Connectivity and closeness among international financial institutions: a network theory perspective

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Abstract: This article focuses on connectivity and closeness between financial institutions. Financial institutions are a subset of multinational corporations and play an important role in our modern economies. By studying connectivity and closeness, this article proposes a network theory approach to the notion of systemic risk. Using network theory, we propose to look at potential networks between financial institutions through their boards of directors. Measures of centrality (degree, closeness, betweenness, eigenvalue) and force-directed networks are provided for each country. We built a large sample (43,399 individuals; 2,209 institutions) across 52 countries using Bureau van Dijk's database. We find corporate interlocks showing – to some degree – the level of concentration within the financial system. The main contribution of this article is to show some evidence of small-world properties of the international financial system; the ramifications of this question could be critical, notably in terms of systemic risk.

Keywords: corporate governance; board of directors; network theory; network graphs; board interlocks.

Reference to this paper should be made as follows: Warin, T. and Sanger, W. (2018) 'Connectivity and closeness among international financial institutions: a network theory perspective', *Int. J. Comparative Management*, Vol. 1, No. 3, pp.225–254.

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1 Introduction

Presenting a comparative corporate governance panorama, this article focuses on the concepts of connectivity and closeness between financial institutions through their boards of directors. After constructing a unique overall sample of 43,399 directors from 2,209 financial institutions in 52 countries, we explore the social networks of financial institutions. These institutions are a subset of multinational corporations (MNCs) and considering the fact that the banking system is such a vital component of our modern economies, it is of the utmost importance to also study financial institutions' networks and their implications. Probably more than any other firms, it is easy to think about financial institutions in terms of a network. Indeed for instance, a bank is a network of subsidiaries across a country and/or across countries. Financial institutions are also connected through a set of networks between them to facilitate the flow of liquidity (the TARGET payment system, for instance). And in terms of governance, financial institutions are also connected through their board of directors, like any other firm. However, in the context of a financial institution, this connectedness can generate risks that would be different from MNCs in other industries. Indeed, as experienced during the 2008 financial crisis, a collapse of the financial markets can spread throughout the whole economy, and may not be limited to one industry. This is why the notion of systemic risk – the industry risk – has a different meaning when it comes to the financial industry.

This is precisely the first contribution of this article. Indeed, to the best of our knowledge, this article is among the first ones to look at the individual level (43,399 directors) for the top 50 financial institutions per country (52 countries) through the lens of the boards of directors. More precisely, this article is an empirical estimation of the importance of connectivity and closeness between boards of directors based on a massive dataset, which we created entirely and for which we carefully validated its quality.

A second contribution is that it adds to the literature on International Business by studying corporate interlocks in multinational companies, while focusing here on the financial industry in an international perspective.

A third contribution is purely methodological and relies on the extensive use of Network Theory to study the financial industry's social network, at the unit of individuals having a seat on multiple boards of directors.

Such a study has many interests and leads to some general laws:

1 It highlights the importance of social networks as captured by the financial institutions' boards of directors in particular in developed economies.

2 It shows how much and how deeply financial institutions are connected and sometimes integrated in 'clubs' ('small-world' in network theory) within certain countries.

3 It can serve as one of the proxies for the study of knowledge pipelines in the financial industry.

The latter have positive and negative ramifications. For instance, information can flow more smoothly between boards of directors and avoid issues related to asymmetries of information within the industry. However, this information flow can create a homogenous culture and raise the level of systemic risk (besides the well studied two other financial risks: systematic and specific risks). This debate goes beyond the scope of this article. For this present article, our goal is to first find whether we have evidence of small-world properties in the financial industry. The results from this article will matter in order to build the basis for further research studying for instance the ramifications in terms of systemic risk.

Individuals associated to multiple institutions in the management or in the board of directors make it possible to connect financial firms together in the same country. From an extensive dataset of 49,399 individuals from 2,209 financial institutions, such cross-countries differences in network characteristics are investigated. Moreover, high-level executives could be studied since they could be connected to other corporations from other industrial sectors too. As such and while not being the focus of this article, spillovers could be observed from an industry to another one.

Researches on social networks are increasingly more popular across disciplines, and are gaining some momentum in the international business field. We concentrate on financial institutions for two reasons. Firstly, financial institutions are established at the international level, sharing knowledge and behaviours across subsidiaries. Secondly, since 2008, systemic risk in the financial industry has been a subject of importance for policymakers. The financial industry is often seen as one of the most innovative and efficient industry in a country. Based on a robust and convincing mathematical framework, financial markets succeeded at convincing regulators to cancel the Glass-Steagall Act in the late 1990s. The decision was based on the diversification principle explaining that the deeper a financial market, the lower the risk. However, the 2008 financial crisis is evidence that the theoretical framework either has a missing piece or that its transposition in the real world through an industry faces some issues. In both cases, the empirical implementation of the financial models has something inherently wrong. The fundamental mathematical framework has highlighted only two categories of financial risks:

1 the systematic risk

2 the specific risk.

The notion of systemic risk was not part of original financial models. While specific risks are lowered by an increase of the depth and breadth of the financial market, the systemic risk increases with the complexity of the financial markets (Warin and Prasch, 2013).

Based on the lessons of the latter article, an interesting research question is to look at one potential factor of tension in the industry: the corporate governance of financial institutions. If boards of directors were too integrated or too close, we could make the assumption that best practices as well as too homogenous analyses could be spread through these 'small-worlds' in the financial industry. This combination could be toxic and thus lead to a rise in the systemic risk during difficult times (high systematic risk times). The 2008 financial crisis and its consequences lead to the need of identifying reliable elements of systemic risk in the literature. As aforementioned, this article does not address this question precisely – it is just for illustration purposes here –, but further work could build on the evidence that small-worlds exist in the financial industry and what their ramifications (positive and/or negative) are.

One of the original contributions of this article is to be at the crossroad of two literatures, both through the lens of the so-called knowledge pipelines:

1 the literature on corporate governance (agency theory and small-worlds)

2 the literature on network theory.

In this article, in particular, we want to investigate the small-world property of networks in the financial industry. Our methodological approach is to use network theory to characterise each country in order to visualise such differences.

With our database linking each institution to its board of directors' members (43,399 directors) – and vice-versa: each person to its affiliated financial firms across the globe - we provide evidence of a complex network. From interbank loans (Minoiu and Reyes, 2013) to the small-world of owners and directors (Kogut and Colomer, 2012), social network analysis has been used to emphasise the importance of key individuals, financial institutions or countries at the international level. Network topology has been used in conjunction with variance decomposition to measure how US financial firms where connected before and during the 2007–2008 financial crisis (Diebold and Yilmaz, 2014). Our research question is summarised as follows: how do social ties approximate financial convergence?

The rest of the paper is organised as follows. In Section 1, we provide a literature review regarding interlocked directorates across various corporate governance regulatory environments. Section 2 describes the dataset we collected to tackle our research question. In Section 3, we present the methodology and the results from the network analysis. This part is divided into three components, i.e., the network characteristics, a graphical approach and the community detection. Finally, we put our results in perspective in the last section.

2 Literature review

2.1 Social networks and knowledge pipelines

Traditionally, knowledge pipelines are the informational links between industrial clusters (Bathelt et al., 2004). Firms within a well-connected cluster will benefit from positive knowledge spillovers in two ways: first, individual firms can collect information from external clusters and then, this information will flow to interconnected firms within the cluster ('local buzz'). Concerning the financial industry, individuals acting on multiple boards of directors may serve as network actors and thus create the connections between firms locally (within the same country) and internationally (across multiple countries and financial institutions). These individuals enact the formation of knowledge pipelines throughout the financial industry.

Indeed, the structure of social relations between and within firms plays an important role on firms. For instance, these social relations have an influence on their level of innovation. In fact, Fritsch and Kauffeld-Monz (2008) explored the impact of network structure on knowledge transfer between 300 firms and R&D organisations. They found that strong ties are prerequisites to more favourable and effective knowledge exchanges between partners. Instead of extensive market research, Ellis (2000) presented that firms tend to capitalise on already existing social ties in the case of foreign market entries. There are reasons to believe that the financial industry is no different and that social networks play an important role, which we explore in this article.

To go a little further, by adopting a cluster categorisation, Bathelt and Li (2012) observed that MNCs tend to set up affiliates in similar specialised clusters. MNCs are viewed as "corporate networks that are embedded in and link[ed] with various cluster networks". Moreover, the social network approach was also used to highlight different behaviours between firms. In particular, Joshi et al. (2002) analysed conflicts between individuals inside a multinational company. They focused on how effective teams were functioning through 28 respondents located in six different countries. Through a panel analysis of 20 years concerning 109 firms, Vasudeva et al. (2012) emphasised the impact of the institutional context on innovation and organisational outcomes.

The rest of the literature review will present some works on the degree of interlocked directorates depending on the legal environment and its implications for firms.

2.2 Interlocked directorates across different corporate governance regulatory environments

The degree of corporate interlocks may depend upon the quality of the regulatory environment in a country. At the end of the 90s, La Porta et al. (1998) established the Anglo-Saxon model as the most efficient legal system in terms of minority shareholder protection (Type II Agency Problems). Scandinavian, Germanic or Civil Law countries did not seem to offer an adequate protection for small shareholders compared to Common Law countries. The main reason why this legal system is seen as the most protective one is that the investor's rights are written in the laws. When property rights are not protected, firms cannot fully capture the benefits of transparency (Durnev et al., 2009).

However, this somewhat simple point of view (i.e., categorising the dynamics of corporate governance into only four different types) has since been challenged. Globalisation has shown different behaviours in terms of corporate governance, especially from emerging countries. These countries are characterised as offering the worst protection for investors in terms of corporate governance practices compared to the US legal system (Gibson, 2002). Nevertheless, South-Eastern Asian countries' economic performances could question this assumption. One mechanism implemented to uphold the highest standards of corporate governance is to be cross listed in another country, in the US, for example, (Doidge et al., 2009). Again here, the US (and the Anglo-Saxon) corporate governance system is seen as a standard to which other systems can be compared.

Scholars tried to understand emerging markets as being more complex entities. For instance, the topic of family and business groups shed light on how connected groups are within each country (Bertrand et al., 2008; Khanna and Palepu, 2000; Khanna and Yafeh, 2007). Hence, La Porta et al.'s (1998) vision may be more complicated. There is not a unique Anglo-Saxon system, nor no difference within regions or countries sharing the same legal system (Kogut and Colomer, 2012). One of the globalisation's consequences is the rise of emerging countries but also a more dense and complex network between firms and countries. Board of directors, power and ownership may not be well distributed, and seems to be concentrated in a few hands, with an increased role for financial institutions. These dynamics amplify the importance of ties between groups in the corporate governance literature.

2.3 Interlocked directorates and their ramifications

At first glance, interlocking directorates may not be an effective mechanism for firms or in a more global perspective for industries. However, having a CEO on the board of directors of another firm is not a seldom event. In fact, 69% of outside directors are active CEOs at other firms (Lorsch and MacIver, 1989) and CEOs of the SandP500 firms held on average 1.87 other directorships in 1990 (Booth and Deli, 1996).

Links between boards of directors through individuals imply challenges and opportunities on three levels, with respects to the industrial sector, the firms and the individuals.

At the industry level, a more connected industry may expose itself to higher systemic risks and to external shocks (Wong and Fong, 2011). For firms, interlocking directorates has led to higher abnormal returns (Byrd and Hickman, 1992), a deterioration of earning quality (Falato et al., 2014; Hashim and Rahman, 2011) but more importantly to a reduction in the monitoring power of each board. The reason behind this last assumption is that executives may be distracted due to their extensive role in many firms (Rosenstein and Wyatt, 1994). Personal benefits may also occur, from an enhancement of the CEO private interests (Fich and White, 2005) to higher wages of reciprocally interlocked CEOs (Hallock, 1997).

On the other hand, many benefits are derived from this corporate behavior. On the industry level, trust (Robins and Alexander, 2004) and political cohesion between firms (Byrd and Hickman, 1992) are amongst the positive incentives of interlocking directorates. For firms, it is a mechanism used in order to assess external resources (Boyd, 1990; Mintz and Schwartz, 1985). More importantly, it is a way of sharing information in order to extract sector trends and corporate strategies (Renneboog and Zhao, 2014), which could participate into spreading best practices from other boards of directors (Haniffa and Cooke, 2002).

Scholars have adopted a social network perspective to link the concept of systemic risk to the financial industry through several empirical papers. Temizsoy et al. (2016) explored how network positioning could affect a bank's ability to borrow through its interest rate in Italy. From 2006 to 2009, they studied two types of centrality measures (local and global): if a bank is locally more connected, its borrowing costs will increase (whereas the cost for lenders will be lower); on the other hand, if a bank is more connected globally, lenders will have to pay a premium (and the borrower will benefit from it). Constantin et al. (2016) used network linkages to predict bank distress in Europe. Their paper highlights the importance of incorporating measures of bank interconnectivity to assess systemic risk in the financial industry, since it provides information on potential vulnerability in case of a bank failure within a highly densified network. Billio et al. (2012) used two quantitative measures to characterise connectedness within and between four financial sectors (hedge funds, banks, brokers/dealers, insurance companies). By using principal component analyses, they obtain a broad view of connections among all four groups of financial institutions; with Granger-causality networks, they identify the pairwise statistical relations among individual firms. They found that the linkages between 1994 and 2008 are highly dynamic and can identify financial crisis periods. Shocks are also asymmetric, since banks and insurance companies seem to play a larger role than the two other sectors.

In Minoiu and Reyes (2013), a network analysis of the global financial system is conducted. Based on data from 1978 to 2010, the authors explore how cross border banking flows react to shocks around periods of financial stress. The connectedness of a country in the international banking system rises and falls around the 2008 financial crisis. This could serve as a measure of systemic risk, since the cross border banking flows could represent liquidity conditions in international markets. Finally, Aldasoro and Alves (2016) clarified large European banks into different types of networks. More precisely, these networks are broken into a combination of two categories: the type of maturity (from long to short term exposure) and the type of instrument (asset, derivatives, off balance sheet, ...). Based on granular data between banks, they stressed that banks that are well connected in a network are also well connected in other networks.

2.4 Research question

Based on the literature review, we can now refine our research question:

- Can we use social networks to find evidence of small-world properties of the financial industry?

The main hypothesis of our paper is that individuals on boards of directors or in a managerial position are the key actors of knowledge pipelines within the financial industry, and provide insights on how closely linked financial institutions are within a country. From this main hypothesis, two sub-questions emerge:

- SQ1. Using social networks, what are the key characteristics of the international banking industry's integration?
- SQ2. What are the cross-country differences in the financial networks and how to portray such differences?

3 Data

To build this massive dataset (available per request), we use the following framing strategy. This study considers 43,399 individuals having at least one seat on the board of directors of one of the top 50 financial institutions (ranked by yearly turnover). We built this dataset around 52 countries: 49 from (La Porta et al., 1998)[1], with the addition of China, Russia and Lebanon. Data was extracted from Orbis, a Bureau van Dijk's database. This database provides information regarding the financial environment of each country. We selected the most important financial institutions in terms of turnover for which information concerning their board of directors or managers was available. If a financial institution was not assigned to any individual, these institutions were discarded from the dataset (on average per country, information concerning 73.8% of the financial institutions was available). At most, 50 financial institutions were selected per country, while this number varies across the dataset (from 7 in the lowest case, to 50 for 34 countries). Hence, as a result of our framing strategy, we have an unbalanced panel. Overall, throughout our sample, a total of 2,209 financial institutions were analysed. The complete database encompasses information on the financial vitality of each financial institution, as well as the name, unique identifier, and position of its board of directors and management members. This unique identifier was used to link financial institutions sharing the same person within a country. For example, if three financial institutions {A; B; C} are connected through two people, A and B, B and C, and A and C are sharing two connections.

In order to represent relationships between vertices in a network, we follow Kogut et al.'s (2012) approach. Their method was used in a corporate governance context to identify influential and powerful vertices. From the list of individuals associated to a specific financial institution, we cross each unique ID to associate which financial institutions are connected together. Hence, the result of the data manipulation is a matrix of N rows and N columns concerning N financial institutions per country, with $N \in 6; \dots;$ 50 depending on the country.

4 Network analysis

In terms of methodology, we used the open source language R and we put together a set of servers with the necessary packages and our algorithms to perform the demanding computations. We present and discuss in this article a relevant snapshot of the 52 countries. The overall results are presented in the Appendix. We have also designed an application that associates the following analysis with some key performance indicators of the 2,209 financial institutions. This application is a very interesting tool, combining Network Theory indicators with the financial institutions' respective financial indicators. The resulting dataset is also interesting for further research, beyond the scope of this article.

To analyse each network (country), we develop a three-fold approach, which will help answer our research question. At first, we obtain four centrality measures for each country based on the links between the financial institutions. Then, we visualise each country as a network on its own, with each financial institution acting as a vertex. Finally, we highlight communities within our networks. These steps are detailed in the following part.

4.1 Network characteristics

A network can be described by the relationship between its vertices. In graph theory, several indicators have been proposed. We compute four different indicators regarding the centrality of each vertex (each financial institution): the degree centrality, the closeness centrality, the betweenness centrality, and the eigenvector centrality. Moreover, a global score regarding each indicator will be provided at the country level. Such global scores will be the subject of a cross-country comparison.

The *degree centrality* captures how a vertex is connected to its surroundings neighbours. It is a relative measure varying between [0, 1] and is function of the number of potential connections in a network. The degree centrality of a node p_k is defined as follows (Freeman, 1977; Nieminen, 1974):

$$C_D(p_k) = \sum_{i=1}^{n} a(p_i, p_k) \tag{1}$$

where

$$a(p_i, p_k) = f(x) = \begin{cases} 1 \text{ if and only if } p_i \text{ and } p_k \text{ are connected by a line} \\ 0 \text{ otherwise} \end{cases}$$

The *degree centrality* could be normalised to be independent of the network size, such as:

$$C'_D(p_k) = \frac{\sum_{i=1}^{n} a(p_i, p_k)}{n-1} \tag{2}$$

with $a(p_i, p_k) = 1$ if the node is connected to another node p_i, and 0 otherwise; with $n - 1$ the potential number of connections in a network of n vertices.

The *closeness centrality* provides the information on how a vertex is closely located next to other vertices. The more a vertex is 'close' to other ones, the more it will be 'central' in a network. As introduced by Sabidussi (1966), the formula of the closeness centrality is expressed as follows:

$$C_D(p_k)^{-1} = \sum_{i=1}^{n} d(p_i, p_k) \tag{3}$$

with $d(p_i, p_k)$ the geodesic distance between two nodes p_i and p_k.

The overall centrality of a point p_k is determined by summing its partial betweenness values for all unordered pairs of points where:

$$C_B(p_k) = \sum_{i<j}^{n} \sum_{i<j}^{n} b_{ij}(p_k) \tag{4}$$

The *betweenness centrality* measures the notion that a vertex is located on the shortest path between two other vertices. $C_B(p_k)$, the betweenness centrality of a vertex p_k is assessed by the following formula (Freeman, 1977; Kolaczyk and Csárdi, 2014):

$$C_B(p_k) = \sum_{p_k \neq p_j \neq p_i \in V} \frac{\sigma(p_i, p_j \mid p_k)}{\sigma(p_i, p_j)} \tag{5}$$

with $\sigma(p_i, p_j \mid p_k)$ is the total number of shortest paths between two nodes p_i and p_j where p_k is located, and $\sigma(p_i, p_j)$ is the total number of shortest paths between p_i and p_j.

Finally, the *eigenvalue centrality* is defined as (Bonacich, 1972):

$$C_{Ei}(p_k) = \alpha \sum_{\{p_k, p_i\} \in V} C_{Ei}(p_i) \tag{6}$$

with $C_{Ei} = (C_{Ei}(1), \ldots, C_{Ei}(N))^T$ the solution to the eigenvalue problem, $AC_{Ei} = \alpha^{-1}C_{Ei}$ where A is the adjacency matrix for the network graph G (Kolaczyk and Csárdi, 2014).

For each of the 2,209 financial institutions in our study, we compute these four centrality measures, expressed relatively to their respective country. Finally, we compare each network (country) through a network-level measure of centralisation, as specified by Csárdi et al. (2015) in the igraph package (Csárdi and Nepusz, 2006) as:

$$C(G) = \sum_v \left(\max_w c_w - c_v \right) \tag{7}$$

where c_v is the centrality of vertex v.

In summary, a global score regarding each indicator will be provided at the country level, which will serve as a cross-country comparison. The four centrality measures are summarised in Table 1.

Table 1 Description of the four centrality measures

Type of centrality	*Authors*	*Formula*	*Characteristics*
Degree	Nieminen (1974) and Freeman (1977)	$\frac{\sum_{i-1}^{n} a(p_i, p_k)}{n-1}$	Connections of a vertex to its surroundings neighbours
Closeness	Sabidussi (1966)	$\sum_{i-1}^{n} d(p_i, p_k)$	How a vertex is closely located next to other vertices
Betweenness	Freeman (1997) and Kolaczyk and Csárdi (2014)	$\sum_{p_i \neq p_j \neq p_k \in V} \frac{\sigma(p_i, p_j \mid p_k)}{\sigma(p_i, p_j)}$	How likely a vertex is located on the shortest path between two other vertices
Eigenvalue	Bonancich (1972) and Kolaczyk and Csárdi (2014)	$\alpha \sum_{\{p_i, p_j\} \in V} C_{Ei}(p_i)$	Solution to the eigenvalue problem described by the adjacency matrix for the network graph

In order to answer SQ1, Table 2 presents these network-level centrality measures per country. Two groups of countries appear to have the same characteristics: Finland, Norway, Hong-Kong, Germany, Nigeria, Spain, Denmark, Switzerland, France and India are the countries with the highest values of degree centrality and betweenness centrality. With the exception of Venezuela and Israel, this list is similar for the closeness centrality. These countries also have the lowest values of eigenvector centrality (with the addition of Taiwan and Portugal; Ecuador and Uruguay are not taken into account since there are no connections between vertices for these two countries). A second group composed of Ecuador, Uruguay, Mexico, Turkey, Argentina, Thailand, Peru, Chile and Brazil seems to share the opposite characteristics (low value of degree centrality, low value of betweenness centrality, low value of closeness centrality and high value of eigenvalue centrality).

The first question (SQ1) requested to differentiate countries by using different values of centrality obtained from our network analysis. Based on Table 2, groups of countries have been identified.

Table 2 Summary of the centralisation measures per country

Country	*Degree*	*Closeness*	*Betweenness*	*Eigenvalue*
Argentina	0.0302	0.0020	0.0016	0.9792
Australia	0.0816	0.0076	0.0240	0.9189
Austria	0.1037	0.0118	0.0659	0.9119
Belgium	0.0588	0.0030	0.0048	0.9539
Brazil	0.0498	0.0021	0.0009	0.9583
Canada	0.0865	0.0034	0.0084	0.9742
Chile	0.0405	0.0042	0.0000	1.0000
China	0.0857	0.0043	0.0135	0.9568
Colombia	0.0996	0.0060	0.0124	0.9149
Denmark	0.1682	0.0179	0.1116	0.8799
Ecuador	0.0000	0.0000	0.0000	0.0000
Egypt	0.0538	0.0049	0.0035	0.9625
Finland	0.2602	0.0669	0.2440	0.4602
France	0.1445	0.0197	0.1287	0.8770
Germany	0.1829	0.0206	0.1215	0.8528
Greece	0.0961	0.0049	0.0093	0.9616
Hong-Kong	0.1927	0.0210	0.1977	0.8866
India	0.1339	0.0200	0.1685	0.8731
Indonesia	0.0686	0.0040	0.0071	0.9668
Ireland	0.1004	0.0067	0.0186	0.9431
Israel	0.1263	0.0240	0.0379	0.8975
Italy	0.0971	0.0129	0.0550	0.9032
Japan	0.0767	0.0076	0.0310	0.9156
Jordan	0.0767	0.0071	0.0000	1.0000
Kenya	0.0589	0.0026	0.0020	0.9734
Lebanon	0.0473	0.0026	0.0032	0.9638
Malaysia	0.1306	0.0097	0.0523	0.9000
Mexico	0.0190	0.0009	0.0000	0.9717
Netherlands	0.0996	0.0118	0.0632	0.9164
New Zealand	0.0533	0.0048	0.0000	0.9565
Nigeria	0.1693	0.0350	0.2185	0.8628
Norway	0.2090	0.0184	0.1301	0.8550
Pakistan	0.0604	0.0063	0.0124	0.9462
Peru	0.0336	0.0031	0.0000	1.0000
Philippines	0.0916	0.0079	0.0183	0.9511

Table 2 Summary of the centralisation measures per country (continued)

Country	*Degree*	*Closeness*	*Betweenness*	*Eigenvalue*
Portugal	0.1041	0.0165	0.0772	0.8647
Russia	0.1012	0.0085	0.0225	0.8906
Singapore	0.0865	0.0043	0.0079	0.9536
South Africa	0.0596	0.0041	0.0092	0.9455
South Korea	0.0637	0.0062	0.0220	0.9360
Spain	0.1690	0.0126	0.1059	0.9150
Sri Lanka	0.0769	0.0154	0.0379	0.9583
Sweden	0.0669	0.0043	0.0099	0.9619
Switzerland	0.1673	0.0284	0.1175	0.8049
Taiwan	0.1135	0.0146	0.0787	0.8403
Thailand	0.0335	0.0013	0.0008	0.9914
Turkey	0.0196	0.0008	0.0000	1.0000
UK	0.0702	0.0051	0.0121	0.9364
USA	0.0661	0.0060	0.0146	0.9419
Uruguay	0.0000	0.0000	0.0000	0.0000
Venezuela	0.0972	0.0260	0.0000	1.0000
Zimbabwe	0.1210	0.0099	0.0166	0.9139

4.2 Graphical approach: from circular to force-directed networks

Since a person sitting in two different boards belongs to both financial institutions, we have until now evaluated each matrix (country) as an undirected network. Apart from network characteristics, let us use some filters to create visualisations that might gives insights on how financial institutions are closely linked in each concerned countries.

In this section, several approaches are explored to detail the interactions between financial institutions. The first visualisation is a circular visualisation. Each financial institution is located on the perimeter of a circle and ordered by its importance in terms of turnover. To compare each financial institution across countries, the diameter of the vertex is a function of the logarithm of their corresponding turnover. Within a country, a person shared by two financial institutions will produce a link between the two vertices representing the corresponding financial institutions.

While providing a snapshot of each network's complexity, the likelihood to have close links between financial institutions is not assessed. Moreover, heavily interlocked networks might overshadow how close vertices are. This could be improved by adopting a force-directed visualisation, i.e., the 'stronger' the relationship between vertices, the 'closer' they will be placed. Such improvement could be obtained by using the Kamada-Kawai algorithm (Kamada and Kawai, 1989). An edge between two vertices i and j is represented by a spring of force k_{ij}. The Kamada-Kawai algorithm tries to minimise the network's total energy E, such as:

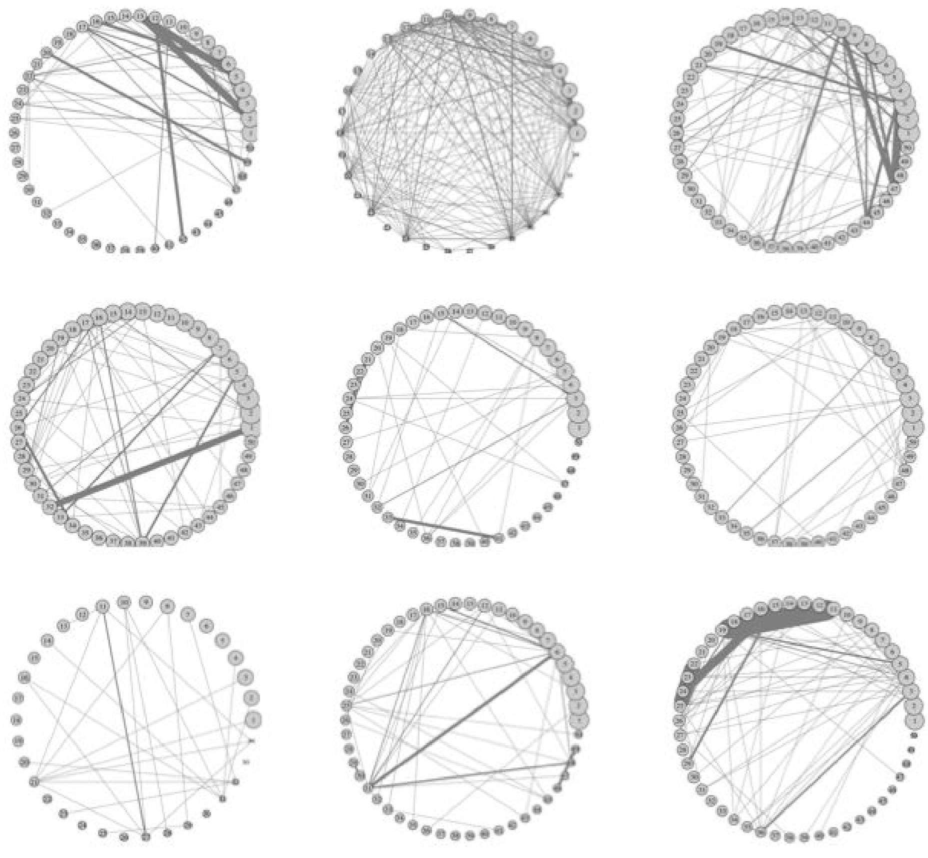
$$E = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{1}{2} k_{ij} \left(\left| p_i - p_j \right| - l_{ij} \right)^2 \tag{8}$$

with n the number of vertices $p_1, p_2, \ldots, p_n$ connected by aforementioned springs. This modelisation is iterative, i.e., that for each step the algorithm tries to lower E. In order to compare each country, we will set the number of iterations to 50. Indeed, for countries with a high level of degrees between vertices, vertices might be aggregated too closely to each other.

Considering this latter aspect, we will apply the Fruchterman-Reingold algorithm. Their algorithm (Fruchterman and Reingold, 1991) tries to avoid vertices to be too close to each other, hence correcting visualisation obtained through the Kamada-Kawai algorithm.

We present the *three steps of visualisations in the following part*. From Figure 1 through three, nine countries are showcased: Denmark, Finland, France, Germany, Hong-Kong, India, Nigeria, Norway and Switzerland. These countries appeared within the top ten countries for at least three of the four centralisation indicators explored in the previous section.

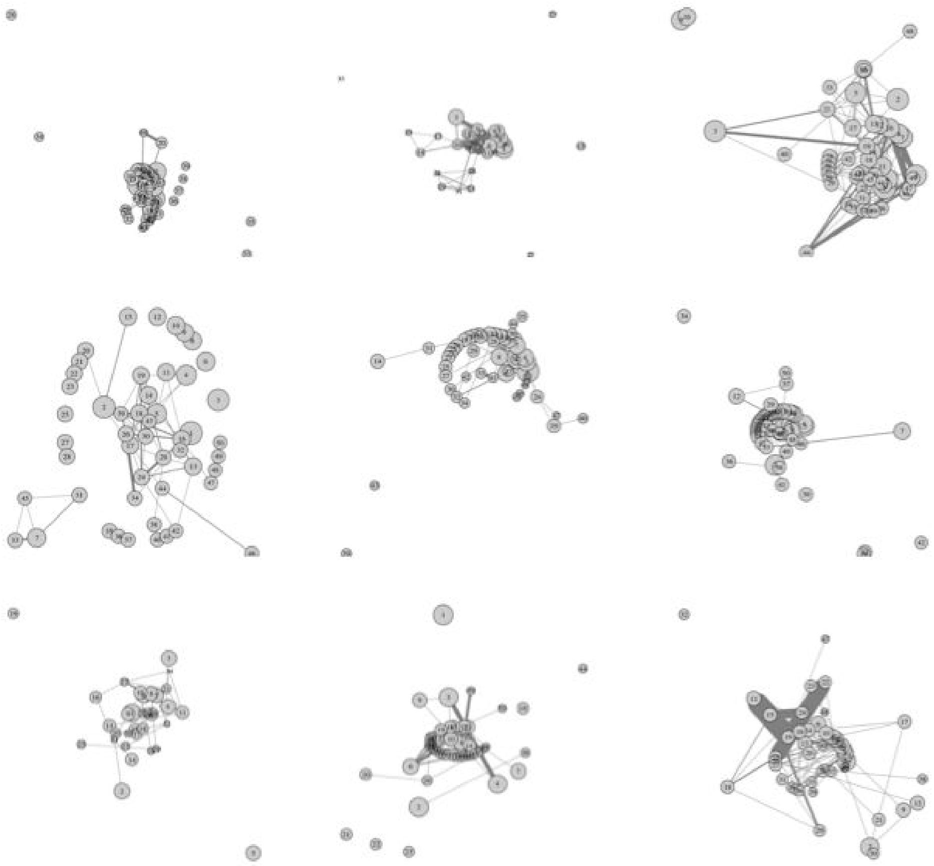
Figure 1 Circular visualisations



Notes: Top row: Denmark, Finland, France. Middle row: Germany, Hong-Kong, India.
Bottom row: Nigeria, Norway, Switzerland.

To answer the first sub-question of our paper (SQ1), the three types of visualisations illustrate different concepts. While the first visualisation (circular) provides insights on how dense the network is (for example, in Finland), it did not reveal groups of financial institutions. This is apprehended through force-directed graphs. In the first place, visualisations are obtained through the Kamada-Kawai algorithm (Figure 2), which brings closer vertices together.

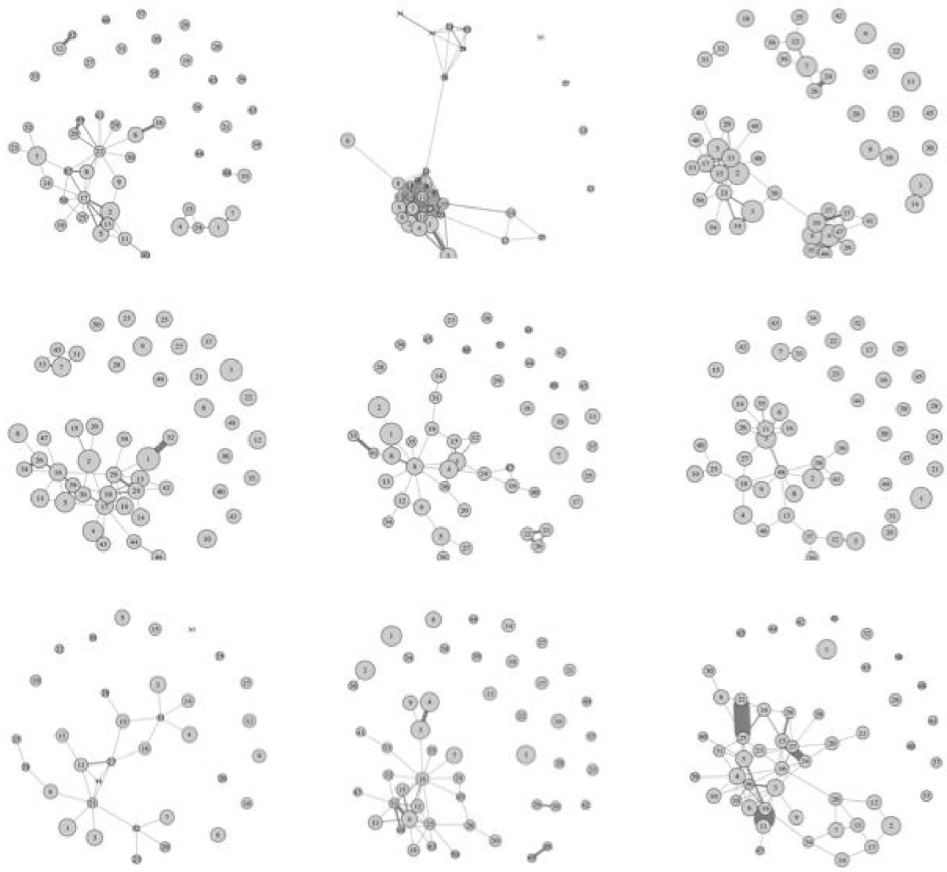
Figure 2 Kamada-Kawai visualisations



Notes: Top row: Denmark, Finland, France. Middle row: Germany, Hong-Kong, India.
Bottom row: Nigeria, Norway, Switzerland.

Such graphs are then corrected by the Fruchterman-Reingold algorithm (Figure 3), providing a clear view of the links between financial institutions.

Figure 3 Fruchterman-Reingold visualisations



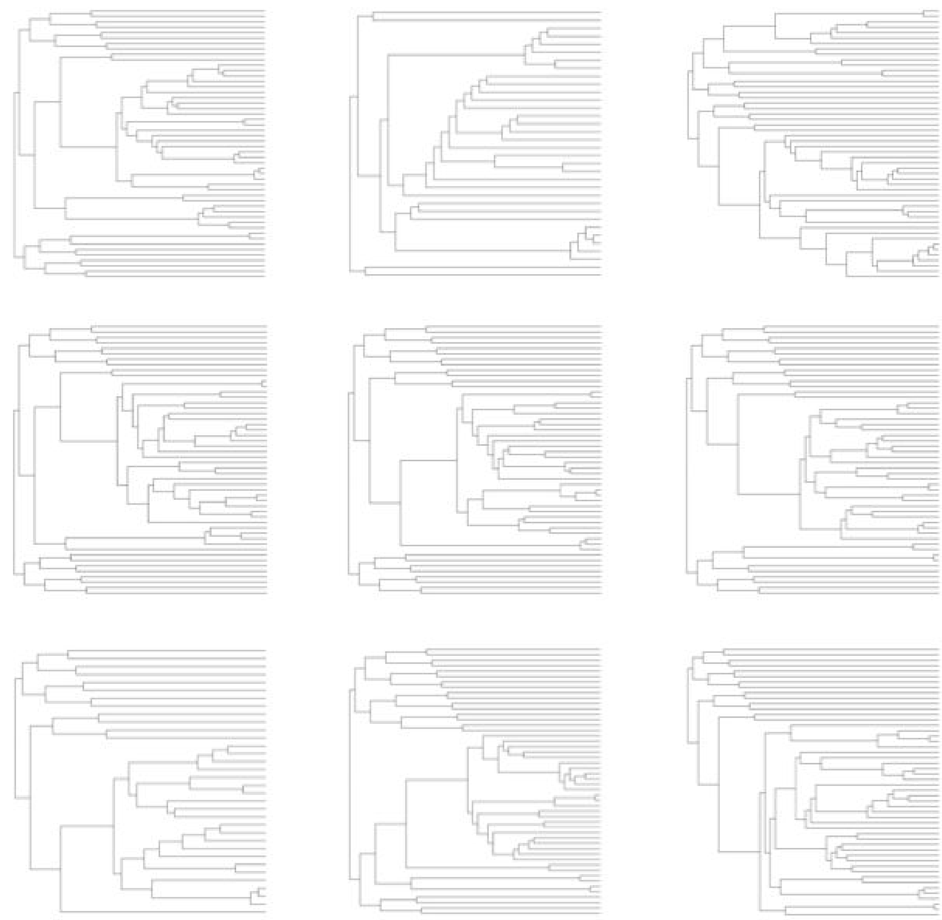
Notes: Top row: Denmark, Finland, France. Middle row: Germany, Hong-Kong, India.
Bottom row: Nigeria, Norway, Switzerland.

4.3 Community detection by partitioning

From Figure 3, communities could be highlighted. The final step of our analysis is to determine the importance of such communities of vertices in our networks through partitioning. To do so, we apply a fast greedy algorithm on the graphs obtained after the Fruchterman-Reingold treatment, which will hierarchically cluster vertices.

A measure of community is used to identify the number of clusters in a network. This property, mod(C), optimises the number of subgroups within a network, i.e., it represents how a graph is divided between subgraphs that are connected by a few edges, while keeping the concentration of internal edges high (Clauset et al., 2004). The fast greedy algorithm will determine in how many communities each network could be divided.

Figure 4 Dendrogram visualisations of community clusters



Notes: Top row: Denmark, Finland, France. Middle row: Germany, Hong-Kong, India.
Bottom row: Nigeria, Norway, Switzerland.

The result of the clusterisation is assessed through a dendrogram. In Figure 4, the nine selected countries are presented, highlighting subgroups within the network. The complete visualisation is located in Appendix 4, as well as online on: http://openscience.nuance-r.com/research.html. We then calculate the largest amount of financial institutions linked together through individuals. This value is compared to the total number of vertices in the network in order to assess the relative importance of all connected institutions.

In Table 3, we provide three variables:

1 the number of communities obtained by clusterisation with the fast greedy algorithm

2 the number of linked institutions

3 the overall importance of the largest amount of linked institutions for each country.

This variable is obtained by dividing the number of linked institutions by the total number of institutions in the corresponding network.

Table 3 Hierarchical clusterisation characteristics per country

Country	*Number of communities*	*Linked institutions*	*Overall importance (%)*
Argentina	39	4	0.08
Australia	34	16	0.32
Austria	33	11	0.22
Belgium	29	6	0.12
Brazil	39	4	0.08
Canada	33	6	0.12
Chile	19	2	0.095
China	34	8	0.16
Colombia	34	9	0.18
Denmark	25	24	0.48
Ecuador	7	1	0.143
Egypt	33	4	0.08
Finland	8	30	0.68
France	16	27	0.54
Germany	25	27	0.54
Greece	29	5	0.1
Hong-Kong	27	27	0.54
India	26	26	0.52
Indonesia	36	7	0.14
Ireland	32	10	0.2
Israel	15	6	0.3
Italy	27	18	0.36
Japan	29	12	0.24
Jordan	16	2	0.118
Kenya	39	4	0.087
Lebanon	36	5	0.1
Malaysia	24	14	0.28
Mexico	40	2	0.045
Netherlands	34	16	0.32
New Zealand	18	3	0.12
Nigeria	17	21	0.618
Norway	26	24	0.48

Notes: We provide

1. the number of communities obtained by clusterisation
2. the number of linked institutions
3. the overall importance of the largest amount of linked institutions for each country.

Table 3 Hierarchical clusterisation characteristics per country (continued)

Country	*Number of communities*	*Linked institutions*	*Overall importance (%)*
Pakistan	35	7	0.163
Peru	20	2	0.087
Philippines	24	7	0.189
Portugal	24	18	0.419
Russia	35	12	0.24
Singapore	37	7	0.14
South Africa	29	7	0.14
South Korea	31	10	0.2
Spain	20	19	0.38
Sri Lanka	13	7	0.14
Sweden	34	7	0.14
Switzerland	19	35	0.7
Taiwan	29	20	0.4
Thailand	41	3	0.06
Turkey	49	2	0.04
UK	28	9	0.18
USA	33	9	0.18
Uruguay	26	1	0.038
Venezuela	8	2	0.04
Zimbabwe	16	7	0.219

Notes: We provide

1. the number of communities obtained by clusterisation
2. the number of linked institutions
3. the overall importance of the largest amount of linked institutions for each country.

With hierarchical clusterisation, we are able to answer question SQ2. Indeed, we can now isolate communities of vertices (financial institutions) and obtain the relative importance of such groups. On the one hand, countries with the largest overall communities are: Switzerland, Finland, Nigeria, Hong-Kong, France, Germany, India, Denmark, Norway and Portugal, with communities representing from 41.9% to 70% of their respective country's network. On the other hand, the ones with the lowest overall communities are: Uruguay, Turkey, Venezuela, Mexico, Thailand, Argentina, Egypt, Brazil, Peru and Kenya, with the largest communities ranging from 3.8% to 8.7% of their respective country's network.

5 Conclusions and discussions

In this article, we analysed the links between financial institutions through their social ties, mainly the individuals sitting on multiple boards of directors or in multiple management teams. More precisely, this article focuses on connectivity and closeness between financial institutions through individuals sitting on their boards of directors.

Financial institutions are a subset of MNCs and play an important role in our modern economies. Using Network Theory, we proposed to look at individual social networks within and between financial institutions. We built a large sample of 43,399 individuals, and 2,209 financial institutions across 52 countries. We show strong evidence of the large degree of the financial system's concentration through boards of directors' corporate interlocks. The main contribution of this article is to show evidence of small-world properties of the international financial system. It is an important question, for the ramifications can be critical, notably in terms of systemic risk. As such, measures of closeness in the financial industry at the country level could be assessed. In terms of policy implications, monitoring such proxies could complement the traditional assessment of systemic risk in different countries. In fact, when comparing the financial industry of two countries together, it is possible to use the CAGE model (measuring the cultural, administrative, geographic and economic distances between these two countries) from Ghemawat (2001). Such network-oriented approach could serves as numerical proxies for this distance framework.

In the paper, three different approaches have been explored. First, for each country we obtained four different centralisation variables. Secondly, every country was visualised to reveal in the first time density of linkage between financial institutions then groups of nodes. Thirdly, we applied a clustering algorithm to separate and highlight how connected financial institutions are within countries.

This method led us to a value of the largest proportion of financial institutions connected for every considered country.

Since the study relies on information registered in the Orbis database, we can say that at most, the phenomenon of linked financial institutions is undermined. In fact, two aspects could explain why clusterisation of financial institutions might be higher.

1 26.2% of the financial institutions listed were not associated to any individual, which is why we did not take them into account.

2 At most, the 50 financial institutions with the highest turnover were selected.

For certain countries (Uruguay or Israel for instance) this number was enough to cover all listed financial institutions. However, for other countries, the total number of financial institutions is much higher.

Finally, another approach would be to adopt a cluster-level view. For example, the automotive industry tends to be specialised in clusters depending on its activities (Sturgeon et al., 2008). Bathelt and Li (2013) explored connections between clusters in Canada and in China by studying FDI flows. Multinational cluster firms preferred to set up affiliates in similar specialised clusters in both countries (telecommunications, finance, auto parts, computer parts). In the case of the financial industry, it would be interesting to study how ties between financial institutions vary across countries within specific clusters, and in particular in important financial centres.

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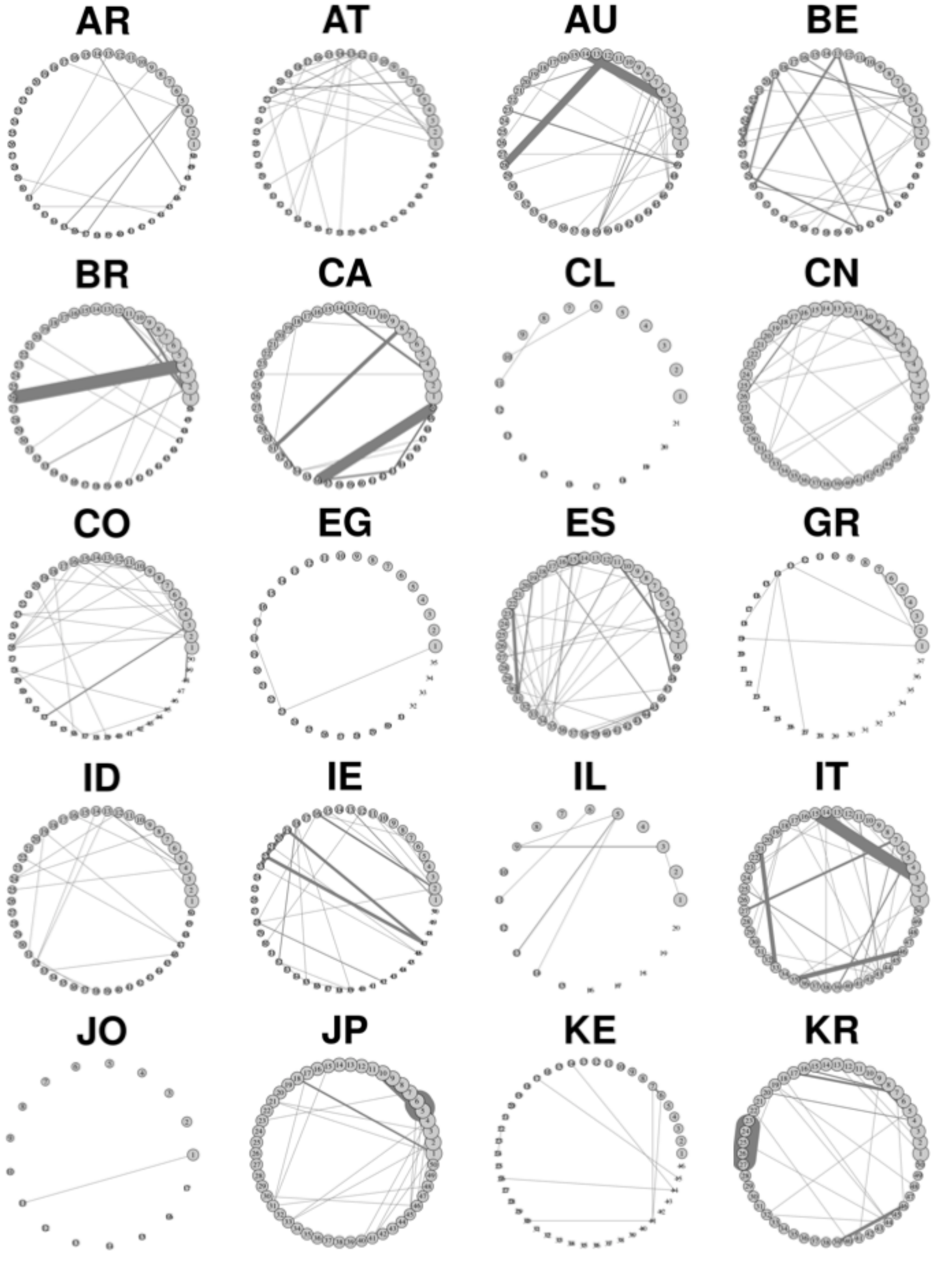
Note

1 Original countries from La Porta et al. (1998): Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Denmark, Ecuador, Egypt, Finland, France, Germany, Greece, Hong-Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kenya, Malaysia, Mexico, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Portugal, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK, Uruguay, USA, Venezuela, Zimbabwe.

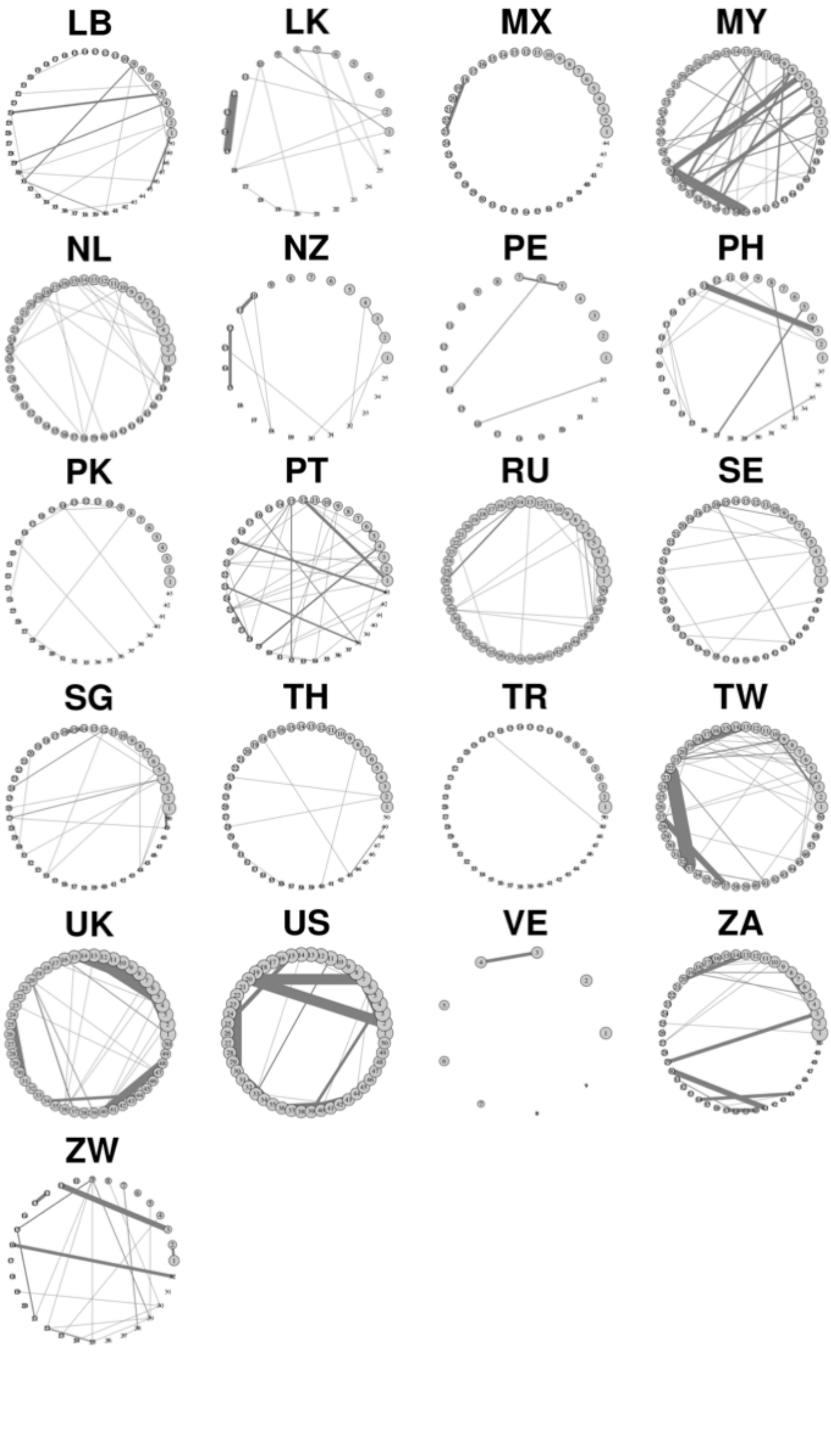
Appendix 1A

Figure 5 Circular visualisations, AR-KR



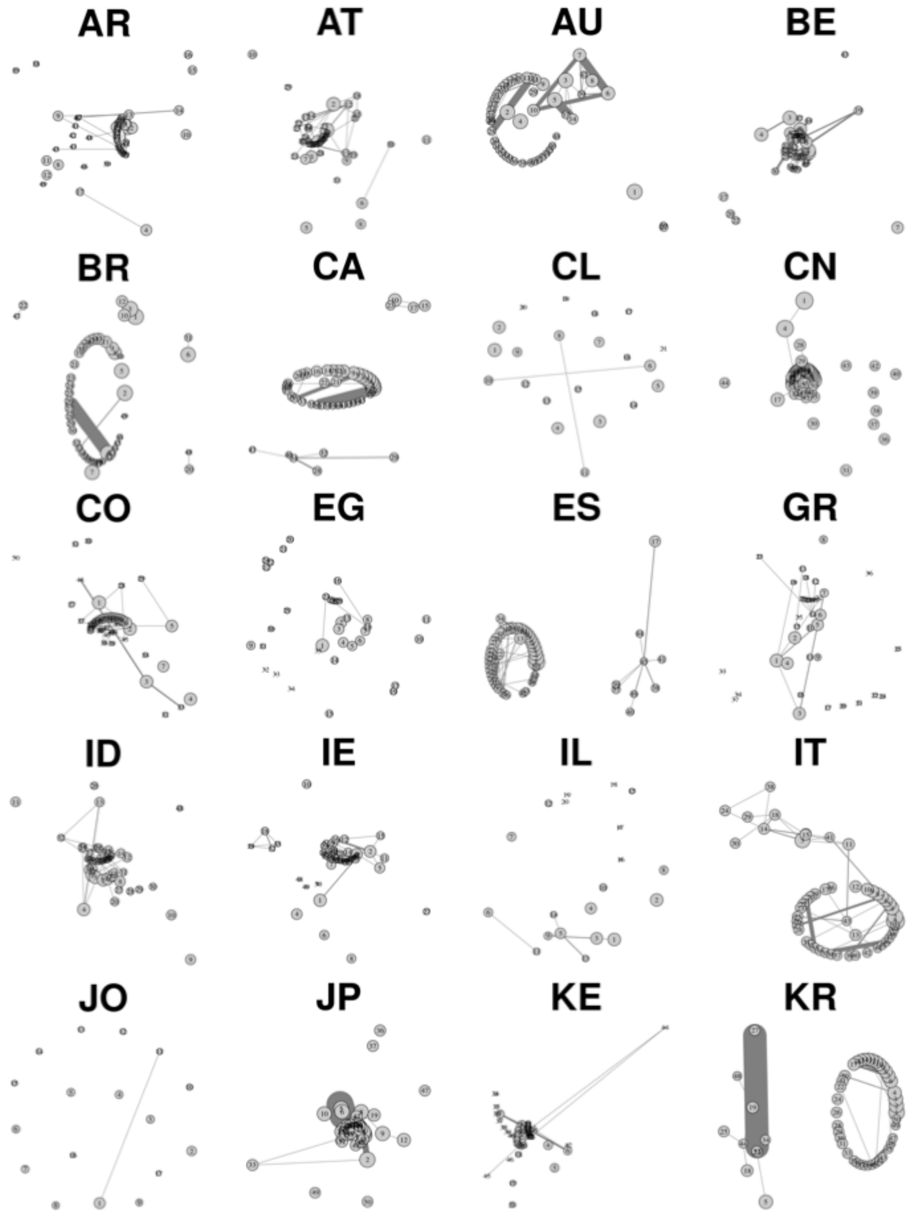
Appendix 1B

Figure 6 Circular visualizations, LB-ZW



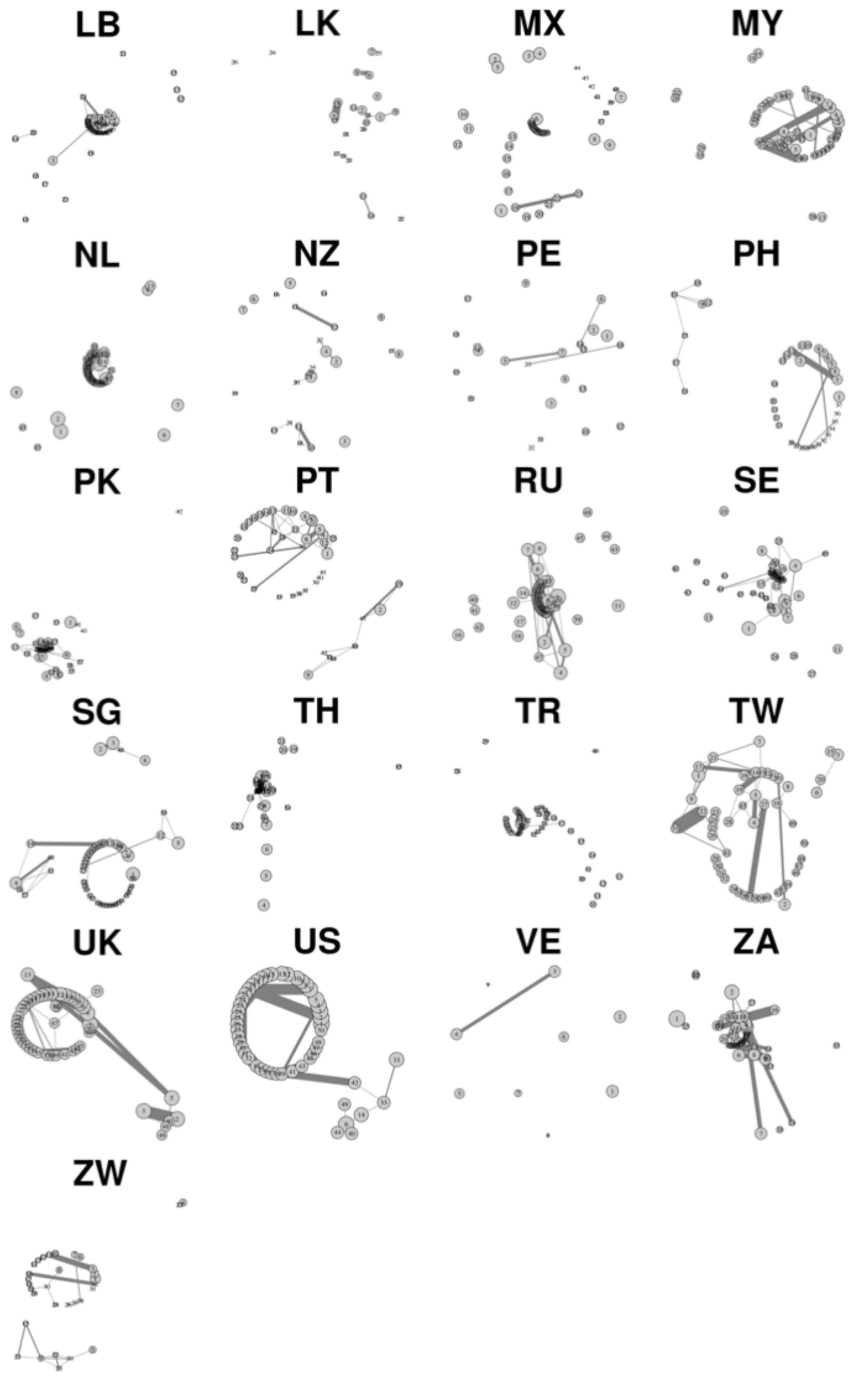
Appendix 2A

Figure 7 Kamada-Kawai visualizations, AR-KR



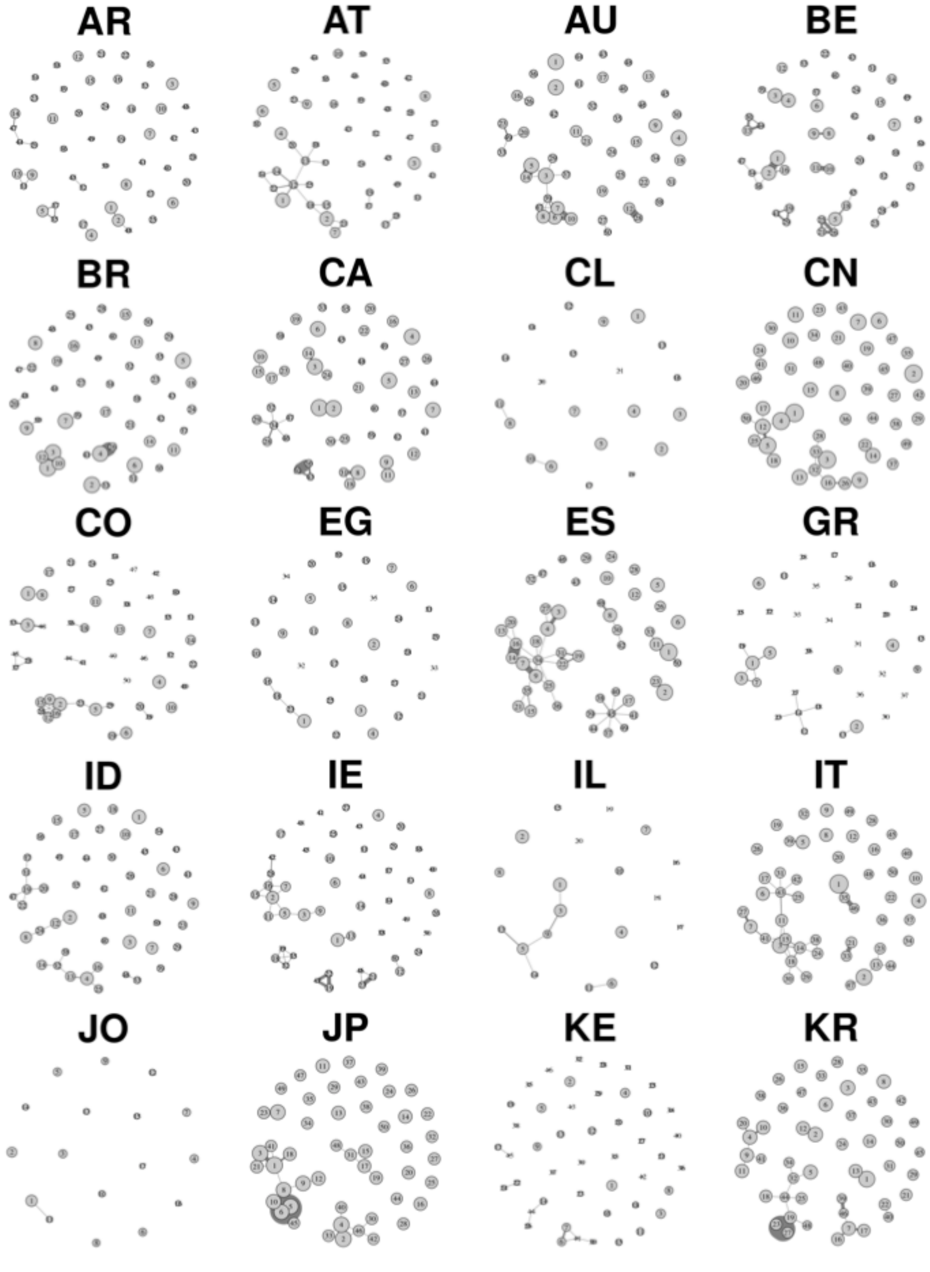
Appendix 2B

Figure 8 Kamada-Kawai visualisations, LB-ZW



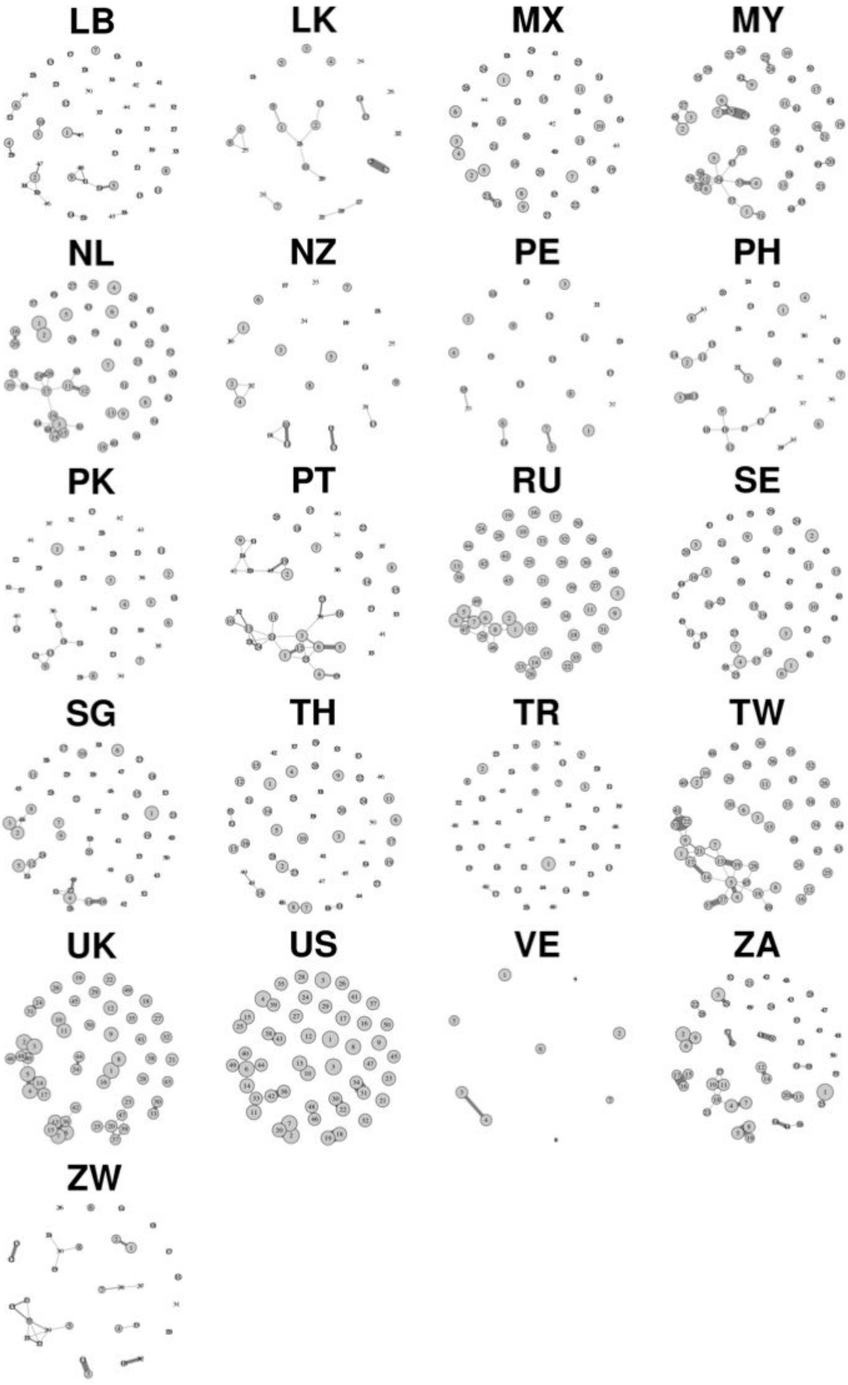
Appendix 3A

Figure 9 Fruchterman-Reingold visualisations, AR-KR



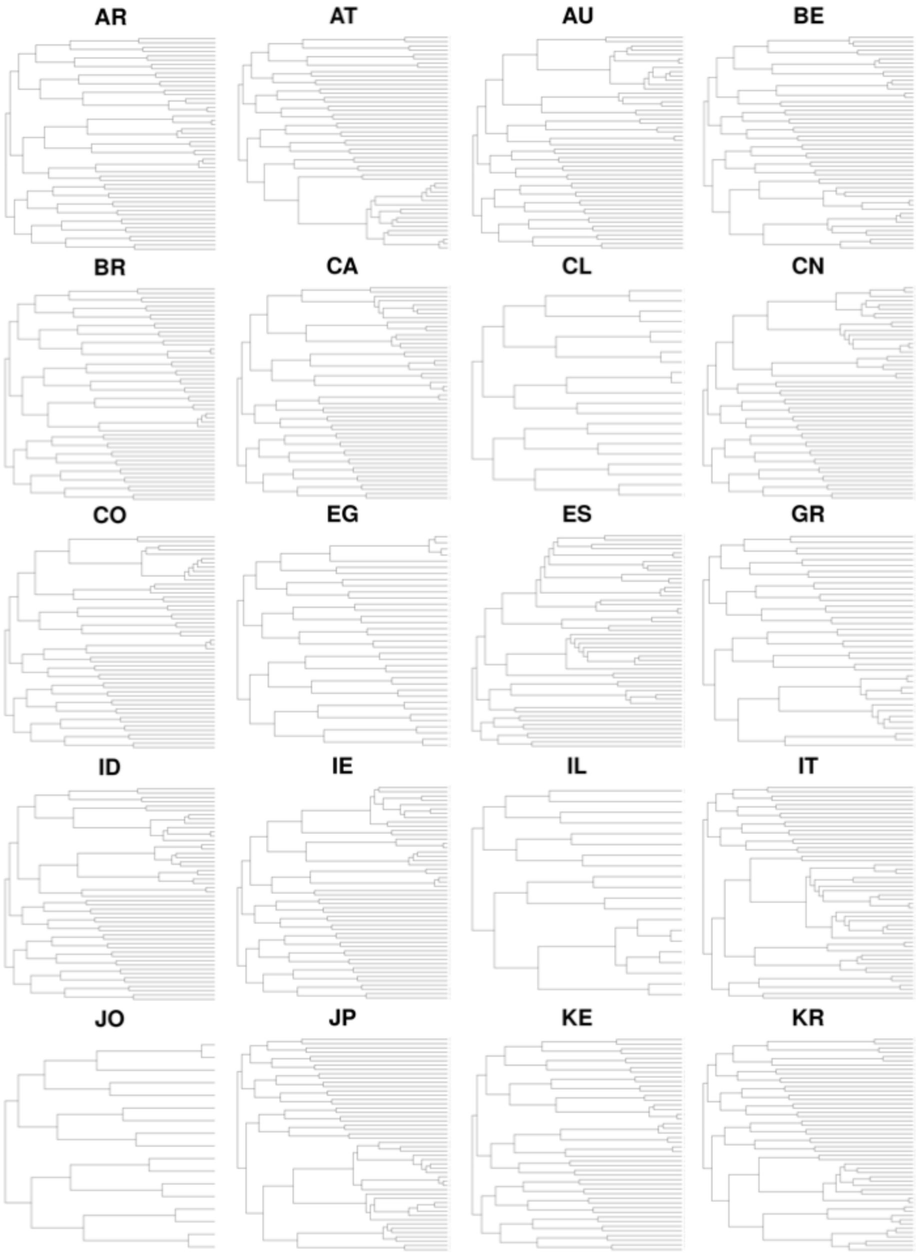
Appendix 3B

Figure 10 Fruchterman-Reingold visualisations, LB-ZW



Appendix 4A

Figure 11 Hierarchical clusterisation with dendrograms, AR-KR



Appendix 4B

Figure 12 Hierarchical clusterisation with dendrograms, LB-ZW