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Working Paper

From physical to financial contagion: the COVID-19 pandemic and increasing systemic risk among banks

From physical to financial contagion: the COVID-19 pandemic and increasing systemic risk among banks

[short version of the full-length article]

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Abstract

Over the last few decades, large banks worldwide have become more interconnected, and as a result, the failure of one can trigger the failure of many. In finance, this phenomenon is often known as financial contagion, which can occur as a domino effect. In this paper, we show an unprecedented increase in bank interconnectedness during the outburst of the COVID-19 pandemic. We measure how extreme negative stock market returns for one bank spill over to all other banks within the network, and on this basis, we propose a new measure of systemic risk among banks. Our results indicate that the systemic risk and the density of the spillover network have never been as high as they have been during the pandemic, not even during the 2008 global financial crisis. Policy makers and regulatory authorities should be particularly cautious regarding this interconnected financial environment, as second waves of the pandemic could pose a significant danger to the worldwide economy, and the "it's-just-a-flu" narrative will no longer be an option.

Keywords: systemic risk, banks, COVID-19, pandemic, cross-quantilogram, financial networks, interconnectedness

JEL classification: G01, G15, G21, G28, C21

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Author Contributions

Shahzad and Hoang conceived the study. Baumöhl and Výrost performed estimations and took the lead in writing the manuscript. Bouri retrieved the data. All authors discussed the results and contributed to the final manuscript.

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Introduction

The debate on systemic risk in the banking system occurs in the context of financial innovations and deregulation (Das and Uppal, 2004; Billio et al., 2012; Adrian et al., 2016; Black et al., 2016; Silva et al., 2017; Demirer et al., 2018). Large banks have increased in size and are more involved in market-based activities while being more global and interconnected (Härdle et al., 2016; Hué et al., 2019; Chen et al., 2019). After the global financial crisis (GFC) in 2008, the President of the European Central Bank (ECB) at that time, Jean-Claude Trichet, declared that understating the nature of systemic risk is a precondition for financial and economic stability.[1]

Systemic risk is the risk that can be triggered and disseminated by the failure of one financial institution, which in turn can lead to the failure of other financial institutions. This chain reaction jeopardizes financial stability and adversely affects the real economy by decreasing the capital supply and market liquidity, which leads to the disruption of real sector activities and entails heavy costs for the economy that can reduce the population's level of economic well-being.

So-called financial contagion (Forbes and Rigobon, 2002)—when financial shocks experienced in one country or one market are transferred to another—characterized by simultaneous instances of financial instability on the aftermath of market innovations and shocks, appears to be at the heart of systemic risk.[2] Thus, measuring and analysing contagion and interconnectedness among the largest banks through the construction of a new measure of systemic risk is a primary motivation for our study. It has implications regarding how risk and supervision affect financial stability.

[1] In a conference organized by the University of Cambridge on December 10, 2009.

[2] During the last few years, the "contagion" became a standard term for economists to describe the transmission of a crisis and/or shocks among international financial markets. Forbes (2012) provided results from a Factiva search of the monthly use of the term "contagion" in economics and finance press articles, and before 1995, this term was used only rarely. Media references to contagion exploded during the GFC, most notably, during the European sovereign debt crisis (ESDC). Practically the same results are obtained when we search the term "contagion" in titles, keywords, and abstracts within the Scopus database using only economics, econometrics, and finance areas of research. There are only 17 hits before 1995, while in 1999, contagion appeared in 25 research papers. Beginning in 2010, there were more than 100 papers dealing with financial contagion every year. The most influential (and cited) are, of course, only a few of the total (e.g., Kaminsky and Reinhart, 2000; Allen and Gale, 2000; Forbes and Rigobon, 2002; Bae et al., 2003; Bekaert et al., 2005).

1. New systemic risk indicator at-a-glance

We propose a new index to measure financial systemic risk within a network framework. The index is based on the cross-quantilogram (Han et al., 2016; CQ hereafter, see the next section for details) methodology, and it allows for the measurement of risk spillovers and their directional source between pairs of individual banks at different market states (determined by different quantile levels of the variables' distribution). In addition, it allows for the identification of banks that transmit and receive risk through spillover effects.

Our sample covers 83 large banks from three regions – North America, Europe, and Asia & Pacific – from September 2003 to April 2020. These banks play an important systemic role in international banking systems due to their size and scale of operations.

First, we take stock market returns of selected banks in our sample and estimate their CQs. The systemic risk index in this study is built based on the so-called "directional predictability" between all possible pairs of banks in the sample, to be more specific, for their extreme negative stock market returns (5^{th} quantile of the joint return distribution). The underlying idea of directional predictability simply means that extreme negative returns of the *i-th* bank at time t can predict extreme negative returns of the *j-th* bank at time $t+1$ (e.g., next trading day) – which corresponds to the notion of financial contagion.

Second, the directional predictability between all pairs of banks results in an $N \, x \, N$ adjacency matrix that allows us to measure directional spillover effects across financial institutions and to characterize their evolution as a system within a network framework. The term "network" refers to a (directed) graph with a set of vertices (banks) and a set of edges (links). Based on the constructed networks, we build our systemic risk indicator, which also takes into account the size of each bank—overall systemic risk within a network can be thus induced by its connectedness (CQs) or by the compromise level of nodes (in our case, the market capitalization of banks), or even both.

2. Data and methodology

The stock price data are obtained from Bloomberg for the period from September 11, 2003, to April 17, 2020, for a total of 4332 daily observations of closing prices. To avoid the nonsynchronous trading effects, we calculate rolling-average two-day returns as in Forbes and Rigobon (2002). To construct the systemic risk indicator, we use market capitalization, expressed as an index relative to the average value of market capitalization of all banks in 2004, the first full year in our sample.

Our analysis is based on the cross-quantilogram of Han et al. (2016), which is defined for strictly stationary time series $\{(\mathbf{y}_t, \boldsymbol{x}_t) : t \in \mathbb{Z}\}$, with real valued components $\mathbf{y}_t = (y_{1t}, y_{2t})^T \in \mathbb{R}^2$ and $\mathbf{x}_t = (x_{1t}, x_{2t})^T \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$. Based on the conditional distribution function $F_{y_i|x_i}(\cdot\,|x_{it})$ of y_{it}, $i = 1{,}2$, the conditional quantile function is defined as $q_{i,t}(\tau_i) = \inf\{v\colon F_{y_i|x_i}(v|x_{it}) \geq \tau_i\}$ for quantile $\tau_i \in (0{,}1)$.

The measurement of serial dependence in quantiles is based on the examination of the quantile hit processes $\left\{I\left(y_{it} \leq q_{i,t}(\cdot)\right)\right\}$, which alternate between 0 and 1, depending on the exceedance of the specific quantile. To generalize, define $\psi_a(u) = I(u < 0) - a$.

The sample cross-quantilogram $\hat{\rho}_\tau(k)$ at lag $k \in \mathbb{Z}$ for quantiles $\tau_1, \tau_2 \in (0{,}1)$ is defined as

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T} \psi_{\tau_1}\left(y_{1t} - \hat{q}_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T} \psi_{\tau_1}^2\left(y_{1t} - \hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T} \psi_{\tau_2}^2\left(y_{2t} - \hat{q}_{2,t}(\tau_2)\right)}} \tag{1}$$

Following this definition, the values of the sample cross-quantilogram are constrained to $[-1{,}1]$, and the cross-quantilogram is invariant to any strictly monotonic transformation applied to both series (Han et al., 2016).

Apart from obtaining the value of the cross-quantilogram specifying the strength of the dependence in quantiles, one may also be interested in inference, e.g., a test of the hypothesis of directional predictability in quantiles of events in up to $p \in \mathbb{N}$ lags. Han et al. (2016) propose a Box-Ljung type statistic for this purpose to test the hypothesis $H_0\colon \rho_\tau(1) = \cdots \rho_\tau(p) = 0$ with alternative $\rho_\tau(k) \neq 0$ for some k and a selected quantile $\tau \in (0{,}1)$. As the asymptotic null distribution for the cross-quantilogram is complicated and depends on nuisance parameters, the critical values for the statistic were obtained using the stationary bootstrap of Politis and Romano (1994), as suggested by Han et al. (2016). The results presented in this paper were obtained by using 1000 replication samples for hypothesis testing.

To construct a network representing the quantile dependence in returns, we have estimated bivariate cross-quantilograms for all banks in the sample. While the vertices in the network represent individual banks, the edges were created only between banks, where the Box-Ljung type test in any of up to 10 lags provided evidence for quantile dependence.

As the cross-quantilogram measures the dependence of lagged values of one of the banks against a contemporary value of the other, the adjacency matrix is not symmetric, and the network is represented by a directed graph.

To calculate the overall risk score, we follow the idea of Das (2016), in that the total systemic risk score of the network of $N = 83$ banks is calculated from the adjacency matrix ($\mathbf{A}$) of the network created in the previous step, together with a vector of compromise loadings ($\mathbf{c} = (c_1, \dots, c_N) \in \mathbb{R}^N$), represented as nodal market capitalization. The elements of $\mathbf{A}$, a_{ij} denote the values of the cross-quantilogram from bank i to j. The aggregate risk score $S(\mathbf{A}, \mathbf{c})$ is then defined as

$$S(\mathbf{A}, \mathbf{c}) = \mathbf{c}^T \mathbf{A} \mathbf{c} \tag{2}$$

The aggregate risk score may be decomposed into the contributions of each bank (S_i), as

$$S(\mathbf{A}, \mathbf{c}) = \sum_{i=1}^{N} S_i = \sum_{i=1}^{N} \left(\frac{\partial S}{\partial c_i} C_i \right) \tag{3}$$

where $\frac{\partial S}{\partial c_i} = 2 \sum_{j=1}^{N} a_{ij} c_j$.

The aggregate risk score, as well as its decompositions, are analysed for the full sample period from September 11, 2003, to April 17, 2020. To capture the dynamics of the change in the risk score, we also quantify the cross-quantilogram over rolling subsamples spanning 6 consecutive quarters, with a drift of one quarter.

3. Main results

Here, we present our major findings; additional details are available in the Appendix material. Our data span the period from September 11, 2003, to April 17, 2020, for a total of 4332 daily observations of stock market closing prices. Apart from the full-sample estimations, two major subsamples were considered: (1) the GFC from August 3, 2007, to July 2, 2009, and (2) the ESDC from January 5, 2010, until August 3, 2012. Notably, our sample also covers sharp declines in stock markets around the world during the outburst of the COVID-19 pandemic within the first months of 2020, and by using a rolling analysis, we are able to provide the results for this recent period as well.

3.1 Increasing connectedness among banks

To obtain a better perspective on the extent to which the international banking sector is connected, we show a network of CQs among banks estimated over the full sample in Figure 1. Note that this directional network captures only co-movements of extreme negative returns (5^{th} quantile of joint return distribution) that are highly statistically significant, i.e., at the

7.35x10^{-6} significance level (Bonferroni *p*-value adjustment). Despite this rather strict threshold, the density of the network is 98%, meaning that out of the maximum number of all possible connections (in our case, 6806, N x N-1), almost every connection is made. Visually inspecting such a network is practically impossible.

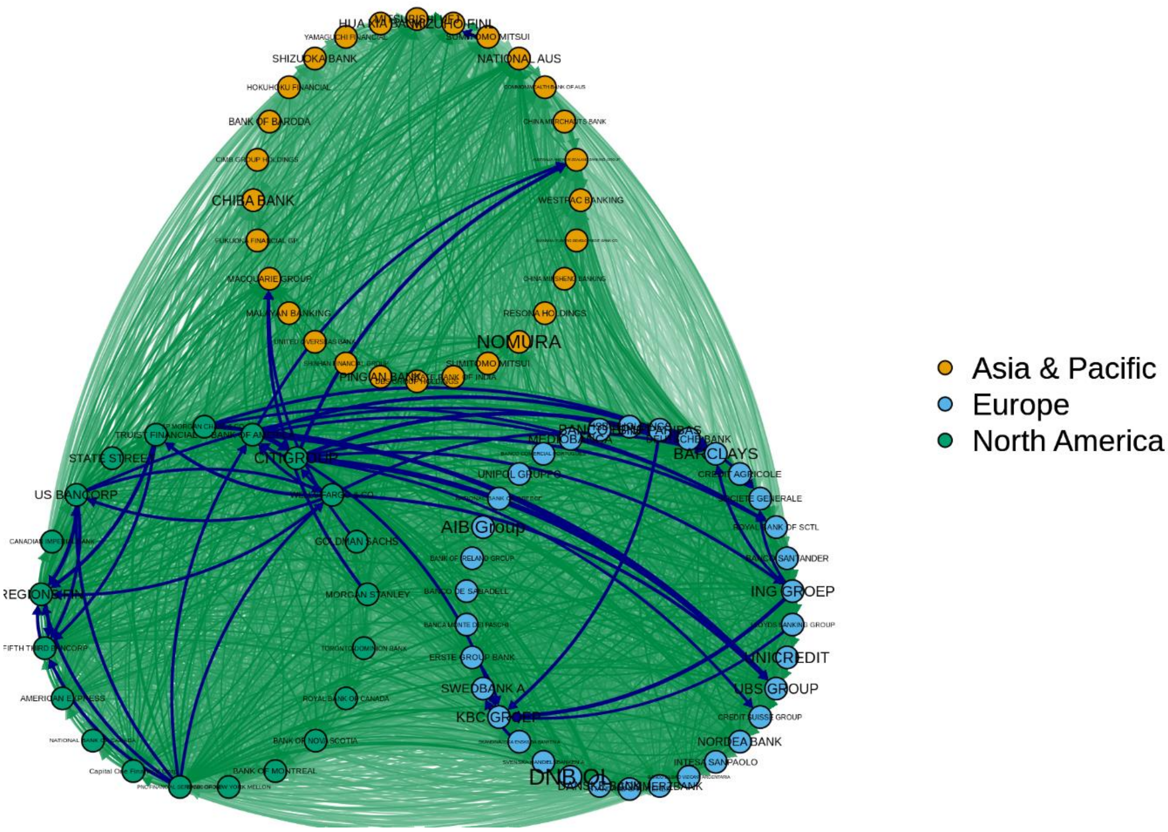

Figure 1: Network of CQs (highlighted edges are above the "top 100 average" threshold)

We can create a threshold graph to extract only those relationships that satisfy some predetermined conditions. As an example, we removed the values smaller than the average of the first 100 largest individual bank risk scores and highlighted these connections in Figure 1. After such extraction, we can easily identify the most influential nodes within the bank network, which might be particularly interesting for supervising authorities. Furthermore, after computing some basic topological properties of created networks, we can precisely pinpoint which banks are the largest transmitters of negative shocks and which are more likely to be receivers (see Appendix, Table 1).

3.2 Overall systemic risk index

Figure 2 captures the evolution of our systemic risk index together with the network density. These two measures are closely related, as negative shocks are propagated more as a network becomes denser. However, network density does not reflect the aspect of size in spillover transmission. For example, while the systemic risk index spikes in 2007, accompanied by rather small network density, both indicators jointly peak in 2008. Subsequently, during the ESDC period, banks become more interconnected, but the overall systemic risk is slightly smaller than the network density. Then, again in 2015 and 2016, systemic risk rises significantly above the density, as the so-called "2015–16 stock market selloff"[3] occurs.

This is the point at which we would like to highlight our main result. To illustrate Figure 2 into an interval of 0 to 100, the index is normalized to its maximal value, in our case, to the end of our sample. Over the first few months of 2020, economies faced an unprecedented economic lockdown. Stock markets around the world experienced sharp drops that were comparable only to the drops during the Great Depression in 1929 or the outbreak of the GFC in October 2008. As we can see, the systemic risk during the COVID-19 pandemic is even higher than that during the GFC. Stock markets rebounded in April 2020 as investors believed in a quick recovery after many countries began re-opening their economies. However, if a second wave of the pandemic hits the world and governments will again be forced to apply dramatic non-pharmaceutical interventions (such as lockdowns), the consequences for the financial world might be dire.

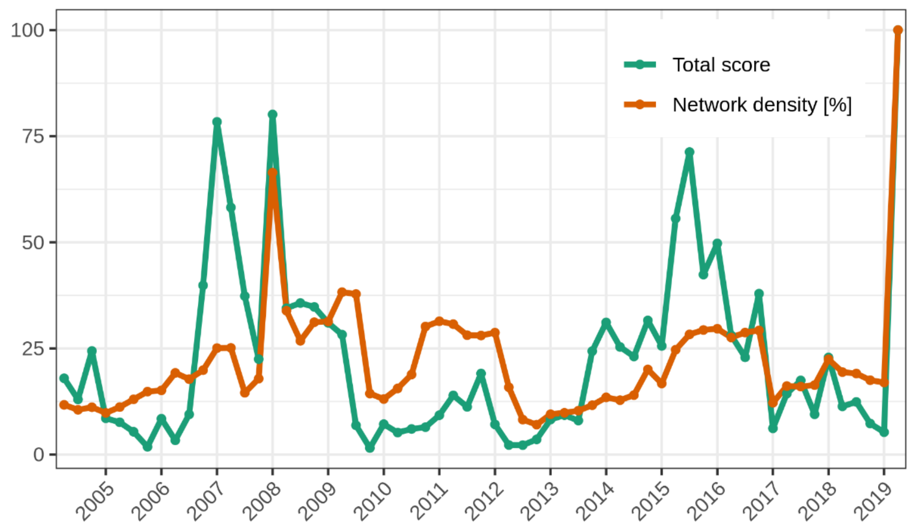

Figure 2: Overall systemic risk index

[3] A few sources include the Chinese stock market turbulence, GDP slowing growth in China, the Greek debt default, the end of quantitative easing in the US, and, finally, the Brexit vote.

3.3 Decomposition of the systemic risk index

From the perspective of policy makers and regulatory authorities, it will be more important to decompose the overall systemic risk and to obtain more detailed results about the risk transmission. The decomposition can be performed with respect to the region or country of origin (Figure 3) or even be broken down to individual banks (see Appendix, Figure 7). In this paper, we focus on risk transmitters, but the opposite side of this coin can be easily checked as well (i.e., risk receivers).

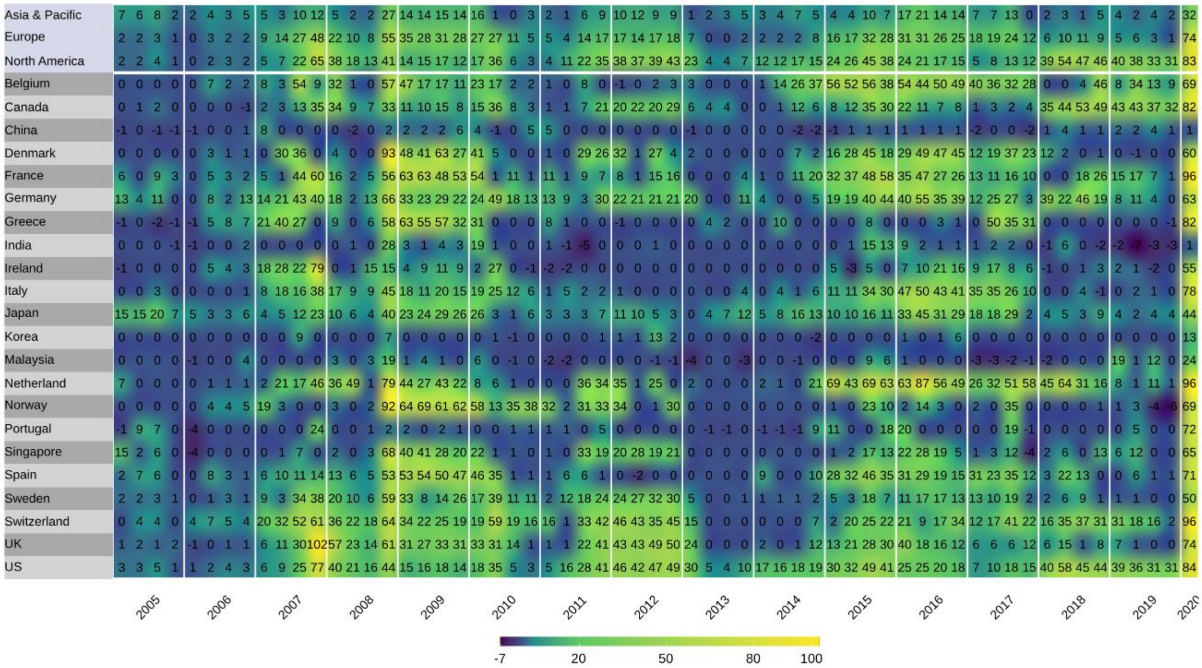

Figure 3. Systemic risk decomposition by country

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Appendix

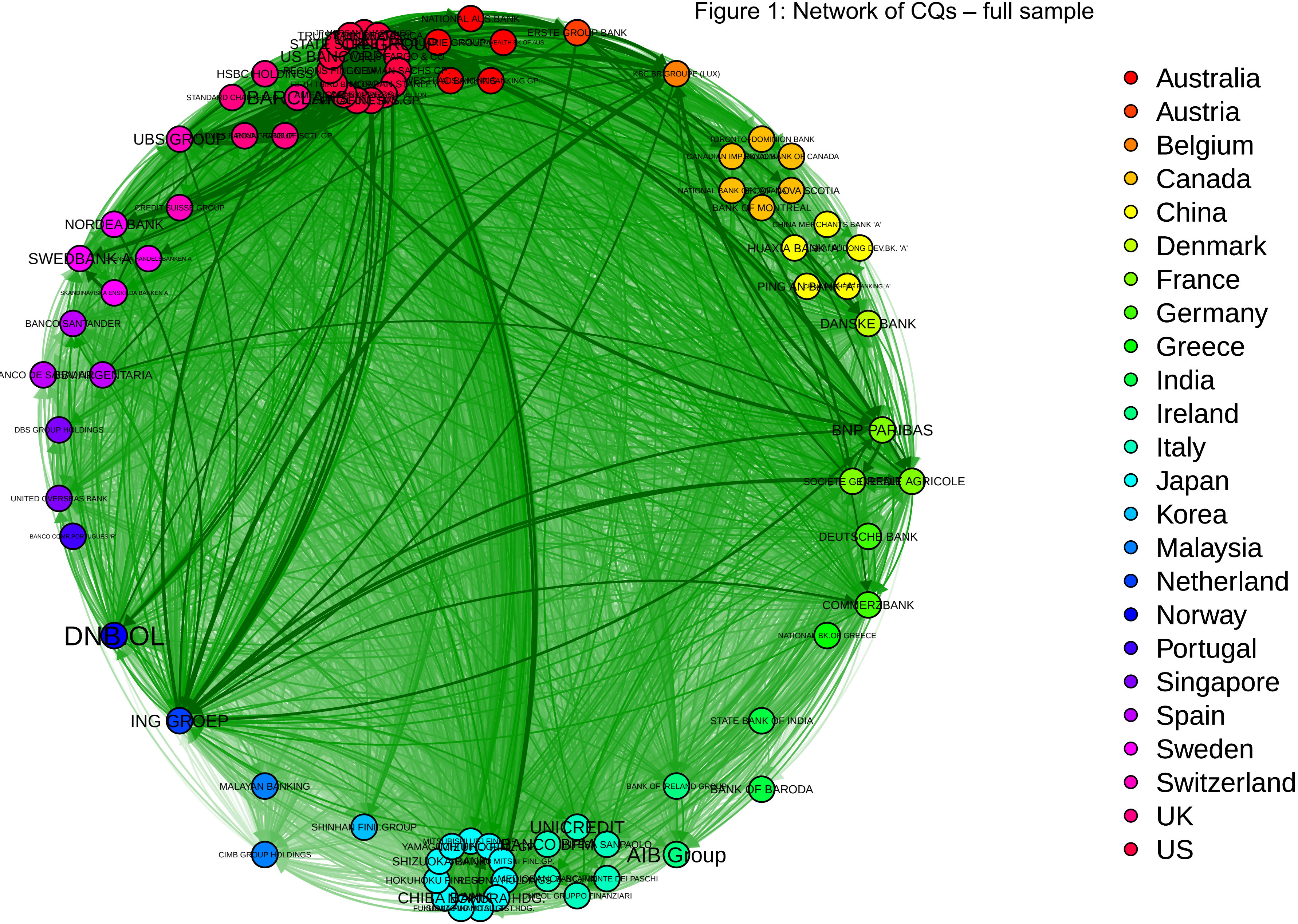

Figure 1: Network of CQs – full sample

Figure 2: Network of CQs – full sample, threshold graph

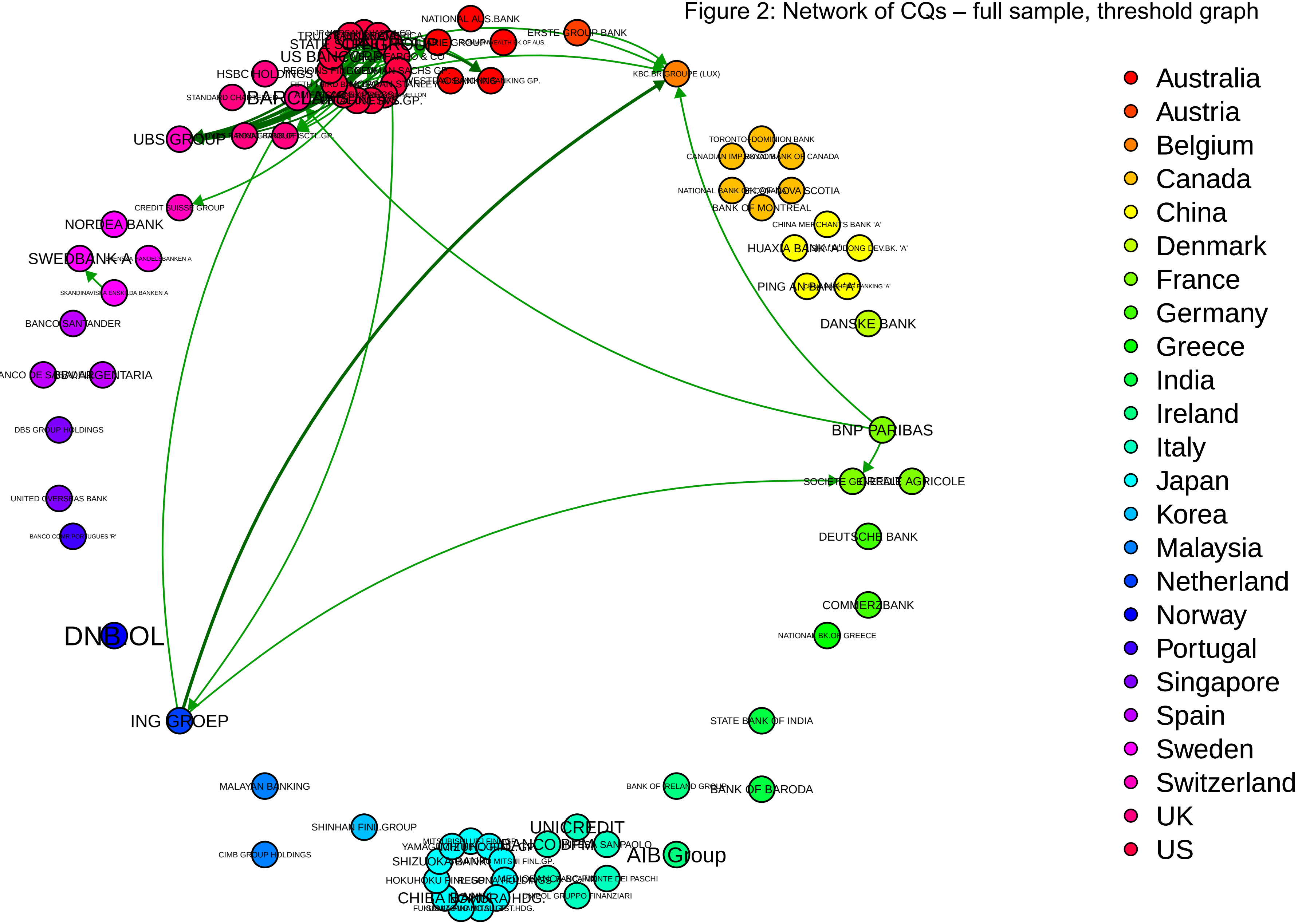

Figure 3: Network of CQs – GFC sample

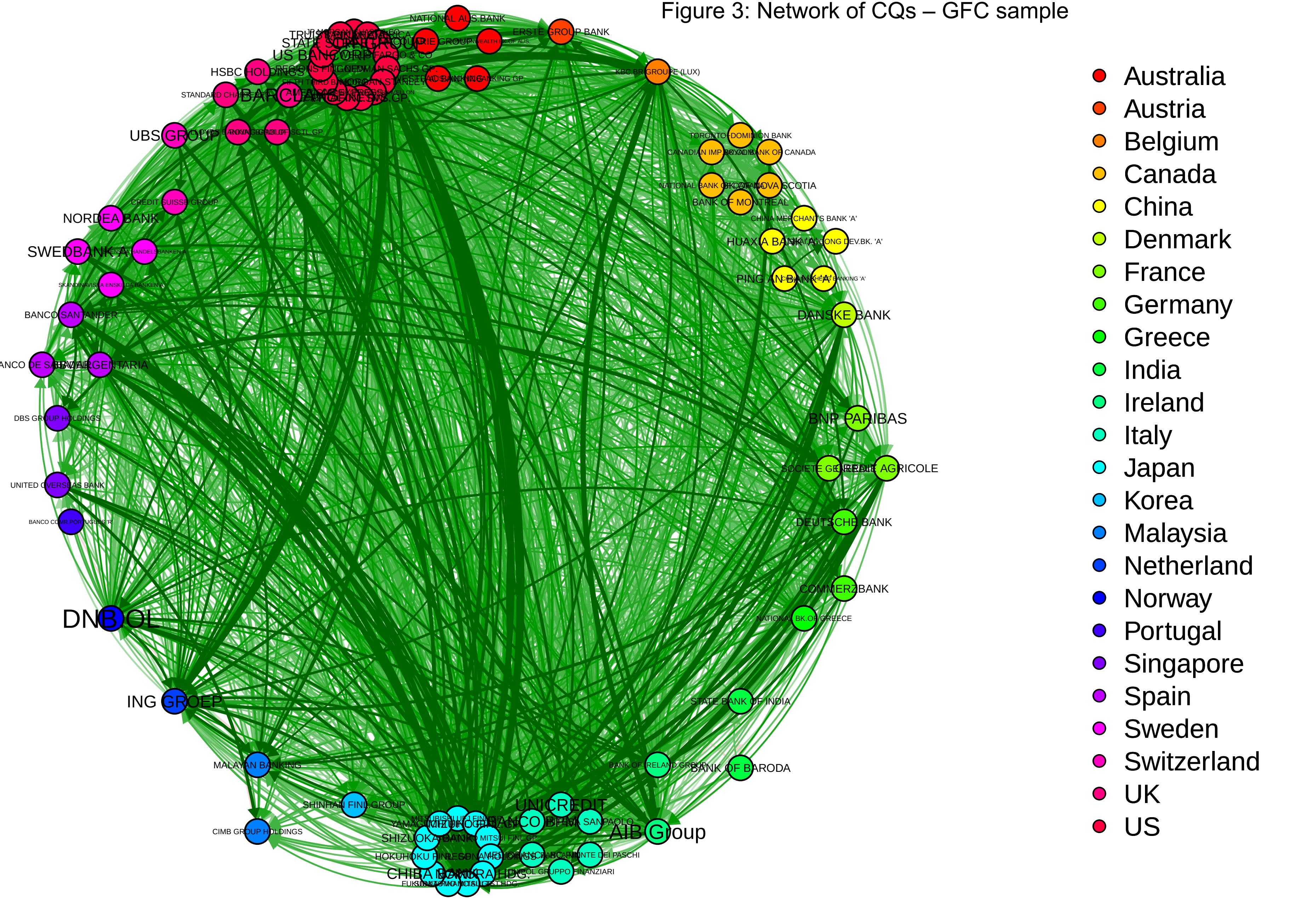

Figure 4: Network of CQs – GFC sample, threshold graph

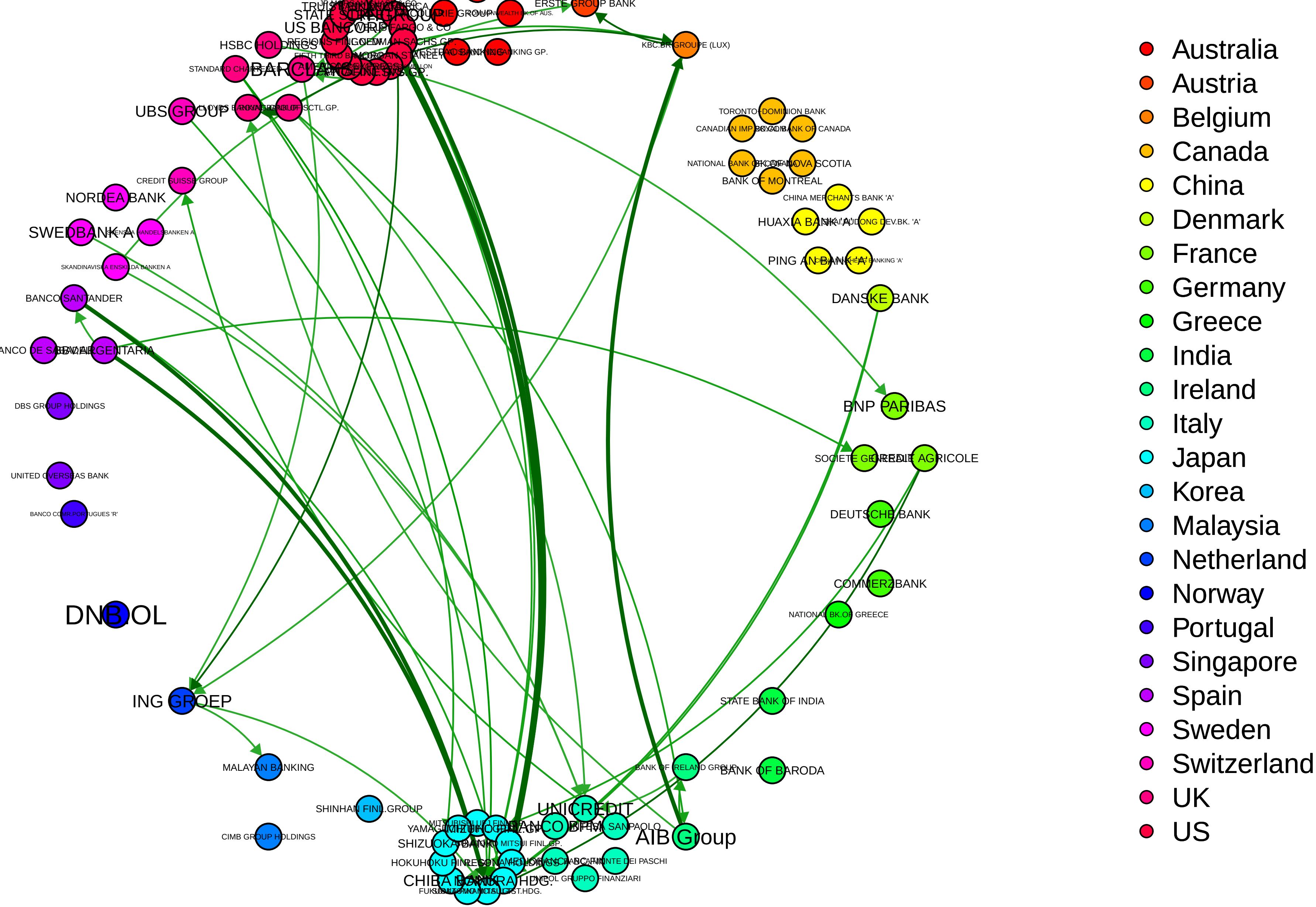

Figure 5: Network of CQs – ESDC sample

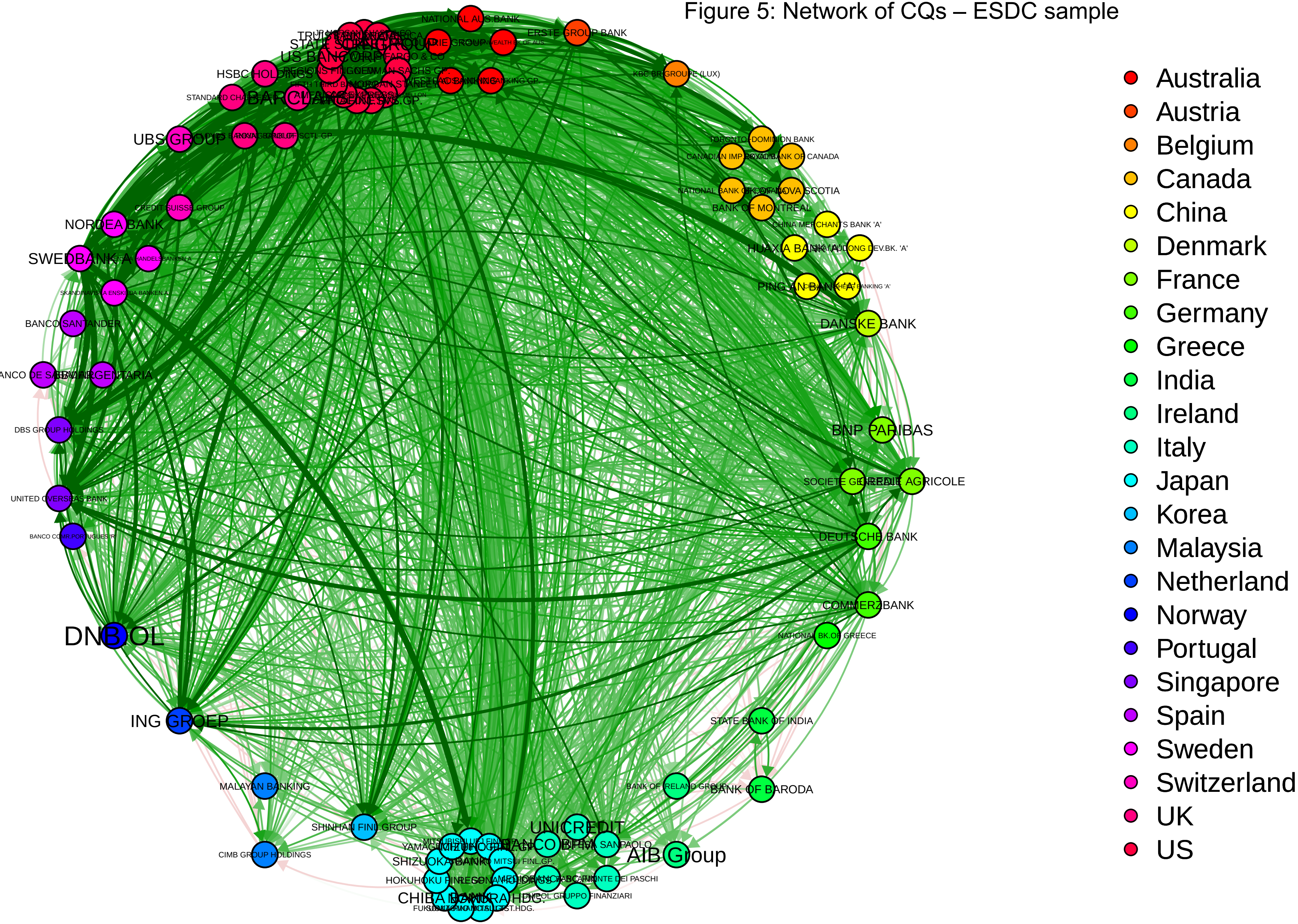

Figure 6: Network of CQs – ESDC sample, threshold graph

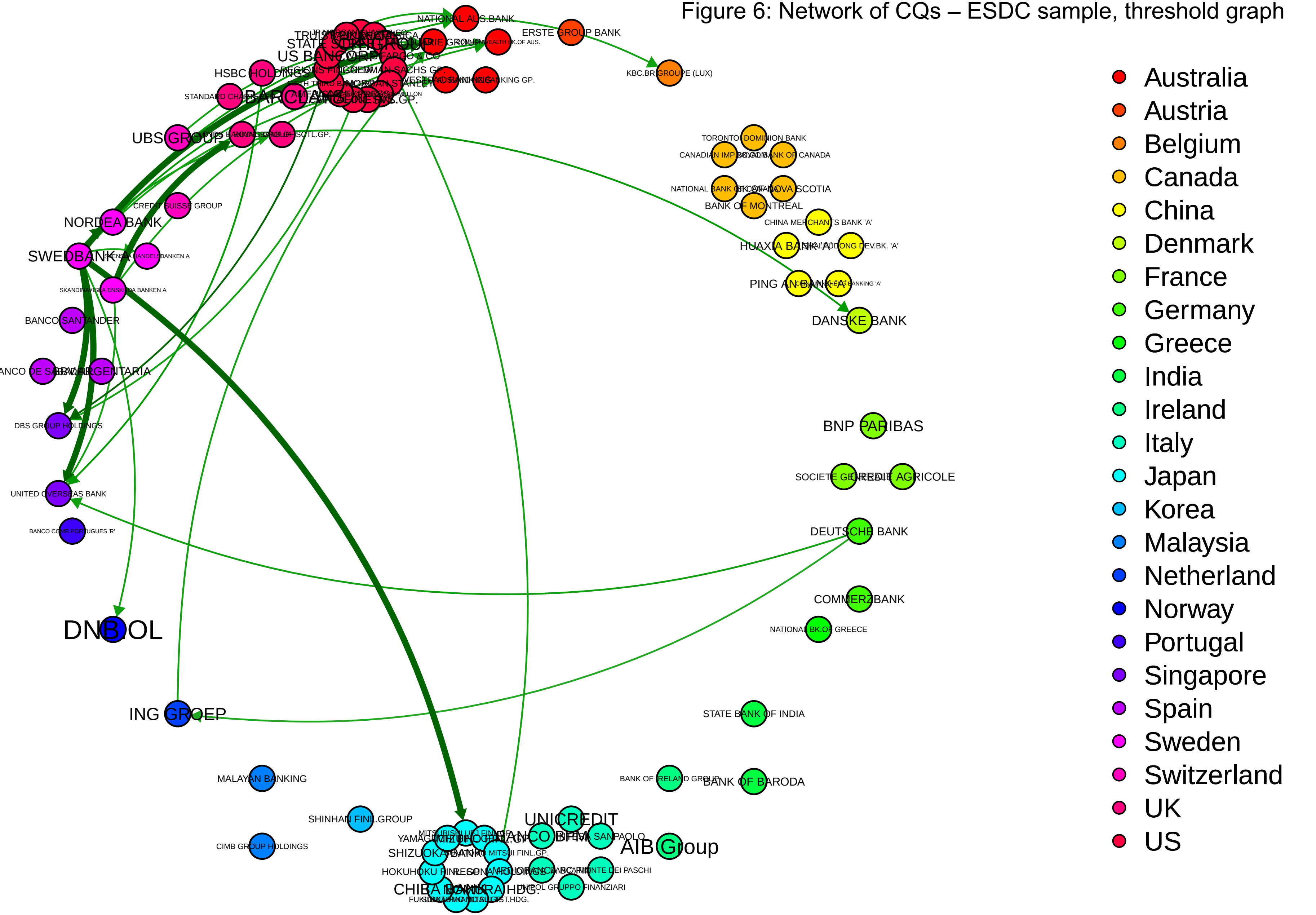

Figure 7: Systemic risk decomposition by individual banks

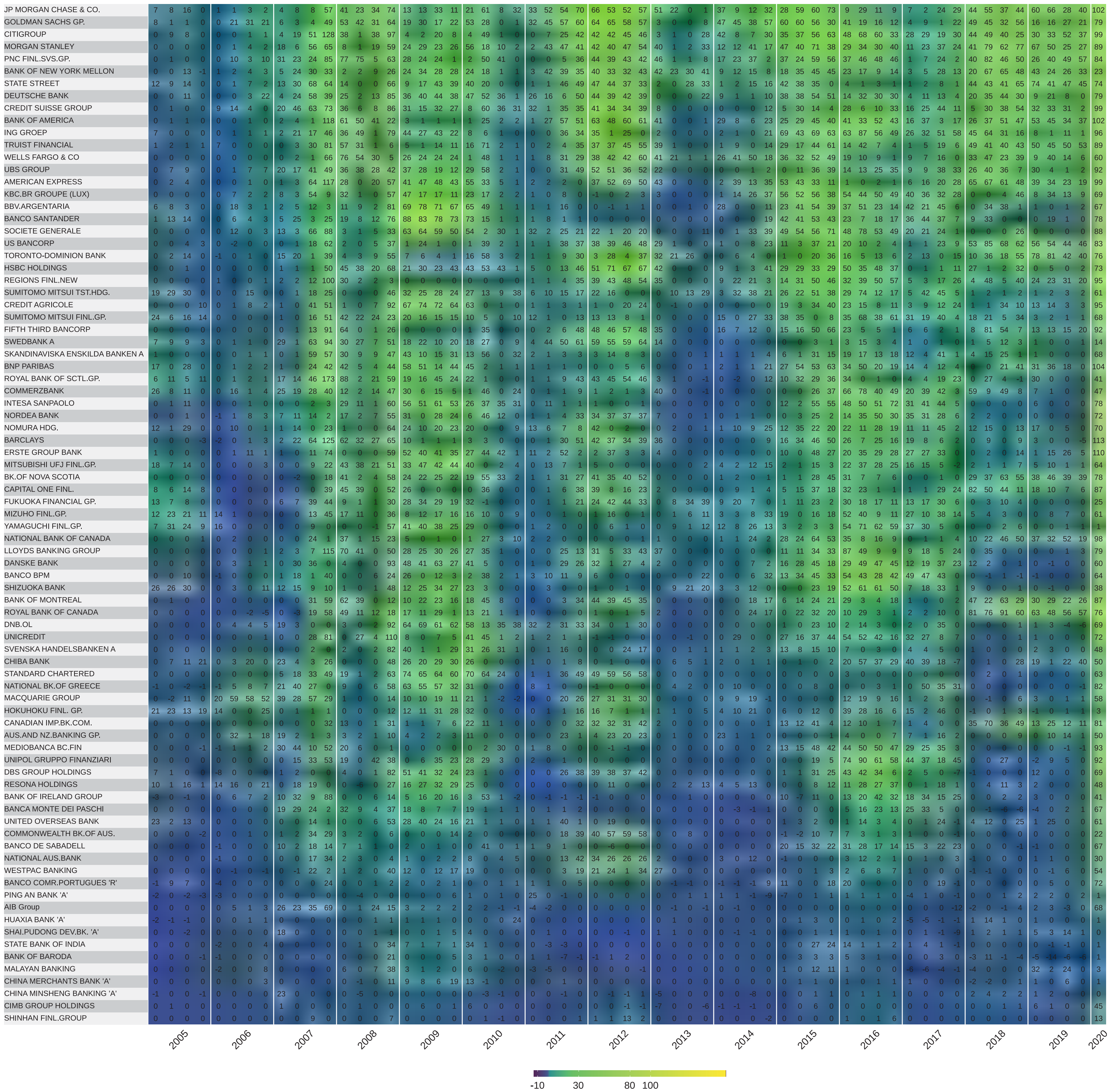

Table 1: Topological properties

Bank	degree_in	degree_out	degree_total	betweenness	eigen
			FULL sample		
HSBC HOLDINGS	82	82	164	2.2246	1.0000
MITSUBISHI UFJ FINL.GP.	82	79	161	1.6630	0.9834
BNP PARIBAS	80	82	162	1.3965	0.9901
JP MORGAN CHASE & CO.	82	82	164	2.2246	1.0000
DEUTSCHE BANK	80	82	162	1.7569	0.9891
BARCLAYS	82	82	164	2.2246	1.0000
CREDIT AGRICOLE	81	82	163	1.7617	0.9952
BANK OF AMERICA	81	82	163	1.7617	0.9952
CITIGROUP	82	82	164	2.2246	1.0000
MIZUHO FINL.GP.	82	79	161	1.6630	0.9834
SOCIETE GENERALE	80	82	162	1.3965	0.9901
ROYAL BANK OF SCTL.GP.	82	82	164	2.2246	1.0000
SUMITOMO MITSUI FINL.GP.	82	81	163	1.9788	0.9948
BANCO SANTANDER	79	82	161	1.2449	0.9845
WELLS FARGO & CO	80	82	162	1.6002	0.9900
ING GROEP	81	81	162	1.6990	0.9901
LLOYDS BANKING GROUP	81	81	162	1.6990	0.9901
UNICREDIT	80	79	159	1.3183	0.9738
UBS GROUP	82	82	164	2.2246	1.0000
CREDIT SUISSE GROUP	82	82	164	2.2246	1.0000
GOLDMAN SACHS GP.	82	82	164	2.2246	1.0000
NORDEA BANK	81	82	163	1.7617	0.9952
INTESA SANPAOLO	78	81	159	1.0777	0.9734
MORGAN STANLEY	82	82	164	2.2246	1.0000
TORONTO-DOMINION BANK	81	82	163	2.0631	0.9948
ROYAL BANK OF CANADA	82	82	164	2.2246	1.0000
BBV.ARGENTARIA	81	82	163	1.8593	0.9949
COMMERZBANK	82	81	163	2.1559	0.9944
NATIONAL AUS.BANK	82	82	164	2.2246	1.0000
BK.OF NOVA SCOTIA	82	82	164	2.2246	1.0000
COMMONWEALTH BK.OF AUS.	82	82	164	2.2246	1.0000
STANDARD CHARTERED	82	82	164	2.2246	1.0000
CHINA MERCHANTS BANK 'A'	80	76	156	1.0871	0.9551
AUS.AND NZ.BANKING GP.	82	82	164	2.2246	1.0000
WESTPAC BANKING	82	82	164	2.2246	1.0000
SHAI.PUDONG DEV.BK. 'A'	76	76	152	1.1067	0.9311
DANSKE BANK	81	82	163	1.8593	0.9949
CHINA MINSHENG BANKING 'A'	74	61	135	0.3132	0.8293
BANK OF MONTREAL	82	81	163	1.9788	0.9948
RESONA HOLDINGS	81	78	159	1.5580	0.9716
NOMURA HDG.	82	82	164	2.2246	1.0000
SUMITOMO MITSUI TST.HDG.	82	81	163	2.0498	0.9943
STATE BANK OF INDIA	81	81	162	1.8442	0.9892
DNB.OL	81	82	163	1.7617	0.9952
SVENSKA HANDELSBANKEN A	82	82	164	2.2246	1.0000
SKANDINAV. ENSKILDA BANKEN A	82	82	164	2.2246	1.0000
BANK OF NEW YORK MELLON	82	82	164	2.2246	1.0000
KBC.BR GROUPE (LUX)	79	81	160	1.1822	0.9793
PNC FINL.SVS.GP.	80	82	162	1.3965	0.9901
DBS GROUP HOLDINGS	82	81	163	1.9788	0.9948
PING AN BANK 'A'	78	75	153	1.0230	0.9373
CAPITAL ONE FINL.	82	82	164	2.2246	1.0000

	FULL sample (cont.)				
Bank	degree_in	degree_out	degree_total	betweenness	eigen
SHINHAN FINL.GROUP	81	80	161	1.6425	0.9839
SWEDBANK A	82	82	164	2.2246	1.0000
ERSTE GROUP BANK	82	82	164	2.2246	1.0000
BANCA MONTE DEI PASCHI	67	71	138	0.1665	0.8492
BANCO DE SABADELL	71	80	151	0.5810	0.9261
UNITED OVERSEAS BANK	81	82	163	1.8593	0.9949
BANK OF IRELAND GROUP	80	81	161	1.2361	0.9852
NATIONAL BANK OF CANADA	81	82	163	1.7617	0.9952
MALAYAN BANKING	81	78	159	1.4564	0.9723
AIB Group	79	77	156	0.8127	0.9573
AMERICAN EXPRESS	82	82	164	2.2246	1.0000
NATIONAL BK.OF GREECE	73	78	151	0.4537	0.9275
MACQUARIE GROUP	82	82	164	2.2246	1.0000
FUKUOKA FINANCIAL GP.	82	82	164	2.2246	1.0000
FIFTH THIRD BANCORP	81	82	163	1.7617	0.9952
REGIONS FINL.NEW	82	82	164	2.2246	1.0000
CHIBA BANK	82	82	164	2.2246	1.0000
UNIPOL GRUPPO FINANZIARI	75	80	155	0.7317	0.9505
BANCO COMR.PORTUGUES 'R'	75	80	155	0.7370	0.9504
CIMB GROUP HOLDINGS	81	78	159	1.7631	0.9710
BANK OF BARODA	71	57	128	0.2064	0.7864
HOKUHOKU FINL. GP.	82	82	164	2.2246	1.0000
SHIZUOKA BANK	82	82	164	2.2246	1.0000
MEDIOBANCA BC.FIN	77	81	158	0.9725	0.9677
YAMAGUCHI FINL.GP.	82	81	163	1.9788	0.9948
CANADIAN IMP.BK.COM.	81	82	163	1.7617	0.9952
US BANCORP	81	82	163	1.7617	0.9952
HUAXIA BANK 'A'	77	72	149	0.7719	0.9132
STATE STREET	82	82	164	2.2246	1.0000
BANCO BPM	75	76	151	0.4010	0.9283
TRUIST FINANCIAL	82	82	164	2.2246	1.0000

	GFC subsample				
Bank	degree_in	degree_out	degree_total	betweenness	eigen
HSBC HOLDINGS	25	33	58	40.7692	0.5837
MITSUBISHI UFJ FINL.GP.	37	19	56	59.0757	0.5081
BNP PARIBAS	37	13	50	24.9765	0.4723
JP MORGAN CHASE & CO.	30	39	69	49.0418	0.6791
DEUTSCHE BANK	44	55	99	103.4337	0.9355
BARCLAYS	48	32	80	56.5671	0.7832
CREDIT AGRICOLE	40	32	72	52.3531	0.6874
BANK OF AMERICA	14	39	53	13.9388	0.5116
CITIGROUP	25	50	75	94.8150	0.7315
MIZUHO FINL.GP.	49	23	72	71.8830	0.6570
SOCIETE GENERALE	50	33	83	82.4554	0.7784
ROYAL BANK OF SCTL.GP.	39	57	96	157.4665	0.8936
SUMITOMO MITSUI FINL.GP.	33	10	43	11.1451	0.4024
BANCO SANTANDER	44	54	98	114.2196	0.9363
WELLS FARGO & CO	35	37	72	112.2165	0.7162
ING GROEP	59	32	91	102.6517	0.8341
LLOYDS BANKING GROUP	35	45	80	106.5379	0.7604
UNICREDIT	45	49	94	128.6530	0.8953
UBS GROUP	3	34	37	4.0634	0.3492
CREDIT SUISSE GROUP	40	31	71	39.2222	0.7064
GOLDMAN SACHS GP.	44	58	102	152.2657	0.9377
NORDEA BANK	25	30	55	23.0612	0.5418
INTESA SANPAOLO	49	45	94	90.7768	0.8877
MORGAN STANLEY	34	56	90	96.9285	0.8481
TORONTO-DOMINION BANK	34	23	57	51.9296	0.5415
ROYAL BANK OF CANADA	31	23	54	23.6895	0.5401
BBV.ARGENTARIA	45	45	90	109.8047	0.8488
COMMERZBANK	15	36	51	10.9067	0.5276
NATIONAL AUS.BANK	19	7	26	30.8040	0.2228
BK.OF NOVA SCOTIA	36	33	69	74.0415	0.6729
COMMONWEALTH BK.OF AUS.	20	8	28	38.3431	0.2292
STANDARD CHARTERED	18	47	65	22.5884	0.6277
CHINA MERCHANTS BANK 'A'	6	24	30	66.5543	0.2882
AUS.AND NZ.BANKING GP.	21	8	29	6.2885	0.2876
WESTPAC BANKING	23	10	33	21.1836	0.3070
SHAI.PUDONG DEV.BK. 'A'	4	3	7	5.4628	0.0256
DANSKE BANK	47	54	101	148.0095	0.9359
CHINA MINSHENG BANKING 'A'	5	0	5	0.0000	0.0320
BANK OF MONTREAL	13	23	36	60.3446	0.3335
RESONA HOLDINGS	25	19	44	16.9843	0.4114
NOMURA HDG.	52	37	89	157.7169	0.8181
SUMITOMO MITSUI TST.HDG.	64	24	88	162.6038	0.7993
STATE BANK OF INDIA	6	8	14	9.8184	0.0979
DNB.OL	22	59	81	44.1862	0.7732
SVENSKA HANDELSBANKEN A	30	38	68	26.4022	0.6655
SKANDINAV. ENSKILDA BANKEN A	32	37	69	26.0646	0.7161
BANK OF NEW YORK MELLON	19	33	52	70.6942	0.5242
KBC.BR GROUPE (LUX)	44	49	93	98.8083	0.8941
PNC FINL.SVS.GP.	31	22	53	41.2054	0.4938
DBS GROUP HOLDINGS	28	24	52	31.5853	0.5052
PING AN BANK 'A'	4	5	9	13.5763	0.0334
CAPITAL ONE FINL.	29	13	42	92.1297	0.4175
SHINHAN FINL.GROUP	37	8	45	14.1682	0.4324

	GFC subsample (cont.)				
Bank	degree_in	degree_out	degree_total	betweenness	eigen
SWEDBANK A	32	43	75	50.2919	0.7398
ERSTE GROUP BANK	42	48	90	157.5653	0.8578
BANCA MONTE DEI PASCHI	16	14	30	7.7926	0.2908
BANCO DE SABADELL	13	29	42	5.0844	0.4133
UNITED OVERSEAS BANK	14	15	29	9.1647	0.2706
BANK OF IRELAND GROUP	46	51	97	159.8198	0.9115
NATIONAL BANK OF CANADA	13	18	31	10.5227	0.3093
MALAYAN BANKING	57	25	82	59.7889	0.7811
AIB Group	48	61	109	272.8217	1.0000
AMERICAN EXPRESS	29	54	83	52.7782	0.7984
NATIONAL BK.OF GREECE	36	47	83	72.9666	0.8120
MACQUARIE GROUP	26	16	42	30.3943	0.3916
FUKUOKA FINANCIAL GP.	20	32	52	13.4564	0.5475
FIFTH THIRD BANCORP	31	19	50	15.5345	0.4986
REGIONS FINL.NEW	20	14	34	35.5039	0.2989
CHIBA BANK	29	23	52	22.0200	0.5193
UNIPOL GRUPPO FINANZIARI	40	25	65	22.7115	0.6536
BANCO COMR.PORTUGUES 'R'	0	3	3	0.0000	0.0129
CIMB GROUP HOLDINGS	21	1	22	4.2116	0.1608
BANK OF BARODA	1	7	8	0.8446	0.0484
HOKUHOKU FINL. GP.	12	23	35	5.5436	0.3515
SHIZUOKA BANK	41	33	74	56.6501	0.7276
MEDIOBANCA BC.FIN	20	1	21	0.3978	0.1799
YAMAGUCHI FINL.GP.	35	43	78	126.4201	0.7303
CANADIAN IMP.BK.COM.	24	28	52	13.7692	0.5268
US BANCORP	27	24	51	14.0826	0.5172
HUAXIA BANK 'A'	4	6	10	14.8958	0.0576
STATE STREET	41	51	92	81.3852	0.8838
BANCO BPM	41	41	82	83.8475	0.7794
TRUIST FINANCIAL	12	14	26	16.3225	0.2379

	ESDC subsample				
Bank	degree_in	degree_out	degree_total	betweenness	eigen
HSBC HOLDINGS	34	43	77	102.2522	0.8068
MITSUBISHI UFJ FINL.GP.	45	9	54	34.3101	0.4973
BNP PARIBAS	35	29	64	29.0068	0.6570
JP MORGAN CHASE & CO.	17	49	66	18.6319	0.6737
DEUTSCHE BANK	33	46	79	109.3879	0.7961
BARCLAYS	33	47	80	88.3480	0.8290
CREDIT AGRICOLE	36	29	65	34.6924	0.6875
BANK OF AMERICA	36	44	80	68.3336	0.8453
CITIGROUP	14	48	62	44.7477	0.6315
MIZUHO FINL.GP.	25	9	34	48.5824	0.2824
SOCIETE GENERALE	43	37	80	63.6400	0.8279
ROYAL BANK OF SCTL.GP.	40	51	91	108.8450	0.9630
SUMITOMO MITSUI FINL.GP.	36	6	42	26.8041	0.3734
BANCO SANTANDER	21	32	53	57.8756	0.4976
WELLS FARGO & CO	23	41	64	50.6402	0.6548
ING GROEP	45	23	68	52.9520	0.6594
LLOYDS BANKING GROUP	46	52	98	210.9066	0.9657
UNICREDIT	12	17	29	21.8845	0.2748
UBS GROUP	34	55	89	166.1993	0.9182
CREDIT SUISSE GROUP	35	35	70	51.1525	0.7370
GOLDMAN SACHS GP.	16	48	64	34.6063	0.6747
NORDEA BANK	44	27	71	79.2140	0.7042
INTESA SANPAOLO	25	31	56	43.8926	0.5779
MORGAN STANLEY	7	50	57	49.0380	0.5888
TORONTO-DOMINION BANK	29	43	72	67.2057	0.7306
ROYAL BANK OF CANADA	38	15	53	81.4058	0.5312
BBV.ARGENTARIA	23	33	56	55.3869	0.5469
COMMERZBANK	31	35	66	194.8278	0.6647
NATIONAL AUS.BANK	52	41	93	146.3775	0.9079
BK.OF NOVA SCOTIA	34	28	62	36.7034	0.6383
COMMONWEALTH BK.OF AUS.	48	36	84	61.3310	0.8962
STANDARD CHARTERED	27	33	60	35.1179	0.6246
CHINA MERCHANTS BANK 'A'	11	9	20	22.5481	0.1223
AUS.AND NZ.BANKING GP.	51	27	78	81.0563	0.7834
WESTPAC BANKING	38	18	56	53.5542	0.5585
SHAI.PUDONG DEV.BK. 'A'	7	9	16	20.2254	0.0818
DANSKE BANK	48	39	87	170.6193	0.8937
CHINA MINSHENG BANKING 'A'	7	16	23	73.7420	0.1403
BANK OF MONTREAL	36	34	70	96.2572	0.7255
RESONA HOLDINGS	3	6	9	0.6482	0.0737
NOMURA HDG.	53	7	60	41.4013	0.5958
SUMITOMO MITSUI TST.HDG.	40	8	48	43.3627	0.4591
STATE BANK OF INDIA	7	7	14	38.1100	0.0782
DNB.OL	35	50	85	83.6947	0.8827
SVENSKA HANDELSBANKEN A	33	30	63	41.8182	0.6424
SKANDINAV. ENSKILDA BANKEN A	16	48	64	51.1116	0.6315
BANK OF NEW YORK MELLON	20	45	65	85.0835	0.6710
KBC.BR GROUPE (LUX)	38	20	58	36.7616	0.5920
PNC FINL.SVS.GP.	32	54	86	118.6765	0.8931
DBS GROUP HOLDINGS	50	25	75	38.0230	0.8117
PING AN BANK 'A'	9	4	13	9.2687	0.0642
CAPITAL ONE FINL.	13	48	61	44.7884	0.6209
SHINHAN FINL.GROUP	48	14	62	40.0372	0.6577

	ESDC subsample (cont.)				
Bank	degree_in	degree_out	degree_total	betweenness	eigen
SWEDBANK A	41	62	103	228.0315	1.0000
ERSTE GROUP BANK	39	52	91	194.7379	0.8966
BANCA MONTE DEI PASCHI	6	13	19	2.4030	0.1712
BANCO DE SABADELL	8	9	17	43.3703	0.1199
UNITED OVERSEAS BANK	49	22	71	138.8266	0.7332
BANK OF IRELAND GROUP	5	6	11	12.9859	0.0873
NATIONAL BANK OF CANADA	32	18	50	16.4903	0.5409
MALAYAN BANKING	22	3	25	18.9273	0.2347
AIB Group	16	3	19	5.9079	0.1906
AMERICAN EXPRESS	13	31	44	27.9748	0.4301
NATIONAL BK.OF GREECE	8	8	16	12.4702	0.1519
MACQUARIE GROUP	54	16	70	87.3164	0.7163
FUKUOKA FINANCIAL GP.	35	11	46	80.4132	0.3557
FIFTH THIRD BANCORP	39	47	86	93.1841	0.8979
REGIONS FINL.NEW	29	42	71	57.6782	0.7425
CHIBA BANK	21	7	28	74.1430	0.1971
UNIPOL GRUPPO FINANZIARI	12	1	13	1.0959	0.0945
BANCO COMR.PORTUGUES 'R'	17	9	26	16.3756	0.2469
CIMB GROUP HOLDINGS	22	8	30	120.9490	0.2804
BANK OF BARODA	13	5	18	19.9696	0.1172
HOKUHOKU FINL. GP.	4	9	13	15.8845	0.0691
SHIZUOKA BANK	16	12	28	69.3295	0.1930
MEDIOBANCA BC.FIN	15	15	30	21.8434	0.2548
YAMAGUCHI FINL.GP.	22	7	29	31.5184	0.2418
CANADIAN IMP.BK.COM.	34	20	54	84.3244	0.5186
US BANCORP	24	56	80	66.8840	0.8217
HUAXIA BANK 'A'	7	13	20	44.3514	0.1187
STATE STREET	11	42	53	33.3971	0.5674
BANCO BPM	4	34	38	11.2720	0.3605
TRUIST FINANCIAL	31	40	71	137.8566	0.7502

Table 2: Data description - RIC codes

Bank	RIC	Bank	RIC
HSBC HOLDINGS	HSBA.L	STATE BANK OF INDIA	SBI.NS
MITSUBISHI UFJ FINL.GP.	8306.T	DNB.OL	DNB.OL
BNP PARIBAS	BNPP.PA	SVENSKA HANDELSBANKEN A	SHBa.ST
JP MORGAN CHASE & CO.	JPM	SKANDINAV. ENSKILDA BANKEN A	SEBa.ST
DEUTSCHE BANK	DBKGn.DE	BANK OF NEW YORK MELLON	BK
BARCLAYS	BARC.L	KBC.BR GROUPE (LUX)	KBC.BR
CREDIT AGRICOLE	CAGR.PA	PNC FINL.SVS.GP.	PNC
BANK OF AMERICA	BAC	DBS GROUP HOLDINGS	DBSM.SI
CITIGROUP	C	PING AN BANK 'A'	000001.SZ
MIZUHO FINL.GP.	MZHOF.PK	CAPITAL ONE FINL.	COF_pj
SOCIETE GENERALE	SOGN.PA	SHINHAN FINL.GROUP	055550.KS
ROYAL BANK OF SCTL.GP.	RBS_pt.W^E14	SWEDBANK A	SWEDa.ST
SUMITOMO MITSUI FINL.GP.	8316.T	ERSTE GROUP BANK	ERST.VI
BANCO SANTANDER	SAN.MC	BANCA MONTE DEI PASCHI	BMPS.MI
WELLS FARGO & CO	WFC	BANCO DE SABADELL	SABE.MC
ING GROEP	INGA.AS	UNITED OVERSEAS BANK	UOBH.SI
LLOYDS BANKING GROUP	LLOY.L	BANK OF IRELAND GROUP	BIRG.I
UNICREDIT	CRDI.MI	NATIONAL BANK OF CANADA	NA.TO
UBS GROUP	UBSG.S	MALAYAN BANKING	MBBM.KL
CREDIT SUISSE GROUP	CSGN.S	AIB Group	AIBG.I
GOLDMAN SACHS GP.	GS	AMERICAN EXPRESS	AXP
NORDEA BANK	NDASE.ST	NATIONAL BK.OF GREECE	NBGr.AT
INTESA SANPAOLO	ISP.MI	MACQUARIE GROUP	MQG.AX
MORGAN STANLEY	MS	FUKUOKA FINANCIAL GP.	FKKFF.PK
TORONTO-DOMINION BANK	TD.TO	FIFTH THIRD BANCORP	FITB.O
ROYAL BANK OF CANADA	RY	REGIONS FINL.NEW	RF_pb
BBV.ARGENTARIA	CBKG.DE	CHIBA BANK	8331.T
COMMERZBANK	NABPF.AX	UNIPOL GRUPPO FINANZIARI	UNPI.MI
NATIONAL AUS.BANK	BNS.TO	BANCO COMR.PORTUGUES 'R'	BCP.LS
BK.OF NOVA SCOTIA	CBAXX.AX	CIMB GROUP HOLDINGS	CIMB.KL
COMMONWEALTH BK.OF AUS.	STAN.L	BANK OF BARODA	BOB.NS
STANDARD CHARTERED	600036.SS	HOKUHOKU FINL. GP.	8377.T
CHINA MERCHANTS BANK 'A'	ANZ.AX	SHIZUOKA BANK	8355.T
AUS.AND NZ.BANKING GP.	WBC.AX	MEDIOBANCA BC.FIN	MDBI.MI
WESTPAC BANKING	600000.SS	YAMAGUCHI FINL.GP.	8418.T
SHAI.PUDONG DEV.BK. 'A'	DANSKE.CO	CANADIAN IMP.BK.COM.	CM.TO
DANSKE BANK	SBER.MM	US BANCORP	USB
CHINA MINSHENG BANKING 'A'	600016.SS	HUAXIA BANK 'A'	600015.SS
BANK OF MONTREAL	BMO.TO	STATE STREET	STT
RESONA HOLDINGS	8308.T	BANCO BPM	BAMI.MI
NOMURA HDG.	8604.T	TRUIST FINANCIAL	TFC
SUMITOMO MITSUI TST.HDG.	8316.T		