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Sectoral Analysis of the US Stock Market through Complex Networks

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Abstract:

Purpose: *This study was carried out to analyze the structure of the aggregated network at the level of economic sectors and to reveal the central/peripheral sectors.*
Design/Methodology/Approach: *The study uses the method of complex networks, with the two-step procedure employed to construct the network of economic sectors. First, the MST approach is utilized based on the cross-correlation of 496 stock price returns of the S&P500 Index. Then, the network is aggregated at the level of economic sectors. In addition, to analyze the graph, the network theory, multi-dimensional scaling (MDS), and relative importance approaches are employed.*
Findings: *The results indicate that the sectoral network has a core/periphery structure. Based on the centrality measures, the ranking of sectors is provided. Of the 11 sectors, 3 are classified as central nodes, 4 as peripheral nodes, and the remaining 4 are classified as intermediate. In addition, the network configuration analysis demonstrates that the graph consists of two parts with a star-like structure, connected through the industrials sector.*
Practical Implications: *An analysis of the cross-correlation network of aggregated assets at the level of economic sectors can be applied to ascertain the direction of stock price movements in the stock market. The division of sectors in the network into central and peripheral nodes has important implications for the management of an optimal portfolio of stocks.*
Originality/value: *This study contributes to complex network theory and portfolio strategy design. A unique procedure is proposed to construct the network of economic sectors using the MST-based approach. Detection of the stock market network structure is vital for investors and regulators alike.*

Keywords: *Stock market network, correlation-based network, economic sectors, minimum spanning tree, centrality measures.*

JEL classification: *C69, G10, G11, L14.*

Paper Type: *Research article.*

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1. Introduction

Financial stock markets are well-defined complex systems (Mantegna 1999) consisting of many interacting elements (Mantegna and Stanley 1999; Huang *et al.*, 2017). Complex networks are among the most widely used to investigate the cross-correlation of the series of daily stock price returns (Esmaeilpour Moghadam *et al.*, 2019; Schuenemann, Ribberink, and Katenka 2020; Zhuang and Xiu 2015; Chen *et al.,* 2021). According to Onnela *et al.* (2002), the stock correlation network can be considered as a set of nodes consisting of stocks and edges between nodes denoting relationships obtained from the correlation coefficients. In the sectoral correlation network, nodes denote individual economic sectors and edges are the relationships between them, defined by appropriate aggregation from the level of the asset network. One advantage of correlation-based network analysis is that it avoids the problem of complexity through the network filtration procedure, allowing the selection of the most important connections in the graph.

Recent developments regarding network-based correlations analysis have led to the representation of the underlying relations between industries (Chen *et al.,* 2015). Several studies have found that the most central sector in the cross-correlation of the daily stock price returns network is dominated by the financial sector (Pozzi, Di Matteo, and Aste, 2008; Yao and Memon, 2019; Tabak, Serra, and Cajueiro, 2010; Patwary *et al.,* 2017; Majapa and Gossel, 2016; Kenett *et al.*, 2010; Tang *et al.*, 2018; Di Matteo, Pozzi, and Aste, 2010; Brida and Risso, 2010), industrials (Wu, Zhang, and Zhang, 2019), and consumer services (Yao and Memon, 2019). Furthermore, the stock market network is heavily dominated by the financial sector due to the composition of highly connected assets (Tse, Liu, and Lau, 2010) and stocks from the financial industry form the backbone of the graph tree (Coelho *et al.*, 2007).

Early works in this area focused primarily on different approaches to sectoral analysis for the stock market network, such approaches include: (1) the number of stocks for each sector among the highest values for the selected centrality measures (Huang *et al.,* 2020), (2) the average value of the selected centrality measures computed for each industry based on the entire stock price return network (Coletti 2016), (3) sector analysis based on the pattern of the entire assets network non-aggregated at the industry level (Memon, Yao, and Tahir, 2020), as well as (4) the sectoral stock market network based on the correlations of the sectoral indices returns (Sharma *et al.,* 2017).

The method employed in the literature is originally based on the cross-correlation of stock returns. However, this study applied a different method to analyze the economic sector network. First, I use the standard methodology proposed by Mantegna (1999), based on the Pearson correlation coefficient of log-return of stock price and the minimum spanning tree (MST) approach to reduce the complexity of the network. The MST prunes graph and the most relevant connections in the stock market network are identified. The MST is a tree consisting of N-1 edges connecting N vertices, in which a path exists between each vertex without cycles and loops such that the total distance of the matrix is minimized. Then, I aggregate the stock correlation network to the level of the economic sector. The two-stage procedure is used to isolate the sectoral backbone network.

This study aims to (i) investigate the structure of the sectoral network, (ii) identify the most important sectors occupying a central position in the cross-correlation network, and (iii) reveal the peripheral sectors.

This study examines the structure of the aggregated sectoral network of the US stock market in the 2015-2019 period. Empirical results show that the network of economic sectors consists of two interconnected parts. Both parts of the graph have a star-like structure. Based on a uniform ranking of sectors in terms of centrality measures, my findings reveal a strong core/peripheral structure of the network. This suggests the predominance of the central group of industries over the group of sectors located in the outer parts of the network. The level of relevance of the sector in the network shows the direction of the movements in stock prices in the financial market.

This paper has been divided into the following parts: Section 2 describes the methodology, specifically the construction of the MST-based network of economic sectors and network centrality measures; in Section 3, the data set is presented; Section 4 presents and discusses the results, and finally in the last section, concluding remarks are drawn.

2. Research Methodology

To perform analysis consistent with the purpose of the work, the construction of the MST network at the level of sector aggregation should be introduced. I also present centrality measures dedicated to undirected network analysis.

2.1 Cross-Correlation Network Based on a Minimum Spanning Tree

The stock correlation network consists of nodes denoting stocks and edges connecting the assets based on the cross-correlation coefficient between the log-return series of stocks. The result is a fully-connected network with N vertices and $N(N\text{-}1)/2$ edges. Due to the complexity of the stock return network, the data noise should be filtered out, extracting the most useful information arising out from the relevant connection by pruning the original graph. The most common method of network filtration is the minimal spanning tree (Lee and Nobi, 2018; Jeude, Aste, and Caldarelli, 2019; Bhattacharjee, Shafi, and Acharjee, 2019) as a result of which the dimension of the network is reduced from $N(N\text{-}1)/2$ to N-1. The network construction method based on the MST approach is briefly outlined below.

First, I use the log-return of the stock price defined as:

$$r_i(t) = \ln P_i(t) - \ln P_i(t-1) \tag{1}$$

where $P_i(t)$ is the closing price of the company's stock at day *t*.

Next, I compute the similarity between each pair of stocks *i* and *j* applying the Pearson correlation coefficients among all price return time series:

$$\rho_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left(\langle r_i^2 \rangle - \langle r_i \rangle^2\right)\left(\langle r_j^2 \rangle - \langle r_j \rangle^2\right)}} \tag{2}$$

where $\langle \dots \rangle$ denotes mean value for the investigated period.

The correlation coefficient does not satisfy the three axioms required for the fulfillment of the Euclidean metric. In the next stage, the cross-correlation coefficients constituting elements of the **C** matrix with dimensions *N* x *N* are used to evaluate the distance metric by an appropriate transformation so that all axioms are fulfilled:

$$d_{ij} = \sqrt{2\left(1 - \rho_{ij}\right)} \tag{3}$$

Due to the properties of the Pearson correlation coefficient, which varies from -1 to 1, the value of the distance metric ranges from 0 to 2. If the pair of stocks is completely correlated $\left(\rho_{ij} = 1\right)$, then the distance metric (d_{ij}) is 0, and if the pair of stocks is completely anti-correlated $\left(\rho_{ij} = -1\right)$, then the distance metric (d_{ij}) is 2.

Finally, based on Mantegna (Mantegna 1999) the fully-connected matrix **D** of distance metrics (d_{ij}) is utilized to build the MST network of the stock market such that *N* vertices are connected using *N*-1 edges where the sum of all link weights is minimized. The Kruskal algorithm (Kruskal 1956) has been adopted to construct the MST network. The obtained MST network **T**=[t_{ij}] is weighted and undirected. To obtain a dichotomous network, a transformation was made according to the following formula:

$$\begin{cases} t'_{ij} = 1 \; if \; t_{ij} > 0 \\ t'_{ij} = 1 \; othewise \end{cases} \tag{4}$$

All computations were performed using the NetMiner software (Cyram, 2021).

Next, the network connections are aggregated at the level of economic sectors. For this purpose, the number of connections between enterprises included in individual sectors is summed up:

$$w_{K,L} = \sum_{i \in K, j \in L}^{N_K, N_L} t'_{ij} \quad (K \neq L) \tag{5}$$

$$w_{K,K} = \sum_{i=j \in K}^{N_K} t'_{ij} \quad (K = L) \tag{6}$$

The construction of formula (5) ensures the symmetry of the matrix, and formula (6) allows for a self-loop. As a result, an undirected and weighted network with loops and self-edges is created.

The network of economic sectors is constructed based on the MST method, which by definition does not contain loops and self-edges. First, I normalize each weight of edges where the absolute maximum of elements in the normalized matrix is assigned to the value of the normalized criterion. The transformation is as follows:

$$w'_{K,L} = \frac{w_{K,L}}{\max w_{K,L}} \tag{7}$$

The normalized values are in the range $\langle 0; 1 \rangle$. Next, I use equation (3) to obtain the distance metric, which in this case ranges from 0 to $\sqrt{2}$ due to the range of normalized edge weights $(w'_{K,L})$. Finally, the MST network is built by re-applying Kruskal's algorithm, receiving an undirected and weighted network without loops and self-edges.

The created network is defined as the MST-based network of economic sectors (MST-NES), which consists of 11 vertices with each vertex representing one sector of activity.

2.2 Centrality Measures

Centrality measures describe the network position of nodes in a graph (Freeman, 1978). I used six different centrality measures, a concise description of which is provided below.

1. Degree: In weighted networks, the degree of a vertex is called node strength (Opsahl, Agneessens, and Skvoretz, 2010), expressed as the sum of edge weights connected to that node, defined as follows:

$$k_i = \sum_{j=1}^{N} w_{ij} \quad (i \neq j) \tag{8}$$

where w_{ij} represents an element of the weighted adjacency matrix, which are the weights of the links between nodes *i* and *j*.

2. Degree centrality: The simplest representation of the local position of nodes in a network is the standardized degree centrality, computed as:

$$DC_i = \frac{\sum_{j=1}^{N} w_{ij}}{N-1} \quad (i \neq j) \tag{9}$$

3. Closeness centrality: The closeness centrality index of a vertex is the inverse of the sum of all the shortest paths between the node and all other vertices in the graph, and then normalized by multiplication by the expression *N*-1

$$c_i = \frac{N-1}{\sum_{j=1}^{N} l_{ij}} \; (j \neq i) \tag{10}$$

where l_{ij} means the shortest paths from nodes *i* to *j*.

4. Betweenness centrality: The betweenness centrality index of a vertex *k* is the total number of the shortest paths between each pair of vertices in the graph that pass through node *k*

$$b_k = \frac{\left(\sum_{i<j} \frac{g_{ikj}}{g_{ij}}\right)}{(N-1)(N-2)/2} (i \neq j \neq k) \tag{11}$$

where g_{ikj} expresses the number of the shortest paths from nodes *i* to *j* passing through node *k*; g_{ij} is the total number of the shortest paths from nodes *i* to *j*.

5. Eigenvector centrality: The centrality of the eigenvector of node *i* is recursively proportional to the weighted sum of the eigenvector centralities of its neighbors.

$$e_i = \lambda^{-1} \sum_{j=1}^{N} w_{ij} \cdot e_j \;\; (i \neq j) \tag{12}$$

where λ indicates the proportionality constant (eigenvalue), e_j corresponds to the eigenvector centrality score.

6. Eccentricity centrality: The eccentricity of node *i* is the maximum length of the geodesic distance that connects node *i* to all other nodes in the network.

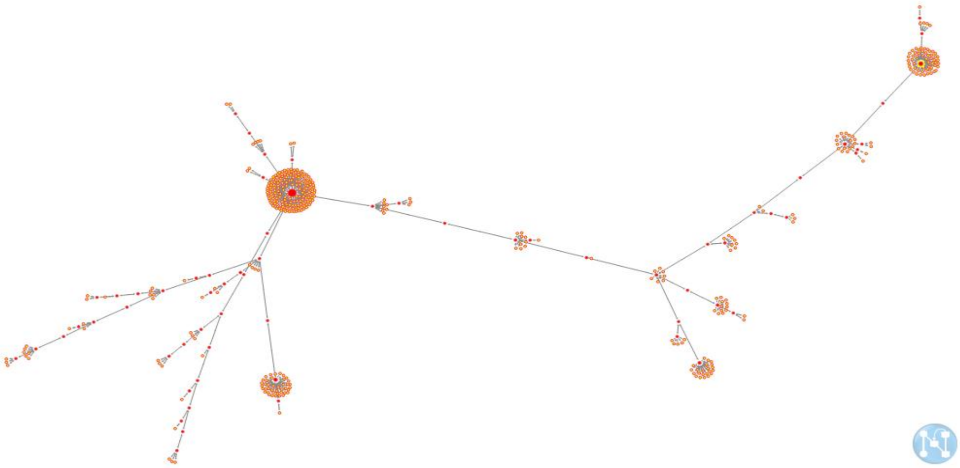
$$ec_i = \max_j l_{ij} \tag{13}$$

The larger the degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and the smaller the eccentricity centrality, the more central the node is.

3. Data Set

I investigated the daily closing prices of *N*=496 stocks of the S&P 500 Index that were continuously traded in the US market from July 7, 2015, to December 31, 2019, including a total of 1,131 trading days. Data time series were obtained from Yahoo Finance (http://finance.yahoo.com). The minimum spanning tree network is presented in Figure 1. The MST is an undirected and unweighted network consisting of 496 nodes and *N*-1=495 edges.

Figure 1. *The MST network of 496 stocks*



Source: *Own elaboration with NetMiner* (Cyram 2021).

The analyzed stocks are classified into 11 sectors within the classification of Yahoo Finance (2019). The specified sectors include Basic materials (BM, 19 stocks), Communication services (CS, 24 stocks), Consumer cyclical (CC, 67 stocks), Consumer defensive (CD, 35 stocks), Energy (EN, 27 stocks), Financial services (FS, 71 stocks), Healthcare (HE, 60 stocks), Industrials (IN, 71 stocks), Real estate (RE, 31 stocks), Technology (TE, 63 stocks), Utilities (UT, 28 stocks).

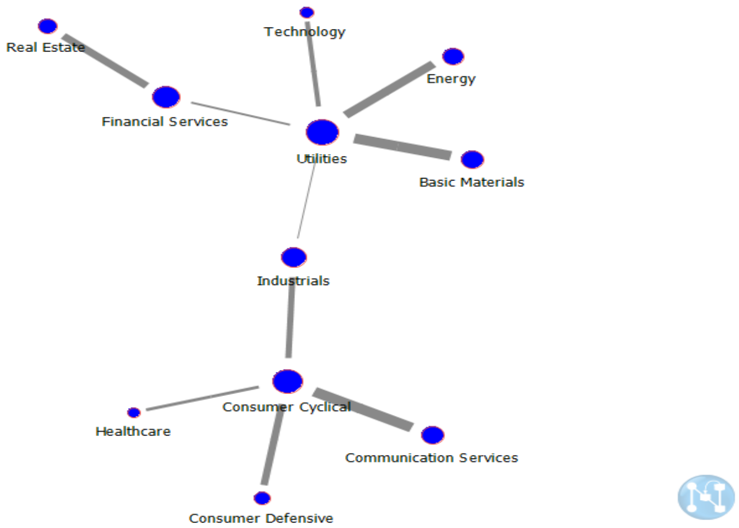
4. Results

4.1 Aggregate Network Structure at the Level of Economic Sectors

The analysis applies to a higher scale of hierarchy in the network by grouping assets at the economic sector level. This approach enables the evaluation of how each sector affects the other industries. The MST-NES network (undirected and weighted) is reported in Figure 2, where the thickness level of the edges is labeled according to their weight, and the size of the vertices is proportional to the size of the degree as the sum of the weights. The MST network of economic sectors provides information about the structure of the US economic system. The MST sector network consists of two parts with a star-like structure, where the central nodes are utilities and consumer cyclical. The industrial sector, acting as an intermediary, plays a bridging role connecting both parts of the network. The MST network shows that these three sectors form the backbone of the tree. The strongest connections exist between the

CC-CS, UT-BM, UT-EN, and FS-RE sectors. The node strength (degree) for each sector is shown in Table 1.

Figure 2. *The MST-NES network. The thickness level of the edges is proportional to the weight of the link. The size of the vertices is proportional to the sum of the weights.*



Source: *Own elaboration with NetMiner* (Cyram 2021).

Table 1. *The node strength for each sector*

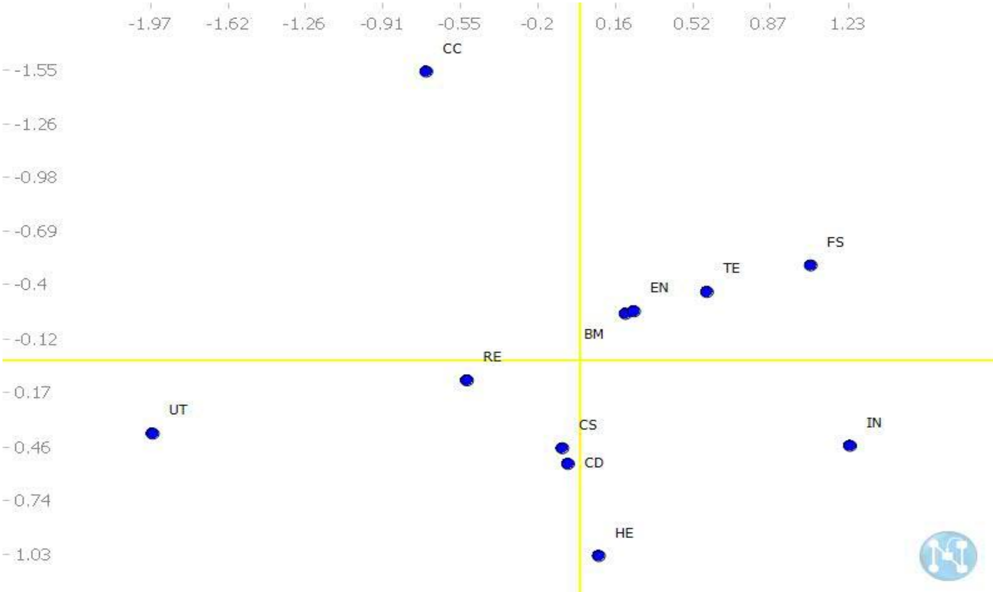
Sector	Degree (sum of weights)
Basic materials	1.246
Communication services	1.246
Consumer cyclical	4.397
Consumer defensive	1.189
Energy	1.218
Financial services	1.991
Healthcare	0.928
Industrials	1.800
Real estate	1.203
Technology	0.983
Utilities	4.999

Source: *Own calculation based on empirical research.*

The utilities sector has the highest degree of 4.999, followed by the consumer cyclical (4.397), financial services (1.991), and industrials (1.8). In contrast, the lowest degree is recorded in the healthcare sector (0.928) and technology (0.983).

I used multi-dimensional scaling (MDS) to analyze the similarity information visually. To generate the MDS map presented in Figure 3, the Principal Coordinate Analysis (PCO) has been applied, also referred to as Torgerson-Gower's classical Multidimensional Scaling (c-MDS). The proportion explained is 0.901 (the larger value means that MDS is a better fit for the data).

Figure 3. *Multi-dimensional scaling map for the MST-NES network*



Source: *Own elaboration with NetMiner* (Cyram 2021).

The MDS map shows two clusters. Cluster 1, marked with a blue loop, includes such sectors as (i) BM, (ii) EN, (iii) TE, and (iv) FS, which are linked by the UT central sector in the MST-NES network. Cluster 2, denoted by a red loop, contains the following sectors: (i) CS, (ii) CD, (iii) HE, which are connected indirectly by sector CC, and sector (iv) RE. However, both the central sectors (UT and CC) and the intermediary sector (IN) are on the outer section of the MDS map. These sectors are quite dissimilar from each other because of the intermediary role they play, connecting different parts of the network.

4.2 Analysis of the Centrality Measures at the Sector Level

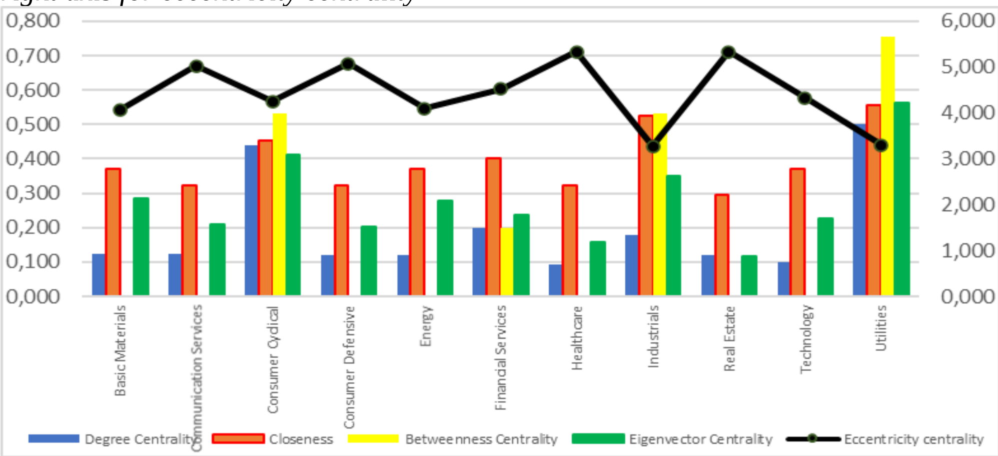
In this section, the MST-NES sector centrality properties analysis is carried out. Additionally, the ranking of economic sectors is analyzed according to the sectors' central position in the network. Centrality measures can be used to identify influential vertices in the network. The more central the nodes in the network, the more important the vertices are. Table 2 shows the centrality measures for the sector network while Figure 4 shows their graphical representation.

Table 2. *Sectoral centrality measures for the MST-NES network*

Sector	Degree centrality	Closeness centrality	Betweenness centrality	Eigenvector centrality	Eccentricity centrality
Basic materials	0.125	0.370	0.000	0.286	4.072
Communication services	0.125	0.323	0.000	0.211	5.020
Consumer cyclical	0.440	0.455	0.533	0.413	4.254
Consumer defensive	0.119	0.323	0.000	0.201	5.077
Energy	0.122	0.370	0.000	0.280	4.100
Financial services	0.199	0.400	0.200	0.238	4.529
Healthcare	0.093	0.323	0.000	0.157	5.337
Industrials	0.180	0.526	0.533	0.351	3.277
Real estate	0.120	0.294	0.000	0.117	5.337
Technology	0.098	0.370	0.000	0.226	4.335
Utilities	0.500	0.556	0.756	0.562	3.306

Source: *Own calculation based on empirical research.*

Figure 4. *Sectoral centrality measures for the MST-NES network. Values on the right axis for eccentricity centrality*



Source: *Own elaboration based on empirical research.*

When analyzing the level of centrality, the sectors should be sorted according to the centrality measures, in ascending order for the eccentricity centrality and in descending order for the degree, closeness, betweenness, and eigenvector centrality, respectively.

From Table 2, one can find that there are three central vertices in the MST economic sector network. The utilities sector achieves the best results for the four measures of centrality, except for eccentricity centrality (it ranks second in terms of this measure). The other most central sectors are consumer cyclical and industrials. It is observed that the sectors of utilities, consumer cyclical, and financial services have the largest degree centrality, which means that these sectors have a relatively high degree of linkage. The most central sectors due to the lowest eccentricity centrality value are (i) industrials (3.277), (ii) utilities (3.306), and (iii) basic materials (4.072). The above observations can be easily confirmed visually by analyzing the bar graph in Figure 4 and the radial plot in Figure 5.

Figure 5. *Radial chart for the following centrality measures: a) degree centrality; b) closeness centrality; c) betweenness centrality; d) eigenvector centrality*

Source: *Own elaboration with NetMiner* (Cyram 2021).

With regard to centrality measures based on the shortest path length – closeness and betweenness centrality – utilities, industrials, and consumer cyclical sectors play a noticeable intermediary role.

The methodological approach to the construction of the centrality measures is varied. This applies to the range of influence of the network structure. For example, degree centrality takes into account connections with the adjacent nodes, while other centrality measures include the broader context of the network structure. It should be noted that, unlike eigenvector centrality, measures such as closeness, betweenness, and eccentricity centrality take into account the shortest paths in the network. However, the specificity of the MST-based sector network means that all possible connections between vertices have the shortest path length (Figure 2). In other words, there are no intermediate paths in the MST-NES network.

To assess the central and peripheral nodes in the sectoral network, the concept of relative importance was utilized. For centrality measures defined as stimulants (degree, closeness, betweenness, and eigenvector centrality), the relative importance is the result of the quotient of the sector centrality measure and its maximum value over the entire network, represented as follows:

$$RI_i = \frac{cm_i}{\max cm_i} \tag{14}$$

where cm_i is the centrality measure value for sector i.

For the eccentricity centrality, which is a destimulant, the relative importance is the result of the relation between the value of the sector centrality measure and its minimum value in the entire network

$$RI_i = \frac{cm_i}{\min cm_i} \tag{15}$$

Next, all sectors are ranked in descending order with respect to the mean relative importance (Table 3).

With regard to the mean relative importance (MRI) according to sectors, Table 3 demonstrates that the following three sectors are central nodes in the MST network: (i) utilities (99.8%), (ii) consumer cyclical (78.2%), and (iii) industrials (72.7%). This classification assumes that if the mean relative importance exceeds 70.0%, then a sector is classified as the central node of the network. At the same time, sectors with mean relative importance below 40% are identified as peripheral vertices. The latter include such sectors as real estate (31.9%), healthcare (33.2%), consumer defensive (36.4%), and communication services (37.2%). Other sectors, including financial services (50.6%), basic materials (44.6%), energy (44.1%), and technology (40.4%), occupy an intermediate position in the network.

Table 3. *The relative importance of sector centrality measures*

Rank	Sector	Degree centrality	Closeness centrality	Betweenness centrality	Eigenvector centrality	Eccentricity centrality	Mean relative importance
1	Utilities	100.0%	100.0%	100.0%	100.0%	99.1%	99.8%
2	Consumer Cyclical	88.0%	81.8%	70.6%	73.6%	77.0%	78.2%
3	Industrials	36.0%	94.7%	70.6%	62.4%	100.0%	72.7%
4	Financial Services	39.8%	72.0%	26.5%	42.5%	72.4%	50.6%
5	Basic Materials	24.9%	66.7%	0.0%	50.9%	80.5%	44.6%
6	Energy	24.4%	66.7%	0.0%	49.8%	79.9%	44.1%

7	Technology	19.7%	66.7%	0.0%	40.2%	75.6%	40.4%
8	Communication Services	24.9%	58.1%	0.0%	37.5%	65.3%	37.2%
9	Consumer Defensive	23.8%	58.1%	0.0%	35.8%	64.5%	36.4%
10	Healthcare	18.6%	58.1%	0.0%	28.0%	61.4%	33.2%
11	Real Estate	24.1%	52.9%	0.0%	20.9%	61.4%	31.9%

Source: *Own calculation based on empirical research.*

There should be no doubts in terms of identifying the three central sectors due to the large difference in MRI between the third and fourth sectors in the ranking, i.e., 72.7% for industrials and 50.6% for financial services, respectively. The results of the sector centrality analysis in the network and the aggregate network structure (Fig. 2) are consistent with the results obtained using the mean relative importance approach.

Nevertheless, the choice of peripheral sectors requires some explanation. For the three measures of centrality, closeness, eigenvector, and eccentricity, sectors at the periphery of the network achieve the worst results in terms of relative importance. The difference in relation to the technology sector, classified as the last one in the group of intermediate nodes, is relatively large. In addition, the betweenness centrality for these sectors is 0, although this result is the same as for the technology, energy, and basic materials sectors.

In summary, objects with an MRI below 40% are classified into peripheral sectors. Sectors of intermediate centrality in the MST network include vertices for which the MRI is in the $\langle 40.0\% - 51.0\% \rangle$ range. Finally, nodes with the MRI value greater than 70% are classified as central sectors.

5. Conclusions

In this study, I have investigated the structure of the sectoral network using the complex network approach. I proposed a unique method to produce the network relationships between 11 sectors. Specifically, the construction of the network is based on the MST-Pearson correlation coefficient of the log-return stock, where the empirical data consist of daily closing prices of 496 stocks from the S&P 500 Index in the 2015-2019 period.

Based on centrality measures, the results obtained indicate that the central nodes in the MST network of economic sectors are utilities, consumer cyclical, and industrials. The first two sectors are also the most connected nodes, and the industrials sector performs an intermediary role. However, the ranking of sectors in terms of individual centrality measures changed insignificantly. The relative importance of the sector centrality measure was used to produce a uniform ranking of sectors in terms of central/peripheral position in the network. This analysis confirmed the conclusions about the importance of the three sectors indicated (utilities, consumer cyclical, industrials). The real estate, healthcare, consumer defensive, and communication services sectors were identified as peripheral nodes. The remaining sectors, i.e., financial services, basic materials, energy, and technology, were classified as intermediate vertices.

The division into peripheral and intermediate sectors corresponds to the prepared MDS map (Figure 3). Four sectors identified as intermediate and four peripheral industries cluster together in cluster 1 and cluster 2, respectively. In other words, the peripheral sectors are similar to each other. The same applies to the nodes of the intermediate group. On the other hand, the three sectors classified as central are scattered on the MDS map due to the bonding of nodes from different areas of the network (Figure 2).

The results of this study highlight that the position of the peripheral sectors is not a direct result of their degree – as opposed to the central sectors. For example, in terms of degree, communication services and real estate are ranked 5^{th} and 8^{th}, respectively. This means that the position of the peripheral sector in the MST-NES network is determined by the centrality measures, taking into account a wider network structure than connections to neighbor vertices.

The results do not confirm previous research by (Pozzi, Di Matteo, and Aste, 2008; Yao and Memon, 2019; Tabak, Serra, and Cajueiro, 2010; Patwary *et al.*, 2017; Majapa and Gossel, 2016; Kenett *et al.*, 2010; Tang *et al.*, 2018; Di Matteo, Pozzi, and Aste, 2010), which showed the importance and central position of the financial sector in the network. In this paper, while financial services rank third in terms of degree, this sector is classified into the group of intermediate industries.

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