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Increasing systemic risk during the Covid-19 pandemic: A cross-quantilogram analysis of the banking sector

Increasing systemic risk during the Covid-19 pandemic: A cross-quantilogram analysis of the banking sector

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Abstract

Over the last few decades, large banks worldwide have become more interconnected. 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 act like a domino effect. In this paper, we show an unprecedented increase in bank interconnectedness during the outbreak of the Covid-19 pandemic. We measure how extreme negative stock market returns from one bank can spill over to the other banks within the network. Our contribution relies on the establishment of a new systemic risk index based on the cross-quantilogram approach of Han et al. (2016). The results indicate that the systemic risk and the density of the spillover network among 83 banks in 24 countries have never been as high as during the Covid-19 pandemic – much higher than during the 2008 global financial crisis. Furthermore, we find that US banks are the most important risk transmitters, and Asian banks are the most important risk receivers. In contrast, European banks were strong risk transmitters during the European sovereign debt crisis. These findings may help investors, portfolio managers and policymakers adapt their investment strategies and macroprudential policies in this context of uncertainty.

Keywords: Systemic risk; Banks, Covid-19 pandemic; Cross-quantilogram; Financial networks
JEL classification: G01, G15, G21, G28, C21

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Highlights

- A new index to measure systemic risk based on the cross-quantilogram approach is proposed.
- We compare the systemic risk among the 83 biggest banks in 24 countries through the GFC, ESDC and the recent Covid-19 crisis.
- Systemic risk has never been as high as during the Covid-19 pandemic – much higher than during the GFC.
- Banks from the United States are risk transmitters, whereas banks from Asia are risk receivers.
- European banks were strong risk transmitters during the European sovereign debt crisis.

1. 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 and Brunnermeier, 2016; Black et al., 2016; Silva et al., 2017; Demirer et al., 2018). Large banks 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]

In December 2010, the ECB established the European Systemic Risk Board (ESRB) with the objective to contribute to preventing or mitigating systemic risks that could cause financial instability in the European Union. The ESRB has provided volumes of quarterly data on systemic risk measures since 2012. The systemic risk topic has also attracted academic researchers and has led to the creation of a website for systemic risk measures by, for example, the NYU Sterns or the London School of Economics. In terms of published research, the number of articles focusing on the measures, determinants and consequences of systemic risk has increased noticeably, mainly since the GFC in 2008. In this regard, Silva et al. (2017) perform a large survey of published research (266 total articles) between 1978 and 2016.

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, leading to the disruption of real sector activities and entailing high costs for the economy that can reduce the population's level of economic well-being. Although this definition captures the essence of the subject, there is no universal definition of systemic financial risk (Summer, 2003). The Bank for International Settlements (1994), for instance, defines systemic risk as the risk that stems from the failure of a participant to meet its contractual obligations and that causes other participants to default in a chain reaction mode. De-Bandt and Hartmann (2000) indicate that systemic financial risk includes widespread events in the banking and financial segments as well as in the payment and settlement systems. The ECB (2009) defines systemic risk as the possibility of an institution to fail to honour its obligations, thus causing the same type of failure of other participants, altogether producing wider effects that

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

impact the stability of the financial system. Systemic risk is also related to systemic events that strongly and systemically impact financial intermediaries or markets (ECB, 2009).

In line with the analysis of the economic environment set forth by the President of the ECB Jean-Claude Trichet (2009), systemic risk is a threat emerging from financial system developments that lead to the failure of large and interconnected financial institutions. Along the same line of thought, Lehar (2005) conceives systemic financial risk as the potential of an economic or financial event to simultaneously and sequentially cause failure in numerous financial institutions. For Adrian and Brunnermeier (2016), systemic financial risk is related to the malfunction of a financial intermediary that, in turn, affects the supply of credit and capital to the economy. In the same vein, Acharya and Richardson (2009) define systemic risk as the joint failure of financial institutions and capital markets that considerably reduces the capital supply to the real economy. Billio et al. (2012) argue that systemic risk is the emergence of sudden regime changes in the economy, whereas Abdymomunov (2013) conceive it as negative shocks at the macro or micro levels that affect the financial and economic system. Patro et al. (2013) define systemic risk as the simultaneous stress of the entire financial system that reduces credit and liquidity and increases capital losses. Das and Uppal (2004) consider systemic risk as the simultaneous jumps that occur at the same time across different assets in different countries. Hence, in light of the aforementioned studies, contagion – characterized by simultaneous instances of financial instability on the aftermath of market innovations and shocks – appears to be at the heart of systemic risk. Thus, measuring and analysing contagion [2] and interconnectedness among large banks, through the construction of a new systemic risk index, is a primary motivation for our study.

In this paper, we propose a new index to measure systemic risk within a network framework. The index is based on the cross-quantilogram (hereafter CQ) methodology developed by Han et al. (2016) to measure the dependence and directional predictability between stock returns at

[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) provides results from a Factiva search of the monthly use of the term ‘contagion’ in economics and finance press articles. Before 1995, this term was used only rarely. Media references to contagion exploded during the GFC and 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 every year dealing with financial contagion. The most influential (and cited) are 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).

different quantile levels. In this study, we focus on the lowest quantile level (5%) of stock returns of 83 large banks from three regions[3] – North America, Europe and Asia Pacific – during the period from September 2003 to April 2020. The lowest quantile level (5%) is used to simulate downside market states or crisis periods in which systemic risk is of great importance (more details in Section 3). Considering that these banks play an important systemic role in the international banking system because of their size and scale of operations, their interconnectedness and the risk spillover characteristics among them are primary motivations for our research contribution[4]. The empirical results show that the systemic risk and density of the spillover network have never been as high as during the Covid-19 pandemic, much higher than during the 2008 global financial crisis. Our approach is also well-suited for identifying the systemic risk profile of each bank as a risk transmitter or risk receiver. In this regard, our results show that the topmost risk transmitters are US banks, whereas Asian banks are the topmost risk receivers. However, during the European sovereign debt crisis, European banks were the most important risk transmitters. These results can help investors, portfolio managers, central bankers and policymakers adjust their investment strategies and systemic risk management programmes for more individualized and focused catering of financial risk according to each bank's systemic risk profile.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on systemic risk in the banking system. Section 3 focuses on the construction of the new systemic risk index and its underlying methodology framework. Section 3 further presents the dataset used. Section 4 discusses the results and their implications. Section 5 concludes the paper.

2. Literature review

In this section, we first review the relevant literature on systemic risk considering various measures and indices that have been used to quantify it. Second, we focus on previously obtained

[3] The selection process of the banks in our study is the same as in Demirer et al. (2018), although some of the banks were delisted (more details in Section 3).

[4] In this regard, the Basel III Accords and financial regulators stress increasing the loss absorption capacity of banks, the acceptance of surcharges and contingent capital and bail-in debt to better address financial turmoil and instability. Financial regulators expressed concern over the economic and social externalities resulting from the excessive interconnectedness and risk undertaking of the largest banks at the local, regional and global levels because the systemic risk involved threatens the stability of the financial system (BCBS, 2011).

empirical results regarding systemic risk among banks while acknowledging our contributions to the relevant literature.

2.1. How to measure systemic risk?

Two types of indicators are used to measure systemic risk: (1) low-frequency indicators based on balance sheets or macroeconomic data, and (2) high-frequency indicators based on market prices and rates (Rodríguez-Moreno and Peña, 2013). In the present study, we focus on the second approach using the daily stock prices of the largest banks in the world. In relation to the first group of indicators, measures such as multivariate densities or aggregates of individual co-risk can be identified. Regarding the second category of indicators, principal component analysis (PCA) of portfolios of credit default swap spreads (CDS) or systemic factors extracted from the CDS indices is often used. Allen and Gale (2000), for instance, propose a measure of preference for liquidity. Freixas et al. (2000) suggest an indicator of risk contagion. De Nicolo and Kwast (2002) measure the correlation of bank stocks, whereas Degryse and Nguyen (2007) prefer the intersection of loss given the default (LGD) among banks. Adrian and Shin (2009) argue in favour of the variation of leverage and the VaR/Assets relationship of a financial institution. Allen and Carletti (2012) identify four types of systemic risk: panics, asset price declines, contagion and foreign exchange mismatches in the banking system.

Adrian and Brunnermeier (2016) recommend the CoVaR as a measure of the value-at-risk (*VaR*) in the system, with the condition that a financial institution is at a given state of financial distress. Acharya et al. (2010) propose the Systemic Expected Shortfall (SES), whereas Brownless and Engle (2010) argue in favour of the Marginal Expected Shortfall (MES). Huang et al. (2011) advocate for the Distress Insurance Premium (DIP), while Billio et al. (2012) measure the degree of connectivity to an institution. Glasserman and Young (2015) suggest considering the fraction of an institution's debts held by other financial institutions. Sandhu et al. (2016) prefer a mathematical concept for topology (the Ricci curvature) as an economic indicator for systemic risk. Indeed, a large panel of measures exists to quantify systemic risk. In this context, Bisias et al. (2012) cite and classify 31 quantitative measures in different categories that are related to macroeconomics, networks, forward-looking risks, stress tests, cross-sectional variables, illiquidity and insolvency. In contrast, Bao et al. (2020) show that an ANOVA-like decomposition method helps determine the systemic importance of individual banks. The authors further underline that this latter is primarily led by the interaction of shocks on the banking system. Interestingly, Brownlees et al. (2020) find that the CoVaR and SRISK methods allow for a coherent ranking of systemically important financial institutions (SIFI) to be obtained for the great depression period (before 1933).

The 2009 joint report by the IMF, Bank for International Settlements (BIS) and Financial Stability Board (FSB) proposes indicators for size, interconnectedness and substitutability to measure the systemic importance of an enterprise (IMF-BIS-FSB, 2009). Thomson (2009) proposes the four Cs (contagion, concentration, correlation and conditions) as criteria for determining the systemic importance of a firm. Regulators generally focus on indicators related to the financial health of banks, such as balance sheets and liquidity indicators. Multiple alternative indices for a comprehensive financial condition analysis have also been introduced, typically constructed using a weighted sum of indicators or a principal components method. Among them, we find the Bloomberg financial conditions index (FCI), Goldman Sachs FCI and Kansas Fed Financial Stress Index. The Financial Stability Board (2010) proposes the ranking of Systemically Important Financial Institutions (SIFI). The European Systemic Risk Board (ESRB) publishes different quarterly indicators, such as the composite indicator of systemic stress (CISS), the probability of simultaneous default by two or more large banking groups, the EU banking sector (the distribution of individual banks' contributions to overall systemic risk based on the CoVaR), the EU insurance sector (the distribution of individual insurance companies' contributions to the overall systemic risk based on the CoVaR) and the cross-border claims of banks (international banking statistics).

Relative to the aforementioned measures and indicators of systemic risk, the systemic risk index that we propose is advantageous in several ways. First, it is based on the cross-quantilogram (CQ) approach recently proposed by Han et al. (2016). This method employs quantile hits rather than average states, as in Diebold and Yilmaz (2012, 2014), for example. Second, moment conditions are not required, and heavy-tailed behaviour is accounted for. Accordingly, through its quantile-based design, the CQ enables drawing measurements of directional predictability among time series while considering different quantiles in the return distributions. This aspect is important because Chiu et al. (2015) find that considering the tail dependence factor and meaning lowest and highest quantile of the return distribution is important when measuring systemic risk. Third, the CQ approach allows for the identification of banks that are risk transmitters and risk receivers. These modelling features are important because banks that are risk transmitters should be managed differently than banks that are risk receivers. This is in concordance with the recommendation of Liang (2013) on the importance of a robust systemic monitoring effort in identifying how risks are indeed propagated. Furthermore, Danielsson et al. (2013) indicate that identifying banks that are systemically risky before requiring them to adjust their capital structure and organization is of primary importance. In this regard, the method used in this research can be useful when distinguishing between risk-transmitting and risk-receiving banks. Last, the CQ method can determine the net spillover impact that one bank has on the others and vice versa. Thus, the sum of all of these net spillover effects for all pairs of banks allows for an examination of the general state of how banks in a network interact among them. The index that we propose is thus constructed on these comparative advantages of the CQ and constitute our main contributions.

2.2. Systemic risk among banks

In this section, we aim to present an overview of previous studies seeking to measure the systemic risk among banks. For example, Acharya and Steffen (2013) show that the most systemic banks are those that receive most of the government support during the aftermath of the 2008-2009 global financial crisis (hereafter GFC). Furthermore, the authors acknowledge that sovereign debt holdings contribute significantly to the level of systemic risk. Pais and Stock (2013) explain that a bank’s size has a weak effect on its individual risk. However, larger banks have higher systemic risk. In contrast, Glasserman and Young (2015) indicate that the interconnectivity of the financial system is a key determinant of the GFC. Meanwhile, Paltalidis et al. (2015) demonstrate that systemic risk in northern Europe is less apparent than in southern Europe, whereas the Euro area is more vulnerable to systemic risk. Laeven et al. (2016) find that bank size matters, whereas bank capital is inversely correlated with systemic risk. Black et al. (2016) show that systemic risk in the European banking system reached its peak in November 2011 during the height of Europe’s sovereign debt crisis. Interestingly, Battaglia and Gallo (2017) find that banks’ governance structure has impacts on their systemic risk. Furthermore, Bougheas and Kirman (2017) show that it is important to consider systemic risk when determining the optimal bankruptcy procedure. Dungey et al. (2017) stress that the financial sector is in the centre of the systemic risk of firms in the economy. However, during some periods, the materials sector can also generate high systemic risk. Duprey et al. (2017) identify 68 systemic financial stress episodes in 27 EU countries during the 1964–2016 period. Kosmidou et al. (2017) point out the importance of individual banks in the financial system, as well as the important role of their clustering in predicting future stock crashes in the banking sector.

For Asian banks, Soedarmono et al. (2017) show that abnormal loan growth has impacts on systemic risk, although better credit information coverage and private credit bureaus help reduce this risk. Bostandzic and Weib (2018) demonstrate that European banks contribute more to global systemic risk than US banks. However, banks from both continents have similar exposure to systemic crises. Khiari and Nachnouchi (2018) show that systemic risk for banks in Tunisia depends strongly on the size of, liquidity of, efficiency of and exposure to the interbank lending market. In contrast, Mohanty et al. (2018) indicate that systemic risk among systemically important banks increased strongly during the GFC but decreased from the post-GFC period to the post-ESDC period. Oordt and Zhou (2019) find that a significant relationship exists between business models of banks and systemic risk that are decomposed in the two dimensions of bank tail risk and systemic linkage. Su and Wong (2018) again show that bank size matters for banks in Taiwan, confirming the finding of Varotto and Zhao (2018) and Kamani (2019). Interestingly, Elyasiani and Jia (2019) find that banks' organizational complexity is highly related to their systemic risk. Huang et al. (2019) show that the method used to measure systemic risk does not impact the ranking of Chinese banks according to their systemic risk levels. Furthermore, the authors find that systemic risk among Chinese banks decreased after the GFC but increased again in 2014. Li et al. (2019) note that systemic risk increases when the lending scale increases. Verma et al. (2019) demonstrate for Indian banks that their systemic risk has a high degree of interdependence during crisis periods. Wang et al. (2019) show for US banks that systemic risk increased from 2004 to 2009. Yang et al. (2019) find that more diversified US banks always face higher systemic risk, with a stronger effect for large and medium banks.

Andries et al. (2020) note that central banks play an important role in the level of systemic risk among banks because of the positive relationship between their transparency and financial institutions' contribution to systemic risk. In contrast, Bats and Houben (2020) demonstrate that the choice between bank-based and market-based financing affects systemic risk. More importantly, the authors suggest that market-based financial systems seem to be more resilient to systemic risk than bank-based ones. Hirata and Ojima (2020) show that competition among

Japanese banks plays an important role in the stability of the financial system. Furthermore, the degree of bank diversification increases the level of systemic risk. Another important factor that affects systemic risk is CEO overconfidence. Indeed, Lee et al. (2020) show that during 1995—2014, US banks with overconfident CEOs had higher systemic risk in both contribution and exposure – and mostly during the GFC. In addition to CEOs' confidence levels, macroprudential policy tools further play an important role in the degree of systemic risk, as demonstrated by Meuleman and Vennet (2020). Indeed, the authors also show that the nature of policy tools such as, for example, credit growth tools and liquidity tools, affects systemic risk. However, the severity of crises has impacts on the contribution of individual banks to systemic risk, according to Zedda and Cannas (2020).

To summarize, the literature review allows us to understand that a high degree of dependence and contagion exists among banks. Fundamental factors, market factors and macroprudential policies can contribute to the degree of systemic risk of both individual banks and of the entire system. More importantly, we note that the degree of interdependence among banks remains a determinant factor of systemic risk. In this regard, we contribute to the literature by using a new method developed by Han et al. (2016) to measure the spillover of risk among banks within a network while considering the lowest quantile of the return distribution of 83 large and listed banks in 24 countries during 2003–2020. More importantly, this method allows us to determine the direction of the spillover effect by distinguishing between risk-transmitter and risk-receiver banks while considering the size of banks as measured by their market capitalization. This aspect is important because numerous studies show that bank size matters (e.g., Su and Wong, 2018; Varotto and Zhao, 2018; Kamani, 2019). Furthermore, we contribute to the literature by seeking to understand how the recent Covid-19 crisis has affected the systemic risk among banks throughout the world. This aspect has not yet been widely analysed in the academic literature (except for Rizwan et al. (2020) and Akhtaruzzaman et al. (2020), to the best of our knowledge).

3. Methodology and data

3.1. An overview of the new systemic risk index

We propose a new index to measure financial systemic risk within a network framework. The index is based on the cross-quantilogram methodology (Han et al., 2016; CQ hereafter). This method is chosen because 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). Furthermore, this method has been proven to be efficient because it has been used in numerous academic studies, such as Shahzad et al. (2018), Shahzad et al. (2019), Uddin et al. (2019), Zhou et al. (2019) or Lindman et al. (2020). More importantly, this method allows for the identification of banks that transmit and receive risk through spillover effects. Finally, the systemic risk index is the sum of all risk spillovers of individual banks at each state of the market (or at each quantile considered). We are particularly interested in the lowest quantile (5%) because it indicates the systemic risk in downside market conditions. The details of the method are explained as follows.

First, we calculate the stock returns of selected banks in our sample and estimate their CQs. The systemic risk index in this study is built using the so-called 'directional predictability' between all possible pairs of banks in the sample for their extreme negative stock market returns situated in the 5% quantile of the joint return distribution. The underlying idea of directional predictability simply means that the 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, or the next trading day in our case. Thus, this predictability corresponds to the notion of financial contagion (see Section 2 for more details).

Second, the directional predictability of all pairs of banks results in an $N \: x \: N$ adjacency matrix that allows us to measure the 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 (representing banks) and a set of edges (representing the links among banks). We use the constructed networks to build our systemic risk index considering each bank's size as measured by its market capitalization. The consideration of bank size in the proposed systemic risk index is important because it has been proven to play an important role in the measure of systemic risk (e.g., Pais and Stock, 2013; Laeven et al., 2016; Khiari and Nachnouchi, 2018). To summarize, the new systemic risk proposed by this research shows the interconnectedness among banks in downside market states when considering their size.

3.2. Connectedness analysis using the cross-quantilogram approach

The objective of the CQ method, developed by Han et al. (2016), is to investigate the cross-correlation between two stationary time series. The first advantage of this method is that it allows for the identification of the direction of the dependence – which variable predicts the other one based on past information – presented by lagged values. The second advantage is that this directional predictability is calculated under various quantile levels of the distribution of the considered time series. This characteristic is important because it accounts for the nonlinearity that can exist in the relation between two variables. In finance, this characteristic allows differentiating various market states in the return level function of financial assets. In our case, we choose to use a low quantile level of stock returns (5% quantile) to simulate turmoil or crisis market states.

The CQ method 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 $q_{i,t}(\tau_i) = \inf\{v\text{: } F_{y_i|x_i}(v|x_{it}) \geq \tau_i\}$ for quantile $\tau_i \in (0{,}1)$.

The measurement of the serial dependence in quantiles is based on an examination of the quantile hit processes $\left\{ I\left(y_{it} \leq q_{i,t}(\cdot)\right)\right\}$ that alternate between 0 and 1 depending on the exceedance of the specific quantile.

To generalize, we 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 then 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 inferences, for example, a test of the hypothesis of directional predictability in quantiles of events up to $p \in \mathbb{N}$ lags. Han et al. (2016) propose a Ljung-Box type statistic for this purpose to test hypothesis $H_0\text{: } \rho_\tau(1) = \cdots \rho_\tau(p) = 0$

with alternative hypothesis $H_A: \rho_\tau(k) \neq 0$, 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 are obtained by using the stationary bootstrap of Politis and Romano (1994), as suggested by Han et al. (2016). The results presented in this paper are obtained using 1,000 replication samples for the hypothesis testing.

To construct a network representing the quantile dependence in returns, we estimate bivariate cross-quantilograms for all pairs of banks in the sample. Although the vertices in the network represent individual banks, the edges are created only between banks for which the Ljung-Box type test provides evidence for a quantile dependence in any of the 10 lags. Because the cross-quantilogram measures the dependence of the lagged values of one of the banks against a contemporary value of another one, the adjacency matrix is not symmetric, and the network is represented by a directed graph.

We calculate the overall systemic risk score by following the idea of Das (2016) 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 ($\mathbf{c} = (c_1, \ldots, c_N) \in \mathbb{R}^N$), 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 follows:

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

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

The aggregate risk score, or the new systemic risk index that we propose and its decompositions, are analysed for the full sample period from 11 September 2003 to 17 April 2020 and for three sub-periods to investigate the impact of crises on systemic risk. These sub-periods are the GFC (from 3 August 2007 to 2 July 2009); the European Sovereign Debt Crisis (ESDC) from 5 January 2010 until 3 August 2012; and the Covid-19 crisis period from 3 January 2020 to 17 April 2020. This sub-period division allows us to capture the effect of different crises on systemic risk – mostly of the Covid-19 crisis. For the third sub-period related to the Covid-19 pandemic, to overcome the limited sample size due to the short period, we use the rolling-window approach (more details in Section 4). In addition, the rolling-window approach allows us to capture the dynamics of the change in the aggregate risk score over time. Concretely, each time window covers six consecutive quarters while the window size is one quarter.

To summarize, the previously described CQ method proposed by Han et al. (2016) is based on quantile hits or quantile exceedance. Therefore, the method does not require any moment conditions, works well for heavy-tailed series and allows considering various lags in predictability. The modelling feature based on different quantiles has a significant comparative advantage relative to those of alternative methods, such as that proposed by Diebold and Yilmaz (2012, 2014) that only focuses on the average state of the market. Also important to note is that the Diebold and Yilmaz (2012, 2014) approach does not distinguish between positive and negative correlation, which is a desired feature in financial applications because systemic risk is induced by positive tail comovements, whereas the negative tail interdependencies are beneficial for risk diversification.

3.3. Data

Stock price data for 83 banks from 24 different countries are obtained from the Bloomberg terminal from 11 September 2003 to 17 April 2020. RIC codes of selected banks are available in the Appendix (Table A.1). The selection process of banks in our sample is the same as in Demirer et al. (2018), who analyse 96 banks from 29 countries during 2003–2014 period. These 96 banks are among the 150 biggest banks in the world (based on their assets) and are designated as globally systemically important banks (GSIB). From this sample of 96 banks, we eliminated 13 banks for a final sample of 83 banks. The reason for eliminating these 13 banks is that some of the banks were delisted or were merged or acquired. Figure A.1 presents the dynamics of the stock prices of all banks during the sample period, whereas Table A.2 presents descriptive statistics of banks' stock returns in each of the 23 considered countries. From Table A.2., we note that approximately half of the sampled banks have a negative rate of return during the study period. We cite examples, such as Ubicredit, Citigroup or Barclays. The other half of the sampled banks has a positive rate of return, such as China Merchants Bank, Ping An Bank, Goldman Sachs or DBS Group. This observation indicates that a high disparity exists in the stock performance of banks worldwide. In future research, it would be interesting to investigate the determinant factors of banks' stock performance. The second piece of information that we can obtain from descriptive statistics is related to volatility. The volatility of the banks also differs significantly, with the lowest for Malayan Banking and the highest for Swedbank. In contrast, we note that almost all of the skewness is negative, meaning that banks' return distributions are skewed to the left, except for Mitsubishi UFJ Financial Group, Wells Fargo & Co, Credit Suisse, Goldman Sachs, Nordea Bank and others. Excess kurtosis for the sampled banks is positive, meaning that stock return distributions have thick tails, which once again shows the necessity to consider different quantiles of stock returns when measuring systemic risk – as we do in this research. Figure A.1. (in the Appendix) shows that the stock prices of all of the sampled banks strongly decrease during the Covid-19 pandemic, which may help understand the systemic risk results obtained using the following cross-quantilogram method.

To avoid the nonsynchronous trading effects, we calculate rolling-average two-day returns, as in Forbes and Rigobon (2002). As previously mentioned, we include bank size in the construction of the systemic risk indicator. More precisely, bank size is expressed as an index relative to the average value of each bank's market capitalization in 2004, the first full year of our sample. As mentioned above, apart from the full-sample estimations, three major subsamples are considered: (1) the GFC from 3 August 2007 to 2 July 2009, (2) the ESDC from 5 January 2010 to 3 August 2012 and (3) the Covid-19 pandemic period from 3 January 2020 to 17 April 2020. Regarding the third sub-period, we can provide the results for this short period using the rolling-window approach (more details below).

4. Results

In this results section, we first present the visualization of the interconnection network of the sampled banks during the entire period and during the three sub-periods. In the second sub-section, we present the new systemic risk index, as presented in Section 3. To present the evolution of this index over time, we make a rolling-window calculation to compare its value through different periods (more details are subsequently presented). In the last sub-section, we go further in our analysis to better understand the source of the systemic risk depending on the country and each individual bank.

4.1. Networks of extreme negative co-movements among banks

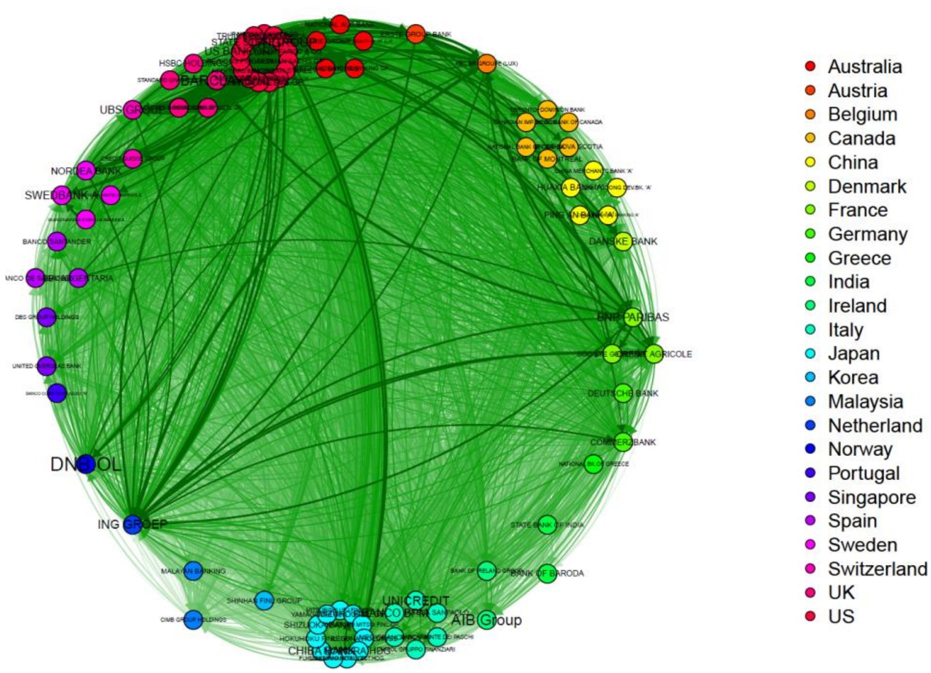
To obtain a better perspective on the extent to which the international banking sector is connected, we show a network of CQs among banks estimated during the entire period (2003–2020) in Figure 1. Important to note is that this directional network captures only co-movements of extreme negative returns (5% quantile of the joint return distribution) that are highly statistically significant, that is, at the 7.35×10^{-6} significance level (Bonferroni *p*-value adjustment). Despite this strict threshold, the density of the network is **98%**. This high percentage indicates that out of the maximum number of all possible pair connections – 6,806 total pairs – 98% are statistically significant. This result shows the high degree of interdependence in the international banking system and, thus, the complexity of managing systemic risk among them. Practically, this high level of significant pairwise connections makes it impossible to visually inspect such a network. Therefore, we create a threshold graph to extract only relationships that satisfy some predetermined conditions. As an example of such thresholding, we retained the values (corresponding linkages) larger than the average of the 100 largest individual bank risk scores from the full sample network provided in Figure 1. After such extraction, we can easily identify the most influential nodes within the bank network, which might be particularly useful for supervising authorities. Furthermore, after computing some basic topological properties of created networks, we can precisely pinpoint the banks that are the largest transmitters of negative shocks and those more likely to be receivers (see Table A.3 in the Appendix).

After visualizing the interconnection network of all sampled banks during the entire period (2003–2020) in Figure 1, Figure 2 shows the threshold networks created for the entire period (Panel A) and the three sub-periods (panels B, C and D) for the GFC, ESDC and Covid-19 crisis periods, respectively. Figure 2 clearly shows that during the GFC, the strongest spillovers were from US banks (most notably Goldman Sachs, Morgan Stanley and Citigroup). During the ESDC, the negative mood stemmed from European banks (mostly from Skandinaviska Enskilda Banken, Swedbank and Deutsche Bank). In contrast, Asian banks seem to be less risk-transmitting relative to US and European banks.

Figure 2 clearly shows that the interconnection among large banks increases dramatically during the Covid-19 pandemic. Indeed, Panel D in Figure 2 shows that the network interconnection has become much more intense during the Covid-19 pandemic from January to

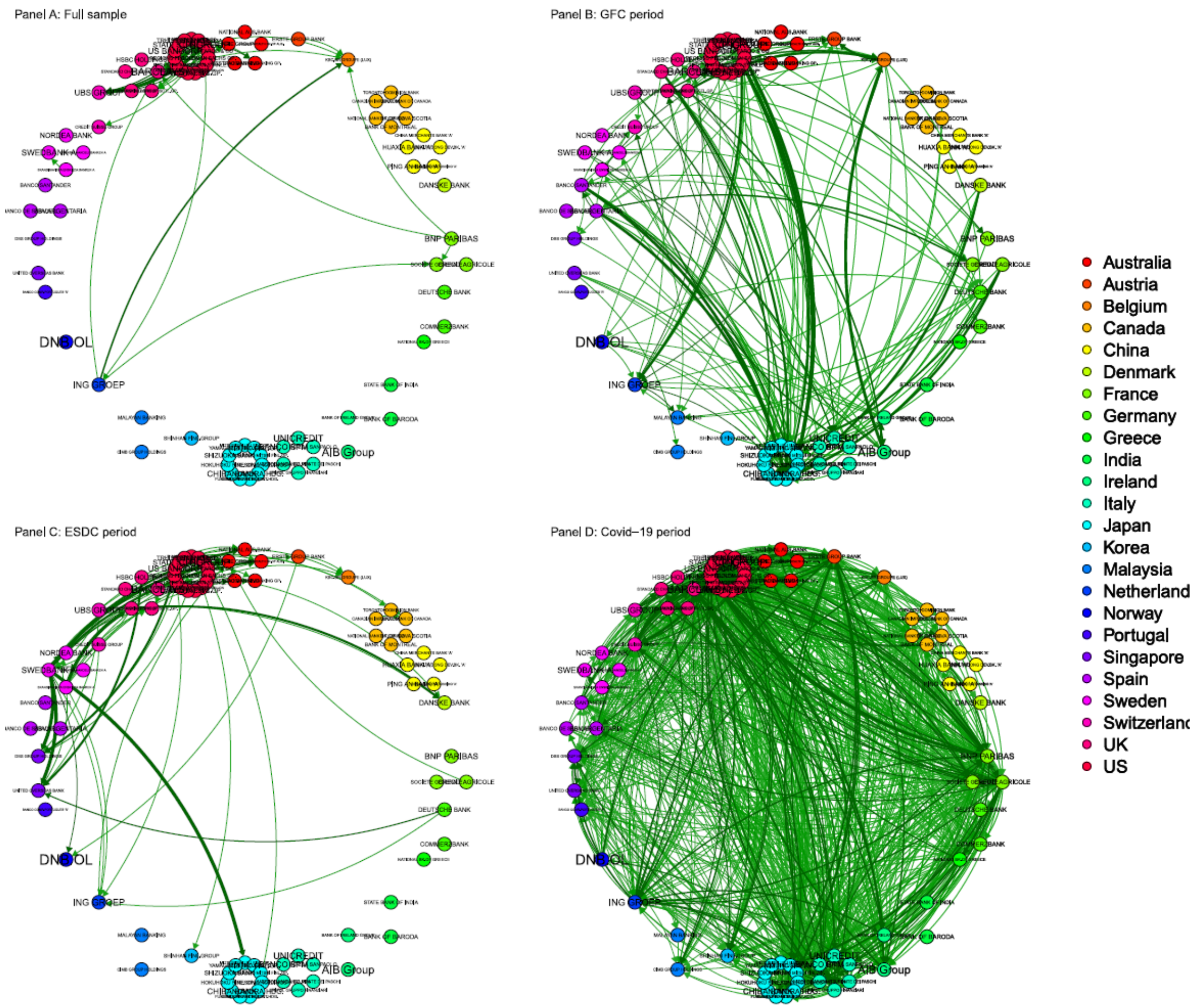
April 2020. Together with Figure 3, we can see that the level of systemic risk among banks is much higher during the Covid-19 pandemic than during the GFC, although previous studies qualified systemic risk as high during the GFC (e.g., Acharya and Steffen, 2013; Glasserman and Young, 2015; Mohanty et al., 2018; among others). In addition, the aggregate systemic risk score is the highest during the Covid-19 pandemic, and its network density is at 70.6% in the third sub-period. This finding convincingly demonstrates the consequences of the outburst of Covid-19 (e.g., Shehzad et al., 2020; Goodell, 2020). In contrast, the threshold graph for this pandemic period clearly shows that there are markedly more significant strong linkages during the Covid-19 pandemic than during the two previous crisis periods (GFC and ESDC). To the best of our knowledge, this result confirms the findings of a few recent studies that investigate the impact of the Covid-19 pandemic on systemic risk, such as Akhtaruzzaman et al. (2020) and Rizwan et al. (2020). This result also suggests that future studies should engage in further investigations to understand the risk spillover mechanism among banks during the Covid-19 pandemic in early 2020.

Figure 1: Network of CQs – full sample



Note: This figure displays the interconnection among 83 sampled banks classified by country. Each country is represented by a colour. This directional network captures co-movements of extreme negative returns (5% quantile of the joint return distribution) that are highly statistically significant, that is, at the 7.35x10-6 significance level (Bonferroni p-value adjustment). To make the figure visible, we only keep the values (corresponding linkages) larger than the average of the 100 largest individual bank risk scores from the full sample network.

Figure 2: Threshold networks in the entire period and three sub-periods



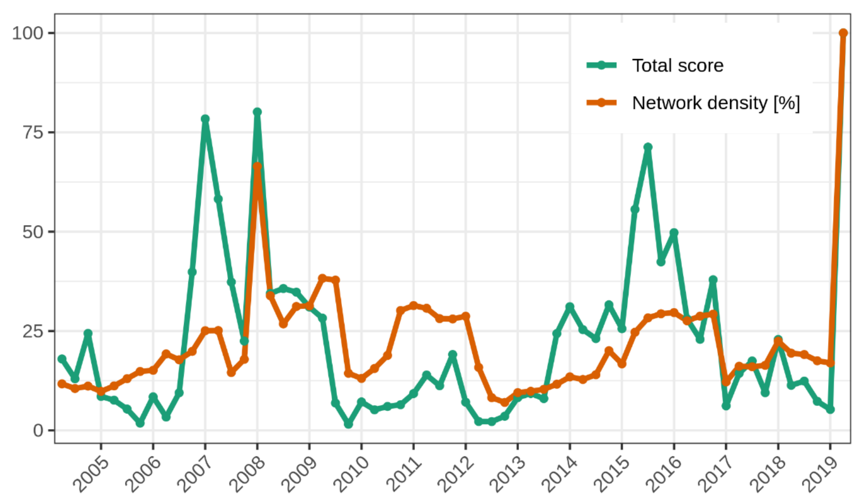
Note: In the four panels, we use the same threshold to preserve comparability among them. We only keep the values (corresponding linkages) larger than the average of the 100 largest individual bank risk scores from the full sample network to make the graphs clearer for reading. For the Covid-19 period, because it is very short (from January to April 2020), we decided to measure the systemic risk through the rolling-window method during the period spreading from 1 October 2018 to 17 April 2020. Because our methodology is based on quantiles of the return distribution, isolating the relatively short pandemic period is not reasonable.

4.2. New systemic risk index

So far, we have been dealing with the estimated directional spillovers among banks in our sample. Our measure of the aggregate systemic risk score further considers the size of each bank, which is measured by its market capitalization (as explained in Section 3). Thus, the overall systemic risk within a network can be provoked by its connectedness (CQs) or the compromise level of nodes (which show the market capitalization of banks), or even both.

Figure 3 shows the evolution of the new systemic risk index and the network density, as measured in the last sub-section. These two measures are closely related because negative shocks are propagated more as a network becomes denser. However, the network density does not reflect the size aspect in the spillover transmission. For example, although the systemic risk index spiked in 2007 accompanied by a rather small network density, both indicators jointly peaked in 2008. Subsequently, during the ESDC period, banks became more interconnected, but the overall systemic risk is slightly smaller than the network density. Then, again in 2015 and 2016, systemic risk increases to be significantly higher than the density because the so-called '2015–16 stock market selloff' occurred due to the Chinese stock market turbulence accompanied by a slower growing GDP in China, the Greek debt default, the end of quantitative easing in the United States and the Brexit vote. However, both the systemic risk index and the network density during the Covid-19 pandemic are the highest for the study period (2003–2020).

Figure 3: New systemic risk index and network density



Note*:* This graph shows the rolling-window measure of the new systemic risk based on the cross-quantilogram approach (more details in Section 3) and the network density (more details in Section 3). To obtain the interval of 0 to 100, the index is normalized to its maximal value – in our case, to the end of the sample, or during the Covid-19 pandemic.

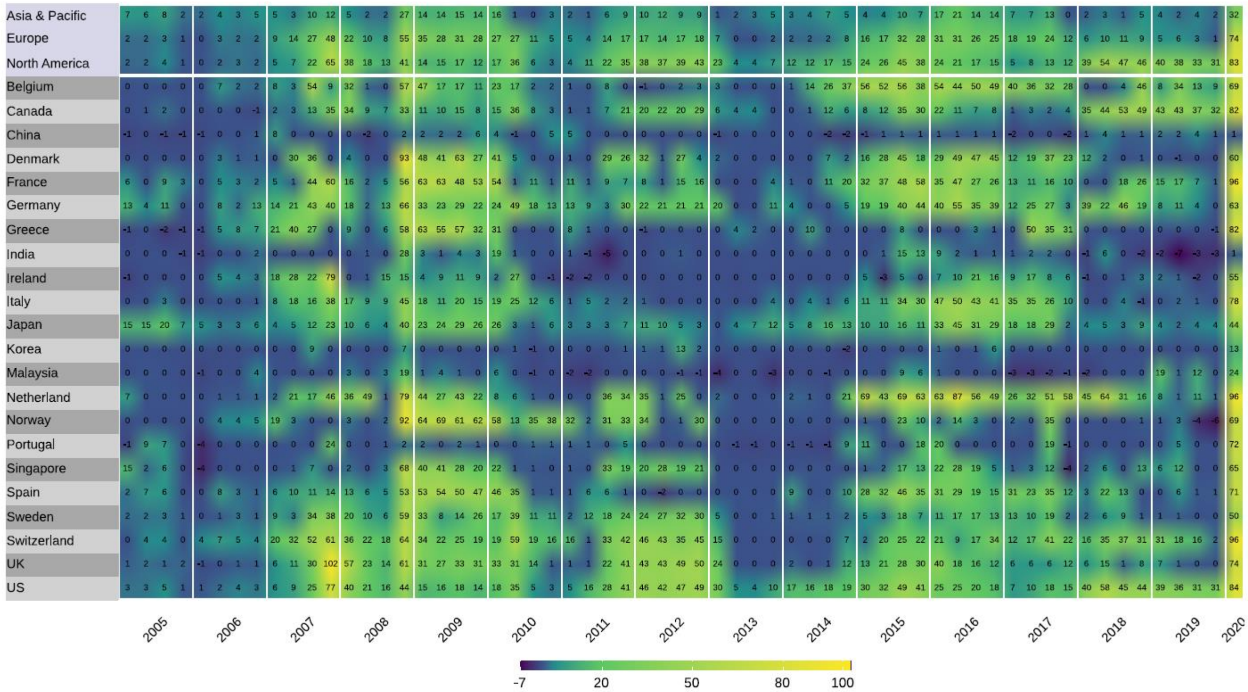
This analysis allows us to make the following observations. First, a low network density does not mean low systemic risk. This observation may be explained by the fact that the risk spillover in downturn market states (5% quantile in our case) can be high even with low network density. Second, Figure 3 confirms the results obtained in Figure 2 on the exceptionally high level of interconnection among banks during the Covid-19 pandemic, in both network density and risk spillover. During the first few months of 2020, economies faced an unprecedented economic lockdown. Stock markets around the world experienced sharp declines that were comparable only to the drops during the Great Depression in 1929 or the outbreak of the GFC in October 2008 (Oldekop et al., 2020). The much higher systemic risk level during the Covid-19 pandemic than that during the 2008 global financial crisis is counterintuitive at first sight. Indeed, the 2008 GFC was a financial crisis caused by the financial sector that underwent the biggest loss. The Covid-19 crisis is originally a health crisis before becoming a global economic crisis. Thus, the Covid-19 crisis is not directly related to the financial sector, but the systemic risk among banks is much higher during this crisis. To explain this result, we may argue that during the Covid-19 pandemic, banks are exposed to a large panel of issues related to, for example, the financing of the real economy, a decrease in assets due to the delay in repayment of SMEs, the volatility of assets under management, the reduced amount of capital exchanged because of the lockdown or the volatility of the reserves resulting from the exchange rate volatility, among others. In this context, future academic studies should further investigate this high systemic risk phenomenon to better understand its determinant factors.

Through the first part of this section, we have learned that both the network density and systemic risk of the 83 sampled banks reach their highest levels during the Covid-19 pandemic. However, for investors, portfolio managers and policymakers, also important to know is the source of systemic risk. Therefore, in the next sub-section, we decompose the new systemic risk to understand the strength of the risk transmission in the function of the country and each individual bank.

4.3. Where does the systemic risk come from?

From the perspective of policymakers and regulatory authorities, decomposing the overall systemic risk to obtain more detailed results on risk transmission is important. The decomposition can be performed with respect to the region or country of origin (Figure 4). It can also be broken down to individual banks (Figure 5). In this paper, we focus on risk transmitters, and the opposite side of this coin can be easily checked (i.e., risk receivers).

Figure 4. Systemic risk decomposition by countries and regions

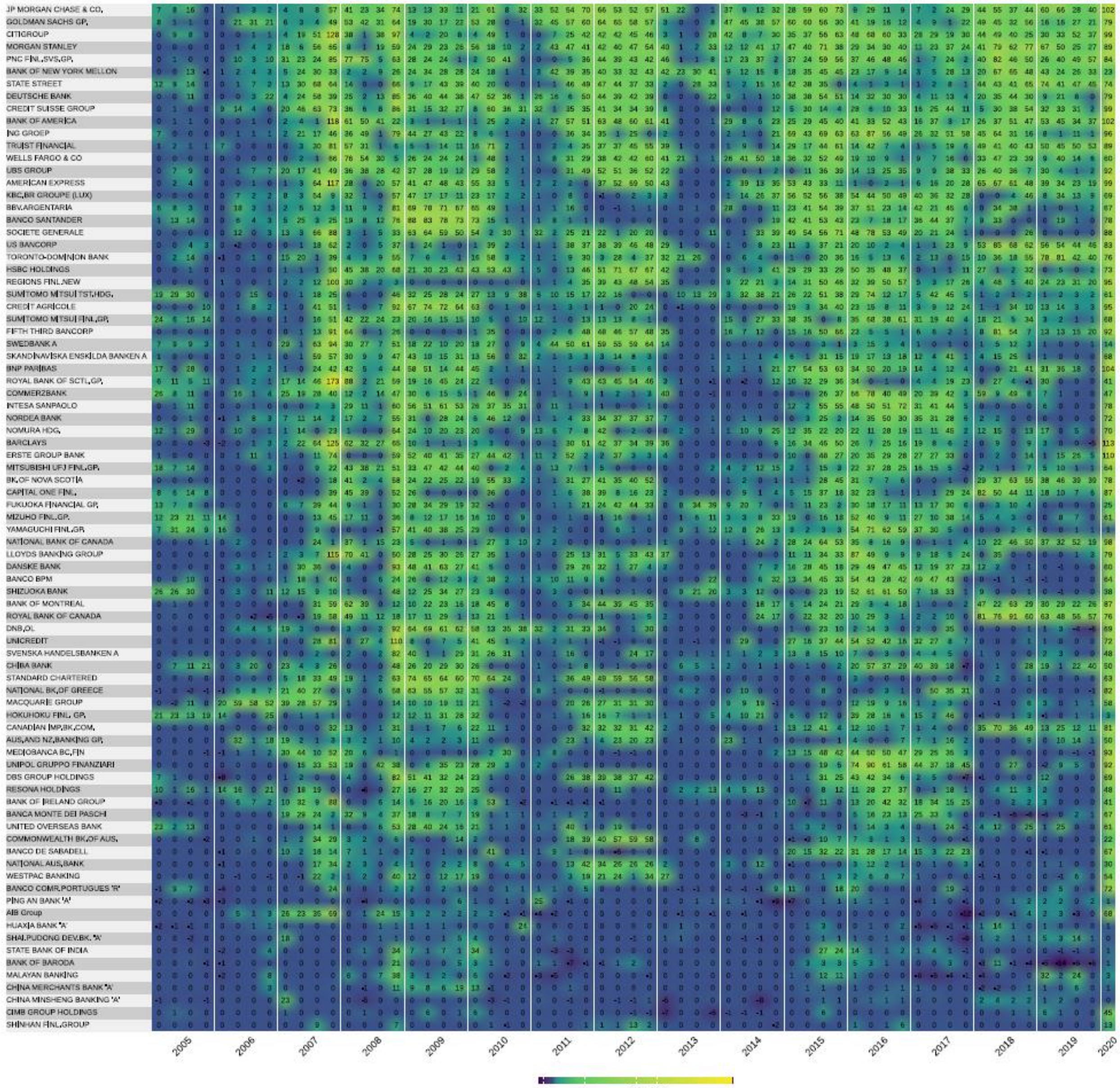


Note: The numbers in this figure correspond to the individual contribution of a given country/region to the aggregate systemic risk score, or the new systemic risk that we propose in this research. Higher numbers are highlighted according to a colour scale: yellow represents a large source of systemic risk transmission and blue indicates a lower systemic risk transmission.

Figure 4 shows that even after the decomposition of the systemic risk index into countries of origin, systemic risk reaches its peak in all three regions (US, EU and Asia) at the end of our sample period – during the Covid-19 pandemic in early 2020. The highest values are reported for France, Netherland, Switzerland, the US, Greece and Canada, with a network density higher than 80 during the Covid-19 pandemic. For all of these countries, it is also the maximal values of systemic risk during the entire period. However, a few countries have peaks in the systemic risk index during the GFC, such as the UK, Norway and Denmark. This finding suggests that country and regional effects exist in the level of systemic risk in the banking system.

The most interesting part of our approach is that it allows for the identification of the source of contagion at the individual bank level (Figure 5). Worth noting is that all banks in Figure 5 are ordered according to their average systemic risk index value. In this regard, we observe that banks at the top of the list have a higher risk transmission level than banks at the bottom of the list. In other words, a higher systemic risk index results in banks transmitting higher risk to other banks within the network.

Figure 5. Systemic risk decomposition by individual banks



Note: The numbers in this figure correspond to the individual contribution of a given bank to the aggregate systemic risk score or the new systemic risk that we propose in this research. Higher numbers are highlighted according to a colour scale: yellow represents a large source of systemic risk transmission, and blue is assigned to a lower systemic risk transmission.

Using this logic, we can see in Figure 5 that, during the GFC, mostly between the beginning and end of 2007, the most important risk transmitters were Citigroup, Bank of America and American Express. They were followed by EU banks, such as Royal Bank of Scotland, Barclays and Lloyds. Not surprising is that the topmost risk transmitters are US banks (such as JPMorgan

Chase, Goldman Sachs, Citigroup and Morgan Stanley), although we also find Deutsche Bank or Credit Suisse within the 'top 10' risk-transmitting banks. Figure 5 also shows that Asian banks are those with a weak systemic risk transmission because they are at the bottom of Figure 5, and there are fewer yellow zones relative to the other banks. We can cite some Asian banks, such as Ping An Bank, State Bank of India, China Merchant Bank or China Minsheng Banking, among others. This result again shows that it is important to distinguish the country and region of origin when investigating systemic risk, which may be explained by the difference in macroprudential policy in different countries and regions throughout the world (e.g., Meuleman et al., 2020).

The findings in this sub-section tell us that the contribution to the overall systemic risk in the banking system depends on the country and region of origin of the bank and on the bank itself. We also note that US banks contribute the most to overall systemic risk, followed by European banks, whereas Asian banks contribute less to the overall systemic risk. Finally, even at the country and individual bank levels, the systemic risk level remained the highest during the Covid-19 pandemic in early 2020.

5. Conclusion

The core of the Basel III accords, in response to the excessive risk-taking of banks and financial intermediaries before the onset of the 2008–2009 global financial crisis, has emphasized the increase in the capital and liquidity requirements to safeguard the financial and economic system from systemic risk. Other sections of the accords also underline the importance of employing adequate methodologies to better estimate and forecast various types of risks, including systemic risk (BCBS, 2011). Motivated by the important role that the banking sector plays as an intermediary of financial transactions, provider of liquidity and credit and reducer of risk through economies of scale and portfolio aggregation, this paper investigates the systemic risk in the network structure of 83 largest banks from 24 countries during 2003–2020. One of our major contributions derives from the construction of a new index to quantify the systemic risk based on the cross-quantilogram methodology proposed by Han et al. (2016). The proposed systemic risk index enables us to quantify the strength of the interdependence between banks in a network according to different market states determined by different return distribution quantiles. In the present study, we consider the 5% quantile level to simulate downturn market states. The method underlying the new systemic risk index is a quantile-hit approach (based on conditional quantiles rather than unconditional quantiles) that does not require any moment conditions and accounts for heavy-tails in time series. Another advantage of the systemic risk index stems from its simplicity of calculation, understanding and interpretation, which is in concordance with the conclusion of Rodríguez-Moreno and Peña (2013) regarding systemic risk measures – 'the simpler, the better'. Concretely, the construction of the new index is based on the aggregation of all spillover effects from all pairs of banks in the considered network.

A data sample consisting of daily stock prices of 83 largest banks from 24 different countries during 2003–2020 is used to show the accuracy and usefulness of the proposed index. Because our sample covers the outburst of the Covid-19 pandemic within the first months of 2020, we extend our approach through a rolling-window analysis to provide the results for this recent and short period. Apart from pinpointing the largest individual risk transmitters among the banks, our main result shows that the systemic risk index has never been as high as during this Covid-19 pandemic period – much higher than during the GFC. Apparently, banks are now more interconnected than ever. At first sight, this result may be counterintuitive because the Covid-19 pandemic is not a financial crisis, such as the GFC. However, the systemic risk in the banking system has never been as high as during the Covid-19 pandemic. This finding may be explained by the fact that the economic crisis caused by the Covid-19 pandemic is more global than the GFC because it affects all sectors of the economy. Then, this global economic crisis affects banks in different ways, such as through liquidity, loan collections, capital positions, asset quality, earnings and costs (Boru, 2020). This finding suggests that academic research needs to conduct further analyses to better understand the reasons for this exceptionally high systemic risk in the banking system. Doing so will help policymakers better regulate banks to prepare for the upcoming recovery process.

In contrast, our results also show that US banks are the most important risk-transmitting banks, followed by European and Asian banks. Our results also indicate the systemic risk level of each bank and each country and region. This result suggests that regulators should consider systemic-risk-adjusted measures for capital requirements that consider each bank's systemic risk profile. This may help in the process of adopting the Basel III accords that could reduce social externalities and bailout costs in the event of failure by large financial institutions. Particular attention should be paid to banks that act as risk transmitters, which could trigger systemic risk across the financial system around the globe. Any sign of losses in the asset portfolios of those banks should alert the financial system for prompt and adequate measures to limit the losses of those banks. From the perspective of banks that are risk receivers, information should rapidly flow through a decentralized banking information system that would motivate adequate responses (e.g. rebalancing asset portfolios and entering hedging positions) to waves of negative spillover effects across the network of the largest banks.

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Appendix

Table A.1: List of sampled banks with 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		

Table A.2: Descriptive statistics – returns

Bank	Mean	St. dev.	Q1	Median	Q3	Min	Max	Skewness	Kurtosis
HSBC HOLDINGS	-0.012	1.105	-0.487	0.000	0.504	-13.913	7.508	-0.850	14.946
MITSUBISHI UFJ FINL.GP.	-0.011	1.571	-0.787	0.000	0.737	-12.260	10.306	0.139	5.228
BNP PARIBAS	-0.012	1.651	-0.738	0.019	0.782	-12.822	10.832	-0.267	7.387
JP MORGAN CHASE & CO.	0.023	1.529	-0.512	0.036	0.628	-15.911	13.705	0.238	17.019
DEUTSCHE BANK	-0.047	1.772	-0.886	0.000	0.818	-12.202	12.328	-0.026	6.821
BARCLAYS	-0.036	2.073	-0.802	0.000	0.768	-19.665	28.201	-0.082	22.554
CREDIT AGRICOLE	-0.020	1.806	-0.803	0.000	0.831	-13.096	11.729	-0.139	5.462
BANK OF AMERICA	-0.012	2.059	-0.622	0.011	0.659	-19.112	21.115	-0.144	22.514
CITIGROUP	-0.054	2.260	-0.651	0.010	0.650	-35.892	23.896	-1.821	44.952
MIZUHO FINL.GP.	-0.010	1.625	-0.710	0.000	0.667	-14.763	12.467	-0.128	8.433
SOCIETE GENERALE	-0.032	1.914	-0.839	0.000	0.839	-15.896	11.373	-0.467	7.635
ROYAL BANK OF SCTL.GP.	-0.086	2.527	-0.831	0.000	0.762	-61.769	19.228	-7.495	173.804
SUMITOMO MITSUI FINL.GP.	-0.012	1.614	-0.800	0.000	0.748	-13.061	9.399	-0.151	5.509
BANCO SANTANDER	-0.019	1.487	-0.703	0.023	0.693	-12.343	8.748	-0.366	6.205
WELLS FARGO & CO	0.002	1.629	-0.536	0.020	0.567	-14.199	15.801	0.441	20.803
ING GROEP	-0.025	2.001	-0.754	0.016	0.812	-24.320	13.829	-0.980	14.598
LLOYDS BANKING GROUP	-0.045	2.111	-0.716	0.000	0.671	-39.347	21.836	-2.470	49.422
UNICREDIT	-0.064	1.990	-0.916	0.000	0.852	-17.802	11.747	-0.602	7.673
UBS GROUP	-0.031	1.668	-0.679	0.010	0.687	-17.302	14.543	-0.327	12.438
CREDIT SUISSE GROUP	-0.038	1.673	-0.770	0.000	0.745	-12.309	19.399	0.004	11.284
GOLDMAN SACHS GP.	0.016	1.502	-0.614	0.051	0.716	-12.050	16.249	0.186	14.009
NORDEA BANK	0.007	1.418	-0.628	0.028	0.681	-8.554	12.748	0.109	8.201
INTESA SANPAOLO	-0.015	1.731	-0.783	0.000	0.827	-18.811	12.566	-0.764	8.975
MORGAN STANLEY	-0.001	2.085	-0.747	0.016	0.793	-27.566	40.912	1.053	55.097
TORONTO-DOMINION BANK	0.025	0.904	-0.349	0.054	0.418	-9.478	9.507	-0.347	15.839
ROYAL BANK OF CANADA	0.024	0.929	-0.360	0.049	0.436	-9.997	8.196	-0.142	14.908
BBV.ARGENTARIA	-0.023	1.484	-0.724	0.000	0.718	-9.667	8.608	-0.187	4.849
COMMERZBANK	-0.075	2.025	-1.012	0.000	0.875	-18.327	12.914	-0.475	7.382
NATIONAL AUS.BANK	-0.013	1.129	-0.487	0.017	0.531	-8.694	10.747	-0.273	9.052
BK. OF NOVA SCOTIA	0.013	0.935	-0.377	0.026	0.428	-9.823	10.163	-0.323	15.462
COMMONWEALTH BK. OF AUS.	0.018	0.983	-0.453	0.041	0.508	-7.532	6.989	-0.329	6.698
STANDARD CHARTERED	-0.012	1.587	-0.731	0.000	0.709	-14.015	16.078	0.138	12.869
CHINA MERCHANTS BANK 'A'	0.050	1.474	-0.681	0.000	0.736	-10.506	9.528	0.018	4.167
AUS.AND NZ. BANKING GP.	-0.001	1.127	-0.472	0.042	0.531	-10.360	10.735	-0.300	10.438
WESTPAC BANKING	0.000	1.073	-0.505	0.038	0.550	-8.580	5.947	-0.302	5.579
SHAI.PUDONG DEV.BK. 'A'	0.035	1.560	-0.657	0.000	0.691	-8.925	9.521	0.044	3.925
DANSKE BANK	-0.011	1.419	-0.601	0.000	0.593	-13.388	11.638	-0.380	8.666
SBERBANK OF RUSSIA	0.073	1.862	-0.707	0.063	0.909	-19.020	23.032	-0.097	16.456
CHINA MINSHENG BANKING 'A'	0.035	1.487	-0.621	0.000	0.645	-16.361	9.595	-0.420	9.978
BANK OF MONTREAL	0.009	0.966	-0.353	0.047	0.399	-11.385	10.707	-0.707	19.481
ITAU UNIBANCO HOLDING PN	0.041	1.535	-0.809	0.000	0.881	-10.773	12.325	0.135	5.547
RESONA HOLDINGS	-0.026	1.701	-0.814	-0.041	0.743	-13.413	12.885	0.269	7.641
NOMURA HDG.	-0.034	1.693	-0.905	-0.045	0.814	-13.280	9.144	-0.236	4.729
SUMITOMO MITSUI TST.HDG.	-0.009	1.746	-0.883	0.000	0.813	-11.617	12.701	0.017	4.766
STATE BANK OF INDIA	0.035	1.676	-0.868	0.043	0.940	-14.797	14.457	0.094	6.736
DNB.OL	0.027	1.564	-0.612	0.030	0.690	-17.084	13.912	-0.515	14.452
SVENSKA HANDELSBANKEN A	0.013	1.195	-0.514	0.000	0.568	-8.065	9.054	-0.003	6.861
SKANDINAVISKA ENSKILDA BAN. A	0.010	1.614	-0.599	0.011	0.714	-13.463	18.205	-0.162	15.627
BANK OF NEW YORK MELLON	0.003	1.455	-0.563	0.035	0.606	-14.535	14.029	0.030	17.500
BANCO BRADESCO PN	0.046	1.517	-0.810	0.000	0.914	-11.426	12.495	0.084	4.686
KBC.BR GROUPE (LUX)	0.005	2.238	-0.730	0.047	0.831	-26.662	24.504	-1.153	23.445
PNC FINL.SVS.GP.	0.016	1.551	-0.521	0.046	0.589	-26.718	14.870	-0.842	34.336
DBS GROUP HOLDINGS	0.013	1.041	-0.483	0.000	0.527	-7.223	7.009	-0.061	5.610
PING AN BANK 'A'	0.035	1.701	-0.805	0.000	0.744	-10.445	9.595	0.165	3.783
CAPITAL ONE FINL.	-0.003	1.888	-0.661	0.044	0.717	-15.038	16.814	0.133	15.460
SHINHAN FINL.GROUP	0.012	1.454	-0.772	0.000	0.745	-10.811	10.431	0.017	4.440
SWEDBANK A	0.003	6.219	-0.578	0.034	0.675	-196.732	176.592	-3.404	751.921
ERSTE GROUP BANK	-0.005	1.921	-0.820	0.000	0.903	-16.309	13.899	-0.654	9.012
BANCA MONTE DEI PASCHI	-0.191	2.640	-1.016	-0.027	0.687	-59.912	19.283	-5.075	119.206
BANCO DE SABADELL	-0.042	1.469	-0.771	-0.010	0.660	-12.612	9.820	-0.101	6.600
UNITED OVERSEAS BANK	0.011	0.988	-0.455	0.000	0.494	-9.199	7.529	-0.050	7.520
BANK OF IRELAND GROUP	-0.114	3.109	-1.121	0.000	0.934	-48.672	30.370	-0.801	28.437
NATIONAL BANK OF CANADA	0.025	1.011	-0.357	0.054	0.434	-10.571	14.190	-0.159	24.760
MALAYAN BANKING	0.003	0.834	-0.349	0.000	0.399	-6.448	6.376	-0.249	7.884
AIB Group	-0.188	3.547	-1.235	0.000	0.857	-58.676	25.642	-2.125	42.691
STANDARD BANK GROUP	0.028	1.308	-0.694	0.017	0.752	-9.404	9.235	-0.086	4.020
AMERICAN EXPRESS	0.017	1.440	-0.502	0.050	0.604	-10.622	13.409	0.144	12.898

NATIONAL BK. OF GREECE	-0.202	3.440	-1.477	0.000	1.274	-35.604	22.977	-1.556	15.393
MACQUARIE GROUP	0.026	1.550	-0.596	0.069	0.732	-17.274	18.615	-0.228	14.248
FUKUOKA FINANCIAL GP.	-0.011	1.556	-0.837	0.000	0.797	-10.382	12.832	-0.032	4.910
FIFTH THIRD BANCORP	-0.031	2.357	-0.650	0.015	0.671	-30.182	28.328	0.130	38.027
REGIONS FINL.NEW	-0.026	2.286	-0.699	0.015	0.729	-25.904	29.984	0.405	29.879
CHIBA BANK	0.003	1.446	-0.734	0.000	0.729	-9.844	11.182	0.163	5.613
UNIPOL GRUPPO FINANZIARI	-0.061	1.713	-0.826	0.000	0.701	-15.665	21.992	0.183	13.684
BANCO COMR.PORTUGUES 'R'	-0.097	1.985	-0.968	0.000	0.789	-10.848	14.331	-0.013	4.853
CIMB GROUP HOLDINGS	0.015	1.098	-0.470	0.000	0.510	-8.534	6.405	-0.130	4.697
BANK OF BARODA	0.013	1.968	-1.047	0.011	1.046	-22.910	17.654	-0.056	9.542
TURKIYE IS BANKASI 'C'	0.034	1.693	-0.905	0.000	1.035	-11.106	8.188	-0.124	2.324
HOKUHOKU FINL. GP.	-0.016	1.562	-0.813	0.000	0.796	-10.034	10.689	0.221	4.241
SHIZUOKA BANK	-0.006	1.256	-0.628	0.000	0.643	-10.118	10.267	-0.083	6.162
MEDIOBANCA BC.FIN	-0.012	1.502	-0.689	0.000	0.742	-18.754	10.314	-0.716	9.594
YAMAGUCHI FINL.GP.	-0.013	1.321	-0.696	0.000	0.667	-10.245	8.069	-0.232	5.240
CANADIAN IMP.BK.COM.	0.008	1.002	-0.375	0.038	0.428	-10.829	9.428	-0.484	16.051
US BANCORP	0.008	1.368	-0.461	0.033	0.519	-16.689	12.830	-0.421	19.276
HUAXIA BANK 'A'	0.016	1.579	-0.677	0.000	0.671	-14.882	9.575	-0.257	6.535
STATE STREET	0.006	1.860	-0.614	0.034	0.695	-44.625	17.120	-4.975	123.856
BANCO BPM	-0.088	2.128	-1.056	0.000	0.904	-16.462	12.156	-0.183	4.478
TRUIST FINANCIAL	-0.004	1.453	-0.551	0.031	0.576	-11.798	16.611	0.278	13.979

Note: Q1 and Q3 designate the first and third quartiles. The returns are calculated as rolling-average two-day continuous returns. For readability, the returns have been multiplied by 100.

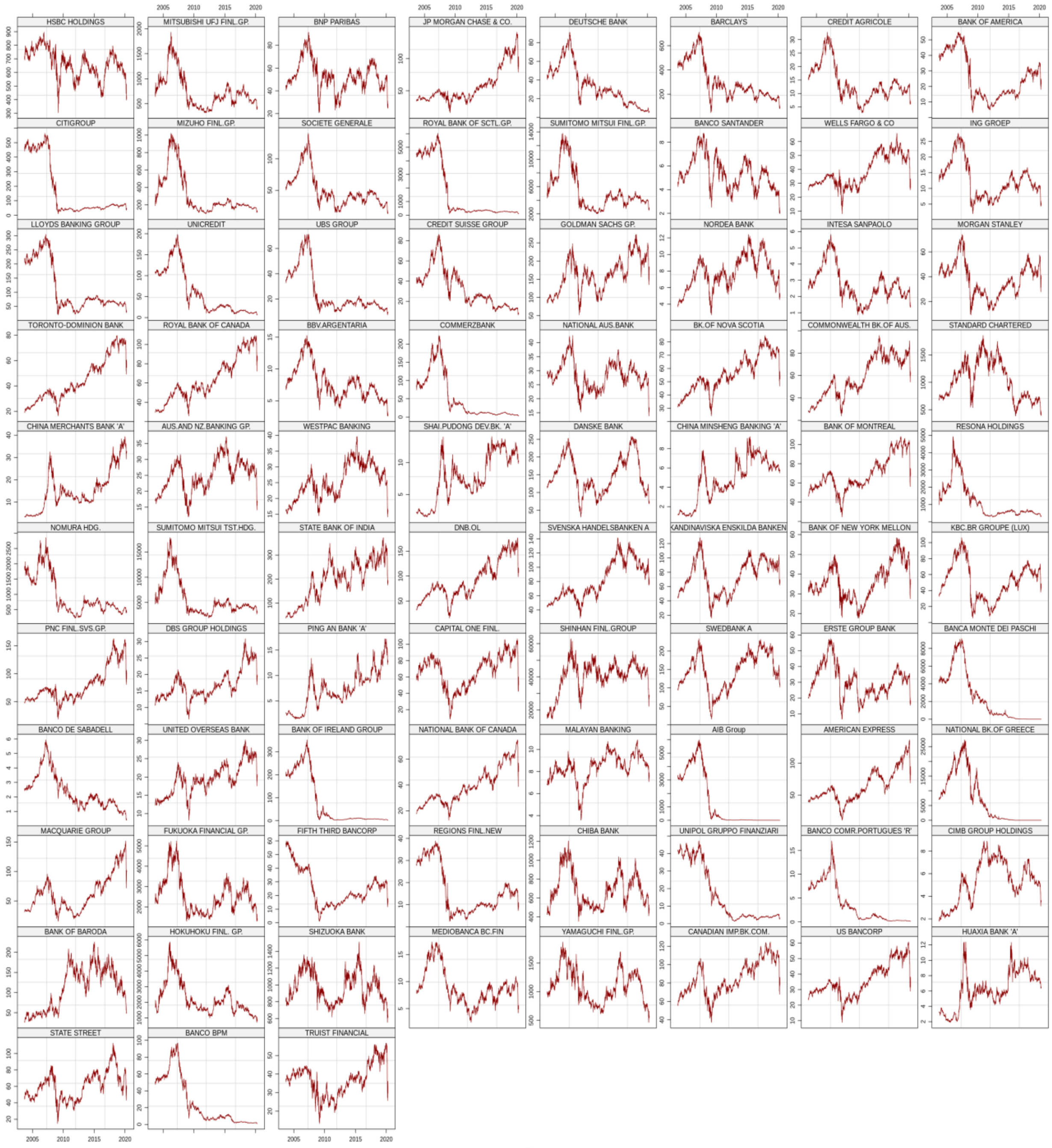
Table A.3: Topological properties – centrality measures (full sample)

Bank	In degree	Out degree	Degree	Betweenness	Eigenvector
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

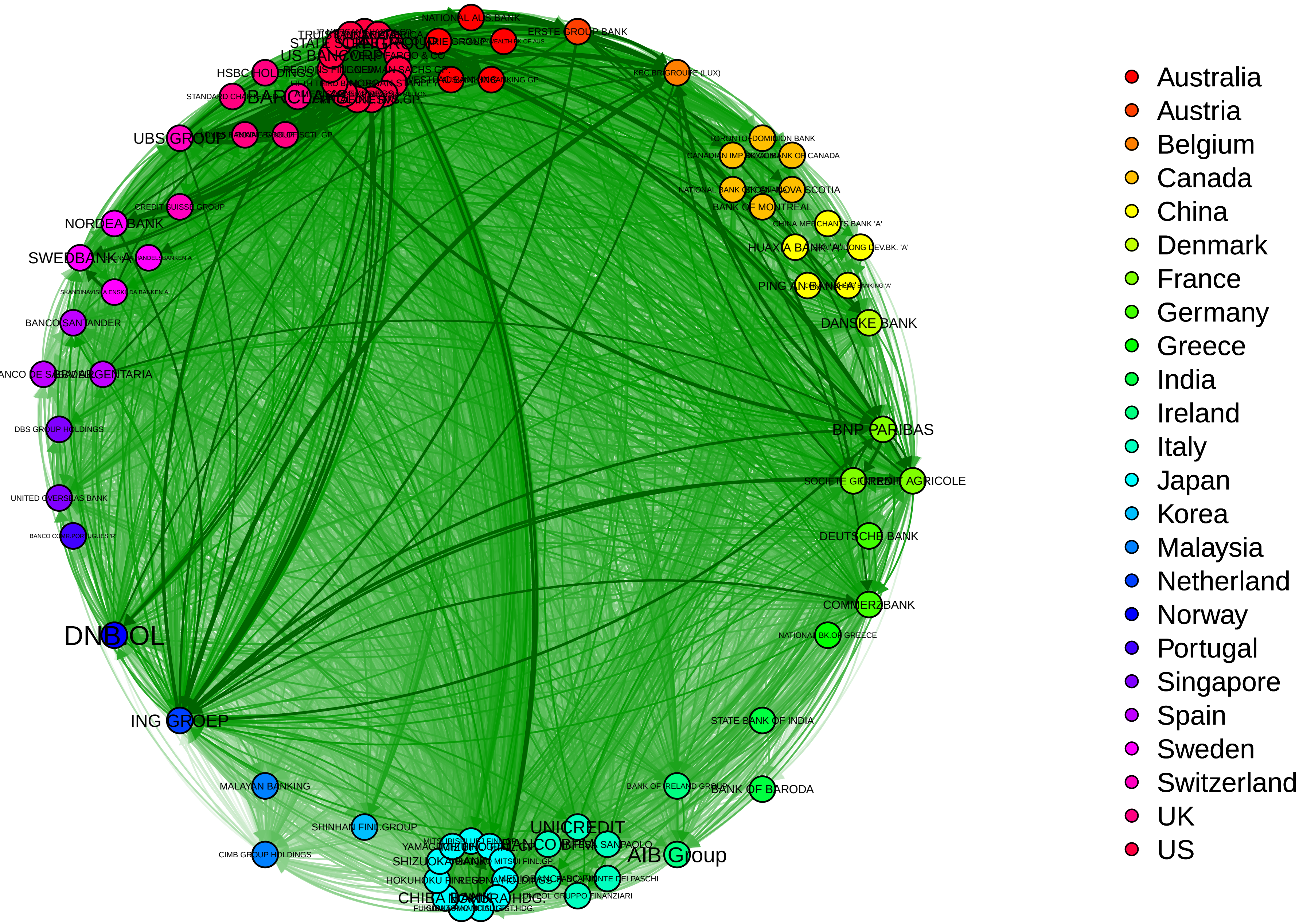
BANK OF NEW YORK MELLON	82	82	164	2.2246	1.0000
KBC.BR GROUPE (LUX)	79	81	160	1.1822	0.9793
PNC FINL.SVS.GP.	80	82	162	1.3965	0.9901
DBS GROUP HOLDINGS	82	81	163	1.9788	0.9948
PING AN BANK 'A'	78	75	153	1.0230	0.9373
CAPITAL ONE FINL.	82	82	164	2.2246	1.0000
SHINHAN FINL.GROUP	81	80	161	1.6425	0.9839
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

Note: Five centrality measures are presented: ‘out degree’ provides the number of links originating in the specific vertex, ‘in degree’ provides the number of edges terminating in the vertex (receiver node), ‘degree’ is the sum of the two, ‘betweenness’ measures the number of shortest paths in the network containing the vertex and ‘eigenvector centrality’ measures the connectedness to high scoring nodes. In all cases, a high centrality score indicates a more prominent position and/or influence of a vertex in the network.

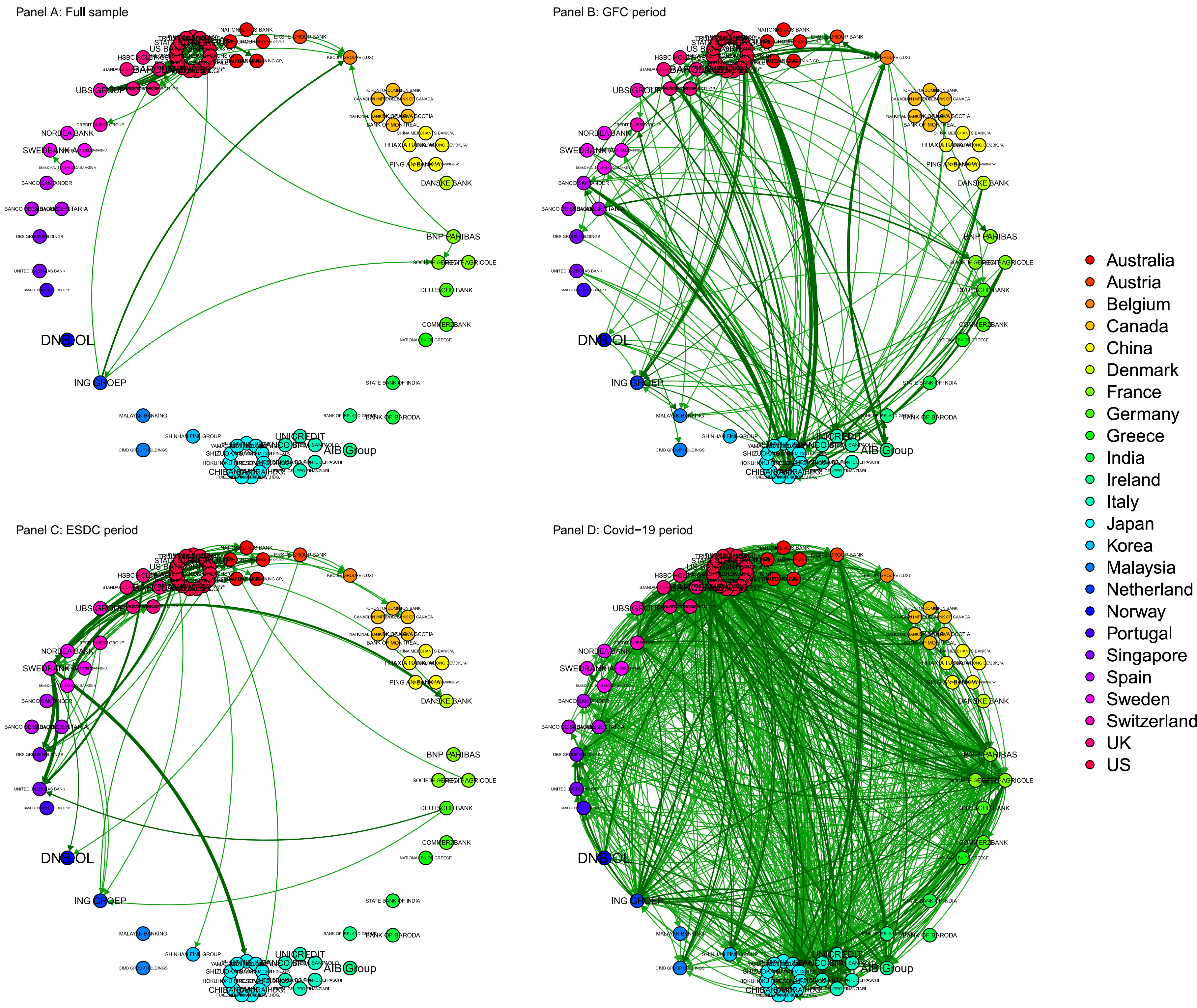
Figure A.1: Dynamics of stock market prices

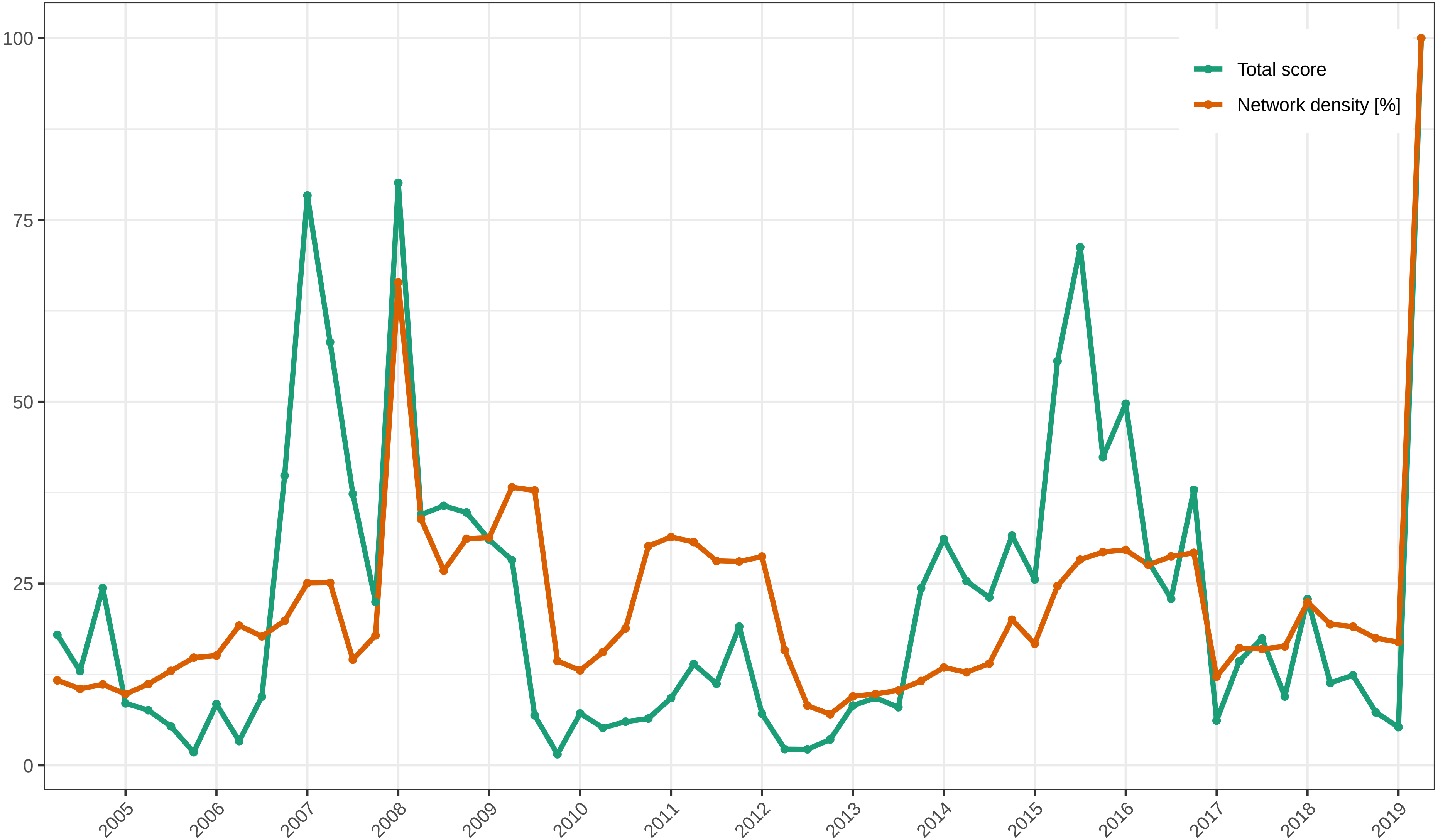


Figures in high resolution



NATIONAL AUS.BANK
ERSTE GROUP BANK
KBC GROUPE (LUX)
HSBC HOLDINGS
STANDARD CHARTERED
BARCLAYS
UBS GROUP
CREDIT SUISSE GROUP
NORDEA BANK
SWEDBANK A
SKANDINAVISKA ENSKILDA BANKEN A
BANCO SANTANDER
DBS GROUP HOLDINGS
UNITED OVERSEAS BANK
BANCO COMR.PORTUGUES 'R'
DNB
ING GROEP
MALAYAN BANKING
CIMB GROUP HOLDINGS
SHINHAN FINL.GROUP
UNICREDIT
AIB Group
BANK OF IRELAND GROUP
BANK OF BARODA
STATE BANK OF INDIA
NATIONAL BK.OF GREECE
COMMERZBANK
DEUTSCHE BANK
BNP PARIBAS
DANSKE BANK
TORONTO-DOMINION BANK
ROYAL BANK OF CANADA
BANK OF MONTREAL
CHINA MERCHANTS BANK 'A'
Australia
Austria
Belgium
Canada
China
Denmark
France
Germany
Greece
India
Ireland
Italy
Japan
Korea
Malaysia
Netherland
Norway
Portugal
Singapore
Spain
Sweden
Switzerland
UK
US


Panel A: Full sample
Panel B: GFC period
Panel C: ESDC period
Panel D: Covid−19 period
Australia
Austria
Belgium
Canada
China
Denmark
France
Germany
Greece
India
Ireland
Italy
Japan
Korea
Malaysia
Netherland
Norway
Portugal
Singapore
Spain
Sweden
Switzerland
UK
US



100
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50
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Total score
Network density [%]
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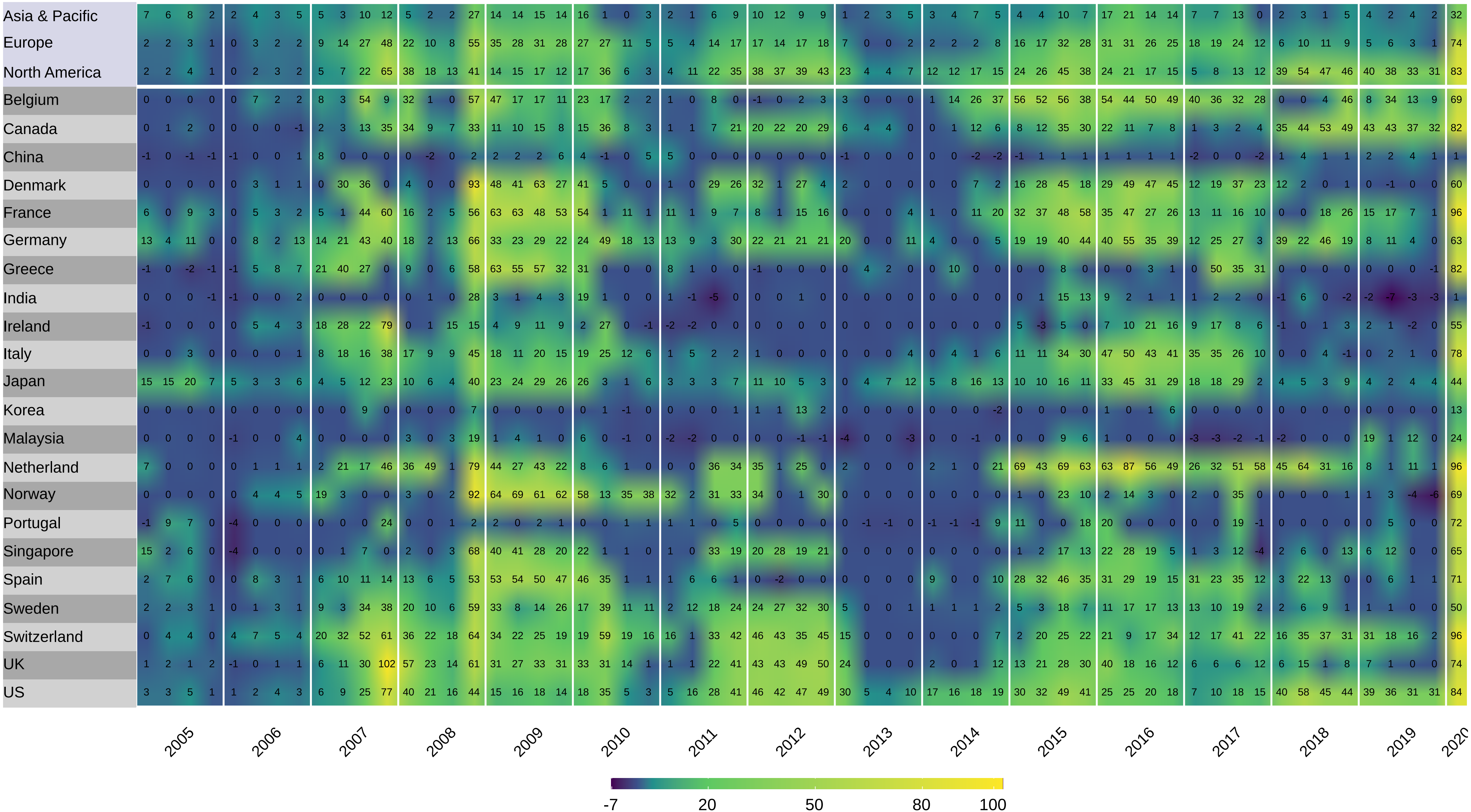
Asia & Pacific 7 6 8 2 2 4 3 5 5 3 10 12 5 2 2 27 14 14 15 14 16 1 0 3 2 1 6 9 10 12 9 9 1 2 3 5 3 4 7 5 4 4 10 7 17 21 14 14 7 7 13 0 2 3 1 5 4 2 4 2 32
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Belgium 0 0 0 0 0 7 2 2 8 3 54 9 32 1 0 57 47 17 17 11 23 17 2 2 1 0 8 0 -1 0 2 3 3 0 0 0 1 14 26 37 56 52 56 38 54 44 50 49 40 36 32 28 0 0 4 46 8 34 13 9 69
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Switzerland 0 4 4 0 4 7 5 4 20 32 52 61 36 22 18 64 34 22 25 19 19 59 19 16 16 1 33 42 46 43 35 45 15 0 0 0 0 0 0 7 2 20 25 22 21 9 17 34 12 17 41 22 16 35 37 31 31 18 16 2 96
UK 1 2 1 2 -1 0 1 1 6 11 30 102 57 23 14 61 31 27 33 31 33 31 14 1 1 1 22 41 43 43 49 50 24 0 0 0 2 0 1 12 13 21 28 30 40 18 16 12 6 6 6 12 6 15 1 8 7 1 0 0 74
US 3 3 5 1 1 2 4 3 6 9 25 77 40 21 16 44 15 16 18 14 18 35 5 3 5 16 28 41 46 42 47 49 30 5 4 10 17 16 18 19 30 32 49 41 25 25 20 18 7 10 18 15 40 58 45 44 39 36 31 31 84
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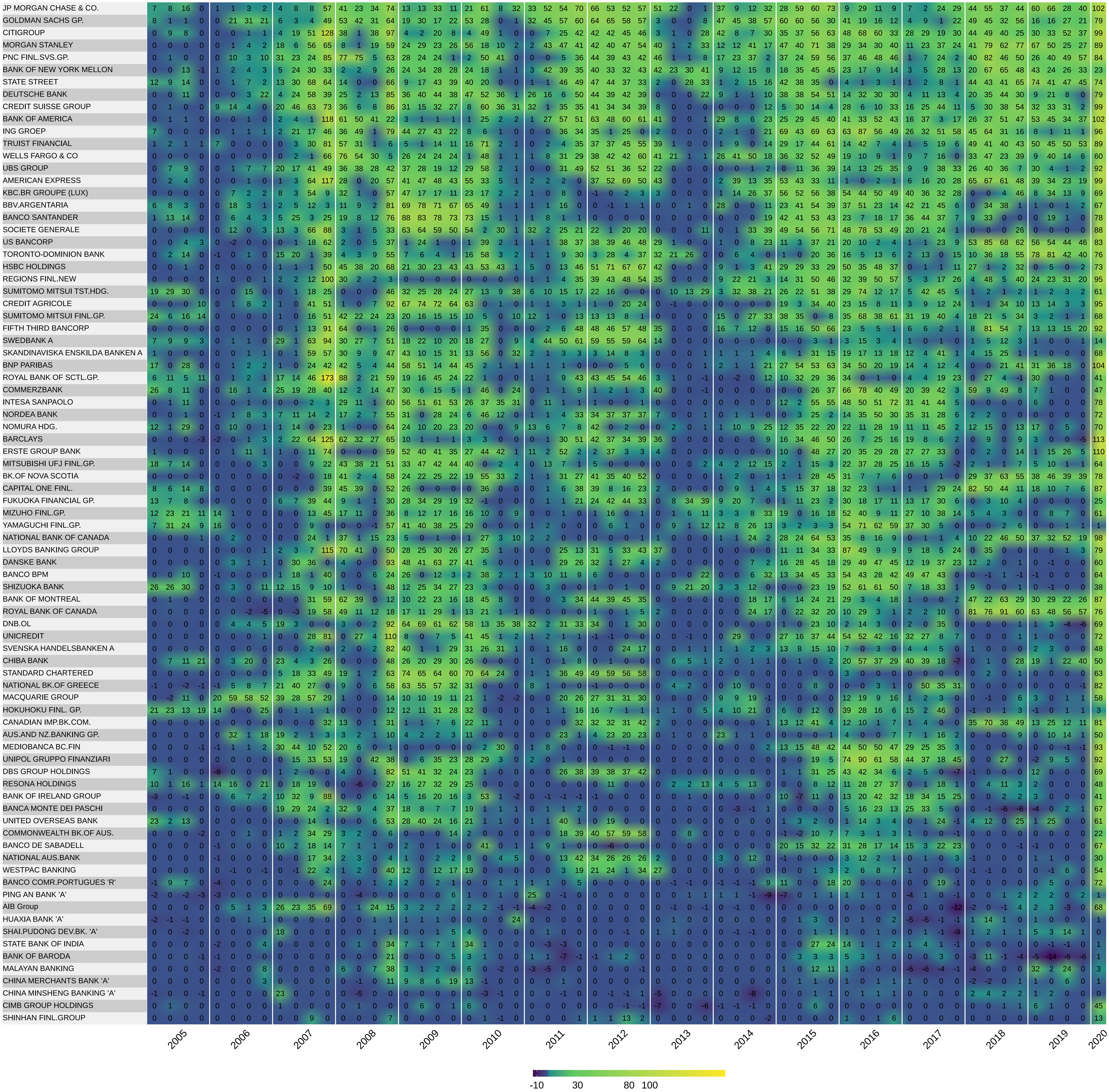
JP MORGAN CHASE & CO.
GOLDMAN SACHS GP.
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BANK OF NEW YORK MELLON
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DEUTSCHE BANK
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BANK OF AMERICA
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UBS GROUP
AMERICAN EXPRESS
KBC.BR GROUPE (LUX)
BBV.ARGENTARIA
BANCO SANTANDER
SOCIETE GENERALE
US BANCORP
TORONTO-DOMINION BANK
HSBC HOLDINGS
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FIFTH THIRD BANCORP
SWEDBANK A
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ROYAL BANK OF SCTL.GP.
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NORDEA BANK
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MITSUBISHI UFJ FINL.GP.
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FUKUOKA FINANCIAL GP.
MIZUHO FINL.GP.
YAMAGUCHI FINL.GP.
NATIONAL BANK OF CANADA
LLOYDS BANKING GROUP
DANSKE BANK
BANCO BPM
SHIZUOKA BANK
BANK OF MONTREAL
ROYAL BANK OF CANADA
DNB.OL
UNICREDIT
SVENSKA HANDELSBANKEN A
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RESONA HOLDINGS
BANK OF IRELAND GROUP
BANCA MONTE DEI PASCHI
UNITED OVERSEAS BANK
COMMONWEALTH BK.OF AUS.
BANCO DE SABADELL
NATIONAL AUS.BANK
WESTPAC BANKING
BANCO COMR.PORTUGUES 'R'
PING AN BANK 'A'
AIB Group
HUAXIA BANK 'A'
SHAI.PUDONG DEV.BK. 'A'
STATE BANK OF INDIA
BANK OF BARODA
MALAYAN BANKING
CHINA MERCHANTS BANK 'A'
CHINA MINSHENG BANKING 'A'
CIMB GROUP HOLDINGS
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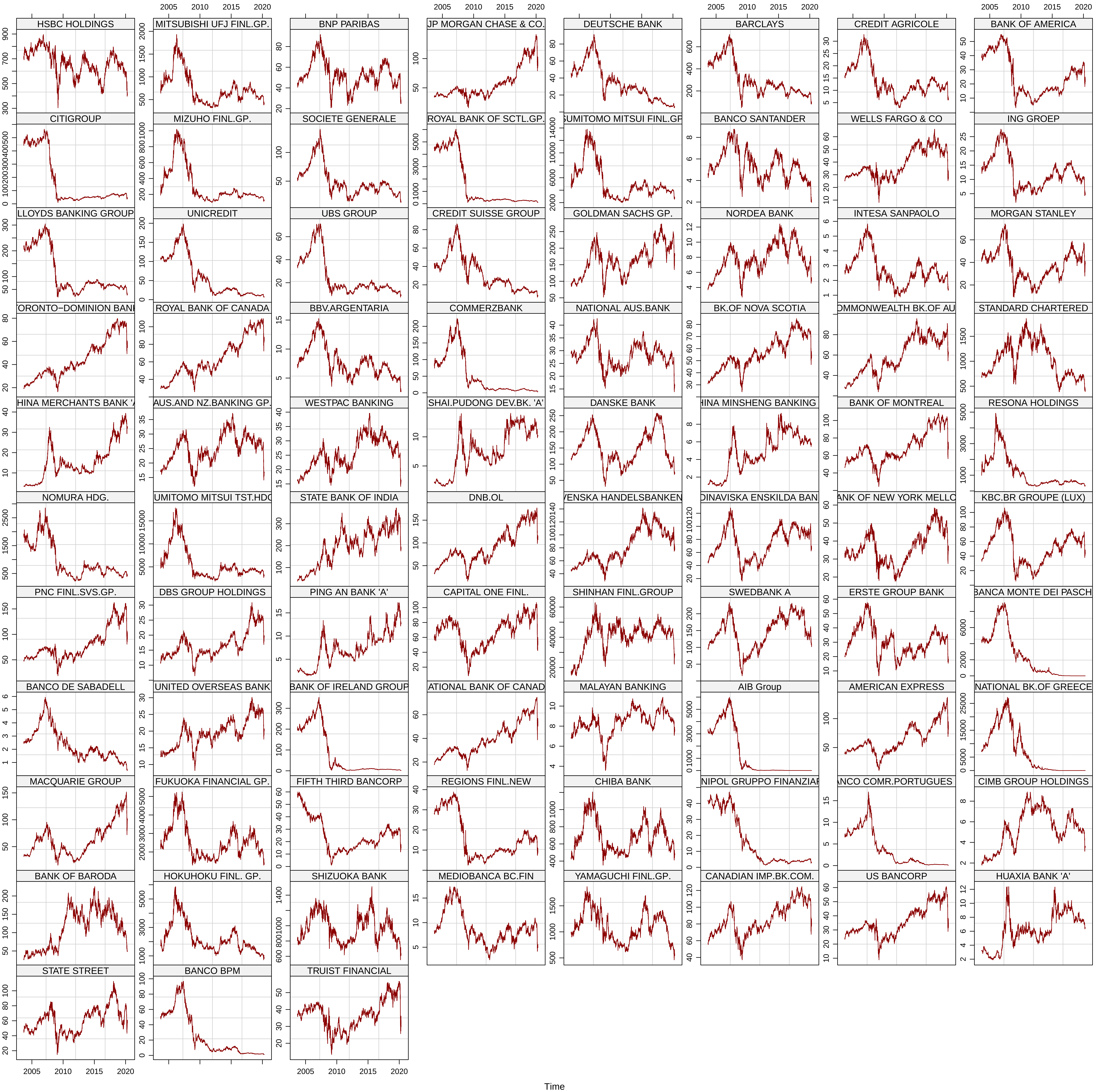

HSBC HOLDINGS
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JP MORGAN CHASE & CO.
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2005 2010 2015 2020
Time