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FOREIGN PORTFOLIO INVESTMENT AND ECONOMY: THE NETWORK PERSPECTIVE

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ABSTRACT

The European Union and the Eurozone present an intriguing case of a strongly interconnected network with a high degree of dependence among nodes. This research focused on the investment network of the European Union and its major trading partners for a specific time period (2001–14). The changing investment patterns within the Eurozone suggest strong financial and trade links with central and large economies. This study is about the association between portfolio investments and economic indicators with respect to financial networks. The analysis used the strongly connected investment network of the Eurozone and its large trading partners. A strong correlation between increasing or decreasing investment patterns with economic indicators of particular economy was found. Interestingly, correlation patterns for network members other than Eurozone states were not as strong and depicted mild behavior. This also explains the significance of the levels of interconnectedness among nodes of one network with varying centrality measures. Investment network visualisation techniques helped to validate the results based on the network's statistical measures.

Keywords: European Union, Eurozone, Investment Network, Economic Indicators, Centrality Measures, Network Visualisation

INTRODUCTION

Portfolio investment is one of the major indicators of investor friendly and good performing equity markets of a single country. The rate of return is certainly the most prominent factor behind investment decisions, but ease of access, financial stability and lower levels of taxation play an evident role in the final decision of investment managers regarding liquidity flows. Being a part of an investment network, either weak or strong, can open up new possibilities to attract foreign investors by making markets more visible and investor friendly. Networks such as the European Union (EU) or the Eurozone are supposed to influence the investment flows for any particular nodes within, due to strong connectivity patterns and the possibility of small clusters. This study explores the details of the individualistic or local characteristics of every node within the investment network, mainly the connectivity patterns, closeness within the network or the possibility of large nodes in the neighbourhood. All these characteristics can influence the portfolio investment flows for any particular country. The objective of this study is to analyse the connectivity patterns with the network and the major economic indicators of any country to find possible connections or correlations in between: in other words, if economic stability or deterioration with respect to certain indicators can be associated with strong or weak connectivity patterns with the network, affecting the economic state of affairs.

Association or linkage does not have implications for causality. The strong linkage with a network and higher or improved economic indicators may or may not represent the underlying causes, but would reflect different possibilities. To understand these phenomena, we used the investment network of the European Union with a focus on individualistic characteristics of nodes. Based on criteria concerning closeness and connectivity, the nodes were divided into different tiers. At least one node from every tier was selected to build a correlation matrix based on network measures and relevant economic indicators to understand the relationship between network position, economic stability and attractiveness for investors.

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The network is based on the coordinated portfolio investment survey (CPIS) database compiled and regularly published by International Monetary Fund (IMF).

THE LITERATURE

The discussion on the relationship between portfolio investment and economy is not new; on the contrary, it is in a continuous process of development, enhancing understanding and the evaluation of different perspectives. Portfolio investment and associated concepts, such as its determinants, investor protection, efficiency of capital markets, flow determinants and patterns, exchange rate movements and information mobility, are too few to mention. Economic relations are also part of widely available literature. Rogoff (1999) focused on the considerable change from debt to equity financing within the economy; equity investment flows increase accordingly. Bekaert and Harvey (1998) confirm the direct impact of private equity investment on the macroeconomic performance of emerging markets. They also confirm the impact of portfolio investment on economic growth and stability of emerging economies (Bekaert and Harvey, 2000). Their later paper (Bekaert and Harvey, 2003) focuses on the impact of increased liquidity and better access to cheaper financing on the economic activity of the host country.

Researchers such as Levine and Zervos (1996) discuss investment's impact on liquidity and the implications for a better and broader market. Issues related to the improvement of foreign portfolio investments for any country, and its contribution towards a more efficient stock market and the elimination of financial constraints for domestic corporations, are discussed in detail by Laeven (2003) and Knill (2004). Besides the positive impact of portfolio investment, such as betterment of capital markets and capital access, there are studies focusing on short- or long-term adverse effects,. The multiplier effect for the growth of capital markets improves the liquidity situation for all investors; the capital flows are the depiction of enhanced economic growth and activity, and add value towards wealth creation and distribution. Efficient capital allocation is the ultimate aim, which can help the host economy grow multidimensional and dynamically. Rajan and Zingales (1998), Wurgler (2000) and Love (2003) contribute towards the better explanation of these issues. There are studies focusing on economic development of different countries due to foreign portfolio inflows, such as Agarwal (1997), focusing on Korea, Indonesia, India and Thailand, and Duasa and Kassim (2009), focusing on Malaysia. Both studies conclude on a positive note in terms of the relationship between portfolio investment and the economy.

Besides the wide spectrum of literature on portfolio investment flows and the resultant efficiency of markets and economic impact, there is scarcity of network perspective, especially on liquidity flows and resultant impacts. There are studies related to the network analysis of capital markets, for example the network analysis of the Chinese stock market by Huang, Zhuang and Yao (2009). The transformation process of investment network is discussed in Hakeem and Suzuki (2016a and 2016b). We have extended our analytical approach to evaluate the characteristics of individual nodes to establish the relationship between portfolio investment flows and economic indicators.

THEORETICAL BACKGROUND

The distinct characteristics of the nodes are explored by using multiple centrality and relevant measures at micro level. Closeness centrality, clustering coefficients, the in-degree and the out-degree are examined for every single node to categorise them accordingly. By using these and other measures, we divide the existing nodes into three classes or tiers. The steps of the analytical process are as follows:

1. Analysis of individual characteristics of nodes by using centrality and relevant measures;
2. Application of classification criteria based on resultant measures;
3. Classification of 26 nodes into three different tiers based on their individual positions within the network;
4. Selection of at least one node from each tier for correlation analysis;

5. Selection of the macroeconomic indicators for designated countries;
6. Correlation matrices based on network analytics and macroeconomic indicators for designated countries; and
7. Identification of correlation patterns and differences according to the nodes and tier classifications.

Centrality Measures

The following centrality measures are used for the investment network to understand the individual characteristics of the nodes. We will briefly introduce a few measures; a detailed description of centrality measures and their implications for network analysis is available in Hakeem and Suzuki (2015).

Degree Centrality

The simplest and earliest centrality measure in a network is the degree of a node and the number of edges connected to it. In directed networks, nodes have both an in-degree and an out-degree, and both may be effective if used in the appropriate circumstances. Although degree centrality is a simple centrality measure, it can be very insightful. In a financial network, for instance, the financial institution or a node connected to all other nodes can have much more influence on other nodes, as well as on the resilience of whole network. The standardised degree centrality of a node is its degree divided by the maximum possible degree.

$$c_i^d = \frac{d}{n-1} \tag{1}$$

The aggregate degree centrality for the whole network is:

$$C^d = \frac{\sum_{i=1}^{n} |c_i^d - c_i^d *|}{(n-2)(n-1)} \tag{2}$$

where *degree centrality* "C^d" is calculated by using the maximum value, while *n* represents the number of nodes within that particular network. The higher the number of nodes, the higher the degree centrality. The degree centralisation of any regular node is 0, while star has degree centralisation of 1.

For a node, the number of edges within it is known as in-degree and the number of edges originating from it is known as out-degree. A node with no in-degrees, only out-degrees, is known as "source", and a node with all in-degrees but no out-degrees is called "sink". A balanced directed graph has an equal number of in- and out-degrees.

Closeness Centrality

This centrality measure is totally different, as it measures the mean distance from one node to other nodes. It is the concept of a geodesic path, the shortest path between two nodes. Closeness centrality has small values for nodes that are separated from others by only a short geodesic distance on average. Such nodes might have better access to information at other nodes, or more direct influence on other nodes. In a financial network, for example, a financial institution with a lower mean distance from others might have better access to liquidity and important financial information. Closeness centrality is a very natural measure of centrality and is often used in different types of network studies. Closeness is based on the length of the average shortest path between a vertex and all vertices in the graph:

$$C_i^c = \frac{n-1}{\sum_{j \neq i}^{n-1} \delta_{ij}} \tag{3}$$

where δ_{ij} represents the geodesic path between i and j. Aggregate centrality for the whole network can be defined as follows.

$$C^c = \frac{\sum_{i=1}^{n} |C_i^c - C_i^c *|}{(n-2)(n-1)(2n-3)} \tag{4}$$

If $C_i^c *$ is the maximum closeness centrality a node can attain, then the aggregate closeness centrality is the variation in the closeness centrality of all nodes divided by the maximum possible closeness centrality for a particular network.
In contrast, Normalised Closeness Centrality is:

$$C_i^{c'} = C_i^c/(n-1) \tag{5}$$

where δ_{ij} is the distance between node i and j, while n refers to the number of nodes within the network.

Clustering Coefficient

The clustering coefficient is the degree by which nodes tend to make groups or clusters. The clustering of nodes having a similar connectivity pattern or other characteristics is evident in network analysis. There are two ways to measure the clustering of nodes in particular networks:

1. Global Clustering Coefficient; and
2. Local Clustering Coefficient

The first type, "Global Clustering Coefficient", is based on a trio of nodes. The trio is a combination of three nodes connected to each other. The clustering coefficient measures the density of triangles in the network:

$$C^{Cl} = \frac{1}{n}\frac{[(k^2)-(k)]^2}{k^3} \tag{6}$$

In a random network of connections between nodes and edges, k^2 and k has fixed or finite values and the quantity becomes as small as $n \rightarrow \infty$, so the clustering coefficient can be small as the size of the network grows. The reality can be very different depending on network type and size. The aggregate clustering coefficient can be calculated by taking the mean of the local clustering coefficient of each node:

$$C^{Cl} = \frac{1}{n}\sum_{i=1}^{n} C_i^{cl} \tag{7}$$

Whereas the local clustering coefficient of a node can be defined as follows:

$$C_i^{cl} = \frac{e_{jk}}{k_i(k_i-1)} \tag{8}$$

where e_{jk} is the path from i to j, and k_i are the number of neighbours of a node. We can also represent it in the following way:

$$C_i^{cl} = \frac{n_i}{k_i(k_i-1)} = \frac{\sum_{jk} e_{ij}e_{jk}e_{ki}}{k_i(k_i-1)} \tag{9}$$

The Correlation

Any statistical relationship between two random variables can be termed a dependence or linkage in a network context. Correlation involves dependence or linkage between two variables, although, in a statistical context, it is the level of linear relationship between two variables. A simple example of a correlation can be the relationship between the supply and price of crude oil on the international market. As supply increases, the price goes down accordingly.

We used "Pearson's product moment correlation coefficient" to explain the linkage between network indices and economic indicators. By considering the basic difference between correlation and causation, we developed matrices to analyse the linkage for different countries during varying time periods.

For a series of n measurements of X and Y, known as x_i and y_i for $i = 1, 2, \dots\dots.. n$, the sample correlation coefficient can be used to estimate correlation r_{xy} between both variables. It can be written as:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - \bar{y})}{n s_x s_y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}\,(y_i - \bar{y})^2}} \quad (10)$$

Where $\bar{x}$ and $\bar{y}$ are the sample means and s_x and s_y are the sample standard deviations of X and Y. We can also express it as follows:

$$r_{xy} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{n s_x s_y} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - \left(\sum x_i\right)^2}\,\sqrt{n\sum y_i^2 - \left(\sum y_i\right)^2}} \quad (11)$$

The correlation coefficient can be +1 to represent a perfectly positive correlation relationship, or -1 to show a perfectly negative correlation between two variables. The range of resultant matrix is $-1 \leq r \leq +1$, which can explain the strength, level and type of relationship.

EXPLORING THE NETWORK

The Investment Network

In our analysis of investment network, we used data from the Coordinated Portfolio Investment Survey (CPIS) compiled and published regularly by the IMF. The same data set is widely used in literature for network or non-network analysis related to global portfolio investment patterns. The CPIS data consists of the aggregate amount received by a single country or invested in one country by foreign individuals, corporations and investment agencies or other vehicles in equity markets. We used data from 2001 to 2014, a total of 14 years. There are 26 countries or nodes within this network. Out of these 26 countries, 24 are European Union (EU) members, while the remaining two, US and Japan, are major partners of the EU in investment and trade. There are 28 EU member states; our sample includes all major and prominent nodes according to economic output and capital market statistics. The countries excluded due to data constraints are Latvia, Lithuania and Slovakia as Eurozone member states, and Croatia as an EU member.

The timespan selected is interesting, as we have seen huge ups and downs within this decade and can easily call it a decade of change. There was the Global Financial Crisis (GFC), impacting housing, equity and debt markets directly, which began around late 2007. Europe also faced a daunting, tough debt crisis after the GFC. The debt crisis compressed weak European economies and had a severe impact on bilateral relations within the European Union. The resulting austerity measures impacted millions of households in affected countries by increasing direct and indirect taxes, reducing employment opportunities and hampering growth and development.

Selection Criteria and Nodes

By considering the centrality measures and observing the flow patterns, we categorised all nodes into three different tiers.

- Tier 1 - Strong level of connectivity
- Tier 2 - Intermediate level of connectivity
- Tier 3 - Low level of connectivity

Table 1: Average Closeness Centrality and Classification (Source: Own Calculations) CC: Closeness Centrality, n= number of nodes

Classification Based on Average Closeness Centrality		
Tier 1	Tier 2	Tier 3
$CC \leq 1.05$	$CC \leq 1.20$	$CC \geq 1.21$
n = 13	*n = 9*	*n = 4*
Austria Luxembourg United States Germany Italy France Netherlands Belgium Ireland Denmark Sweden Cyprus Japan	United Kingdom Estonia Czech Republic Greece Slovak Republic Hungary Finland Spain Portugal	Poland Bulgaria Malta Romania

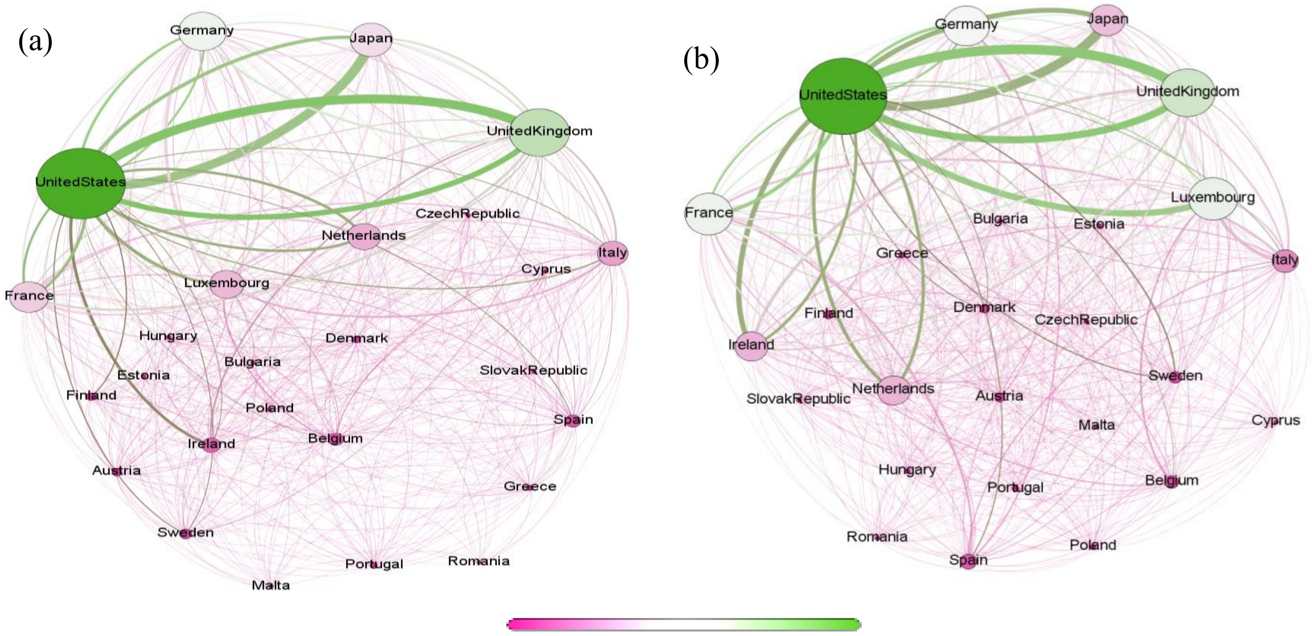
Table 1 explains the classification of all nodes with respect to average closeness centrality. There are 13 nodes in the first tier, which represent the strongly connected nodes of the investment network. The inclusion of these nodes within the first tier is confirmed by in- and out-degree measures. There are no surprise inclusions within this tier, as connectivity and flow of all relevant countries is high enough. Tier 2 represents mid-level connectivity of included nodes with the rest of the network. There is a surprise inclusion within this group: the United Kingdom. London is the capital of the UK and the hub of the international bond market. LIBOR is used worldwide for settlements of debt and relevant contracts. Although the UK is just above the criteria, and can with a small relaxation join Tier 1 countries, our early data indicates the lower level of in- and out-degree measures for the UK at a certain time period. As an attractive investment destination, it might not be able to invest in other foreign markets. The rest of the Tier 2 countries follow their intermediate connectivity levels within the network. Tier 3 includes the least central nodes with less connectivity and flow with other partners. These countries tend to have a higher clustering coefficient as they are not fully connected with the whole network. We believe this group is balanced and accurate according to degree, clustering and centrality measures.

We will select four countries for further analysis to establish our theory about connectivity and economy. The following countries are selected from all tiers:

1. Germany (Tier 1)
2. France (Tier 1)
3. Greece (Tier 2)
4. Romania (Tier 3)

The countries are selected according to their connectivity levels as are represented in Table 1.

Figure 1: Investment Network for the year 2001(a) and 2014(b)
(Source: Coordinated Portfolio Investment Survey, International Monetary Fund 2015)



Lowest Value to Highest Value

Figure 2: Correlation Matrices of France (a), Germany (b), Greece (c) and Romania (d)
N1 to N11 represent network indices, while E1 to E8 represent economic indicators. Colour Patterns: Red represents a negative correlation; Green represents a positive correlation; and Yellow represents data points below threshold value

	E1	*E2*	*E3*	*E4*	*E5*	*E6*	*E7*	*E8*
N1	0.593	0.539	0.594	(0.533)	0.521	0.373	0.457	(0.566)
N2	0.884	0.830	0.886	(0.794)	0.783	0.418	0.683	(0.814)
N3	0.907	0.844	0.909	(0.815)	0.801	0.468	0.700	(0.844)
N4	0.936	0.943	0.926	(0.930)	0.913	0.624	0.849	(0.873)
N5	0.895	0.952	0.875	(0.959)	0.946	0.746	0.912	(0.861)
N6	0.946	0.904	0.944	(0.873)	0.853	0.488	0.762	(0.857)
N7	(0.870)	(0.843)	(0.866)	0.813	(0.798)	(0.501)	(0.701)	0.847
N8	(0.884)	(0.830)	(0.886)	0.794	(0.783)	(0.418)	(0.683)	0.814
N9	(0.785)	(0.766)	(0.784)	0.739	(0.737)	(0.376)	(0.672)	0.713
N10	0.940	0.910	0.937	(0.891)	0.884	0.549	0.806	(0.874)
N11	0.936	0.943	0.926	(0.930)	0.913	0.624	0.849	(0.873)

(a)

	E1	E2	E3	E4	E5	E6	E7	E8
N1	0.836	0.665	0.827	(0.815)	0.798	0.694	0.660	0.872
N2	0.763	0.571	0.751	(0.722)	0.571	0.573	0.565	0.712
N3	0.850	0.658	0.839	(0.818)	0.734	0.676	0.653	0.845
N4	0.929	0.854	0.927	(0.938)	0.853	0.883	0.832	0.958
N5	0.902	0.768	0.895	(0.887)	0.833	0.801	0.747	0.930
N6	0.932	0.898	0.932	(0.957)	0.852	0.923	0.874	0.961
N7	(0.763)	(0.571)	(0.751)	0.722	(0.571)	(0.573)	(0.565)	(0.712)
N8	(0.763)	(0.571)	(0.751)	0.722	(0.571)	(0.573)	(0.565)	(0.712)
N9	(0.824)	(0.790)	(0.831)	0.847	(0.797)	(0.856)	(0.826)	(0.839)
N10	0.932	0.825	0.930	(0.937)	0.838	0.856	0.833	0.947
N11	0.929	0.854	0.927	(0.938)	0.853	0.883	0.832	0.958

(b)

	E1	E2	E3	E4	E5	E6	E7	E8
N1	0.840	0.736	0.842	(0.289)	0.640	(0.105)	0.628	(0.512)
N2	(0.242)	(0.121)	(0.234)	(0.145)	(0.003)	0.176	(0.141)	0.590
N3	0.741	0.677	0.745	(0.325)	0.620	(0.048)	0.566	(0.317)
N4	0.852	0.435	0.852	0.151	0.254	0.131	0.246	(0.727)
N5	0.679	0.083	0.677	0.556	(0.142)	0.193	(0.105)	(0.824)
N6	0.536	0.802	0.540	(0.778)	0.850	(0.096)	0.757	0.033
N7	(0.153)	(0.310)	(0.154)	0.277	(0.323)	0.284	(0.425)	0.141
N8	0.242	0.121	0.234	0.145	0.003	(0.176)	0.141	(0.590)
N9	(0.031)	(0.539)	(0.034)	0.819	(0.681)	0.003	(0.664)	(0.374)
N10	0.658	0.884	0.663	(0.762)	0.917	(0.069)	0.859	(0.099)
N11	0.852	0.435	0.852	0.151	0.254	0.131	0.246	(0.727)

(c)

	E1	E2	E3	E4	E5	E6	E7	E8
N1	0.615	0.616	0.606	0.037	0.663	0.598	0.411	(0.340)
N2	0.914	0.956	0.923	(0.231)	0.942	0.804	0.799	(0.186)
N3	0.919	0.951	0.922	(0.159)	0.958	0.830	0.755	(0.269)
N4	0.736	0.853	0.755	(0.534)	0.876	0.659	0.909	0.120
N5	0.697	0.821	0.716	(0.557)	0.846	0.617	0.901	0.164
N6	0.894	0.954	0.903	(0.338)	0.959	0.837	0.855	(0.162)
N7	0.456	0.481	0.451	0.173	0.521	0.309	0.275	(0.263)
N8	(0.914)	(0.956)	(0.923)	0.231	(0.942)	(0.804)	(0.799)	0.186
N9	0.741	0.622	0.730	0.125	0.611	0.776	0.375	(0.507)
N10	(0.210)	(0.234)	(0.207)	(0.188)	(0.256)	0.046	(0.073)	0.073
N11	0.736	0.853	0.755	(0.534)	0.876	0.659	0.909	0.120

(d)

CORRELATION BETWEEN NETWORK AND ECONOMIC INDICATORS

Economic Indicators

The economic indicators used for analysis were obtained from the International Monetary Fund (IMF). The database of International Financial Statistics (IFS) was used to obtain the relevant measures. The IFS is one of the fund's main databases and has been available since 1948. We used a similar timespan as we did for our network data, from 2001–2014. Total numbers of economic indicators obtained and used in the analysis were in the double digits; a rough estimate stands around 30. At the final stage, eight economic indicators were selected. To elaborate our idea of a correlation between the investment network and the economy, we used the following economic indicators (Table 2).

Table 2: Economic Indicators used for Analysis (Source: IFS 2015, IMF)

S. No.	Economic Indicators	Code Assigned
1	Gross domestic product, current prices	E1
2	Gross domestic product, deflator	E2
3	Gross domestic product per capita, current prices	E3
4	Gross domestic product based on purchasing-power-parity (PPP) share of world total	E4
5	Inflation, average consumer prices	E5
6	General government revenue	E6
7	General government gross debt	E7
8	Current account balance	E8

Network Indicators

The network indicators used for analysis were obtained from the CPIS (Coordinated Portfolio Investment Network) investment network. The CPIS database is compiled and regularly published by the IMF. The network indicators or indices are the outcome of our calculations, unlike the economic indicators, which are available through the database. The methodology and calculation mechanism is briefly explained here; for a detailed theoretical background please refer to Hakeem and Suzuki (2015).

Table 3: Network Indicators used for Analysis (Source: CPIS 2015, IMF)

S. No.	Network Indicator	Code Assigned
1	In-Degree	N1
2	Out-Degree	N2
3	Degree	N3
4	Weighted Degree	N4
5	Weighted In-Degree	N5
6	Weighted Out-Degree	N6
7	Eccentricity	N7
8	Closeness Centrality	N8
9	Betweenness Centrality	N9
10	Clustering Coefficient	N10
11	Strength	N11

Correlation Matrices of Selected Countries

The correlation matrices are presented in Figure 2(a)–(d) for France, Germany, Greece and Romania. These matrices are based on 14 years of data of economic indicators and network indices. These matrices give us insights regarding the relationship or linkages between portfolio investment and the economic conditions of certain countries. The results can be generalised for other countries in the same “tier”.

Tier 1 Countries

Tier 1 is representative of countries having strong connectivity and flow linkages with networks. The group is composed of 13 countries, of which 11 belong to the EU, besides Japan and the US. The correlation matrix for France and Germany is not identical, like their overlapped network indices; but there are more similarities than differences. First, we look at Figure 2a, which represent France’s matrix. There is indeed a correlation pattern and relationship between networks, indices and macroeconomic indicators.

There is a strong correlation between Gross Domestic Product (GDP), Purchasing Power Parity (PPP) with In-Out degree and weighted degree measures. The higher the connectivity level, the higher the impact on economic growth patterns. There is a strong negative correlation between a network’s centrality measures, such as closeness, betweenness and eccentricity with GDP and PPP. This negative correlation depicts the positive impact due to technical reasons; the centrality measures move to the reverse side, or statistically decrease if the level of centrality improves. The more central nodes would have lower values compared to the less central nodes. The correlation matrix takes this on the opposite side. If GDP is increasing and the statistics of closeness are decreasing, it is perfectly negatively correlated. The implications of this strong negative correlation are positive, so the relationship between closeness, betweenness and eccentricity is strong and understandable. There are two other strong relations between network indices: inflation and current account balance. It is interesting to know that the strongly connected nodes have less inflation and better trade relations with trading partners. Cumulatively, for France, there are strong relations between its investment network and economic indicators. The relationship is not causal; there can be other underlying reasons besides the one under consideration in this study.

For Germany, the relationship is of similar nature. The increase in centrality measures has strong connections with economic growth, inflation, current account balance and government debt. The current account balance of Germany is improving with the passage of time; so is its centrality. That makes it positively correlated compared to France, which has a negative correlation with this particular variable. Tier 1 countries have important positions within networks; with strong centrality indices, we can find correlation patterns with their economic indicators. These correlations are not causal; rather, they show the existence of a relationship. The general conclusion should include this trend. The more central a country is, there more relationships or correlations it can have. This can also have implications for countries with less connectivity, to help improve their network position and capture more economic benefits.

Tier 2 Countries

Tier 2 countries are modestly linked with the investment network. Greece is selected as representative of this group. The country has modest linkages with the investment network. It showed improvements regarding connectivity patterns initially and had a good position for a while, before again feeling the heat of the Eurozone debt crisis.

The correlation matrix representing the possible ties between Greece's economy and its network position is shown in Figure 2c. The correlation patterns are there, but if we compare it with Tier 1 countries, then the level of correlation is much lower and scattered. We might not be able to draw any conclusions about any strong relationship between economic indicators and network indices. Being a standalone country and group representative of Tier 2, we can find certain patterns for certain periods of time at least. The connection of In-out degree and weighted degree with GDP and PPP is one of the most prominent. There is also an indication of a link between inflation and general government debt with a clustering coefficient. Tier 2 countries have a higher possibility of joining any cluster, compared to Tier 1 countries; so, the explanation regarding the increase in the clustering coefficient due to the Eurozone debt crisis might have exposed Greece to crisis, which could have been handled with better management of inflation and government debts.

The conclusion on Greece can be generalised for Tier 2 countries due to economic similarities and prevailing circumstances. These nodes do not have strong connectivity patterns, so experience variations in their position within network. The links or correlation between network indices of Tier 2 countries and economic indicators are not high enough due to limited connectivity and exposure.

Tier 3 Countries

Tier 3 countries are weakly linked with the investment network and do not possess a strong position within it. Romania is representative of this small group, which may feel alienated compared to Tier 1 and Tier 2 countries. Romania is an interesting case of connectivity. It had an extremely low level of connectivity initially, and improved at a later stage. Recently, it reached the same degree of connectivity as Greece, so we are able to analyse the changes in connectivity and its consequences.

Figure 2d represents the Romanian correlation matrix. It seems to have a modest degree of correlation between economic indicators and network indices. If compared with Tier 1, then the patterns are not that significant; but for Tier 2 they are not that weak either. It seems Romania may have a better relationship between its economic indicators and networks indices due to an improvement in connectivity. Though its patterns may not exceed the level Greece already has, the case of better connectivity and improved linkages must be taken into consideration. Besides general relationships, it is interesting to understand the association between clustering coefficients and economic indicators. Unlike Greece, Romania represents a negative link there, suggesting that it might be connecting more aggressively and removing the clustering barriers.

The basic relationship between GDP, PPP and centrality indices shows sign of positive correlation. There is a connection in between. The conclusion for Tier 3 can be generalised for

Tier 3 and Tier 2 countries as well. Improvements in connectivity and network position can increase or enhance the correlation patterns. The countries must strive to connect with all nodes to fully capitalise the opportunities for market efficiency and improvements on the economic front.

CONCLUSION

The investment network is not a complete graph, and the connectivity pattern of different nodes varies accordingly. Some nodes have a central position with higher connectivity levels compared to other nodes. The countries can be divided into different groups or tiers based on the resulting centrality and analytical measures. The classification of countries into different groups explains the differences in connectivity patterns for nodes. We divided the nodes into three tiers based on their closeness and/or centrality. The connectivity is not uniformly distributed among all nodes, as assumed in different earlier studies. Tier 1 countries have an important position within the network; with strong centrality indices, we can find correlation patterns with their economic indicators. These correlations are not causal, but show the existence of a relationship. The general conclusion should include this trend: the more central a country is, the more relationships or correlations there are to be found. This can also have implications for countries with less connectivity to improve their network position and capture more economic benefits. The conclusion regarding representative countries of tier 2 can be generalised for the whole group due to economic similarities and prevailing circumstances. These nodes do not have a strong connectivity pattern, and so experience variations in their position within the network. The links or correlation between network indices of Tier 2 countries and economic indicators is not high enough, due to limited connectivity and exposure. The basic relationship between GDP, Purchasing Power Parity (PPP) and centrality indices shows signs of positive correlation. There is a connection between them. The conclusion for Tier 3 can be generalised for Tier 3 countries. Improvements in connectivity and network position can increase or enhance the correlation patterns. The countries must strive to connect with all nodes to fully capitalise the opportunities for market efficiency and improvements on the economic front. The European Union is the case for other investment networks and individual countries to establish strong linkages to increase connectivity patterns. More connected nodes have a strong positive correlation between investment and economy.

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