Progress Report

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MXB362 – Advanced Visualization and Data Science
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Investigating the Correlation Network in Foreign Currency Exchange Market

Summary

The foreign currency exchange (FOREX) market is the biggest financial market in the world. It exerts an enormous impact on all other markets (Ismaila and Dallah, 2010). It is because the currency presents the price of any asset and its value represents the country's economic status. A foreign exchange rate is a relative price of a region's currency in terms of the currency of another region. It can express the economic balance between two regions (Mizuno et al., 2006). The FOREX market is a typical complex system and can be presented by the correlation networks and minimum spanning tree (MST) maps. The measures of centrality (degree, closeness, eigenvector, and betweenness) are all used to describe the characteristics of the FOREX market (Kazemilari and Djauhari, 2013). They can illustrate the significance of each currency inside the FOREX market network by investigating the components and interrelationships.

The project will study a set of currencies rates during the COVID-19 period from 30 December 2019, until 29 June 2021. The expected audience of visualizations will be investors and companies who want to develop the new investment strategy during the pandemic period. There are many benefits for companies and investors when important currencies are identified. The influential currencies tend to exert an impact on others. The increase or decrease in the foreign exchange rate of influential currencies would lead to a change in the trend of related currencies. There are many investors using key currencies as an indicator to take advantage of market opportunities. Those currencies are monitored carefully. For example, the information about events and policies which could affect the trend of influential currencies will be the first priority for the investors to focus on.

The measures of centrality will explore the differences between the behavior of currencies and determine the most influential currencies. The analysis of the Foreign Currency Exchange Network aims to reveal the information about market's structure

and the role of each particular currency. The project centers on quantifying the currencies' importance in the global financial market. To achieve the aim, some currency correlation networks and their minimum spanning tree which contain general currencies information will be constructed.

Aim: Better understand the relationship of currencies and find the most influential currencies.

Project Description

The Data

The daily closing prices of 58 currencies is retrieved from Exchange Rate Service (http://fx.sauder.ubc.ca/). A table is constructed to display the countries' name and their respective currency symbol. The project uses US Dollars as the base currency to state the daily exchange rate.

Correlation Heatmap

The heatmap is a conventional method to illustrate the correlations between sectors [Figure 1]. Constructing the heatmap of the correlation matrix is necessary. It helps to validate the results from the correlation calculations and provides a high-level understanding of relationships between currencies.

Currency network

Although heatmap is helpful, it can only present one dimension of data (the correlation between two currencies). As the outlined purpose of the project, even with a heatmap, crucial issues about the most influential currencies and their behavior remain unanswered. The currency network will be utilized to study further based on initial findings achieved from the correlation heatmap [Figure 2]. The visualization of the currency network also provides a more accessible method to convey meaningful messages.

Minimum Spanning Tree with different bases

The minimum spanning tree is widely used to visualize the financial networks [Figure 3]. While the number of edges displayed in the currency network can be up to N(N – 1) (with N is the number of currencies), the minimum spanning tree only has (N-1) edges. It contains the edges that link all the nodes together, minimize the sum of edge weights, and do not include any cycles. The project will implement Kruskal's algorithm in building the minimum spanning tree, which would aid to understand, simplify and summarize the message obtained from the currency network.

Expected Output

For all three visualizations, I expect to explore the capabilities of Python Libraries such as Numpy, Pandas, Networkx, Matplotlib, Seaborn to pre-process data and construct basic visualizations. I also expect to implement network drawing software Gephi in mapping the currency network in geographical layout. The custom color palette, the scale, the size of each element, and the layout of visualization will be studied carefully to display the information in the most efficient way.

The output obtained from analyzing the visualizations is expected to be particularly helpful in some real-world use cases. For example, the analysis of the correlation between currencies would help investors diversify their portfolios since it helps to identify uncorrelated currencies to invest in. Another example is that by pointing out the most influential currencies, it would be the suggestion for investors to focus more on these currencies.

Proposed Task and Project Timeline

The Gantt Chart

The list of tasks expected to be accomplished is displayed in the Gantt Chart [Figure 5].

Expected outcomes by Week 11

By the end of Week 10, I expect to generate the primitive version of three visualizations. The table showing the statistic about currency network and minimum spanning tree will also be done. A brief analysis and example about practical use case of each visualization will be outlined.

Progress to date

The project journal can be seen in the Figure 4.

a. Background research, reading, and investigations carried out

- Many studies that proposed methods to analyze the correlation network of the world currency exchange rate. Kazemi Lari and Djauhari (2013) examined the network topology of the Forex market from 2009 to 2012 based on centrality measures. Their paper successfully pointed out nine influential currencies during this period and suggested investors and companies should monitor these currencies carefully. Kwapień et al. (2009) provide the analysis of a network structure of the foreign currency exchange market. This paper did identify the clusters of strongly connected currencies and study the network topology of minimum spanning trees constructed by different base currencies such as GPB or USD. The analysis indicates that EUR has played a crucial role in the global Forex market.

- There is an interesting reading that discusses visualizing asset price correlation written by Julian West (2019). In this article, the author showed how to visualize the correlation matrix of asset price as an interactive network graph that provides the audience with a high-level overview of the connection between asset classes.

b. Collected and generated data

- A CSV file named ‘country-currency-region.csv’ contains information about the symbol of currencies and their corresponded country name and region.

- Two CSV files ‘nodes_network.csv’ and ‘edges_network.csv’ contain node and edge data for network visualization using Gephi software. Those files are generated by MatLab script in ‘data_process.mlx’ file.

- A CSV file named ‘fxdata.csv’ contains the daily closing prices of 58 currencies retrieved from Exchange Rate Service (http://fx.sauder.ubc.ca/)

- A table shows information about countries, respective symbols and centrality measures [Figure 17]

- A CSV file named 'pythonData.csv' contains the cleaned data from 'fxdata.csv'. It is ready to be used and processed as a data frame by Pandas library.

c. Algorithm and visualization techniques

- Before constructing the heatmap, normalizing data and converting the absolute asset values into log-returns are of importance. This transformation is prevalent in financial time-series data since investors are more concerned with asset returns than their absolute values. Moreover, it is easier to compare the returns of two currencies when the data is normalized. First, we compute the daily returns of the logarithm rate:
$$\boldsymbol{R_i(t) = \ln\big(P_i(t+1) \;/\; P_i(t)\big)}$$
where $\boldsymbol{i = 1, 2, \ldots N}$ (number of currencies), $\boldsymbol{R_i(t)}$ is the daily return at time t of currency $\boldsymbol{i}$ and $\boldsymbol{P_i(t)}$ is the closing price of currency $\boldsymbol{i}$ at time $\boldsymbol{t}$.

- After the closing prices are converted into log returns, the *corr*() function is used to compute the pairwise correlations between currencies. This function is available in both Python and MatLab, and it will return an NxN correlation matrix. Python provides a data visualization library called Seaborn, which visualizes the correlation matrix as a clustered heatmap via a useful function called *clustermap*(). The clustered heatmap is a conventional approach to illustrate correlations between variables in a dataset, especially if the data is multidimensional because it automatically organizes similar variables into clusters. This improves the structure and readability of the heatmap, making it simpler to notice connections between currencies that act similarly. The result of the visualization is shown in Figure 10.

- The Marchenko–Pastur distribution is implemented to detect and remove insignificant eigenvalues and eigenvectors of the matrix, reduce noise and make the matrix display only meaningful messages. The next step is converting the cleaned correlation matrix into the lists of nodes and edges in order to visualize it as a network. In MatLab, this step is done by using the OutputNetwork.p function, which takes the correlation matrix and an array of currencies' labels as parameters and returns two CSV files: nodes.csv and edges.csv. Then, those files are loaded into Gephi to generate network visualization. To improve the visualization, insignificant edges are removed if their correlation value is below a 0.3 threshold value. Gephi uses the Louvain method to compute the modularity and detect community structure in networks. It successfully detects three major communities in the currency network as shown in Figure 11.

- To produce the minimum spanning tree (MST), a technique of MST introduced by Mizuno et al. (2006) is implemented. The correlation matrix is transformed to the distance matrix as follows:

$$\boldsymbol{d^t_{\mathrm{ij}} = \sqrt{2(1 - c_{ii})}}$$

  The three axioms of Euclidean distance are satisfied: (i) $\boldsymbol{d^t_{\mathrm{ij}}} = \mathbf{0}\ if\ and\ only\ if\ \boldsymbol{i} = \boldsymbol{j}$, (ii) $\boldsymbol{d^t_{\mathrm{ij}}} = \boldsymbol{d^t_{ji}}$, (iii) $\boldsymbol{d^t_{\mathrm{ij}}}\ \leq \boldsymbol{d^t_{ik}} + \boldsymbol{d^t_{kj}}$, where $\boldsymbol{d^t_{\mathrm{ij}}}$ is the distance between the rate of currency $\boldsymbol{i}$ and $\boldsymbol{j}$. Using the distance matrix as a parameter, the OutputNetwork.p function outputs nodes and edges CSV files. Those files are imported to Gephi to generate MST visualization. In Gephi, a plugin called Minimum Spanning Tree implements Kruskal's algorithm to construct the FX network.

- Since centrality is one of the most researched topics in network analysis, a variety of measurements have been proposed such as closeness centrality, betweenness centrality, degree centrality, eigenvector centrality, flow betweenness, the rush index, etc. In this project, the network centrality was examined by evaluating four particular node-level centrality metrics that are essential in most network studies (Kazemi Lari and Djauhari, 2013). Degree, closeness, betweenness, and eigenvector centralities are calculated for each node in a network.
    - Degree Centrality shows the degree of importance of information for each currency (Niemincn, 1974). It is calculated as follows:

$$\boldsymbol{C(v) = \frac{degree(v)}{n-1}}$$

- Betweenness Centrality illustrates the frequency for each currency in the shortest routes between indirectly linked nodes (Freeman, 1977). It is calculated as follows:

$$\boldsymbol{c}_{(\boldsymbol{v})} = \sum_{s \neq v \neq t} \frac{\boldsymbol{\sigma}_{st}(\boldsymbol{v})}{\boldsymbol{\sigma}_{st}(\boldsymbol{N}-\mathbf{1})(\boldsymbol{N}-\mathbf{2})}$$

  Where $\boldsymbol{\sigma}_{st}$ is the total number of shortest paths from ***s*** to ***t***, and $\boldsymbol{\sigma}_{st}(\boldsymbol{v})$ is the number of those paths that pass through node ***v***.

- Closeness Centrality: measures the time to transfer information between a node ***v*** to each other reachable node. The higher the closeness centrality score is, the more important the currency is (Sabidussi, 1966). It is calculated as follows:

$$\boldsymbol{c}_{(\boldsymbol{v})} = \sum_{v \neq t} \frac{\boldsymbol{n}-\mathbf{1}}{\boldsymbol{d}_{\boldsymbol{G}}(\boldsymbol{v},\boldsymbol{t})}$$

  Where ***n*** is the size of the connected component that node ***v*** can reach

- Eigenvector Centrality identifies which currency is connected to the most connected nodes (Banocicha, 2007). The eigenvector centrality of node ***i*** is calculated as follows:

$$\boldsymbol{e}_{(\boldsymbol{i})} = \frac{\mathbf{1}}{\lambda_{max}} \sum_{j=1}^{n} (\boldsymbol{A}_{ij}\boldsymbol{x}_{j})$$

d. Visualization analysis

- The clustered heatmap [Figure 10]
  - A diverging colorblind-friendly color palette is used to colorize the heatmap. The positive correlations are green, uncorrelated currencies are white and negative correlations are brown. Looking at the clustered heatmap visualization, there are interesting insights the audience could gain.

  - Overall, the strongly negative correlations are hardly seen between currencies. The currencies that are close to each other according to geographic regions tend to be grouped in the same cluster. For example, it is shown in the visualization that the list of currencies run from CHF (Switzerland) to PLN (Poland) are mostly European currencies. CAD (Canada), GPB (United Kingdom), SGD (Singapore), AUD (Australia), and NZD (New Zealand) are grouped into a cluster. It could be because they are Commonwealth countries that have political and cultural backgrounds in common. There is also a cluster of non-European regions, which consists of the list of currencies run from IDR (Indonesia) to ZAR (Africa). Most of those currencies come from the Asian region. It is also noticeable that HKD (Hong Kong) and JPY (Japan) are not correlated with Asian currencies; otherwise, they are correlated with European currencies. The event that the CNY (China) and JPY (Japan) joined XDR (the special draw rights) could be the reason for that. SAR (Saudi Arabia), ARS (Argentina), and PKR (Pakistan) are three currencies that are uncorrelated with all others.

- The currency network [Figure 11]
  - A qualitative color palette is used to colorize the nodes based on the communities detected in the currency network. The network visualization provides the audience with a better picture of the data. By removing insignificant edges with correlation values smaller than 0.3, the graph only displays the meaningful correlations between currencies. The edge thickness is scaled based on the magnitude of correlation. The Louvain method successfully detects which groups of currencies behave similarly. There are four clusters that can be seen from the graph: orange, green, blue, and grey. It is noticeable that all of the nodes in the orange cluster (except JPY) come from the European region. The European currencies are strongly correlated to each other and have a significant correlation to other currencies. Looking at the green cluster, there are four currencies namely COP, PEN, BRL, and CLP located in the left part of the cluster. All of them are from South/Latin America and they only connect to the currencies within the same cluster. Therefore, it is true to say that there is no correlation in the currency exchange rate between South/Latin

America and Europe. It is also noteworthy that even TRY and RUB come from Europe, they have no correlation with European currencies. It might be because of their unique geographic position, both Turkey and Russia are lying partly in Asia and partly in Europe. Regarding the blue cluster, it contains 12 currencies (9 of them are in Europe and 3 of them are in Asia). It is shown that European currencies are grouped into two different clusters. Moreover, even though MYR, PHP, and THB are from South East Asia, they tend to be more correlated with European currencies.

- The minimum spanning tree [Figure 12, Figure 13, Figure 14, Figure 15, Figure 16]
    - A qualitative color palette is used to colorize the nodes based on their region [Figure 12] (i.e., Europe, orange; Asia & Pacific, dark green; South/Latin America, blue; Africa, pink; North America, light green; Middle East, yellow). The minimum spanning tree is a more readable and well-structured version of the previous network graph. There is some knowledge obtained from the minimum spanning tree. The NOK is at the center of the FX network since it connects currencies from four different regions (i.e., Asia, South/Latin America, Middle East, and Europe). The majority of the currencies are grouped together based on geographical regions. The currencies of Commonwealth countries are connected together such as MYR, CAD, AUD, NZD, and SGD. The currencies of Europe are the most closely linked. EUR has a predominant position in the European monetary system. JPY is connected to European currencies, whereas CNY is more attached to the Asian cluster despite the fact that both currencies join the special drawing rights.

e. Interactive visualization

- The code for the website can be access via my GitHub: https://github.com/hoangqwe159/forex-analysis-covid19

- The live demo of the website can be access via the link: https://forex-network.herokuapp.com
- The website allows the audience to interact with visualization such as hovering for additional information, highlight the connected nodes, drag, and zoom the network. The application is only displaying the draft version of the visualizations. An update version will be deployed as the output of the project

Foreseen problems and risks

One of the most major problems of the project is choosing the optimal tools to prepare and process data. While Python provides a wide range of professional libraries and is supported by the larger community, MATLAB is the language I am more familiar with. There is a risk that some problems I might not solve by using Python, then the integration between two technologies is necessary for me to complete the project. Another problem is that mapping currencies node into their nation on the geographical map can only be done manually if I utilize Gephi Software.

Reference

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Appendix

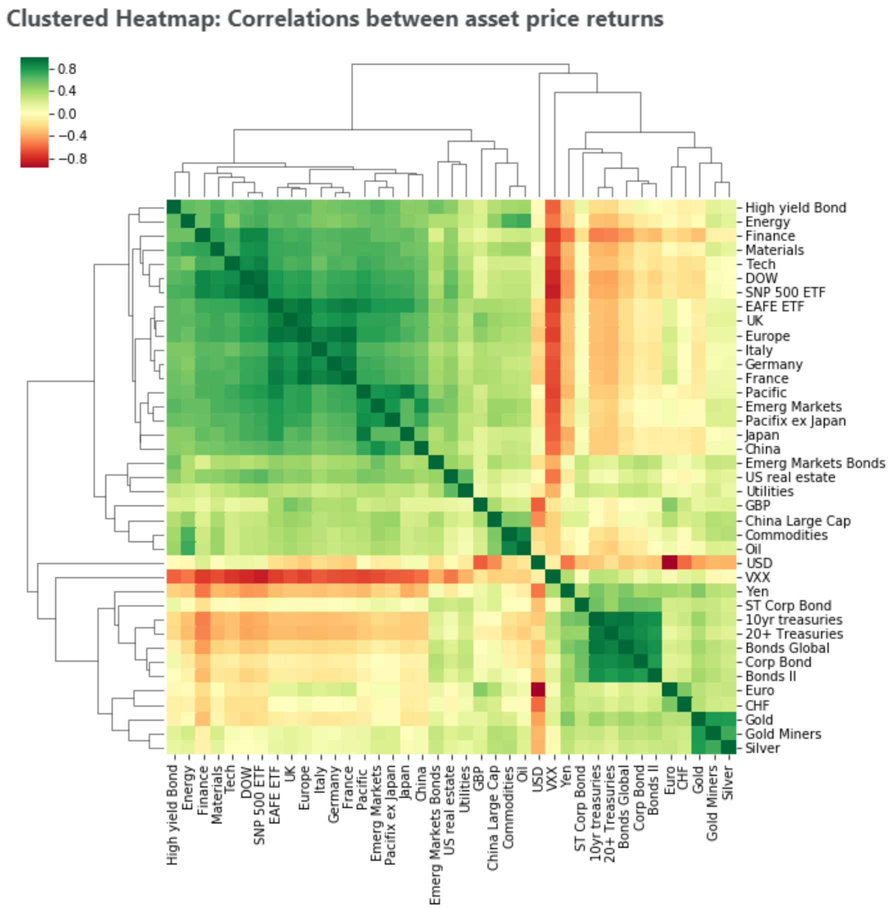

Figure 1: Illustration of the Heatmap Correlation Matrix (Julian, 2019)

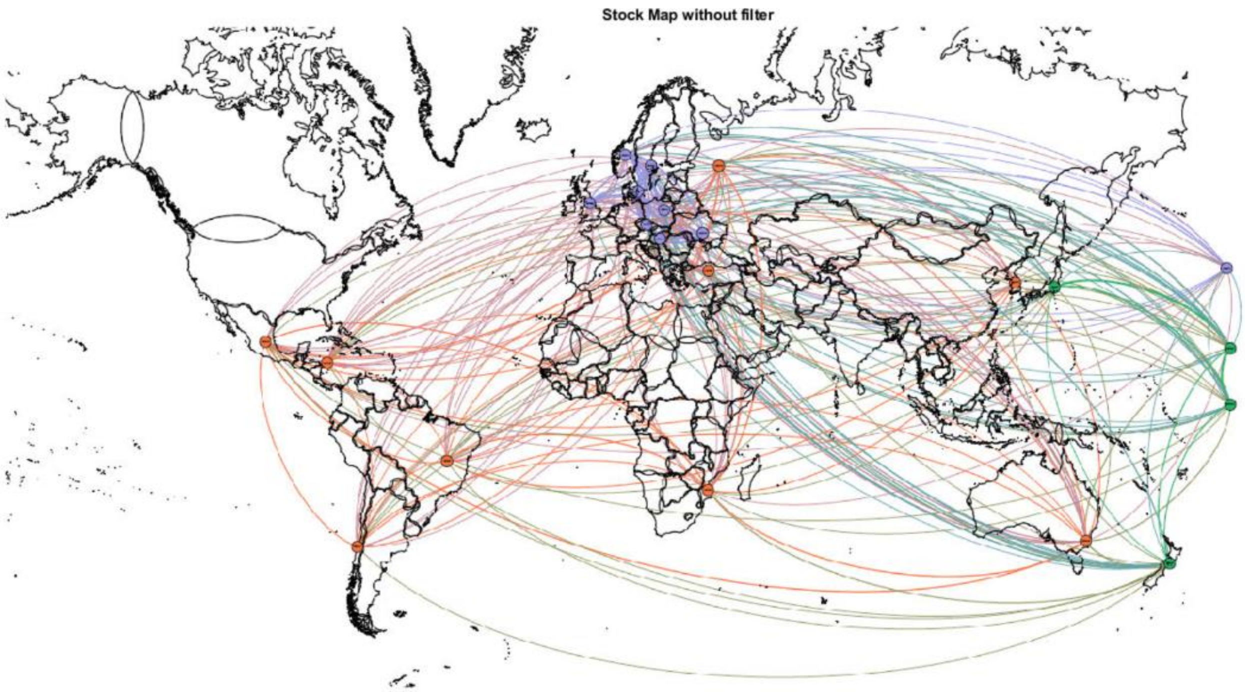

Figure 2: Illustration of the Currency Network using Geographical Layout

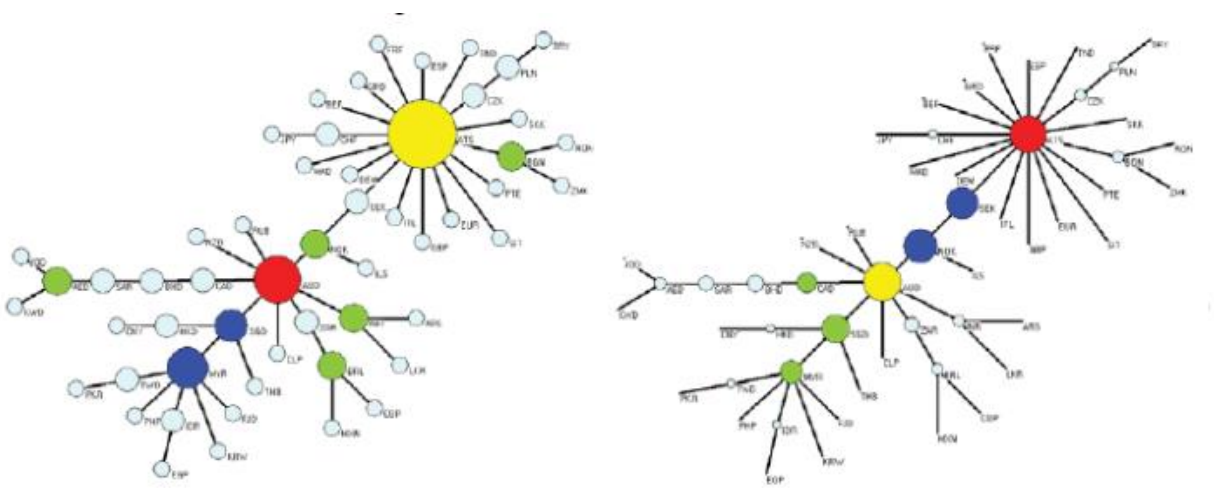

Figure 1. MST based on degree centrality

Figure 2. MST based on betweenness centrality

Figure 3: Illustration of Minimum Spanning Tree with different bases (Kazemilari and Djauhari, 2013).

Date	Task	Time allocated (hours)
1/08/2021	Reading some research related to analyzing and visualizing the currency network	3
4/08/2021	Study the related term and understand the purpose of different visualizations.	2
7/08/2021	Finalize to determine the expected output.	1
10/08/2021	Study some methods to clean the noise from the correlation matrix.	3
13/08/2021	Study some community detection methods and Kruskal's algorithm.	3
16/08/2021	Loading a small set of data and load it to MATLAB and play around with it. Try to construct a very basic correlation matrix and network currency.	10
24/08/2021	Load data into Python and using some visualization libraries to generate clustered heatmap	5
1/09/2021	Apply studied algorithm and generate node and edge tables from data. Load data into Gephi and visualize the currency network	6
8/09/2021	Calculate distance matrix from correlation matrix. Output node and edge tables from distance matrix. Add region information into the node table. Load data into Gephi and visualize the MST	6
15/09/2021	Generate different MST visualizations based on four measures of centrality	4
22/09/2021	Provide analysis for each visualization. Choosing optimal color scale for the visualization.	4
30/09/2021	Build a website displaying interactive visualization	15
2/10/2021	Gather the findings and write the progress report.	6
Total Time		**68**

Figure 4: Project Journal to 02/10/2021

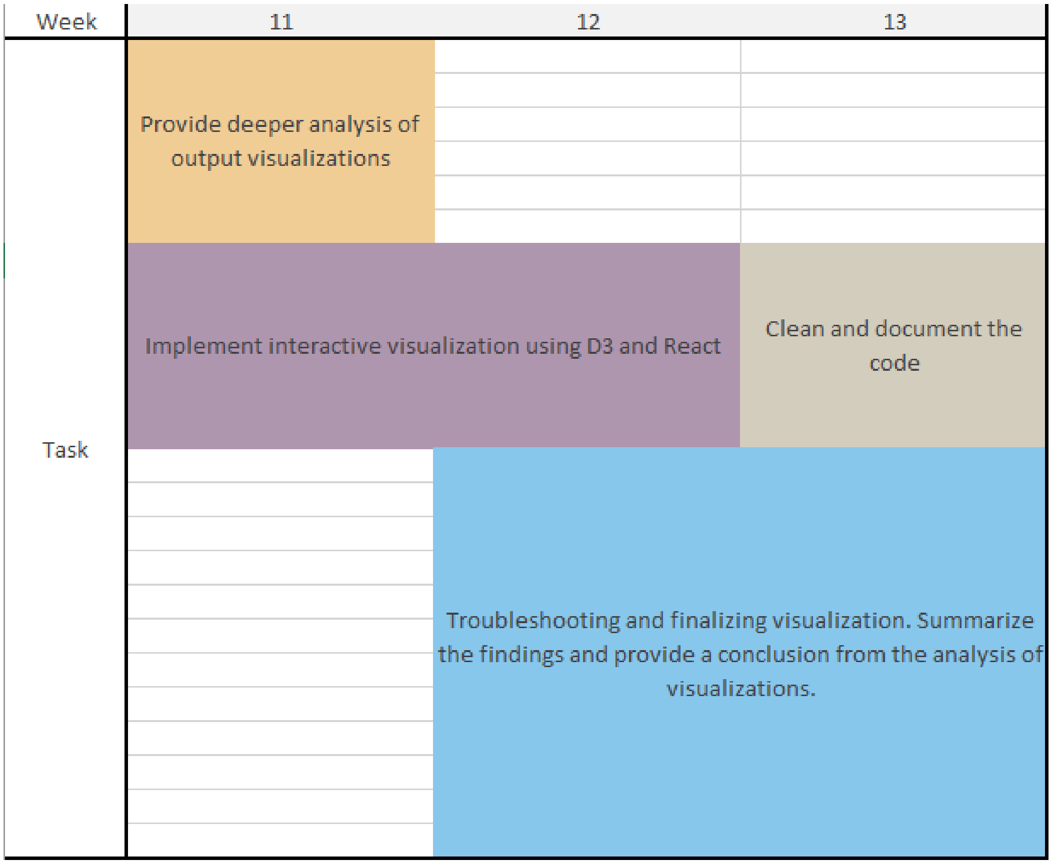

Figure 5: Gantt Chart

```
% Load the data
load("fx-19jun.mat");
day = 504; % Number of days to look at
total_day = size(data, 1); % Total days of data
n_tickers = size(data, 3); % Total numbers of tickers
mt_tickers = 22; % Number of most traded tickers

% Get the data for 504 days of trading price
data = data(total_day-(day - 1):total_day,:, :);
times = times(total_day-(day -1):total_day, :);

% Find 22 most traded tickers among 37 tickers
changes = zeros(1,n_tickers);
for n=1:n_tickers
   data(:,:,n) = data(:, :, n) / data(1,:,n);
   changes(n) = change(data(:,:, n));
end

% Remove unwanted tickers based on threshold
threshold = min(maxk(changes, mt_tickers));
index_to_remove = zeros(1, n_tickers - mt_tickers);

i  = 0;
for n = 1:n_tickers
    if change(data(:,:, n)) < threshold
        i = i + 1;
        index_to_remove(i) = n;
    end
end

data(:,:, index_to_remove) = [];
tickers(index_to_remove,:) = [];

% Format the data
data = squeeze(data);
data_table = array2table(data);

for i = 1:22
    data_table.Properties.VariableNames{i} = tickers(i,:);
end
```

Figure 6: Load and pre-process data

```
daily_returns = zeros(503, 22); % Initialization

% Compute the daily returns
for j =1:22
    for i=1:503
        daily_returns(i,j) = (data(i+1,j) - data(i,j)) / data(i,j);
    end
end

% Compute the correlation matrix of daily returns
correlation = corrcoef(daily_returns);
```

Figure 7: Compute Daily return and Correlation matrix

```
% Identify the range
lamda = mt_tickers/day;
lamda_plus = (1+sqrt(lamda))^2;
lamda_minus = (1-sqrt(lamda))^2;

%Calculate eigevalue/vectors for the correlation data
correlation(1:1+size(correlation,1):end) = 1;
[V1, D1] = eig(correlation);
D1_abs = abs(D1);

% Set the eigenvalues that are  indistinguishable from noise to 0
D1_filter = (D1_abs >= lamda_plus);
D1_reconstitued = D1 .* D1_filter;

%  A*V = V*D.
correlation_reconstituted = V1 * D1_reconstitued * inv(V1);
correlation_reconstituted = abs(correlation_reconstituted);
```

Figure 8: Reduce noise from Correlation Matrix

```
lon = ones(1, 22);
OutputNetwork(correlation_reconstituted,string(tickers));

% Edit the node table
node_table = readtable("nodes.csv");
node_table{:, 3} = v;

% The longitude and latitude of the capital corresponding to tickers
location = [
59.3293,  18.0686;
55.6761,  12.5683;
31.234680, -153.979789;
-29.0852, 26.1596;
50.0755, 14.4378;
19.4326, -99.1332;
-35.2809, 149.1300;
39.9334, 32.8597;
13.234680, -153.979789;
47.4979, 19.0402;
0, -153.979789;
-15.8267, -47.9218;
37.5665, 126.9780;
35.6762, 139.6503;
52.2297, 21.0122;
-33.4489, -70.6693;
44.4268, 26.1025;
-10.5395658, -91.7800721;
51.5074, -0.1278;
55.7558, 37.6173;
-41.2924, 174.7787;
59.911491,  10.757933;
];

% Add location data to node table
node_table.Latitude = location(:, 1);
node_table.Longitude = location(:, 2);

% Output the node table
writetable(node_table,'nodes.csv','Delimiter',';');
```

Figure 9: Output nodes and edges file for Gephi

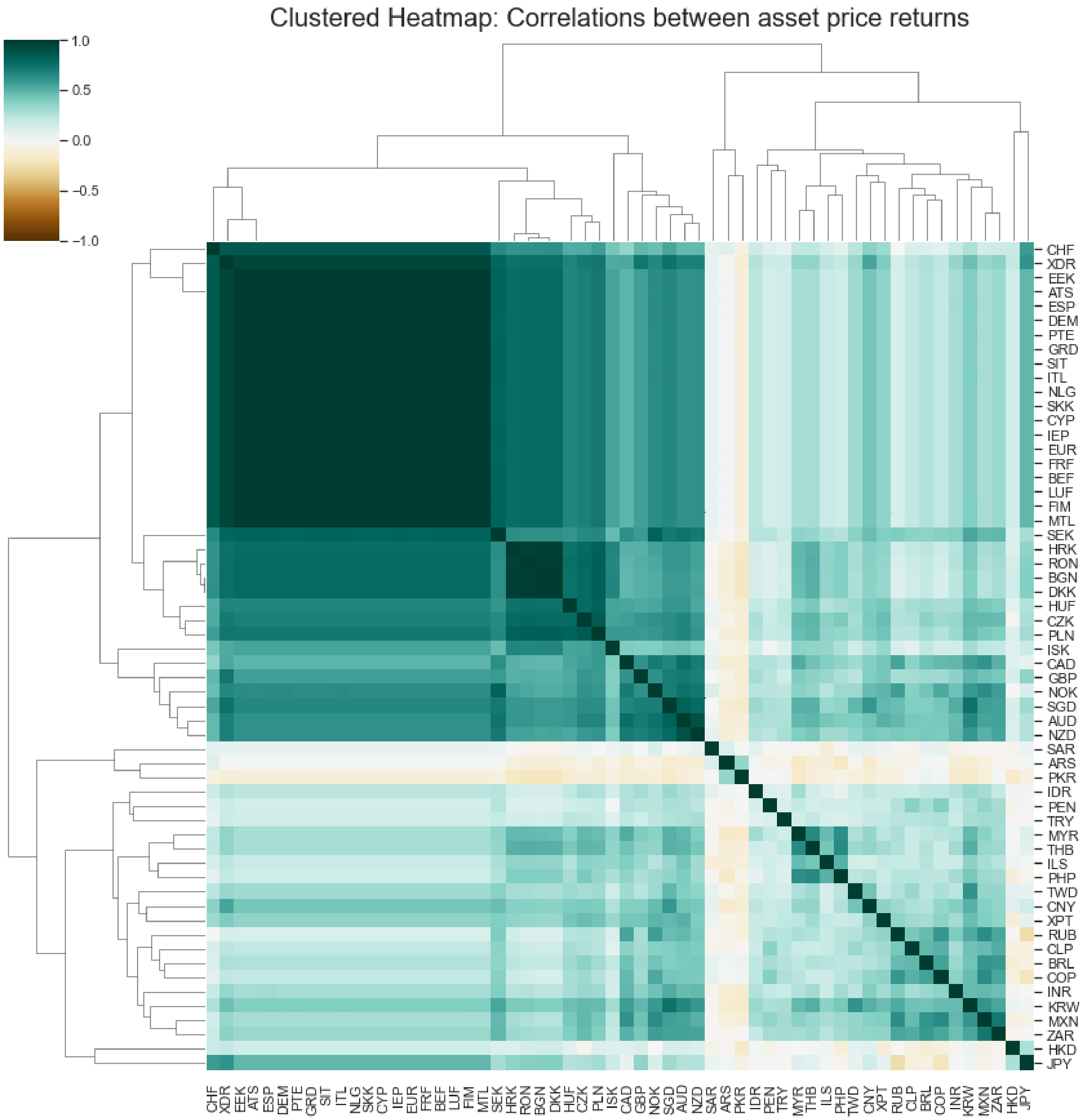

Figure 10: Clustered Heatmap

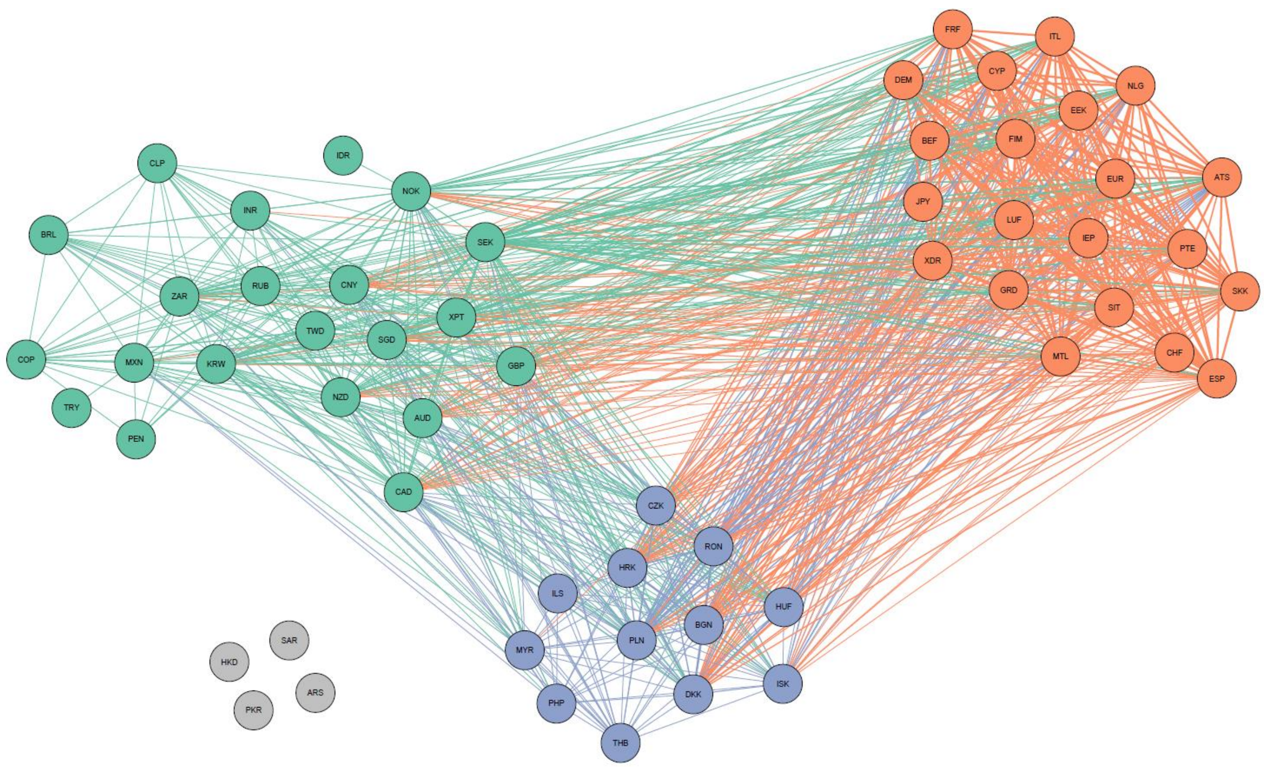

Figure 11: Currency network. The currencies from the same cluster have same color.

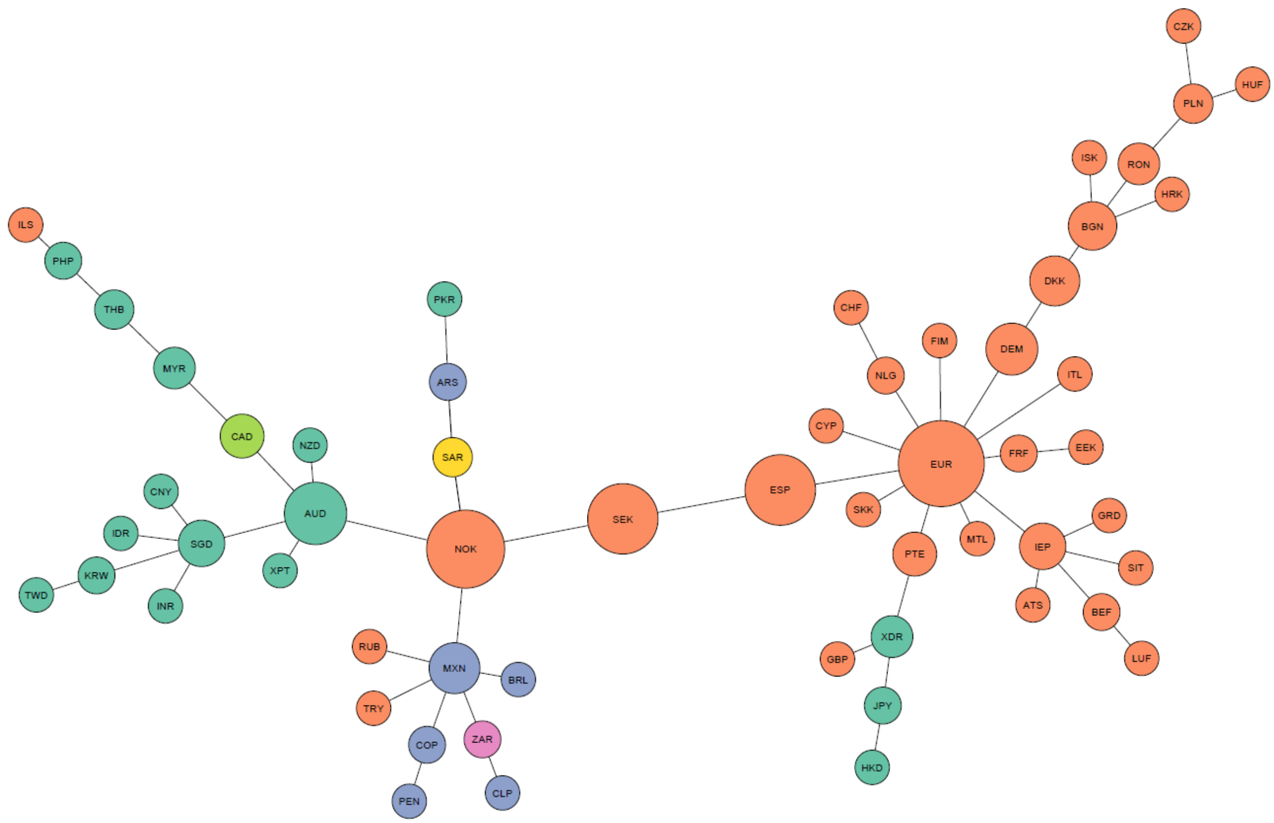

Figure 12: Minimum Spanning Tree. The currencies from the same region have same color. (i.e., Europe, orange; Asia & Pacific, dark green; South/Latin America, blue; Africa, pink; North America, light green; Middle East, yellow)

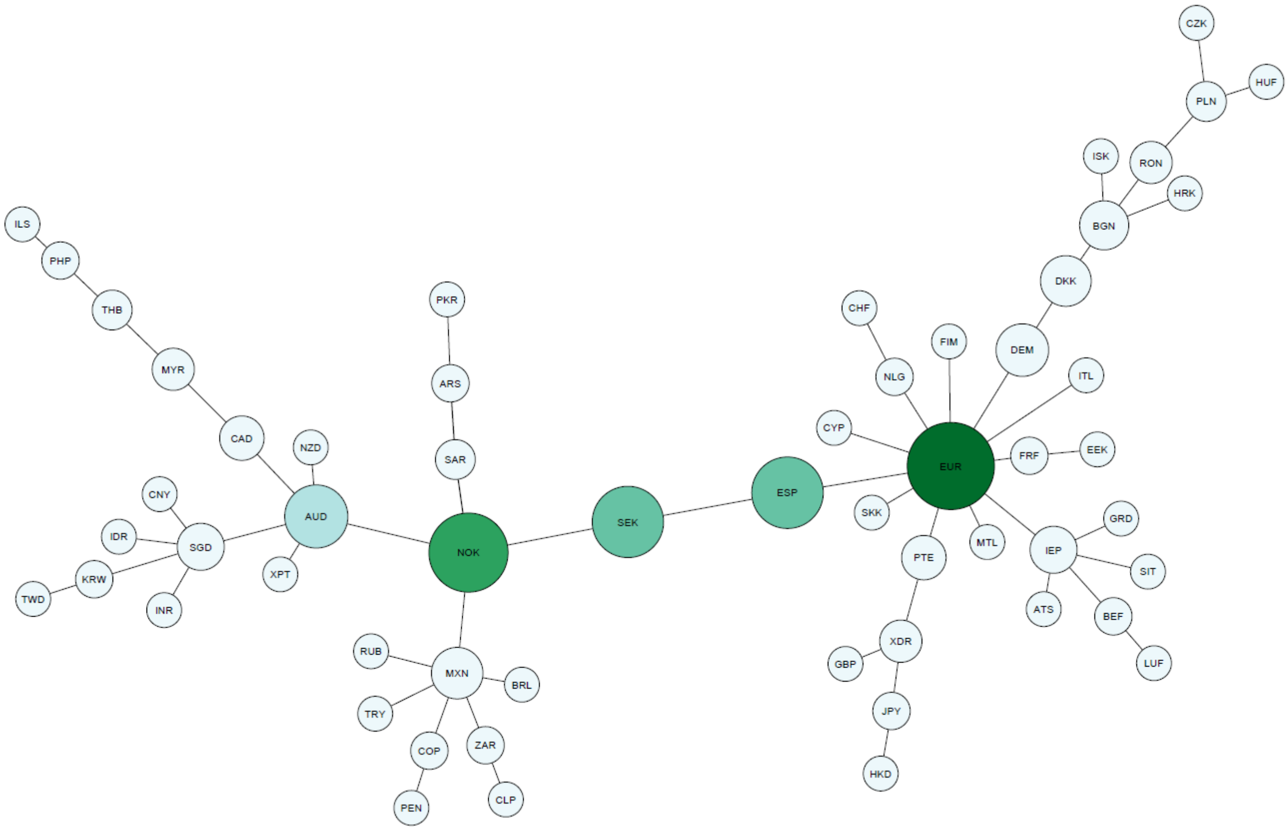

Figure 13: MST based on betweenness centrality

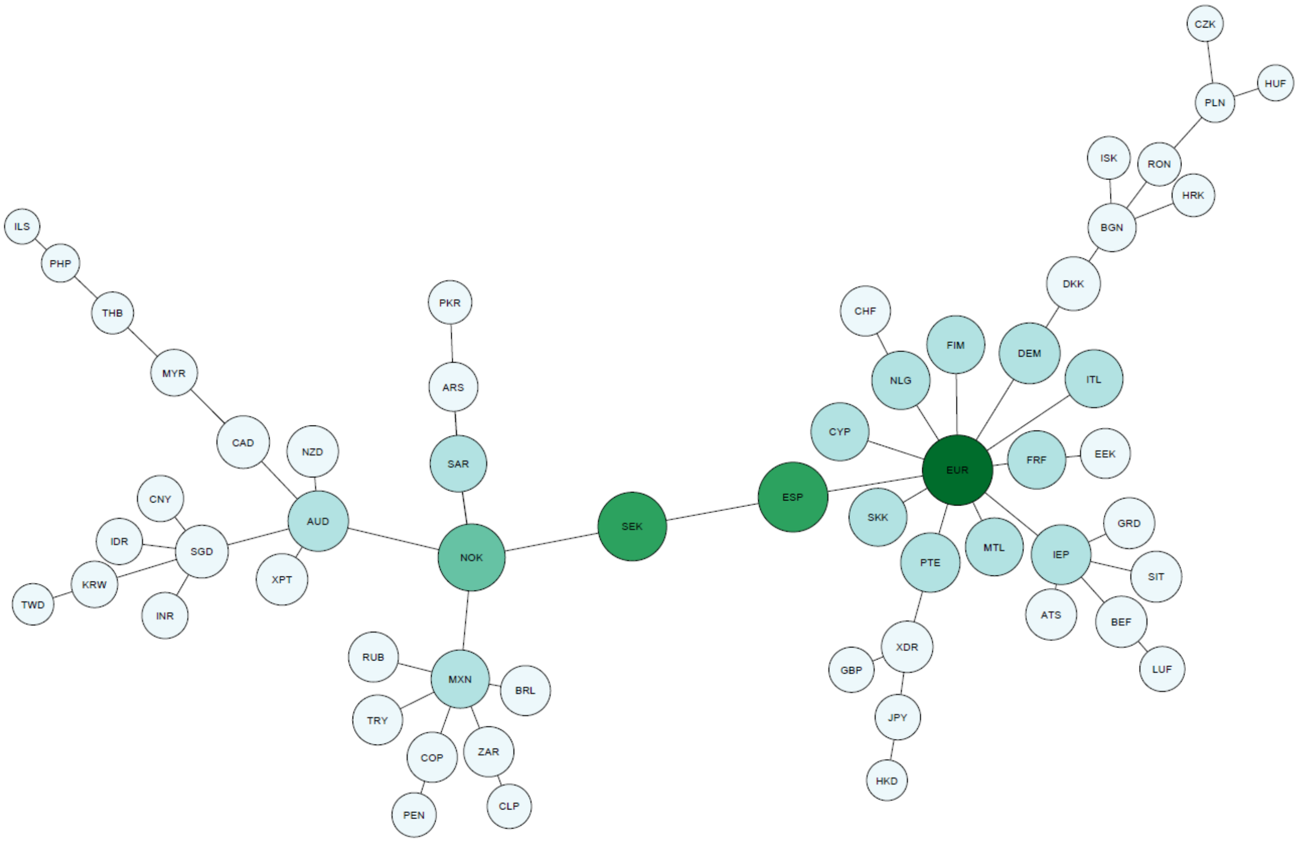

Figure 14: MST based on closeness centrality

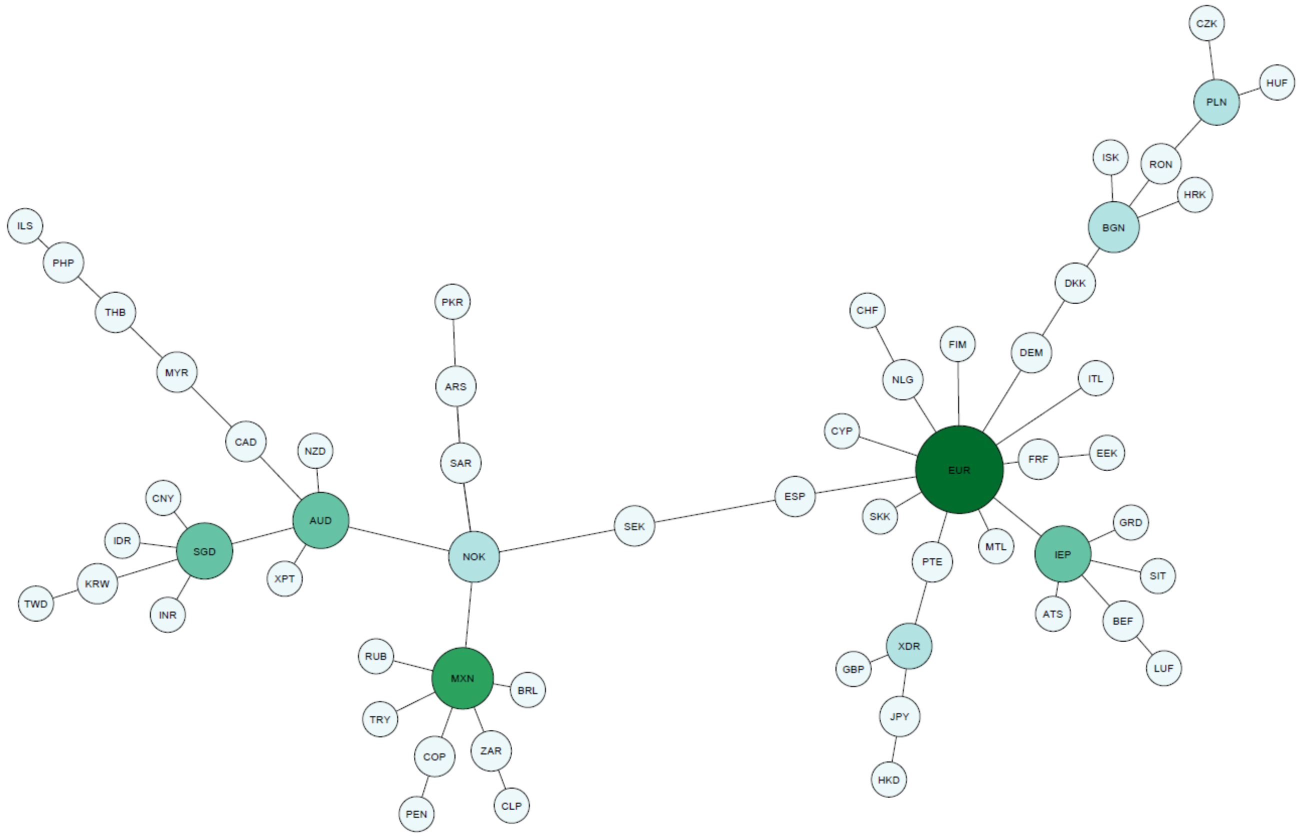

Figure 15: MST based on degree centrality

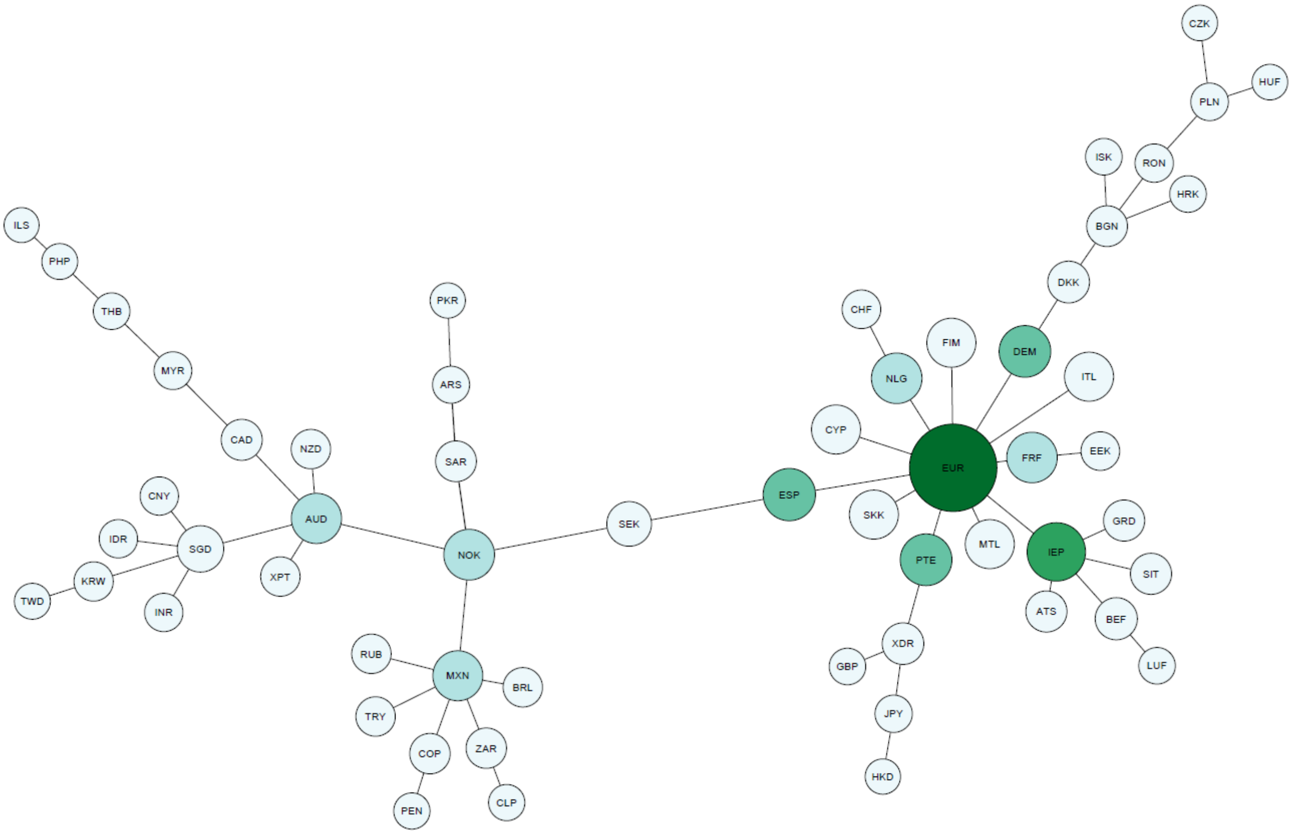

Figure 16: MST based on eigenvector centrality

ID	Label	Country	Region	Closeness	Betweeness	Eigenvector	Degree
1	ARS	Argentina	South/Latin America	0.170	56	0.059	0.034
2	AUD	Australia	Asia & Pacific	0.219	625	0.305	0.086
3	ATS	Austria	Europe	0.178	0	0.135	0.017
4	BEF	Belgium	Europe	0.179	56	0.155	0.034
5	BRL	Brazil	South/Latin America	0.174	0	0.104	0.017
6	GBP	United Kingdom	Europe	0.153	0	0.050	0.017
7	BGN	Bulgaria	Europe	0.166	315	0.129	0.069
8	CAD	Canada	North America	0.185	212	0.133	0.034
9	CLP	Chile	South/Latin America	0.149	0	0.044	0.017
10	CNY	China	Asia & Pacific	0.157	0	0.083	0.017
11	COP	Colombia	South/Latin America	0.175	56	0.122	0.034
12	HRK	Croatia	Europe	0.143	0	0.052	0.017
13	CYP	Cyprus	Europe	0.208	0	0.283	0.017
14	CZK	Czech Republic	Europe	0.114	0	0.033	0.017
15	DKK	Denmark	Europe	0.190	350	0.147	0.034
16	NLG	Netherlands	Europe	0.210	56	0.311	0.034
17	EEK	Estonia	Europe	0.174	0	0.089	0.017
18	EUR	Europe	Europe	0.261	1155	1.000	0.190
19	FIM	Finland	Europe	0.208	0	0.283	0.017
20	FRF	France	Europe	0.210	56	0.311	0.034
21	DEM	Germany	Europe	0.221	392	0.332	0.034
22	GRD	Greece	Europe	0.178	0	0.135	0.017
23	HKD	Hongkong	Asia & Pacific	0.134	0	0.027	0.017
24	HUF	Hungary	Europe	0.114	0	0.033	0.017
25	ISK	Iceland	Europe	0.143	0	0.052	0.017
26	INR	India	Asia & Pacific	0.157	0	0.083	0.017
27	IDR	Indonesia	Asia & Pacific	0.157	0	0.083	0.017
28	IEP	Ireland	Europe	0.216	269	0.458	0.086
29	ILS	Israel	Europe	0.110	0	0.021	0.017
30	ITL	Italy	Europe	0.208	0	0.283	0.017
31	JPY	Japan	Asia & Pacific	0.154	56	0.064	0.034
32	LUF	Luxembourg	Europe	0.152	0	0.050	0.017
33	MYR	Malaysia	Asia & Pacific	0.159	162	0.072	0.034
34	MTL	Malta	Europe	0.208	0	0.283	0.017
35	MXN	Mexico	South/Latin America	0.210	369	0.301	0.103
36	NZD	New Zealand	Asia & Pacific	0.180	0	0.103	0.017
37	NOK	Norway	Europe	0.248	978	0.314	0.069
38	PKR	Pakistan	Asia & Pacific	0.145	0	0.025	0.017
39	PEN	Peru	South/Latin America	0.149	0	0.044	0.017
40	PHP	Philippines	Asia & Pacific	0.123	56	0.037	0.034
41	XPT	Platinum Ounce	Asia & Pacific	0.180	0	0.103	0.017
42	PLN	Poland	Europe	0.128	111	0.069	0.052
43	PTE	Portugal	Europe	0.214	212	0.333	0.034
44	RON	Romania	Europe	0.145	162	0.084	0.034
45	RUB	Russia	Europe	0.174	0	0.104	0.017
46	SAR	Saudi Arabia	Middle east	0.202	110	0.129	0.034
47	SGD	Singapore	Asia & Pacific	0.186	269	0.234	0.086
48	SKK	Slovakia	Europe	0.208	0	0.283	0.017
49	SIT	Slovenia	Europe	0.178	0	0.135	0.017
50	ZAR	South Africa	Africa	0.175	56	0.122	0.034
51	KRW	South Korea	Asia & Pacific	0.158	56	0.100	0.034
52	ESP	Spain	Europe	0.259	810	0.345	0.034
53	XDR	Special drawing rights	Asia & Pacific	0.180	164	0.144	0.052
54	SEK	Sweden	Europe	0.254	806	0.202	0.034
55	CHF	Switzerland	Europe	0.174	0	0.089	0.017
56	TWD	Taiwan	Asia & Pacific	0.137	0	0.038	0.017
57	THB	Thailand	Asia & Pacific	0.139	110	0.051	0.034
58	TRY	Turkey	Europe	0.174	0	0.104	0.017

Figure 17: Countries, respective symbols and centrality measures