NBER WORKING PAPER SERIES

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THE EVOLUTION OF STOCK MARKET INTEGRATION SINCE 1913

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Working Paper 26166
http://www.nber.org/papers/w26166

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2019

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NBER Working Paper No. 26166
August 2019
JEL No. C38,F36,G15,N20

ABSTRACT

We examine equity market integration for 17 countries from 1913-2018. We use network analysis to measure the evolution of global stock market integration as well as stock market integration between and across countries. The empirical results suggest that long-run stock market integration looks like an unstable hook. Equity market integration first peaked in 1913 during the first era of globalization (1870-1913) when unfettered markets ruled the day. Integration declined over the next 60 years as countries experienced the Great Depression and shunned international capital markets. The end of the Bretton Woods system in the early 1970s ushered in the second period of globalization. Our empirical analysis suggests that stock market integration in the recent period of globalization has surpassed the first era of globalization in the last 10 years and currently has the highest level of equity market integration and network instability in world history.

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1. Introduction

There are many studies of long-run financial and economic globalization. Taylor (2002) studied the evolution of purchasing power parity since the late 19th century. Jacks et al. (2008, 2011) examined the evolution of bilateral trade costs from 1870 to the modern period. Obstfeld and Taylor (2004) looked at several different measures of market globalization including short-term interest rates, real interest parity, covered interest parity, and the policy trilemma from the classical gold standard to the recent era of globalization. Bordo et al. (1998) compared financial market globalization of the classical gold standard period with the modern period since the collapse of Bretton Woods era. Many of these studies have found that financial globalization has followed a U-shaped pattern since the late nineteenth century. Economic and financial market globalization was very high just prior to the outbreak of World War I. This was followed by the interwar and Bretton Woods periods where globalization declined. Financial integration then rebounded during the recent period of globalization that started in the early 1970s following the collapse of the Bretton Woods system. Only in the last 20 years have markets experienced the high levels of economic and financial globalization seen during the classical gold standard period (Bekaert and Mehl, 2017).

We break new ground and provide one of the first long-run studies of the evolution of global equity market integration since the early 1900s. Using a new monthly database of country stock market indices for 17 countries, we employ a network analysis to examine financial market integration (Mantegna, 1999; Bonnano et al., 2001; Tumminello et al., 2007). Network representations have the advantage of allowing a scholar to differentiate between two crucial aspects of globalization: the degree of globalization on the one hand, which is measured in this study by distance indicators; and the links between the countries of the sample on the other hand, which are studied using connectivity indicators. We use shortest distance from one stock market to another as one of our baseline measures. This is called the nearest neighbor indicator of distance. The average distance to the nearest neighbor accounts for the distance from a given stock market to other markets that it is connected with. We also use two path length measures, which account for the distance to all other stock markets within the network. Distances should fall as markets become more integrated. With respect to connectivity, we use indicators of connectivity in level and standard deviation. Connectivity in level captures the structure of the network that is defined by the average degree (number of neighbors) of the nearest neighbors of a given stock market for a given period. Connectivity in standard deviation measures the dispersion of the number of links by which the stock markets are connected to the network. Connectivity increases in level and standard deviation as global stock markets become more integrated.

The empirical results reveal several insights about the evolution of equity market integration since the early 1900s. First, stock market integration looks like an unstable hook as opposed to an inverted U-shape that has been observed in many other markets. Two results from the empirical analysis point to this interpretation. The network indicators show that stock market integration is significantly higher now than in 1913 at the end of the gold standard period. A significant portion of the increase in stock market integration can be attributed to the large rise in financial market integration in the European Union, especially during the 1980s. Second, the empirical results also suggest that the global network of equity markets is becoming increasingly unstable. Both the US and the UK are major contributors to the growing level of financial instability.

The remainder of this paper is organized as follows. Section 2 presents the database and network methodology, consisting in building financial networks and in particular price networks of stock markets. Section 3 is devoted to the cliometric discussion of the network structures and network indicators derived from our database. In Section 4 we present some additional outcomes regarding country specific effects. In Section 5 we highlight the contribution of the network approach to the literature on financial globalization.

2. Database and methodology

2.1. Descriptive statistics

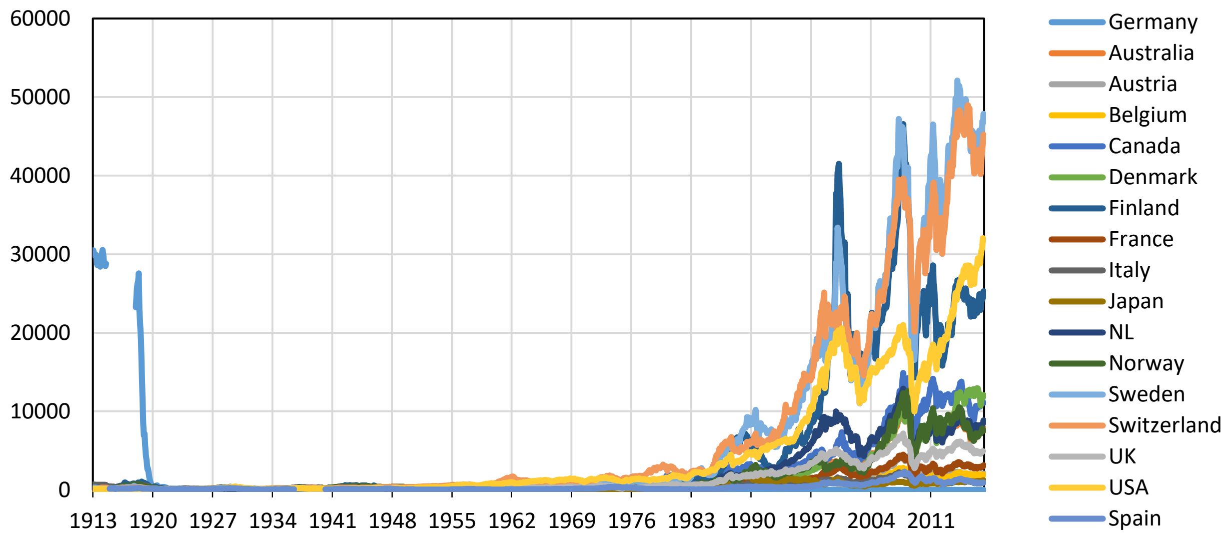


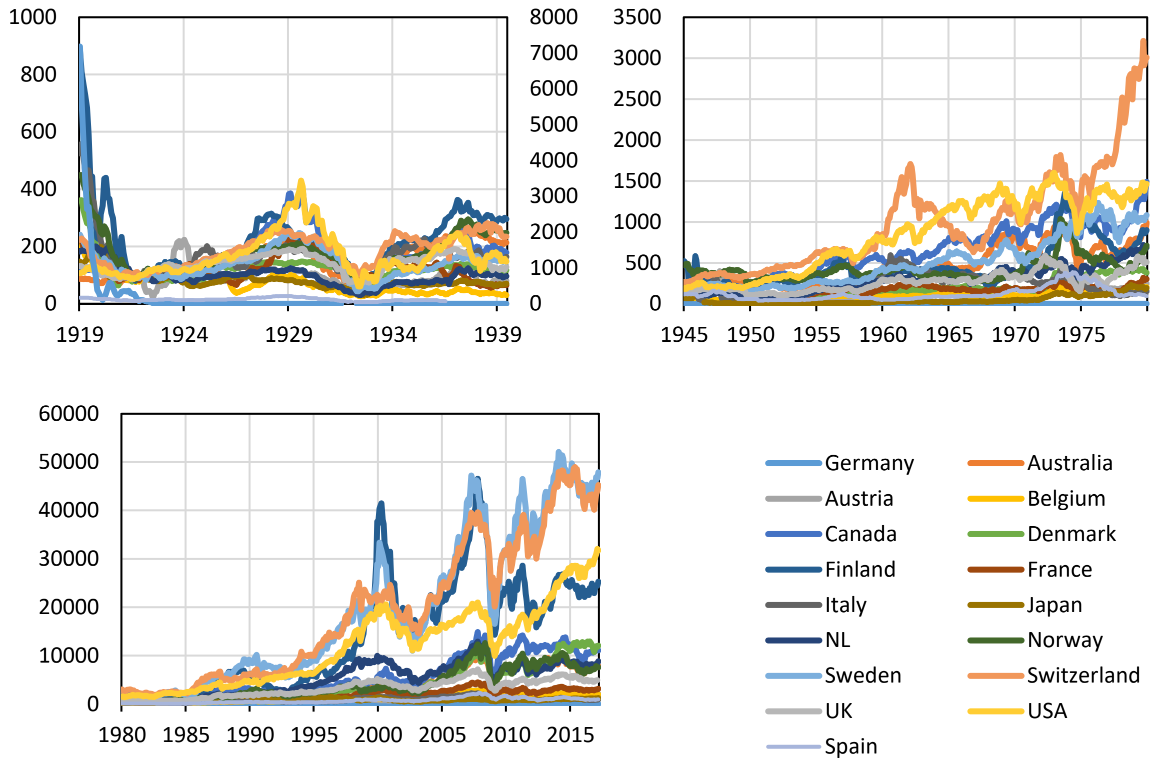
Figure 1 Equity indices in level (100 = 31/01/1922)

Variable	Mean	Median	S.D.	Min	Max	Skew.	Kurtosis	5%	95%
Germany	692,49	1,1718e-8	4195,1	1,3593e-10	30545,	6,3168	38,767	8,5548e-10	229,56
Australia	1673,7	446,93	2464,2	71,056	11284,	1,9055	2,5793	83,449	8088,4
Austria	574,29	136,90	843,33	7,7727	4400,4	2,1460	4,6170	23,097	2314,8
Belgium	452,82	114,18	630,74	25,132	2807,1	1,7348	2,0101	37,590	1964,6
Canada	2374,6	754,43	3531,3	70,790	14862,	1,8875	2,4155	112,08	11607,
Denmark	1559,0	194,33	2861,2	61,487	12929,	2,3934	4,9625	89,205	8713,5
Finland	5285,9	493,71	9391,8	79,975	46547,	1,9871	3,0876	133,18	25702,
France	737,19	192,08	1030,9	39,304	4480,1	1,6347	1,4606	64,060	2996,1
Italy	463,57	299,89	423,35	47,882	2225,3	1,5947	2,3201	86,493	1321,5
Japan	366,19	95,593	461,99	1,4909	1879,6	1,1838	0,051370	5,9868	1300,9
NL	2156,6	363,07	3177,0	29,320	12897,	1,4130	0,57047	75,476	8835,1
Norway	1714,7	443,14	2629,6	75,235	12593,	2,1022	3,4754	124,35	8482,2
Sweden	7157,0	513,94	12968,	43,033	52080,	1,9715	2,6952	102,32	42324,
Switzerland	7311,1	1094,7	12291,	86,836	48956,	1,8513	2,2527	132,57	37669,
Spain	343,49	134,31	433,04	37,593	2300,6	2,0200	3,6996	49,937	1301,1
UK	1289,2	281,93	1796,9	67,888	7164,8	1,4280	0,62226	100,94	5203,5
USA	4566,7	1070,7	7275,0	60,099	32043,	1,7710	2,0795	108,26	19799,

Table 1 Descriptive statistics, 1913:01 - 2017:03 (100 = 31/01/1922, not including missing values)

The monthly database is composed of 17 equity market indices belonging to some of the largest and most important markets. The country stock indices included in the study are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and the United States.[1] The data are taken from Global Financial Database that chain links historical stock market indices with overlapping sample periods to construct long-run equity market data. Table 1 reports the descriptive statistics for each of the exchanges as well as different subperiods of financial globalization in Figures 1 and 2. Financial globalization is typically divided into four distinct periods: 1) the classical gold standard period (1870-1913); 2) the interwar-period (1914-1939); 3) Bretton Woods (1945-early 1970s); and the recent era of globalization (early 1970s-present). All stock indices are normalized such that January 1922 is set equal to 100. Figure 1 shows that the indices are characterized by a slow increase until the beginning of the 1980s. Then they exhibit a sharply increasing trend which is also strongly cyclical. This increase is also highly differentiated: for example, final values are close to 45,000 for Switzerland and Sweden, 25,000 to 30,000 for the United States and Finland, 11,000 or less for the other countries. Germany is a special case since the index is divided by 100 between 1911 and 1917.

[1] Emerging economies, and in particular China, are not in our sample. Indeed, emerging markets equity markets indices are only available over a recent period. Integrating them would imply that the composition of the sample would not be stable.



For the interwar period Germany is represented on the right axis.

Figure 2 Equity indices in level (100 = 31/01/1922), (a) Interwar, (b) Bretton Woods, (c) 2nd Era of Globalization.

For the classical gold standard period, we use the year 1913 as a benchmark given that it is only at the end of the first era of globalization that we have sufficient stock market coverage to apply the network analysis. The interwar period exhibits a large decline in stock market prices with the outbreak of World War I. This is followed by the bull market runup of the 1920s and the large decline in global equity prices after the Great Crash of 1929 and the onset of the Great Depression. The dispersion of the country stock market indices falls during the first part of the 1930s only to increase as markets began to recover from the Great Depression. The early Bretton Woods period, shown in Figure 2b, is characterized by both a globally increasing trend and a strong divergence. For example, the end of period stock indices are 130 for Italy, 1,300 for the United States and Canada, and almost 3,000 for Switzerland. The recent period of globalization reported in Figure 2d also exhibits significant divergence. Despite the rising dispersion, the country stock market indices increase much faster during the recent period (up to a factor 20 against 9 previously) and appear to be affected by major crises. These crises, however, do not affect the obviously upward trend of the indices over the whole sub-period.[2]

2.2. Stock Market Networks

We study global stock market networks using equity price data. The literature on asset price networks describes topological graphs obtained from the correlations matrix of the time series of equities prices (Mantegna, 1999; Bonnano et al., 2001; Tumminello et al., 2007). The most commonly used representations are minimal spanning trees (Held, 1970) and hierarchical trees. Minimal spanning trees are network representations strictly speaking since they are composed of nodes and edges. Hierarchical trees are classification methods allowing us to compare distances within the minimal spanning tree network representation. As detailed in Section 3.2. below, this network representation is obtained by selecting the most economically meaningful relationships between the nodes. In topological terms, the relevant edges of the subgraph (network representation) are determined by the underlying network model, which in the case of the minimal spanning tree is the sub-dominant ultrametric of the complete graph derived from the full database (Mantegna, 1999). An interesting property of topological graphs is that, by analogy with ecosystems, their structure changes depending on the environment in a broad sense, in particular in the event of multiple equilibria (May, 2008, Johnson, 2013). [3]

Our network analysis of country stock market indices makes two contributions to the literature on financial market integration. First, we characterize the price dynamics of the different country stock market indices in our sample using topological graphs. Then we compare the price dynamics of the country stock market indices. The common component of global stock prices should become more similar as financial globalization increases. Second, this study is the first long-run analysis of price networks for stock markets dating back to the first era of globalization.

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[2] All equity markets indices in the database are general indices. Some sectoral indices, in particular in the field of new technologies, have recently emerged as being also reference indices (NASDAQ). However, with the exception of the Dotcom bubble of 2001 rise and burst, these technological indices remain very highly correlated with general indices. In addition, using general indices insures comparability over the sample.

[3] It has to be noted that MSTs are also used as a representations of food webs (from the microbian level to large ecosystems), as optimization tools of power distribution webs, in the analysis of the structure of particles systems, etc.

2.3. Price networks of stock markets

The methodology of the minimal spanning tree is as follows. The first step consists in calculating a time series correlation matrix. All time series are log-differentiated. We are using Pearson correlations, as in a majority of the econophysics literature.[4] The times series of log-differentiated indices being denoted by p_i and p_j for assets (countries) i and j, the corresponding crossed correlation is given by:

$$\boldsymbol{\rho_{ij}} = \frac{\boldsymbol{Cov(p_i, p_j)}}{\boldsymbol{\sigma_{p_i} \,.\, \sigma_{p_j}}} \tag{1}$$

In a second step, the correlations matrix is transformed into a distances matrix validating the conditions of an Euclidean metric (equation (2)), which is required to run the topological algorithms generating network representations.

$$\boldsymbol{d_{(i,j)}} = \sqrt{\boldsymbol{2(1 - \rho_{ij})}}$$

$$\begin{gathered} \boldsymbol{d_{(i,j)} = 0 \text{ if and only if } i = j} \\ \boldsymbol{d_{(i,j)} = d_{(j,i)}} \\ \boldsymbol{d_{(i,j)} < d_{(i,k)} + d_{(k,j)}} \end{gathered} \tag{2}$$

The first condition states that the distance between two nodes can be zero if and only if they coincide. The second condition states that the distance between two nodes does not depend on the starting point. Finally, the third condition ("triangle inequality") states that there is no shorter path between two nodes than the path going directly from the first to the second node.

The last step of the minimal spanning tree method consists in implementing the topological algorithms of construction of the minimal spanning trees in order to select the relevant edges within the full distance matrix. To this end, we use the Kruskal's algorithm and

[4] Topological representations of assets portfolios necessarily rely on price correlations. The main argument against Pearson linear correlations is that they would be biased in times of high volatility. However we are using monthly data, which show attenuated volatility episodes. In addition, correlations are calculated with sliding windows of 100 datapoints which corresponds to more than 8 years. Finally, all our results have been double checked using Spearman rank correlations. The results are available upon request.

the Prim's algorithm as a robustness test. The minimal spanning tree which is associated to a given distance matrix is unique. It is associated with a hierarchical tree of identical branching which displays the hierarchy of distances within the network. We construct this hierarchical tree using the nearest neighbor method.

3. Network structures and network indicators

3.1. Network structure of the database

In this section, we explain how the minimal spanning tree network representation is dervied which will be used to calculate time series of network indicators. We use the interwar period as an example to illustrate the methodology. First, equation (2) is used to construct the full distance matrix which is shown in Figure 3. This corresponds to a complete network in which all the relationships between the nodes appear, either strong (short distance, wider edge) or weak (long distance, thinner edges). The minimal spanning tree is obtained by isolating within this complex set of relationships the ones which are the most economically meaningful. Figures 4-6 show different representations of the minimal spanning tree. Figure 4 combines in a 2-layer representation the full distance matrix represented in Figure 3 (1st layer, in blue), and the minimal spanning tree (2^{nd} layer, in grey). In Figure 5, the 1^{st} layer is removed to represent the sole relationships belonging to the minimal spanning tree. Finally, the same relationships are shown so that the edges do not cross in Figure 6. The last method provides an easily readable network representation.

Globalization is measured by the importance of the common component of the country stock market indices. The MST is a network representation based on the importance of this common component. The common component can generally be classified into three different groups: 1) the absence of an edge (relatively low common component); 2) the existence of an edge with a long distance (mid-level common component); 3) or the existence of an edge with a short distance (relatively high common component). For example, consider the stock market index for the United Kingdom during the interwar period. The UK equity market index has three edges which indicates a high level of integration. This is also the case for Canada, which shows strong relations both with the United States, United Kingdom, and the continental Europe subtree.

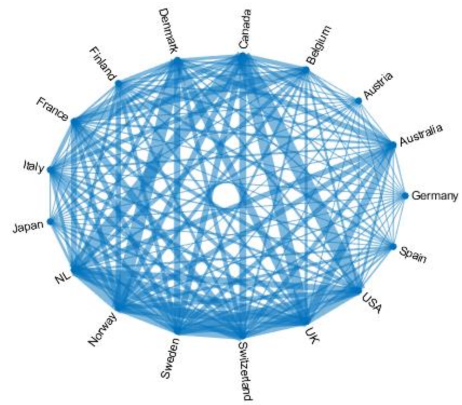


Figure 3 Complete network. Graph of the full distances matrix, edges widths representing the distances between pairs of nodes (interwar period)

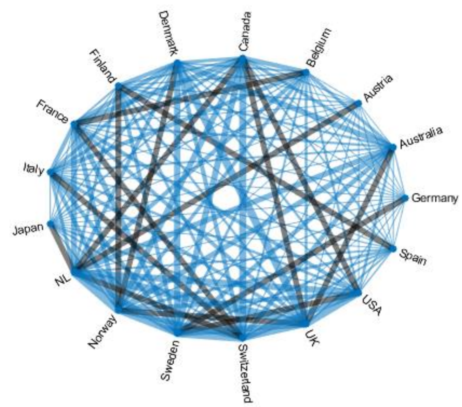


Figure 4 Minimal spanning tree. MST highlighted as a subgraph of the complete network (interwar period)

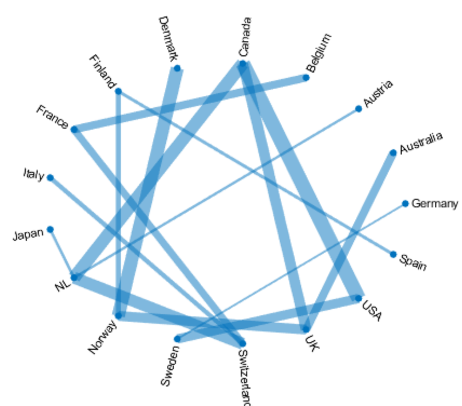


Figure 5 Minimal spanning tree. MST, edge widths representing the distances between pairs of nodes (interwar period)

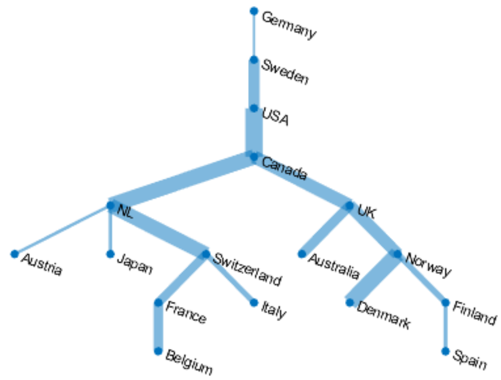
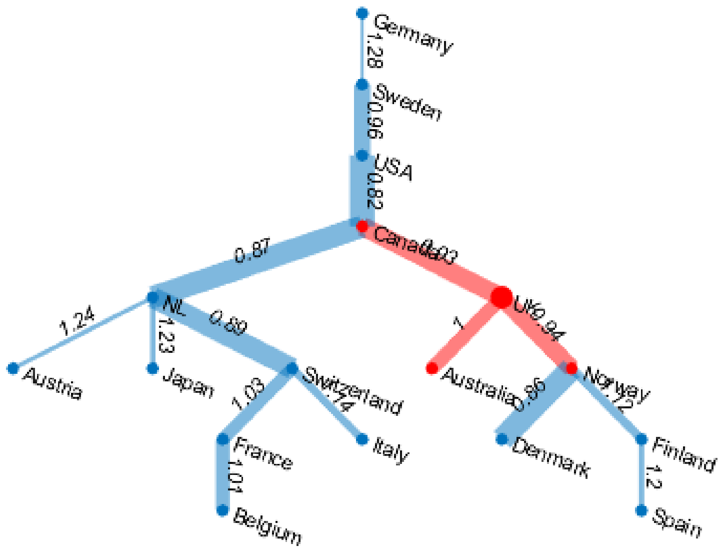


Figure 6 Minimal spanning tree. MST, hierarchical representation, edge widths representing the distances between pairs of nodes (interwar period)

3.2. Network indicators of distance and connectivity derived from the minimal spanning tree

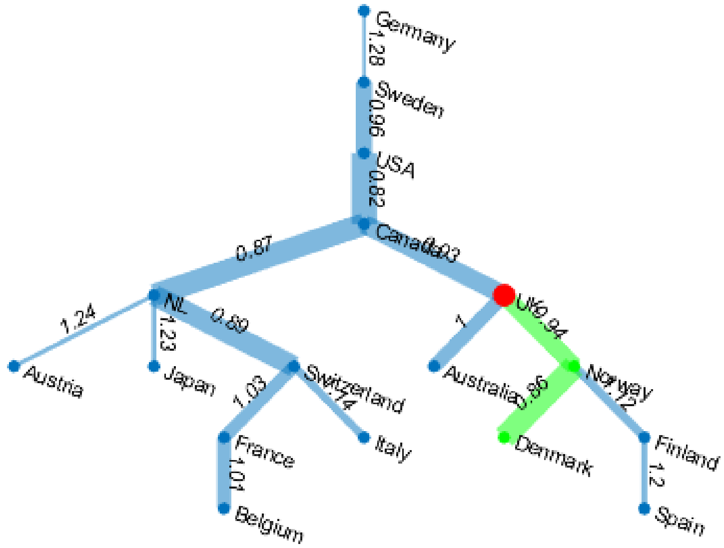
One of the advantages of our network analysis is that it enables us to describe different aspects of the process of financial globalization, for a given market segment. In particular, it is possible to calculate several types of distance and connectivity indicators. The purpose of this section is to show how these indicators are calculated and interpreted. We will again use an example from the interwar period.



In this example the UK has three nearest neighbors: Canada, Australia and Norway. In the case of the UK the distance to the nearest neighbors is given by the average of the distances of the corresponding edges (0.96). The average distance to the nearest neighbors at the network level is given by the average of node level measures (1.06).

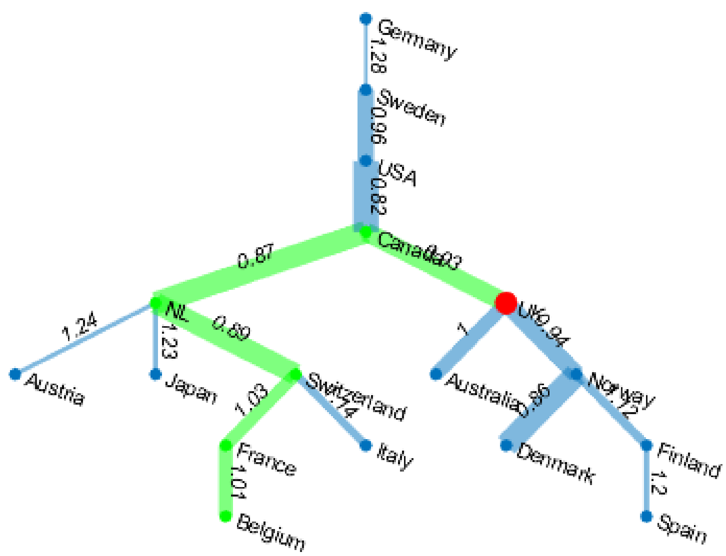
Figure 7 Average distance to the nearest neighbors (distance indicator). MST, interwar, distances on the edges, nearest neighbors of the UK

We use three types of distance indicators. Our first distance indicator is the average distance to the nearest neighbors (Figure 7). The average distance to the nearest neighbors is considered the most basic distance indicator. The nearest neighbor measures allow us to characterize local vs. global integration. The average distance to the nearest neighbors is expected to decrease when integration to the close neighborhood rises. We also use two path length measures taking into account distances to the whole network. The average path length is one of the most commonly used distance indicators. It takes into account for each node the total path length to each of the other nodes in the network. In other words, the average path length from a given node takes into account both local and global integration. The average path length is expected to decrease when financial globalization rises. Finally, eccentricity is the largest possible path length within the network for a given node (country stock market index). The dynamics of eccentricity also measures convergence within the sample since for each node it represents integration with the node with which it is the less integrated, and at the network level it represents the weakest link within the sample. The eccentricity is expected to decrease when integration to the furthest part of the world rises.



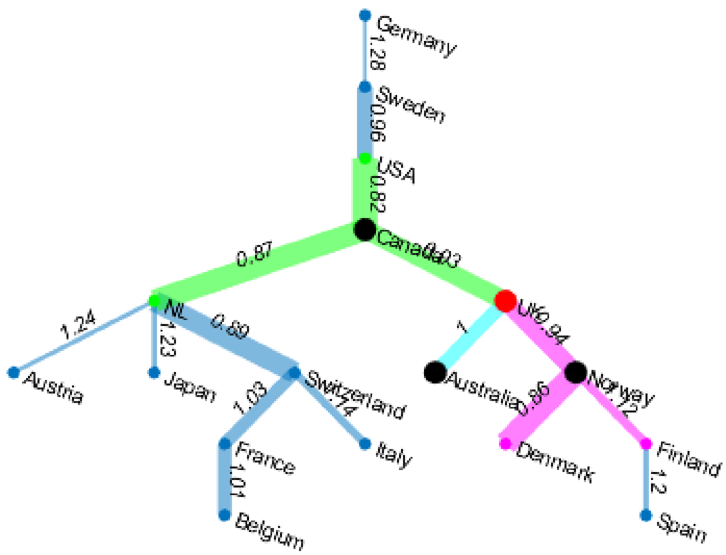
The example shows that the path from the UK to Denmark is composed of two steps: from the UK to Norway, and from Norway to Denmark. The total path length between the UK and Denmark is then 0.94 + 0.86 = 1.8. In the case of the UK the average path length is given by the average of all possible paths starting from the UK (2.58). The average path length at the network level is given by the average of node level measures (3.59).

Figure 8 Average path length (distance indicator). MST, interwar, path from the UK to Denmark



The example shows the path from the UK to Belgium, which is the longest possible path starting from the UK in this network. In the case of the UK the eccentricity is given by the total length (sum of distances) within this path (4.72). The eccentricity at the network level is given by the average of node level measures (7.99).

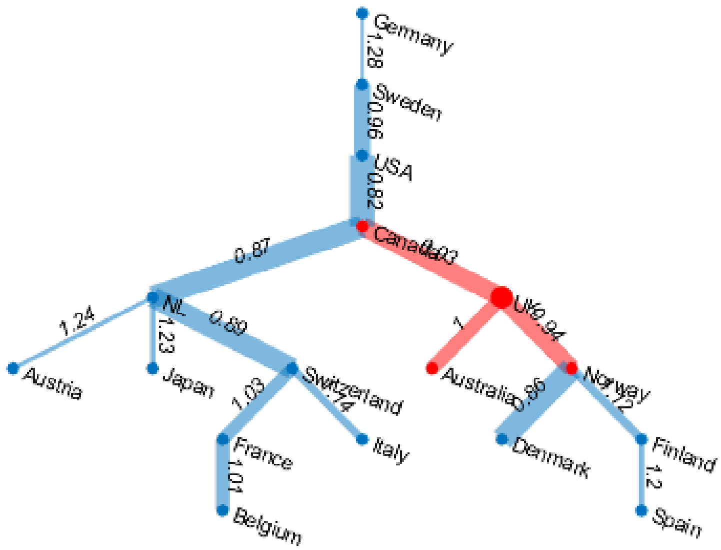
Figure 9 Eccentricity (distance indicator). MST, interwar, eccentricity of the UK corresponding to the path from the UK to Belgium



The example shows the degrees (number of nearest neighbors) of the nearest neighbors of the UK. In green: degree of Canada (3), in light blue: degree of Australia (1), in pink: degree of Norway (3). In the case of the UK the average degree of the nearest neighbors is given by the average of 3, 1 and 3. The degree of the nearest neighbors at the network level is given by the average of node level measures.

Figure 10 Average degree of the nearest neighbors (connectivity indicator). MST, interwar, degrees of the nearest neighbors (NN) of the UK.

In addition, we also use two types of connectivity indicators. The first connectivity indicator is the average degree (number of neighbors) of the nearest neighbors. It tends to rise when the structure of the network evolves from a basic and merely linear structure to multi-star and finally a star structure. In network terms, the reason why a star structure is considered as more integrated is that the path between any two nodes will be shorter because the number of steps is shorter (in comparison with a merely linear structure). The average degree of the nearest neighbors is expected to increase when globalization increases. In the case of the UK the high degree of the nearest neighbors likely reflects the role of London as a global financial center and as a propagator of the common shock of the 1929 Wall Street Crash.



The example shows the degree (nearest neighbors) of the UK. In the case of the UK the degree, or number of nearest neighbors, is 3 (Canada, Australia, Norway). The standard deviation of the degree of the nodes at the network level is given by the standard deviation of node level measures.

Figure 11 Standard deviation of the degree of the nodes (connectivity indicator). MST, interwar, degree of the UK

Finally, the standard deviation of the degree of the nodes measures the dispersion of the network nodes connectivity. It is also increasing when the structure of the network becomes less linear (where all nodes have one or two connections) and closer to a star network (where a single node has a high number of connections and the remainder of the sample one or two connections only). Thus, the standard deviation of the degree of the nodes is expected to increase when globalization increases.

4. Results

4.1. Time series of network indicators

We analyze long-run stock market integration by computing rolling windows of the distance and network indicators. The integration measures are calculated by replicating the construction of minimal spanning trees over rolling periods of 100 data points, starting from the beginning of the sample period in 1913 (Abry et al., 2019). The method produces time series of network indicators, where each point corresponds to the structure of the network over the previous 100 months.[5] Figure 12a-12c report the distance measures while Figures 12d-12e show connectivity measures.[6]

The end of the 1st era of globalization (1913)[7] is characterized by high nearest neighbor distances which would indicate a low level of financial integration. On the other hand, the path length measures (average distance to the nearest neighbors, eccentricity) are relatively low. Connectivity measures are also relatively high, which combined with the previous observation of low path length measures suggest that the end of the 1st era is a high point of globalization in stock market networks.[8]

Moving forward, we find that the interwar period is a period of disintegration. However, the 1920s witnessed integration with the common rise in stock markets following the US lead. This was followed by a common response of the global stock market network to the 1929 crash. The large decline in stock prices in 1929 that ushered in a global bear market was accompanied by decreasing distances and increasing connectivity in the global network of the major stock exchanges. The reduction in distances likely reflected enhanced contagion of assets prices in the aftermath of the crisis of 1929 (Maveyraud and Parent, 2017). However, between 1935 and 1940, distance measures increase again and reach pre-1929 levels, possibly as a consequence of the rise in protectionism during this period. Connectivity measures display the same pattern as distance measures during the interwar period. The 1920s and the second half of the 1930s are characterized by increasing distances and declining connectivity. The five-year period after the 1929 stock market crash shows increasing connectivity likely reflecting contagion or a common

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[5] As a robustness check, in order to ensure comparability with Bekaert and Mehl (2017) who use 12 months rolling windows, all time series of network indicators were double-checked with 12 data points windows. The trend and break dates are robust for all indicators. However the short 12 data points window results in volatile and thus less legible time series. This version of network indicators is available upon request.

[6] The break in the time series of network indicators during the 1910s and the interwar reflects missing data for 9 countries because their stock markets were closed. For 4 countries the markets were closed for the duration of the conflict. These were Austria, Belgium, Germany and the Netherlands. By contrast during World War II the data is missing for only 3 countries and only for a few months. The superimposed U-shaped pattern in sub-figures a) and b) is obtained by a quadratic regression.

[7] See section 3.1. for the definition of the sub-periods.

[8] The methodology is robust with regards to the increase in the size of the sample (10 countries in 1913, full coverage since 1922). Indeed, the average nearest neighbors distance and the connectivity measures we are using do not depend in any case on the size of the underlying network. As regards path lengths measures a strong robustness check is that working on the same database as Bekaert & Mehl (2017) we get time series which are very close to their global betas (calculated as the ratio between the covariance between the returns of a given asset and the market portfolio, and the variance of the return of the market portfolio) obtained with a CAPM. For more details see Figure 6 p.47 in Bekaert & Mehl, 2017.

Great Depression shock. Overall, the interwar period is an era of disintegration, which is expressed in terms of network indicators by an increase in distances and a reduction in connectivity.

The Bretton Woods period (1950-early 1970s) is characterized by large, but stable distances between country stock markets based on the distance to nearest neighbor indicator. There is also a decline in the average path length and eccentricity that indicates increasing integration. In contrast, the connectivity indicators are clearly on the rise and increasingly volatile. This may reflect the role of capital controls. The early Bretton Woods era seems to share the (high) distance characteristics of the classical gold standard and interwar periods, and the (increasing) connectivity dynamics of the recent period of globalization. On balance, financial globalization of stock markets in the Bretton Woods period is probably not higher than in the classical gold standard based on 1913 levels of integration. This likely reflects the presence of binding capital controls under Bretton Woods.

The second period of financial globalization is characterized by unprecedented levels of all distance and connectivity indicators. Connectivity indicators are also characterized by unprecedented volatility, meaning that the structure of the network is less stable than ever. The major stylized fact is the drastic reduction in distances and increase in connectivity in the aftermath of the 2008 crisis. It is also interesting to note that the stock market crash which accompanied a major financial crisis in 2008 affects network characteristics much more than the stock market crash of 2001. The decrease in the distance measures accelerates. Connectivity indicators begin rising again, while they are temporarily decreasing between 1995 and 2008. At the end of the period, distance measures fall outside their historical range. For example, the average path length ranges from about 2.5 to 5.5 between 1930 and the end of the 1990s. Its value is about 1.3 in 2017. Connectivity indicators also reach unprecedented levels and volatility. The post 1980 is historically atypical from the point of view of all network indicators.

Overall, the nearest neighbor measure indicates that integration is much higher during the recent period of globalization than any other period. With respect to the path length indicators reported in Figures 12b and 12c, the distance indicators show that stock market integration is considerably higher during the recent period of globalization than any other period in modern financial history. Indeed, the distance indicators suggest that equity market integration is best described as a hook rather than a U-shape as many studies have found for other economic and financial markets. Integration was high during the first era of globalization followed by 60 years of decreasing integration. Since the early 1970s, integration has dramatically increased to a point which is significantly greater than the high levels of integration seen during the pre-1913 period.

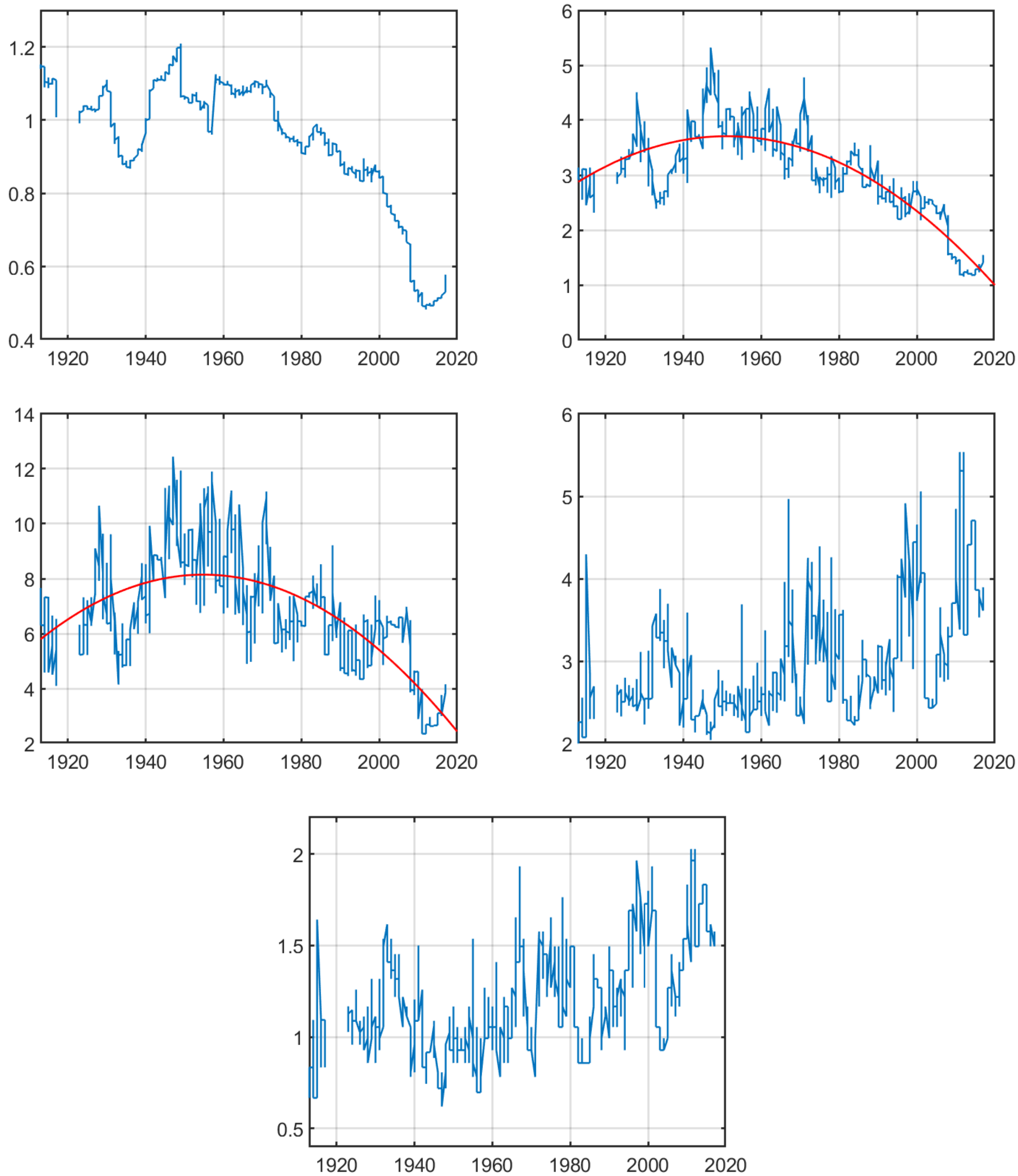

Figure 12 Network indicators. (a) distances to the nearest neighbors, (b) average pathes lengths, (c) eccentricity, (d) average nearest neighbors degree, (e) standard deviation of degrees

4.2. Country specific effects

In this section, we discuss some additional results at the country level. One of the advantages of our network method is that it allows us to characterize both the dynamics of financial globalization at the network level, and the dynamic of any given country stock market (node) within the network. To this end, the most commonly used representation is the hierarchical tree, which is discussed below. The hierarchical tree displays the hierarchy of distances within the network. We also propose histograms of distance matrices, which enable us to observe how the distribution of distances changes over time; and time series of network indicators at the node level for a selection of countries (France, Germany, Japan, UK, USA), which enable us to observe country specific declinations of the global pattern.

As discussed in Section 3.3, the minimal spanning tree displays the structure of the network. The nodes correspond to stock markets, and the edges that connect the nodes represent the most significant relationships extracted from the distance matrix. By definition, the minimal spanning tree is connected (all nodes are connected to the network by at least one edge) and is cycleless (no path starting from a node of the network returns to this node). The hierarchical tree (Figure 13) displays in a hierarchical way the distances by which the nodes of the minimal spanning tree are connected to the network. That is, the lowest the value on the x-axis of the hierarchical tree, the shortest the distance.

Figure 13 shows the hierarchical trees by sub-periods. As expected, the USA always belongs to the shortest edge, with the exception of the recent period of globalization where they remain among the shortest but are less integrated than a small cluster of European economies. Interestingly, the UK is among the most integrated in the recent period, but less so in the interwar and Bretton Woods period. This may reflect the 1931 devaluation of the pound and the binding capital controls and exchange controls under Bretton Woods and the general relative weakening of the UK economy and the declining role of sterling as a global currency. Regarding the less integrated nodes, Japan and Spain are always characterized by distances which are among the highest in the global stock market network. Japan had extensive capital controls and exchange controls in Bretton Woods. Spain was an emerging country until the 1980s and was not well connected to the rest of Europe. It was engulfed by the Civil War in the 1930s. It also had capital and exchange controls throughout this period. Germany, is an interesting case study. The German equity market was among the least integrated markets during the interwar and Bretton Woods periods. This reflected the chaos of the hyperinflation in the 1920s and the extensive exchange and capital controls in the Nazi regime as well as capital controls under Bretton Woods. Since then, the German stock market has become one of the most integrated markets in the modern period of globalization reflecting the rise of Germany as an export driven economic superpower in the past five decades. The German experience highlights the rise of the European Union and the Eurozone which has led to greater stock market integration in Europe as shown by the hierarchical tree in Figure 13c where seven European stock markets have the smallest distance measures in the recent period of financial globalization.

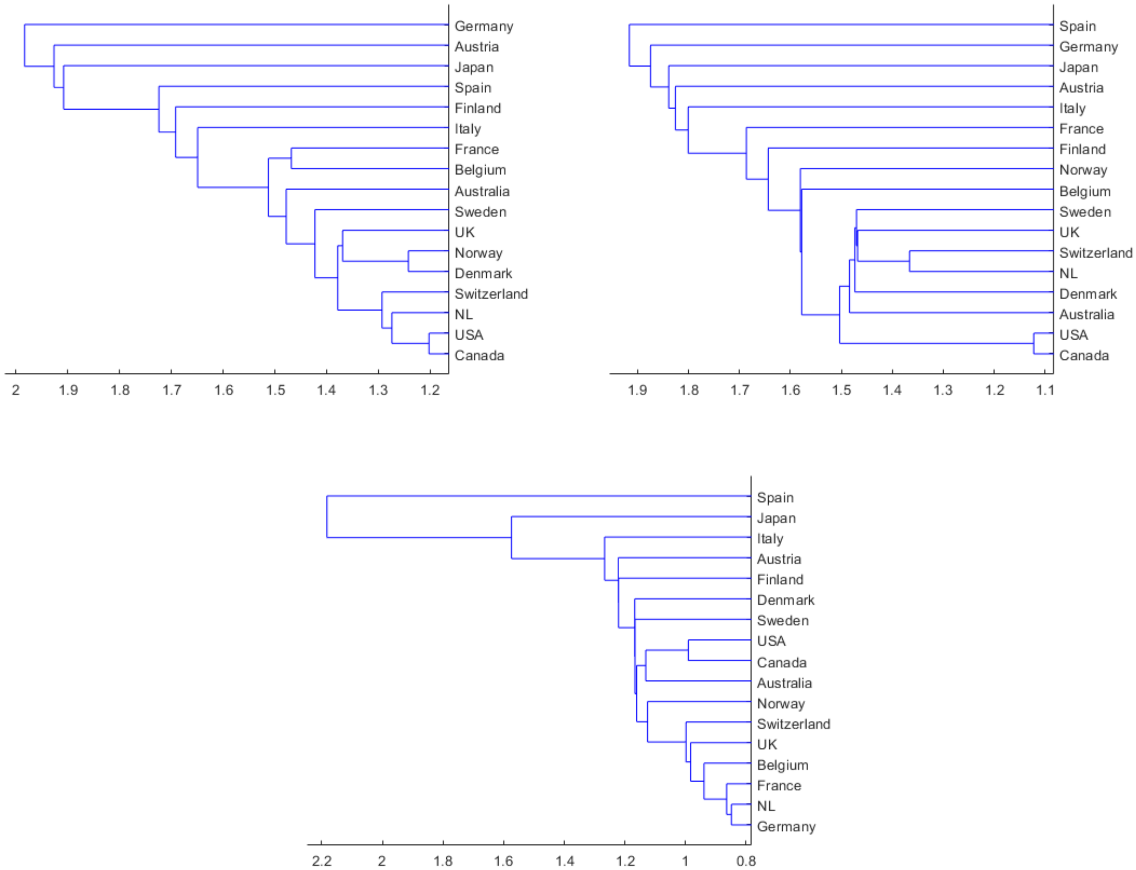

Figure 13 Hierarchical trees. (a) interwar, (b) Bretton Wood, (c) Second Era of Globalization, hierarchy of the distances by which the nodes are connected to the network

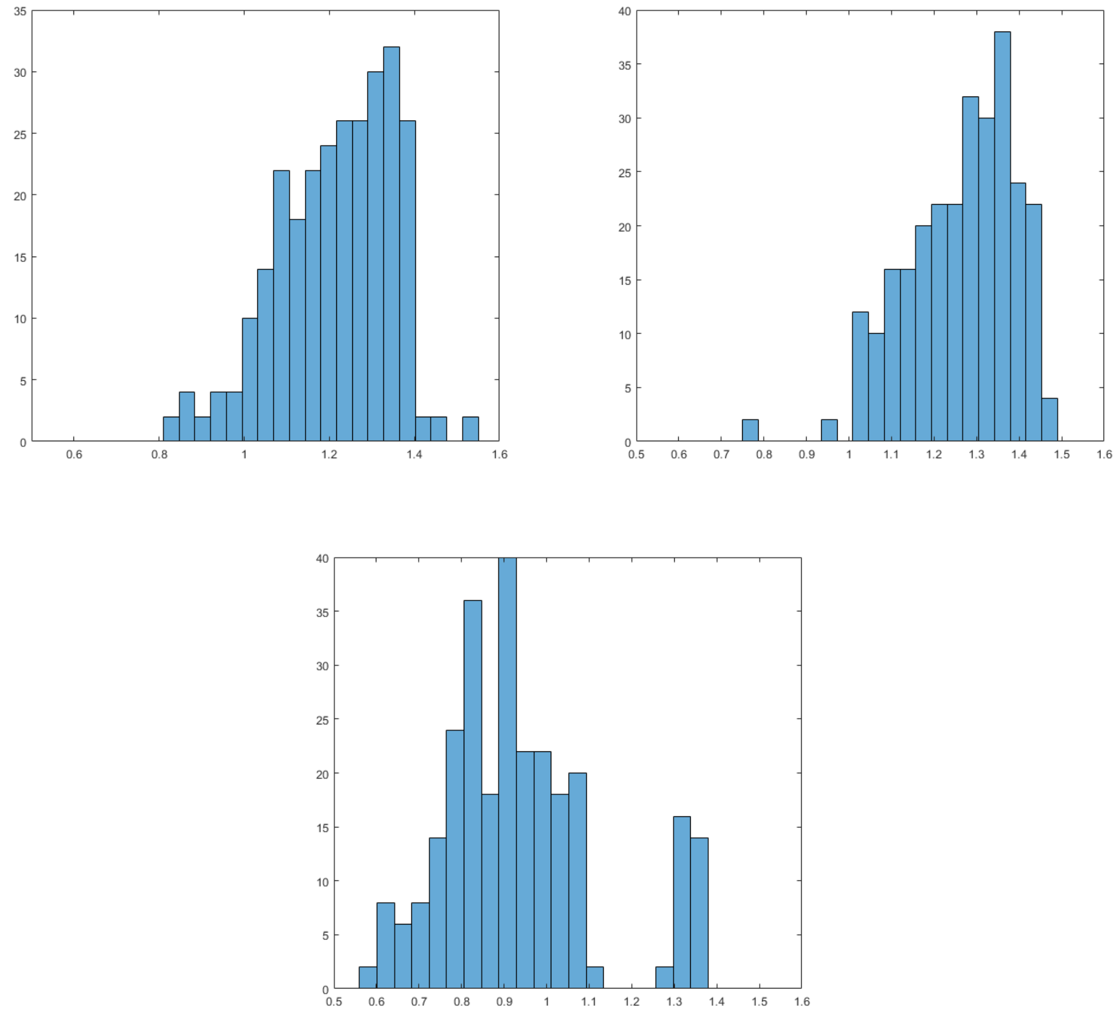

Figure 14 Histograms of distance matrices. (a) interwar, (b) early 2nd era, (c) late second era, increasing globalization corresponding to a translation to the left and a less negatively skewed distribution

The histograms of distance matrices (Figure 14) also enable us to highlight additional features of the global hook since they display the distribution of distances within the network. The most striking feature is the highly specific distribution of distances of the late 2nd era, that supports the results of Section 5.1. While the distributions of distances in all previous sub-periods are in the range of about 1 to 1.5, the distribution in the recent era is in the range of about 0.6 to 1.1. In addition, contrary to the previous distributions, it is not rightly skewed, i.e. it is not distorted in the sense of the highest values. This may suggest that the return of financial globalization in the post World War II period was slow to appear. The histograms of distance matrices also highlight the lasting divergence, within the atypically high integration in recent period of globalization, of a small group of nodes (Spain, Japan). This likely reflects the huge Japanese housing and stock market boom in the 1980s followed by the crash of 1990 from which Japan has yet to fully recover. Spain experienced two serious house price booms and busts and several stock market crashes in this period (Bordo and Landon Lane (2014)). The finding highlights the growing instability of the global stock market network in the recent age of globalization.

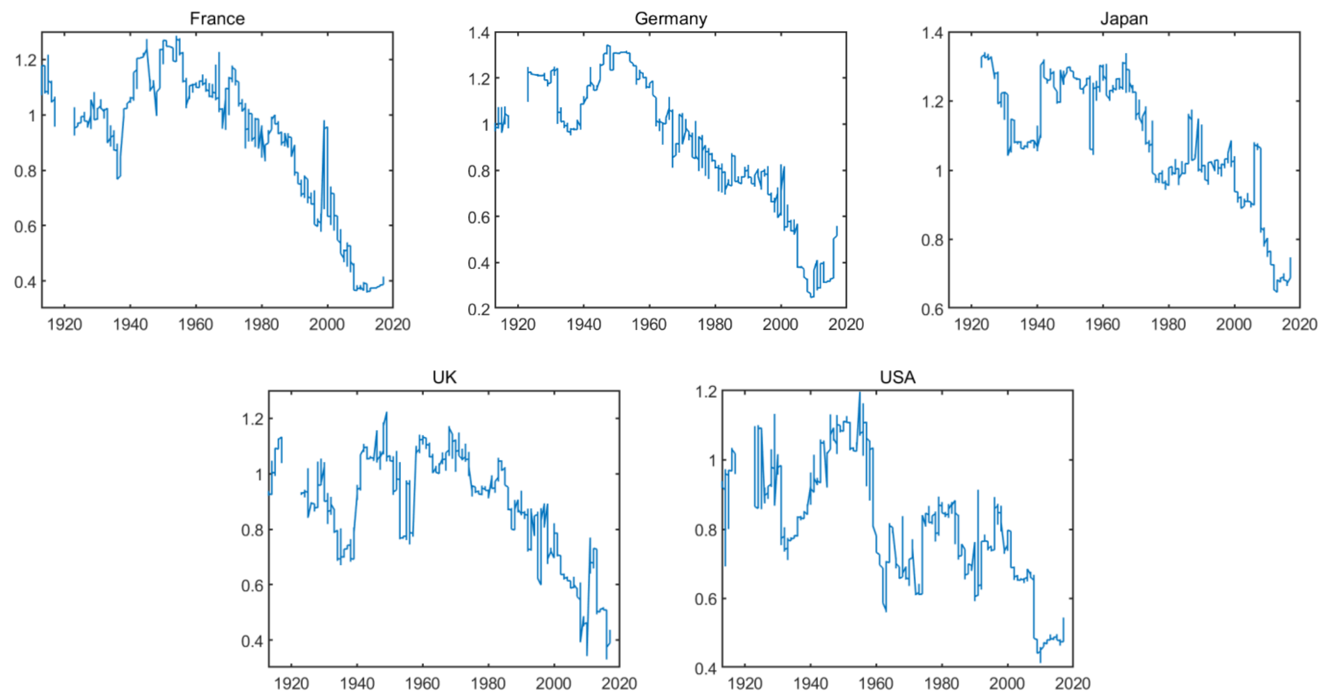

Figure 15 Average path length, node level. (a) France, (b) Germany, (c) Japan, (d) UK, (e) USA

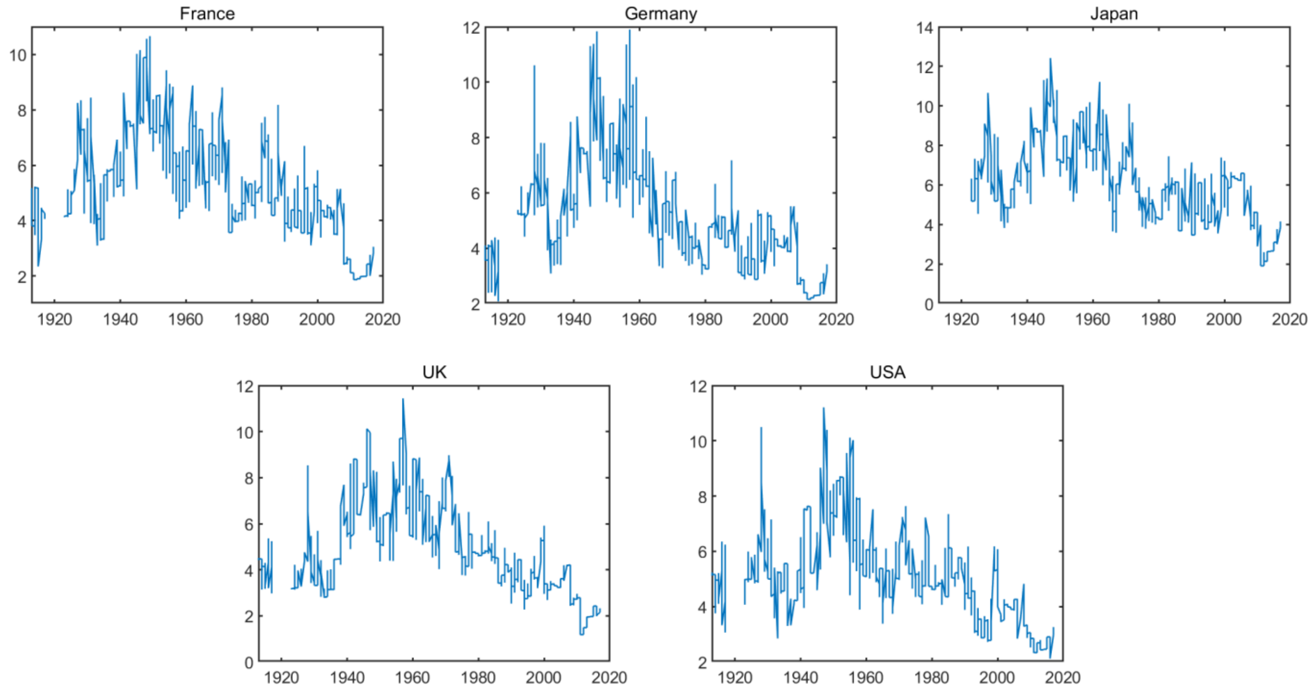

Figure 16 Eccentricity, node level. (a) France, (b) Germany, (c) Japan, (d) UK, (e) USA

Finally, time series of the network indicators at the country level also provide additional findings. The average distance to the nearest neighbors is presented in Figure 15 and the eccentricity is presented in Figure 16. Both sets of figures show the dramatic decrease in the distance measures for the stock markets in the five countries. In all cases, the average path length has fallen by more than 50 percent since their peak value that usually occurred in the 1950s or 1960s. The decline in the distance measures really shows the increase in financial integration of the global stock market network over time. With respect to eccentricity (largest distance to another market), we once again see large declines which is consistent with the interpretation that the second era of globalization has the highest level of stock market integration in world history.

5. Conclusion

We provide one of the first long-run studies of the evolution of stock market integration since the early 1900s. We employ a network analysis of 17 markets to study the history of global stock market integration as well as the integration between countries over time. The empirical analysis suggests that stock market integration can be described as an unstable hook. Our findings indicate that equity market integration was very high at the end of the gold standard period based on the average distance between stock markets and the connectivity measures from the network analysis. It is important to note, however, that stock market integration during the first period of globalization was not very high based on a nearest neighbor criteria. With the outbreak of World War I, financial integration retreated as the global markets experienced the Great Crash of 1929 and the Great Depression. This led to protectionist measures as countries look inward. Stock market integration declined.

Following the end of World War II, the global stock market network largely remained unchanged from the interwar period for almost the next 30 years as measured by the distance indicators and connectivity measures of the network analysis. This most likely reflects the capital and exchange controls under Bretton Woods as well as the presence of major controls on the domestic financial markets and institutions of most countries until the 1980s and 1990s.

Only with the collapse of the Bretton Woods system and the subsequent rise of the recent period of globalization have we seen a dramatic rise in stock market integration. The nearest neighbor and path length distance indicators show that the modern period of globalization has an unparalleled level of financial integration. A significant portion of the increase in integration can be attributed to the creation of the European Union and the Eurozone. This has led to increased integration in trade and capital market. For example, Germany's stock market was poorly integrated in the interwar and Bretton Woods period. Presently, it is one of the most integrated stock markets in the world based on the distance measures. The high level of global financial integration has also come with a cost. The connectivity measures indicate that the second era of globalization not only has the highest level of stock market integration, but the global stock market network also has the highest level of financial instability in world history as measured by the network analysis.

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