processes, which in turn give rise to the time series that we intend to analyze. It is important to note that we usually have just one sequentially observed data set, i.e., a time series and try to infer the properties of the generating process from this single trajectory. However, as the time series data available is very small, other traditional methods used to infer causality or dependence in time series such as transfer entropy, Granger causality, method of mutual information, symbolic dynamics, Hurst exponent etc. [35–40] may not yield useful results and are thus avoided in the current study.

A few methods to infer causality or dependence in data with small time series have been proposed in literature [41–43]. We however, choose to implement inner composition alignment between given time series as not only this method which can be implemented on short time-series identifies directionality of coupling, infers auto-regulation and does not depend on time, but at the same time we found it easier to implement as compared to other methods. Inner composition alignment (IOTA) as a method has been successfully implemented to derive functional brain networks using short electroencephalogram (EEG) data [44] and to infer causality in gene regulatory networks in case when the time-series data related to regulatory processes is very small [28].

2.2. Inner composition alignment networks

Inner composition alignment (IOTA) is a directionality preserving, permutation based measure between two time series which can be applied to time series of same size [28]. Consider two time series \( X \) and \( Y \) of equal length \( n \). Now consider a permutation \( \pi \) which when applied to the time series \( X \) returns a non-decreasing time series \( \pi(X) \) i.e., \( \pi(X)_i \leq (\pi(X))_{i+1}, \forall i : 1 \leq i \leq n - 1 \). Let \( \tilde{Y} \) be the series which is returned when the permutation \( \pi \) is applied to the time series \( Y \) i.e., \( \tilde{Y} = \pi(Y) \). Inner composition alignment from time series \( X \) to \( Y \), represented \( I_{X \rightarrow Y} \), in
effect measures the number of times the series $\tilde{Y}$ intersects (cross-crosses) the series $\pi(X)$ i.e., if $\tilde{Y}$ becomes a monotonic sequence (non-decreasing or non-increasing) on application of permutation $\pi$ on time series $Y$, then $X$ and $Y$ are highly coupled, otherwise the more fluctuations are found in series $\tilde{Y}$, the lesser the coupling.

The inner composition alignment from time series $X$ to $Y$ under the permutation $\pi$ can be calculated as

$$i_{X\rightarrow Y} = 1 - \frac{\sum_{j=1}^{n-2} \sum_{j=1}^{n-1} w_{ij} \Theta [ (\tilde{Y}_{j+1} - \tilde{Y}_j)(\tilde{Y}_i - \tilde{Y}_j) ]}{\Delta},$$

where $\Delta = \frac{(n-1)(n-2)}{2}$ is a normalization constant, $w_{ij}$ is a weight and $\Theta$ is Heaviside step function i.e., $\Theta [x]$ is 1 for positive values of $x$ and zero otherwise. For the purpose of our analysis we choose weight $w_{ij} = 1$.

It must be noted that inner composition analysis will rate coupling between two time series higher or close to one if they are monotonic in the above mentioned sense i.e., despite if one series is increasing and the other is decreasing. For financial data however this property is undesirable, since it is important if the stock price of a company is increasing or decreasing as the change in values of stock prices makes all the difference between profit and loss. To overcome this limitation, we devise a method that allows IOTA to differentiate between increasing and decreasing sequences.

We call a time series as up trending if the mean of first half of the series is less than the mean of the series which in turn is less than the mean of the latter half of the series i.e., for a time series $T$ of length $n$, $n \geq 5$, if $T_1 < \tilde{T} < T_n$, $1 \leq i \leq \lfloor \frac{n}{2} \rfloor$, $\lfloor \frac{n}{2} \rfloor \leq j \leq n$. Similarly, a time series $T$ is down trending if $T_1 > \tilde{T} > T_n$, $1 \leq i \leq \lfloor \frac{n}{2} \rfloor$, $\lfloor \frac{n}{2} \rfloor \leq j \leq n$. We modified inner composition alignment, $i_{X\rightarrow Y}$, to take a positive value as its outcome if both series $X$ and $Y$ are either up trending or down trending. If one of the series $X$ or $Y$ is up trending and the other is down trending, we take the value of IOTA as negative, and we take this value as zero if no such trend could be established.

We further wish to assess if for a given time series $T$ of a stock, there are no points in these time series such that due to presence of these few points the overall mean of either the first half or the second half of the time series change significantly enough to render the ordering of $T_i$, $T_j$ and $T_{\tilde{t}}$, $1 \leq i < \lfloor \frac{n}{2} \rfloor$, $\lfloor \frac{n}{2} \rfloor \leq j \leq n$. That is to say for example if there are very small number of points $p_1, \ldots, p_k$, where $k$ is typically small such that there is a clear trend $T_i = \{p_1, \ldots, p_k\}$ mean of first half of the time series calculated without including the points $\{p_1, \ldots, p_k\}$ while no such trend can be established when these points are included in $T_i$, $1 \leq i \leq \lfloor \frac{n}{2} \rfloor$. Thus we wish to establish that there are no such points in the time series studied here the values of which jump so much that by including these points we can no longer call the time series as up trending or down trending while the same can be done when these points are not included. In order to establish the same we take difference of time series $D_i(t) = T_i(t + 1) - T_i(t)$ and calculate the Z-score $Z_i = \frac{D_i(t) - \bar{D}_i}{\sigma(D_i)}$, where $D_i(t)$ is the maximum of the differenced series $D_i$, $\bar{D}_i$ is the mean and $\sigma(D_i)$ is the standard deviation of the series $D_i$. The idea here is that for a jump point the difference from previous (or latter) value will be very large where the differences otherwise shall follow a normal distribution. For the three periods considered in this study i.e., the pre-lockdown, the lockdown and the post-lockdown period, we found the maximum Z-score across time series for all 743 stocks to be 5.97718, 6.7095 and 6.8571 respectively. Thus we conclude that there are likely no jump points in the data considered in this study. However, we present a detailed framework to qualify such jump points in time series data as supplementary information and rigorously establish absence of jump points in the data used in the study. The added framework provides a detailed justification of the validity of proposed definitions of up trending and down trending time series and provides an explanation as to how the proposed definitions can be employed in the analysis of time series data in a generalized setting.

To derive a network from time series which show significant coupling strength with respect to IOTA, we first calculate a coupling matrix $(C)_{ij}$ where $i$ and $j$ represent the time series data corresponding to some specific companies incorporated in the current study. In order to find a given entry $c_{ij}$ in the coupling matrix $C$, we first permute or sort the time series $i$ such that it becomes a strictly increasing time series and register such a permutation $\pi$. Next we apply this permutation $\pi$, which returns a strictly increasing or sorted time series $\bar{i}$ to rearrange the entries in time series $\bar{i}$ into another time series $\bar{j}$. Thereafter we apply the formulation used in (1) on $\bar{j}$ to calculate the value of IOTA.

Once the values of IOTA are derived, we proceed to find if the time series $i$ and $j$ are up trending or down trending as defined earlier by comparing the value of mean of time series with means of first half and latter half of the time series and thus compute the modified IOTA values by comparing the trends in the timeseries. We likewise find the modified coupling matrix $\bar{C}$, in which every entry $(\bar{C})_{ij}$ is modified IOTA value between time series $i$ and $j$. In order to keep only significant coupling strengths in the directed network as arcs, we derive the directed network from the modified coupling matrix $C$ by keeping only the values above a given threshold and discarding the rest of the values as zero.

We took 150 closing indices of 286 Global Fortune 500 (other than Indian and US) companies, 408 Fortune 500 US companies and 49 large-scale Indian companies, and divided the data into three equal parts of 50 indices each, representing pre-lockdown, lockdown and recovery phase. We then calculated the pairwise inner composition alignment for each of the series for the three mentioned periods, keeping in mind if the series are up trending and down trending, and obtained three $[743 \times 743]$ matrices for each period, whose values represent the strength of coupling as captured by modified IOTA. We obtain directed networks for the three periods from the coupling matrices by considering vertices $X$ and $Y$ (companies represented by their time series) as connected by a directed edge if the modified value of IOTA, $i_{X\rightarrow Y}$, is greater than a threshold value (say $\theta$) of the modified IOTA. For the data corresponding to pre-lockdown period, we arrive at a threshold value of 0.9 by trial and error, considering that for thresholds below this value, the obtained networks...
become very dense and for values above 0.9, the networks become very sparse. We further keep the threshold value as 0.9 for the other two periods in order to make comparisons possible between the three considered periods. We have presented these results with the help of Fig. 1, where we show the change in the values of arc density and the number of strongly connected components of the networks generated hence, with change in the threshold value $\theta$. The data related to Fig. 1 is tabulated in supplementary information.

2.3. Analysis of inner composition alignment networks

We study the directed networks obtained for three periods to get an insight into the effect of COVID-19 situation on the markets. We first study the local properties of these networks, to quantify how individual companies are fairing in the situation. Network centrality is a basic idea in the study of networks, which proposes that some vertices in a network are more important than the others. Network centrality can be thought of as a real valued function on the set of vertices or edges in a network, that induces a total order on the set [45]. In a directed network, vertices with higher in-degree and out-degree can be considered as central vertices [46].

We consider a vertex to be more central if it lies on a large number of shortest directed paths between other vertices in the network [47]. Let $\delta_{st}(v)$ denotes the fraction of directed shortest paths between vertices $s$ and $t$ that contain $v$, such that, $\delta_{st}(v) = \frac{\sigma_{st}(v)}{\sigma_{st}}$, where $\sigma_{st}$ is the number of directed shortest paths between $s$ and $t$. The betweenness centrality of a vertex is given by, $C_B(v) = \sum_{s \neq t \neq v} \delta_{st}(v)$ such that, the sum is being calculated for all the pairs of distinct vertices in the networks.

Furthermore, we wish to quantify the global structural properties of inner composition alignment networks which may reveal how the market is fairing as a whole during the different periods. A network is said to show assortative mixing if vertices of higher degrees are connected to other vertices with higher degrees, and the vertices with lower degree tend to be connected to other vertices with lower degree [48]. In a network, vertices with high degree tend to be adjacent to vertices with low degrees, then such a network is said to be disassortative. In a directed network, if we consider the end vertices of an edge as source and sink vertices (such that the direction is oriented from the source vertex to the sink vertex), then we can find the assortative mixing for in-degree to in-degree, out-degree to out-degree, in-degree to in-degree and in-degree to out-degree cases using an index called assortativity [49,50].

We find the community structure for the networks representing three different periods to understand which set of companies are forming closely-knit groups during this time and hence may be affecting each other more than companies outside of these groups or communities. A community in a directed network is a partition of the set of vertices into smaller sets with relatively larger number of edges between the vertices in the sub-network [51]. An arbitrary partition of the vertex set of a graph is said to form a good community structure if the value of modularity associated with the defined communities is close to one. We use an algorithm proposed by Louvain et al. to find the community structure [52]. We further find the strongly connected components in each network. A strongly connected component in a directed network is a set of vertices, such that, a directed path exists between any two vertices of the set [53]. The findings of this study are presented and discussed in the following section.

3. Results and discussion

We obtain networks with 743 vertices for three periods under study i.e., pre-lockdown, lockdown and recovery phase, using a threshold coupling strength of 0.9. By considering a threshold value of 0.9, we choose to consider only significant coupling between time series under study and thus companies under investigation. The choice of threshold is further justified using an example as shown in Fig. 2, where we visualize three time series with mutual different values of inner
composition alignment. As can be seen in the figure, the time series with higher IOTA coupling strength appears similar to each other as compared to time series with lower IOTA coupling strength.

We find that the number of directed edges or arcs in the pre-lockdown phase for the threshold coupling strength of 0.9, is equal to 77743. The arc density (number of arcs present divided by total number of arcs possible, which is \(n(n-1)\), where \(n\) is the order of the graph) for the pre-lockdown period is 0.1410 (number of vertices being 743). For the same value of threshold, the number of arcs found in the lockdown period is 12835, which is a very steep decrease in the number of directed edges for a network of same order i.e., 743 vertices. The arc density for lockdown period reduces to 0.0233, making the network a sparse network. For the recovery phase the number of arcs further reduces to 7899 with an arc density of 0.0143, making the connections in the network even rarer for the same choice of threshold.

This trend in the reduction of number of edges clearly shows that as a result of COVID-19 situation, companies throughout the world show a propensity to de-couple from their global counterparts and a flourishing network of coupled interactions between companies all over the globe vanished to a very sparse network of coupling during lockdown period. Thus companies during and immediately after the COVID-19 situation tend to operate independent of each other shielding any influence other companies may be inducing on them.

A clear trend is observed when we look at best-ranked centrality indices for betweenness centrality, in-degree and out-degree centrality measures over the three periods considered for this study. It is observed that all the best-ranked centrality indices for the aforementioned measures over the three periods are dominated heavily by Chinese and Japanese companies. This trend is softly diluted for the lockdown phase, where companies from other countries (mainly US) appears in the best-ranked list along with Chinese and Japanese companies. However, for both pre-lockdown and recovery phase, the best ranked vertices are dominantly Chinese or Japanese organizations irrespective of centrality measure chosen for study. Since a high value for betweenness for a vertex indicate the greater degree of control the vertex has over disseminating information across the network, it seems only natural to conclude that these Chinese and Japanese companies that are frequently ranked high as per betweenness centrality, play a key role in channeling the COVID-19 situation across the network. The set of companies ranked higher by betweenness centrality are also ranked higher by in-degree and out-degree centralities, thus further supporting our inference.

It is further observed that the first five best-ranked vertices (or companies) as per betweenness centrality in the recovery phase belong to financial sector, indicating a key role played by the financial sector in mitigating the COVID-19 crisis situation. This observation is in contrast with our study of 2008 financial crisis [26], where we found that financial institutions dropped out of network in order to shield themselves from the effect of global recession. In COVID-19 situation however, banks are playing a role in recovery and thus the situation is fundamentally different as compared to global slowdown. The ten best-ranked companies as given by betweenness centrality for recovery period is given here as Table 1. The remaining tables for betweenness centrality, in-degree and out-degree centrality measures over the three periods are shared as supplementary information.

The values of assortativity calculated for all networks over the three periods are close to zero with exception of in-degree to in-degree assortativity value and out-degree to in-degree assortativity value for the recovery phase being −0.4374 and −0.4319, indicating that in vertices with both high in-degree and high out-degree tend not to be connected to vertices with high in-degree to some extent. For other degree combinations in the different periods of study however, no such trend could be established.
Table 1
Best ranked companies as per betweenness centrality for the inner composition alignment network for the recovery period.

| S. No. | Company (Sector) | Company abbreviation | Betweenness |
|-------|------------------|----------------------|-------------|
| 1     | People's Insurance, China (Financial) | PINXY | 5.3209E+04 |
| 2     | Sompo Holdings, Japan (Financial) | NHALF | 2.8849E+04 |
| 3     | China Vanke Co., China (Financial) | 000002.SZ | 1.6211E+04 |
| 4     | Japan Post Holdings, Japan (Financial) | JPHLF | 1.1795E+04 |
| 5     | Chubu Electric Power, Japan (Utilities) | CHJHF | 7.4806E+03 |
| 6     | China Minsheng Banking Corp, China (Financial) | CGMBF | 7.4193E+03 |
| 7     | Shandong Weiqiao Pioneering Group, China (Consumer Discretionary) | WQTEF | 6.7725E+03 |
| 8     | JFE Holdings, Japan (Materials) | JFEF | 6.2523E+03 |
| 9     | China Shenhua Energy Co. Ltd., China (Energy) | CUAEF | 4.9838E+03 |
| 10    | Ford Motors, USA (Consumer Discretionary) | F | 4.1345E+03 |

The global structure of inner composition alignment networks over the three periods show interesting results upon observation. It is seen that for pre-lockdown phase their are 20 communities with modularity of 0.1388, the largest of which are four communities of size 207, 166, 165, 103 and 87 vertices and the rest are singleton vertices. The very low value of modularity indicate that the community is poorly formed i.e., the number of arcs between the members of the communities are similar to number of arcs outside the members of the communities. It is further observed that most Indian companies belong to the largest and second largest community in pre-lockdown period, while US companies are evenly distributed across communities.

The value of modularity increases slightly to 0.3609 for the lockdown period, forming 14 communities, the largest of which are communities of size 356, 143, 141 and 93 while the rest are singleton vertices. The Indian companies belong mostly to the largest two communities. For the recovery period, the value of modularity increases to a further of 0.4956, indicating that for recovery period the network show the best community structure out of the three periods of study. It means that the number of arcs between the members of the community are considerably more than number of arcs between vertices outside the members of the community. The community structure for recovery period consists of 58 communities, three of which are large communities with 268, 289 and 131 members, while the others are singleton vertices.

Thus we infer that during the recovery phase, factions of companies are forming that are coupled strongly within a group to which the company belongs rather than to companies outside of the group, while no such trend existed before global lockdown. It also indicates that a large number of companies have isolated (or completely uncoupled) themselves from other companies in the recovery period for COVID-19 situation, as 55 companies in this phase does not belong to any community.

The evidence for global isolation of companies in response to COVID-19 situation is further supported by the study of strongly connected components in the networks for the three periods, where it is observed that the for the pre-lockdown phase there were a total of 56 strongly connected components, of which the largest strongly connected components were of order 628 and 61, while the rest were singleton vertices i.e., belonging to trivial strongly connected component of size one. For the lockdown phase, the number of strongly connected components become 293, while the size of largest strongly connected components decrease to 407 and 43, indicating that the rest of the vertices are singleton vertices.

For the recovery phase, two large strongly connected components of size 305 and 163 are observed and the rest of 275 observed strongly connected components are singleton vertices or strongly connected components of size two.

Strongly connected component in a network is a set of vertices which can be reached by any other vertex from the set through a directed path. In terms of financial networks, it means that the company belonging to a strongly connected components can influence another company from the set and can be influenced by another company from the set in return. Thus there is a greater propensity of bidirectional financial information flow within the members of a strongly connected components. A decrease in the size of strongly connected components and increase in the number of trivial strongly connected components show that in response to COVID-19 situation, companies globally are trying to shield the influence of extra players on their organization and operation.

We further wish to assimilate the effect COVID 19 had on different economies across the globe and in the current study we have chosen to look at Indian, Asian (other than India), European (including Britain) and US economies as standalone economies and in relationship to each other as give by the induced subgraphs of the global network of aforementioned companies. It should be noted that an induced subgraph for a given economy show the vertices i.e companies in relationship to other companies from the same economy. Thus a singleton vertex in an induced subgraph would mean that the company representing that vertex is not influencing any other company in the same economy, nor getting influenced by other companies from the local economy. However, it is possible that such a company may be experiencing global influences (from companies other than from its own economy).

We find that initially in the pre-lockdown phase, the network structure of all the four economies mentioned above show presence of a giant component, which in financial terms indicate that the companies in each economy are coupled together or co-moving with each other as one large group with exception of a few companies in each market. However, a completely different picture begin to emerge during lockdown and post-lockdown phase where it is found that generally two large components emerge in each economy, showing that the market may be getting dismantled into two groups,
such that companies in each group may be coupled or co-moving with companies from within the group and not with companies within the other group. That is to say all economies show a divide in companies, possibly facing different market pressures.

It is further noticed that a lot of companies in the US and European markets have isolated themselves from the local economy (as is indicated by presence of a large number of singleton vertices in these economies), thus indicating that a lot of these companies are not co-moving with either of the groups emerging in these economies and thus the nature of forces influencing them (if any) are global. These results are presented as Fig. 3, 4 and 5. Thus the current study presents a comprehensive view of how COVID-19 affected different economies and how the financial impacts of global lock-down were mediated and eventually begin to get mitigated across the globe by organizations raking high on different centrality indices. The role of network based study, especially in light of inner composition alignment capturing coupling between different organizations is thus acknowledged as a viable method in the study of complex adaptive systems.

4. Conclusion

We analyzed financial time series data (closing indices of stock price) of 743 companies from across the globe for a period ranging roughly between 1 January, 2020 to 15 August, 2020 to study the impact of lockdown imposed in response to COVID-19 situation on markets. We used inner composition alignment, a method developed to find coupling between short time series data, to come up with a network structure of the aforementioned 743 companies over three time periods i.e., pre-lockdown, lockdown and recovery phase.

We conclude that companies all across the globe have shown a tendency to decouple themselves from other organizations in response to COVID-19 situation. We find evidence in form of arc density, community structure in
networks studied and strongly connected components present in networks in different periods to support our hypothesis. We further observe that Chinese and Japanese companies are ranked higher by different centrality indices over the studied time periods and thus some of these companies play a key role in channeling financial information flow before, during and after the lockdowns imposed due to COVID-19 situation. We further conclude that financial sector play a key role in mitigating the COVID-19 situation, as indicated by high values of betweenness centrality attained by the sector during the recovery phase.

We further conclude that as a result of COVID-19 situation, companies across different economies seems to be getting divided onto two major co-moving or coupled groups. We also notice that a lot of companies belonging to the US and European market seems to be shielding local influences or couplings.

We end by emphasizing that complete effects of COVID-19 situation on entire global economy may only be clear with adequate passage of time, which could be as long as a decade if not more, yet our study characterizes an initial indicative picture of crisis situation as excellently captured by inner composition alignment networks, which as a method has shown great promise to study short time series.

**CRediT authorship contribution statement**

**Shashankaditya Upadhyay:** Conceived the idea upon discussion and devised the methodology, Collected and curated the data, Performed the analysis and wrote the manuscript. **Indranil Mukherjee:** Conceived the idea upon discussion and devised the methodology, Collected and curated the data, Revision. **Prasanta K. Panigrahi:** Conceived the idea upon discussion and devised the methodology, Revision.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Data availability**

Data will be made available on request.

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**Appendix A. Supplementary data**

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.physa.2022.128341.
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