

Baumöhl, Eduard; Bouri, Elie; Hoang, Thi-Hong-Van; Hussain Shahzad, Syed Jawad; Výrost, Tomáš

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Measuring systemic risk in the global banking sector: a cross-quantilogram network approach

Eduard Baumöhl^{a,b}, Elie Bouri^c, Thi-Hong-Van Hoang^{d,*}, Syed Jawad Hussain Shahzad^{d,e},
Tomáš Výrost^{a,b}

Abstract

We propose a new systemic risk index based on the interdependence of extreme downside movements of stock returns using the cross-quantilogram and network analysis approach. While quantile dependence allows for sensitivity in times of market downturn, the topological network properties allow for capturing the interconnectedness of the banking system and identification of the specific contribution of each individual bank. Using this design, the proposed systemic risk index is not only easy to calculate and interpret but identifies the banking system's significant transmitters and receivers of extreme downside risk. For the empirical evaluation of the proposed risk index, we use a sample of 83 large banks during the 2003-2020 period, spanning multiple recent crises affecting the banking market. The proposed index is found to be robust in comparison to major alternative systemic risk measures.

Keywords: Systemic risk; Downturn interdependence; Network; Cross-quantilograms, Global banks; COVID-19 pandemic.

JEL classification: G01, G21

Highlights

- A new network-based systemic risk index for the banking sector is introduced.
- The index captures quantile dependence to offer sensitivity to market downturns.
- The index is easier to calculate, interpret and identifies major risk transmitters.
- Empirical evaluation is performed on a sample spanning several crisis periods.
- Robust performance compares favourably to alternative systemic risk indices.

^a University of Economics in Bratislava, Slovakia

^b Institute of Financial Complex Systems, Masaryk University, Czech Republic

^c School of Business, Lebanese American University, Lebanon

^d Chair of Social & Sustainable Finance, Montpellier Business School, Montpellier, France

^e South Ural State University, Russia

1. Introduction

Connections among banks are crucial for financial stability and policy decisions. Systemic risk intensifies during crisis periods, and such connections become stronger (Cerruti et al., 2012). The Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC), and the COVID-19 pandemic exemplify the importance of risk transmission and contagion from the banking sector to other financial markets and the real economy. The purpose of this paper is to analyse bank connection dynamics in downturn periods captured in the tails of bank equity return distributions. We use the cross-quantilogram approach to propose a systemic risk index that tracks time-varying connections in the tails of the return distribution of 83 large banks from 24 countries. Our approach complements previous approaches measuring systemic risk for two reasons. First, it allows examining the network structure and the network density while considering the size of the banks. Second, it allows tracking individual bank risk transmission and reception capacity. Our main results show that systemic risk and network density surge during crisis periods and peaked during the first wave of the COVID-19 pandemic. More importantly, U.S. banks are the main risk transmitters in the network, while Asian banks are the main risk receivers. During the ESDC, European banks dominate the risk transmission throughout the system.

The existing literature allows us to understand that a high degree of dependence and contagion exists among banks within and across countries and regions during crisis periods (Paltalidis et al., 2015; Black et al., 2016; Dungey et al., 2017; Duprey et al., 2017; Mohanty et al., 2018; Huang et al., 2019; Verma et al., 2019; Wang et al., 2019; Zedda and Cannas, 2020). Furthermore, various determinants, such as fundamental factors, liquidity, market factors, interbank loans, and macroprudential policies, can contribute to the degree of systemic risk (Acharya and Steffen, 2013; Pais and Stock, 2013; Acemoglu et al., 2015; Battaglia and Gallo, 2017; Soedarmono et al., 2017; Varotto and Zhao, 2018; Su and Wong, 2018; Elyasiani and Jia, 2019; Yang et al., 2020; Andries et al., 2020; Bats and Houben, 2020; Brunnermeier et al., 2020; Meuleman and Vennet, 2020).

To construct a new systemic risk, it is necessary to identify possible risk spillover channels within the banking sector. The first risk spillover channel is related to instability acting as a common risk factor (Hubrich and Tetlov, 2015). Second, Acemoglu et al. (2015) provide evidence for the importance of the structure of the banking sector. While denser connections between banks enhance the stability of the whole system with infrequent shocks of small magnitude, they can also accelerate the propagation of frequent and large shocks within the bank network. Third, Paltalidis

et al. (2015) show that the propagation of risk increases with higher exposure of local banks to foreign economies. Above all, the degree of interdependence among banks appears to be the most important determining factor of systemic risk (Acemoglu et al., 2015; Glasserman and Young, 2015; Kosmidou et al., 2017; Bardoscia et al., 2017). In this regard, we contribute to the academic debate on systematic risk in the global banking sector by proposing a new systemic risk index that allows us to measure the spillover of downside risk among banks within a network while considering the lowest quantile of the return distribution of 83 large and listed banks.

Our paper is different from previous studies that use frequency-based and mean-based network methods (e.g., Demirer et al., 2018). Indeed, the tail-event-driven measure of systemic risk in this study is based on the cross-quantilogram (CQ) approach of Han et al. (2016). This approach relies on quantile hits rather than the average states used in previous studies (e.g., Diebold and Yilmaz, 2012, 2014; Baruník and Křehlík, 2018, Ellington and Baruník, 2020). This quantile-based design in the CQ approach enables the measurement of directional predictability among time series and thus allows for the identification of banks that are risk transmitters and risk receivers under various market states, including the downturn market state (meaning 5% quantile of the return distribution in our study). This latter is identified through the lowest quantile in the return distribution of banks' stocks. The distinction between risk-transmitting and risk-receiving banks is important for central banks and policymakers, as they need to adapt their operations and policies to the systemic risk profile of each bank. In sum, considering the bank network under a downturn market state in the measurement of systemic risk is important because systemic risk is a consequence of the interdependence among banks in the network.

Our main contributions are as follows. First, we propose a new systemic risk index by focusing on the left tail of the return distribution, which simulates a downturn market state and thus crisis periods. Therefore, this new systemic risk index aims to capture the interdependence within the banking system in extreme negative events. Second, we consider the new systemic risk index in three major crises, the GFC, ESDC, and the recent COVID-19 crisis. This point is important because the level of systemic risk is strongly related to crises. It is therefore important to know how systemic risk differs according to the nature of crises. Third, we clearly show the systemic profile of each bank in the network as a risk transmitter or a risk receiver. This aspect is important because individual banks, central banks, and policymakers need to adapt their policies to the systemic risk profile of each bank. Fourth, we consider various alternative methods of measuring

systemic risk to check the robustness of our main findings. These additional methods are from Chen et al. (2019), Brownlees and Engle (2017), and Holló et al. (2012). To the best of our knowledge, this is the first study to add these contributions to the related literature on systemic risk in the global banking sector.

The remainder of this paper is organized as follows. Section 2 describes the data sample and the methodology framework used in the construction of a new systemic risk index. Section 3 presents and discusses the results as well as their economic rationales. Section 4 is dedicated to the robustness check. Finally, Section 5 concludes and provides policy implications.

2. Data and Methodology

2.1. Data

Daily stock price data for 83 large and listed banks from 24 countries covering three regions (America, Europe, and Asia) are obtained with the Bloomberg terminal for the period from 11 September 2003 to 17 April 2020. The RIC codes of the selected banks are given in the online supplementary material (Table A.1). The selection process for the sampled banks is the same as that of Demirer et al. (2018). These latter analyse 96 banks from 29 countries over the 2003-2014 period. These 96 banks are among the 150 largest in the world, according to the value of total assets. These banks are also designated globally systemically important banks (GSIBs). From this initial sample of 96 banks, we eliminate 13 banks and obtain a final sample of 83 banks. Among the 13 eliminated banks, some were delisted, merged, or acquired. Table A.2 in the online supplementary material presents descriptive statistics of the sampled banks' stock returns: the skewness values are mostly negative and excess kurtosis is omnipresent. This indicates thick tails in the stock return distributions and thereby the suitability of measuring systemic risk using quantile-based models.

To avoid nonsynchronous trading effects, we calculate rolling-average two-day returns, as in Forbes and Rigobon (2002). Furthermore, we include bank size in the construction of the proposed systemic risk indicator, as the literature has shown that bank size impacts systemic risk (e.g., Pais and Stock, 2013; Yang et al., 2020). This point is important because it helps avoid our proposed systemic risk index being simply driven by correlations across banks. The consideration of the size of banks is thus important to avoid the black-box issue in empirical analysis focused on simple

correlations among different variables.¹ Specifically, 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.

2.2. Connectedness measure with the cross-quantilogram method and systemic risk index

The objective of the cross-quantilogram method (CQ) developed by Han et al. (2016) is to investigate the cross-correlation between two stationary time series.² As indicated above, the first advantage of this method is its ability to identify the direction of the dependence, that is, which variable predicts the other one's past information, presented by lagged values. The second advantage is that the directional dependence, meaning the predictability, can be calculated under various quantile levels of the return distribution. Furthermore, the method of Han et al. (2016) differs from other network-based methods, such as Belloni et al. (2016), Zhu et al. (2019), and Chen et al. (2019).³ For example, Belloni et al. (2016) construct two forms of quantile graphical models: conditional independence quantile graphical models (CIQGMs) and prediction quantile graphical models (PQGMs). CIQGMs reflect the conditional independence of distributions by estimating the distributional dependence structure at each quantile. On the other hand, PQGMs reflect dependencies via the graphs of the superior linear predictors. In addition, Zhu et al. (2019) construct a network quantile autoregression (NQAR) by focusing on quantile autoregression models. In this process, the adjacency matrix enters the calculation as exogenous, and its estimation is not addressed. In other words, the NQAR is estimated conditional on the given adjacency matrix. On the other hand, the tail-event driven network quantile regression (TENQR) model of Chen et al. (2019) is similar to that of Zhu et al. (2019) but different in the concrete construction of the adjacency matrix. The TENQR model accommodates the definition of systemic risk, which is a large downside widespread impact with a ripple effect. This aspect goes beyond the work of Zhu et al. (2019), who focus on the asymptotic of the involved parameters. Indeed, the work of Chen et al. (2019)⁴ enables the adjacency matrix to be calculated using an empirically estimated threshold for the cosine similarity of conditional expected shortfalls (a quantile

¹ We would like to thank the Editor, Professor Sushanta Kumar Mallick (School of Business and Management, Queen Mary University of London), for his comment on this aspect.

² This methodology has been proven to be efficient as evidenced by its numerous applications in academic studies (e.g., Bouri et al., 2018; Shahzad et al., 2019).

³ We would like to thank an anonymous referee for noting these alternative methods.

⁴ To check the robustness of the results obtained with the Han et al. (2016) method, we use other methods from Chen et al. (2019) (see above), Brownlees and Engle (2017), and Holló et al. (2012) (more details below).

measure). Thus, in this case, the adjacency matrix, and consequently the risk scores, are empirically estimated.

Given the abovementioned advantages of the method of Han et al. (2016), we decided to use this method to measure the systemic risk in the lowest quantile (5%). This approach allows us to calculate the systemic risk in extreme downturn market conditions, as banks are the most vulnerable in these conditions. The underlying idea behind the Han et al. (2016) method, which is based on the directional predictability principle, is that extreme negative returns of the i -th bank at time t can predict extreme negative returns of the j -th bank at time $t+1$, which represents the next trading day in our daily data sample. This predictability indeed corresponds to the notion of financial contagion, which is at the centre of all systemic risk measures. The directional predictability of all pairs of banks then results in an $N \times N$ adjacency matrix that allows us to measure the directional spillover effects across banks and 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).

To construct the network, we use the algorithm outlined in Han et al. (2016), following which the CQ is calculated directly based on quantile hit functions instead of OLS quantile regressions (see Eq. (1) and Eq. (2) in Han et al. (2016)). This algorithm allows for the use of either unconditional or conditional quantiles based on some exogenous variables ($\mathbf{x}_t \in \mathbb{R}^d$). These latter may be used to define a conditional probability distribution for the pair of stationary time series to be analysed. In our case, we focus on the primary unconditional case. For one time series at time t , the quantile hits are evaluated against the lags of the other time series. This procedure allows for the identification of directional dependence at various quantile levels in the return distribution. We consider 10 lags to evaluate the quantile dependence.

The CQ method is defined for strictly stationary time series $\{(\mathbf{y}_t, \mathbf{x}_t): t \in \mathbb{Z}\}$ 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 $q_{i,t}(\tau_i) = \inf\{v: F_{y_i|x_i}(v|x_{it}) \geq \tau_i\}$ for quantile $\tau_i \in (0,1)$. The measurement of the serial dependence in quantiles is based on an examination of 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 CQ $\hat{\rho}_\tau(k)$ at lag $k \in \mathbb{Z}$ for quantiles $\tau_1, \tau_2 \in (0,1)$ is then defined as:

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

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

Apart from obtaining the values of the CQs that specify the strength of the dependence in a quantile of the return distribution, one may also be interested in inferences, with, 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) proposed a Ljung-Box type statistic for this purpose to test the hypothesis $H_0: \rho_\tau(1) = \dots = \rho_\tau(p) = 0$ against the 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 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 hypothesis testing.

To construct a network representing the quantile dependence in returns, we estimate the bivariate CQ 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 statistical significance for a quantile dependence in any of the 10 lags considered. As CQ measures the dependence of the lagged values of one bank against a contemporary value of another, the adjacency matrix is not symmetric, and the network is represented by a directed graph.

Finally, we calculate the overall systemic risk score by following the idea of Das (2016) that the total systemic risk score of a 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 the nodal market capitalization. The elements of \mathbf{A} , a_{ij} , denote the values of the CQ from bank i to bank j . The aggregate risk score $S(\mathbf{A}, \mathbf{c})$ is then defined as:

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

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

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

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

The aggregate systemic risk score is thus the sum of all the cross-quantilograms of all the pairs of banks in our network, and this is the systemic risk index that we propose in our study. This aggregate systemic risk score is then analysed for the whole period from 11 September 2003 to 17 April 2020 and for three sub-periods to investigate the impact of crises on the systemic risk of the banking sector. These sub-periods are the GFC from 3 August 2007 to 2 July 2009, the ESDC from 5 January 2010 to 3 August 2012, and the COVID-19 crisis period from 3 January 2020 to 17 April 2020. The time variation in the systemic risk is captured using the rolling-window approach, through which we calculate the systemic risk index for each quarter based on a time window over the past 6 quarters. This procedure is repeated for each quarter and forms a time series for the proposed systemic risk. The window's length (6 quarters) is chosen as a compromise between larger windows, where the dynamics might be more averaged-out, and smaller windows, which might be too short to estimate quantile behaviour with sufficient confidence.

By using the method of Han et al. (2016), we confirm the definition of systemic risk, which stems from contagion and interconnectedness based on high-frequency data, such as market prices and rates (Rodríguez-Moreno and Peña, 2013). Therefore, our systemic risk index measures the interdependence among the banks in the network, including their capacity to both transmit and receive risk, as mentioned above. This view of systemic risk is confirmed by Acemoglu et al. (2015), who suggest that a high network density permits a stronger ability to absorb systemic risk, and beyond a certain threshold, financial stress begins to emerge as a result. In addition, Bardoscia et al. (2017) show that the more the networks are connected, the higher the probability of “creating cyclical structures which tend to amplify financial distress, thereby undermining systemic stability and making large crises more likely.”

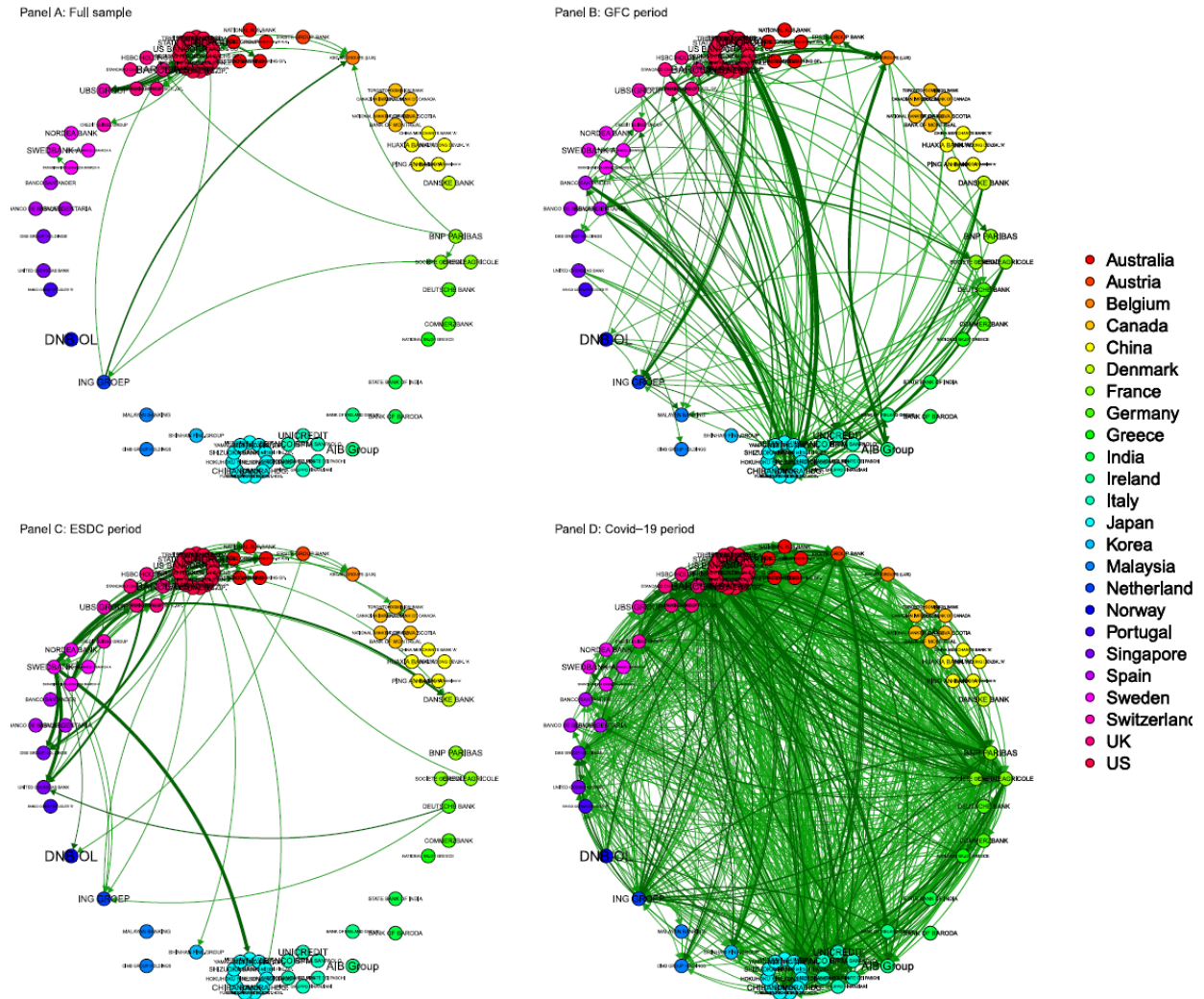
3. Results

3.1. The risk spillover network among banks

To obtain a better perspective of the tail-based interconnection in the global banking sector, we show in Panel A of Figure 1 a network of CQs among sampled banks, estimated over the whole period (2003–2020). Notably, this directional network captures only comovements of extreme negative returns (5% quantile of the joint return distribution, i.e., $\tau_1 = \tau_2 = 0.05$) that are highly statistically significant at the 7.35×10^{-6} significance level (Bonferroni p -value adjustment). Despite this strict threshold, the density of the network is 98%, which means that among the total number of all possible pair connections (6,806 pairs in total), 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 banks. Practically, this high level of significant pairwise connection makes it impossible to visually inspect such a network. Therefore, we generate a threshold graph to extract only those relationships that satisfy some predetermined conditions. Specifically, we only keep values (corresponding linkages) larger than the average value of the 100 largest individual banks' cross-quantilograms; see Panel A of Figure 1. After this extraction, we can easily identify the most influential nodes within the bank network. This information might be particularly useful for supervising authorities. Furthermore, after computing some basic topological properties of the network, we can precisely pinpoint the banks that are the largest transmitters of negative shocks (lowest quantile of the return distribution) and those that are the largest receivers (see Table A.3 in the online supplementary material).

After visualizing the interconnection network of all sampled banks during the whole period (2003–2020) in Panel A of Figure 1, we present in Panels B, C, and D the threshold networks constructed for the three sub-periods considered, the GFC, ESDC, and COVID-19 crisis periods. During the GFC, the strongest risk spillover was from U.S. 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 appear to be less risk-transmitting than U.S. and European banks.

Figure 1: Threshold networks in the whole period and three sub-periods



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

This result is further confirmed by Table A.3 in the online supplementary material, which shows that the banks with the highest risk spillover degree (at the top of the table) are from the U.S., such as JP Morgan, Barclays, Bank of America, and Citigroup. In contrast, Asian banks, such as Hokuohoku, Shizuoka, Yamaguchi, and Huaxia, are at the bottom of the table. It is thus appropriate

to conclude that U.S. banks are major risk transmitters, while Asian banks are major risk receivers. This fundamental difference between U.S. and Asian banks may be due to several reasons.⁵

The first reason is that Asian banks are smaller than US banks, on average, except for Chinese banks (based on market capitalization). Indeed, the academic literature shows that the size of banks plays an important role in systemic risk measurement (e.g., Pais and Stock, 2013; Yang et al., 2020). In addition, Lu and Hu (2014) confirm that the size of a bank is a determinant factor of its systemic importance within a network. Furthermore, U.S. banks are known to have large international operations due to the international status of their currency, the USD (e.g., McGuire and von Peter, 2016). This is the first reason why U.S. banks are major risk transmitters, while Asian banks are major risk receivers.

The second reason arises from the differences among countries regarding their institutional and regulatory frameworks. According to Cerruti et al. (2012), these differences can affect the magnitude and direction of shocks, as well as their propagation among banks. Indeed, the American economy is essentially based on market-financing methods, while the Asian economy is based on bank-based financing methods (e.g., Allen et al., 2014). Regarding this difference, Bats and Houben (2020) indicate that the choice between bank-based and market-based financing affects systemic risk. They further suggest that market-based financial systems are more resilient to systemic risk than are bank-based ones.

This difference between the U.S. and Asian economies contributes to explaining our findings that U.S. banks are major risk transmitters, while Asian banks are major risk receivers. Similarly, Acemoglu et al. (2015) argue that the financial system architecture is important for the level of systemic risk. Another factor that can explain our finding about the difference between U.S. banks and Asian banks is related to monetary policy tools used in the US and Asia. Indeed, Meuleman and Vennet (2020) show that the nature of policy tools, such as credit growth tools and liquidity tools, affects systemic risk. In this regard, Miyajima et al. (2014) find that unconventional U.S. monetary policies spill over to Asia through bond yields and the growth of domestic bank credit.

In addition, the panels in Figure 1 show that the interconnection among large banks increases dramatically during the COVID-19 pandemic. Indeed, Panel D in Figure 1 shows that the network interconnection became much more intense during the first wave of the COVID-19 pandemic from

⁵ We would like to thank the Editor, Professor Sushanta Kumar Mallick (School of Business and Management, Queen Mary University of London, UK), for underlying this aspect in our analysis.

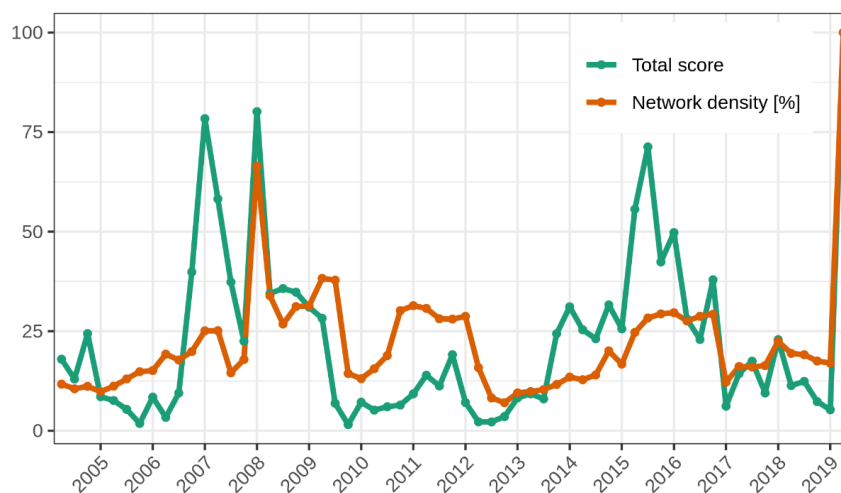
January to April 2020. Together with Figure 2 in sub-section 3.2, we see that the level of systemic risk among banks is much higher during the COVID-19 pandemic than during the GFC, although previous studies quantify systemic risk as high during the GFC (e.g., Acharya and Steffen, 2013; Glasserman and Young, 2015; Mohanty et al., 2018). Furthermore, the aggregate systemic risk score, that is, the systemic risk index that we propose in this study, is the highest during the COVID-19 pandemic, with a network density of 70.6%. This finding convincingly demonstrates the consequences of the outbreak of COVID-19 on the banking sector (e.g., Goodell, 2020). The threshold graph for this pandemic period clearly shows that there are markedly stronger linkages during the COVID-19 pandemic than during the two previous crisis periods (GFC and ESDC). This result is in line with the findings of a few recent studies that investigate the impact of the COVID-19 pandemic on systemic risk, such as Akhtaruzzaman et al. (2021). This suggests that future studies should engage in further investigations to understand the risk spillover mechanism among banks during the COVID-19 pandemic.

3.2. Analysis of the new systemic risk index

Thus far, we have considered the estimated directional spillover among banks within the network. In this subsection, we present a unique index to measure the systemic risk of the whole network of the 83 largest banks around the world. As mentioned in Section 2, this new systemic risk index is the sum of all directional predictabilities (or cross-quantilograms) of all pairs of banks in the network. This unique systemic risk index allows banks, central banks, and policymakers to easily visualize the systemic risk situation. In addition, it allows them to analyse systemic risk in a time-varying framework. Furthermore, this new systemic risk index considers the size of the banks in the network while incorporating their market capitalisation into the calculation. Therefore, the proposed systemic risk can be affected by interconnectedness (CQs), the compromise level of nodes (which shows the market capitalization of banks), or even both. Thus, the value variation of the systemic risk index over time depends not only on the tail interconnectedness among banks but also on the size of banks in the network (Pais and Stock, 2013; Varotto and Zhao, 2018; Su and Wong, 2018). In addition, other factors can affect the level of systemic risk among banks, such as government support and sovereign debt holdings (Acharya and Steffen, 2013), interconnectivity

of the financial system (Glasserman and Young, 2015), banks’ governance structure (Battaglia and Gallo, 2017, and banks’ organizational complexity (Elysiani and Jia, 2019).⁶

Figure 2: 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 2) and the network density (more details in Section 2). To obtain an interval of 0 to 100, the index is normalized to its maximal value during the COVID-19 pandemic.

Figure 2 shows the time-varying dynamics of the new systemic risk index and the network density, as measured in the previous sub-section. These two measures are closely related because shocks are propagated more strongly when the network becomes denser. However, the network density does not reflect the size aspect of the risk spillover. For example, although the systemic risk index spiked in 2007, the network density was small. However, both indicators jointly peaked in 2008. Subsequently, during the ESDC period, banks became more interconnected. However, the overall systemic risk was slightly smaller than the network density. Then, in 2015 and 2016, systemic risk increased to be significantly higher than the density because of the so-called “2015–16 stock market selloff.” This occurred due to 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 were the highest over the whole period (11 September 2003 to 17 April

⁶ We would like to thank the Editor, Professor Sushanta Mallick, School of Business and Management, Queen Mary University of London, United Kingdom, for his suggestion to underline the determining factors of the level of systemic risk.

2020). To understand this difference, it is important to mention the different natures of each of the three crisis periods. The first sub-period, the GFC, was a global financial crisis. Although it had a major impact on the economic system, the main consequences were on the financial and banking system. The second sub-period, the ESDC, was a local crisis affecting countries in the Eurozone due to the weakness of the sovereign debt structure. Finally, the recent COVID-19 crisis is entirely different because it started as a health crisis before becoming a global economic crisis that has impacted every country and economic sector.

The above analysis allows us to make the following observations. First, a low network density does not mean a low systemic risk. This is because the risk spillover in downturn market states (5% quantile returns in our case) can be high even with a low network density. Second, Figure 2 confirms the results shown in Figure 1 for the exceptionally high level of interconnection among banks during the COVID-19 pandemic in both network density and risk spillover. During the first months of 2020, economies faced an unprecedented economic lockdown that led stock markets around the world to experience sharp declines, comparable 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 during the 2008 GFC is counterintuitive at first sight. Indeed, the GFC was a financial crisis caused by the financial sector, which underwent the largest loss. The COVID-19 crisis was originally a health crisis before becoming a global economic crisis affecting all economic sectors. Thus, the COVID-19 crisis is not directly related to the financial sector. However, the systemic risk among banks is much higher during the COVID-19 pandemic than during the GFC. To explain this result, we argue that during the COVID-19 pandemic, banks were exposed to a large panel of issues related to the financing of the real economy, a decrease in assets due to the repayment delay of SMEs, volatility of assets under management, a reduced amount of capital exchanged because of the lockdown, and volatility of reserves resulting from exchange rate volatility. In this context, future academic studies should further investigate this high systemic risk phenomenon to better understand its determinant factors.

Thus far, we have learned that both the network density and systemic risk of the 83 sampled banks reached their highest levels during the COVID-19 pandemic. However, for investors, portfolio managers and policymakers, it is also important to understand 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 and reception of each individual bank.

3.3. The systemic risk profile of individual banks

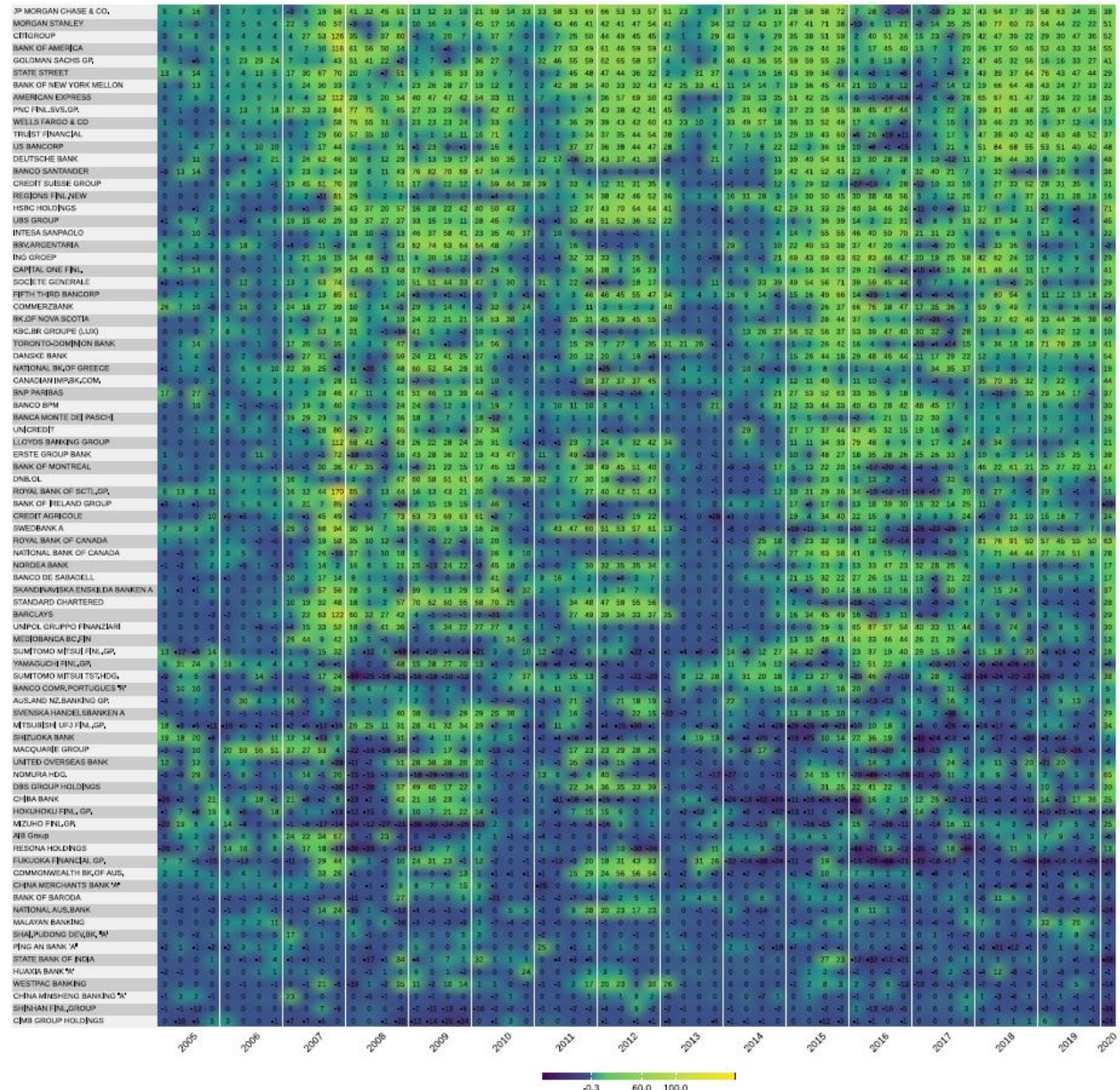
From the perspective of investors, policymakers, and regulatory authorities, it is helpful to decompose the overall systemic risk to obtain more detailed results for each bank's risk transmission and reception capacity.

Therefore, we focus on three aspects of the risk spillover among banks: the risk transmission from each bank to other banks, the risk reception of each bank from other banks, and the net position (net effect = risk transmission – risk reception).⁷ With this objective, Figure 3 presents the net effect, Figure 4 presents the risk transmission effect, and Figure 5 presents the risk reception effect.

A close look at Figures 4 and 5 confirms our findings on the network structure presented in Section 3.1, following which American banks are primary risk transmitters, while Asian banks are primary risk receivers. Indeed, we see from Figure 4 that the banks at the top of the list (top risk transmitters), such as JP Morgan Chase & Co, Goldman Sachs, Citigroup, Morgan Stanley, and PNC Financial Services, are from the U.S. In contrast, Figure 5 shows that the banks at the top of the list (top risk receivers) include Asian banks, such as the Mitsubishi UFG Financial Group, Mizuho, Fukuoka, Nomura, and China Bank. Therefore, Figures 4 and 5 confirm one of our main findings: U.S. banks act as major risk transmitters, while Asian banks act as major risk receivers. Furthermore, regarding the net effect (transmission – reception), Figure 3 shows that the top net risk-transmitting banks in the list include major U.S. banks, such as JP Morgan Chase, Morgan Stanley, Citigroup, Bank of America, and Goldman Sachs. This result means that even after excluding the reception effect, to calculate the net effect, U.S. banks are still the major risk transmitters in the network.

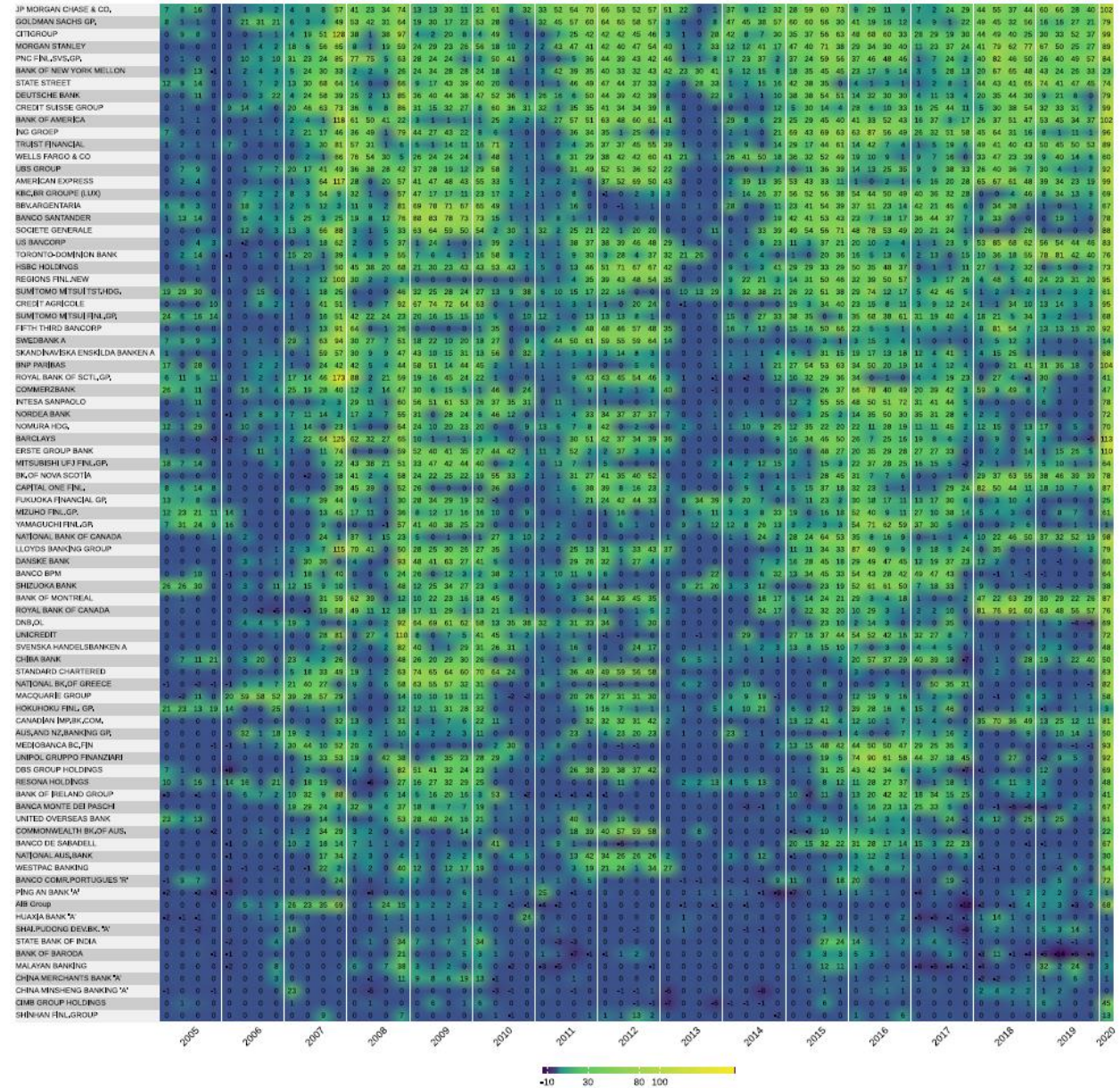
⁷ We would like to thank an anonymous referee for the suggestion to detail the risk reception measures.

Figure 3: Systemic risk decomposition by individual banks – Net effect (transmission – reception)



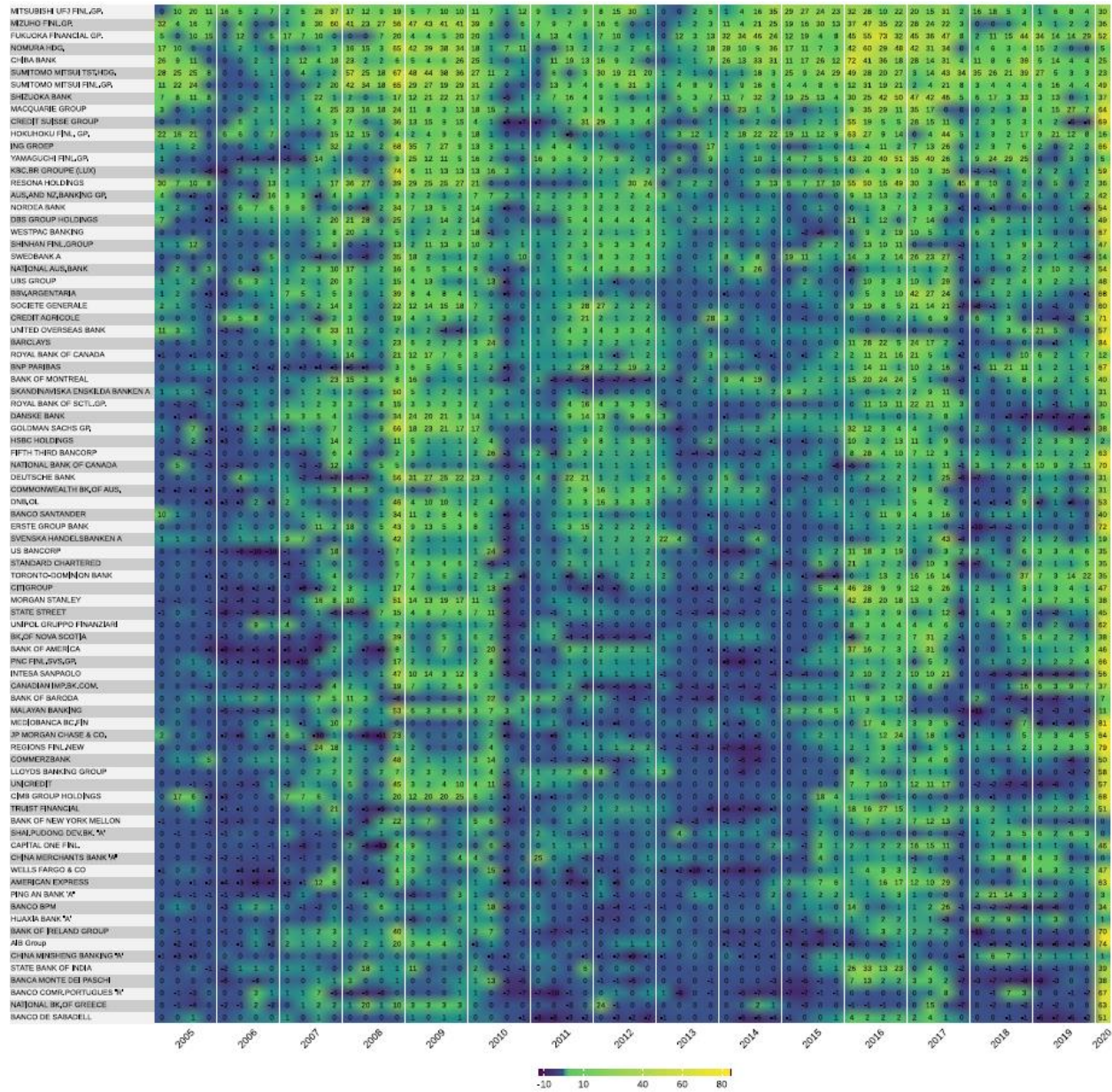
Note: The numbers in this figure correspond to the risk contribution of a bank when considering the net effect (risk transmission – risk reception). Higher numbers are highlighted according to a colour scale: yellow represents the net position as a risk transmitter, and blue represents the net position as a risk receiver.

Figure 4: Systemic risk decomposition by individual banks – Risk transmission effect



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

Figure 5: Systemic risk decomposition by individual banks – Risk reception effect



Note: The numbers in this figure correspond to the individual risk contribution of a given bank to the aggregate systemic risk score based on risk reception. Higher numbers are highlighted according to a colour scale: yellow represents a strong risk receiver, and blue is assigned to a weaker risk receiver.

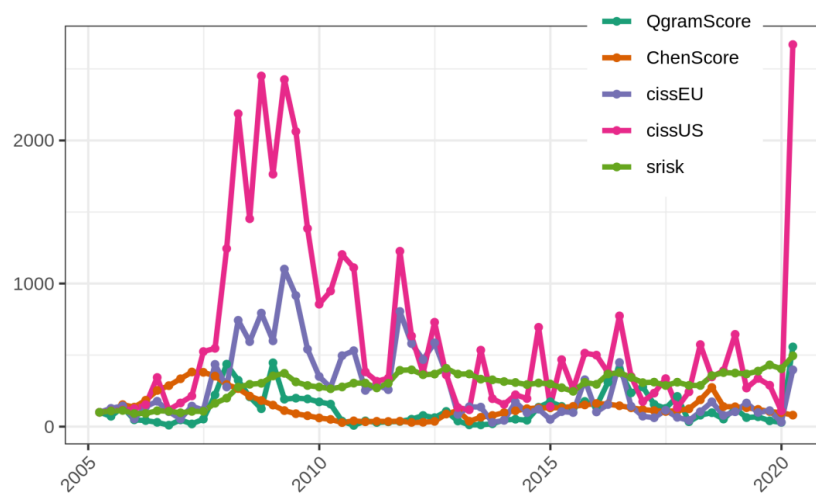
Thus, considering both the network structure and each bank's individual position, the results remain robust in all cases. Even though the European banks are not at the top of the results in Figures 3, 4, and 5, we can see from Figure 4 that the risk contribution rises between 2010 and 2012 for European banks, such as Société Générale, Crédit Agricole, Swedbank, and Danske Bank. Therefore, we can confirm that European banks became major risk transmitters during the ESDC.

The findings from Figures 3, 4, and 5 highlight the importance of considering the systemic risk profile of each individual bank. As mentioned above, this difference may be due to the size of the bank, monetary policy tools, or the major financing method in the country (market-based or bank-based) (e.g., Allen et al., 2014; Bats and Houben, 2020; Meuleman and Vennet, 2020; Miyajima et al., 2014).

4. Robustness check

In this section, we check the robustness of the main findings about the high level of systemic risk during the COVID-19 pandemic and the difference between U.S. banks and Asian banks.

Figure 6: Systemic risk index – robustness check with alternative methods



Note: This graph shows the rolling-window measure of the systemic risk based on four methods. The method of Han et al. (2016) is presented as “QgramScore”. The method of Chen et al. (2019) is presented as “ChenScore”. The CISS is presented for banks in the EU and those in the U.S., separately. The SRISK⁸ method is presented as “srisk.” For more details on the rolling-window method, refer to Section 2. All systemic risk indexes are rescaled to reflect the percentage change with respect to the origin date (I_{t0}) (i.e., $I_t = 100 \times (I_t - I_{t0})/I_{t0}$).

To achieve this aim, we calculate the systemic risk index based on three alternative methods: the method of Chen et al. (2019), the systemic RISK method (SRISK) from Brownlees and Engle (2017), and the composite indicator of systemic stress (CISS) from Holló et al. (2012). Figure 6 presents the time-varying systemic risk index obtained by these three alternative methods compared to that obtained with our main method of Han et al. (2016). This allows us to check the robustness of our second main finding according to which the systemic risk reaches its peak during

⁸ We would like to thank Brian Reis from the V-Lab for providing the global SRISK series from the GMES analysis.

the COVID-19 pandemic. Figure 6 shows that there can be differences in the level of systemic risk as a function of the method used. However, for most of the methods, the level of systemic risk reaches its peak during the COVID-19 pandemic, except for the method of Chen et al. (2019) and the CISS method for European banks. Figure 6 also confirms that U.S. banks are major risk transmitters because the CISS index for U.S. banks is the highest. Therefore, Figure 6 confirms the robustness of our main findings that the systemic risk is the highest during the COVID-19 pandemic and U.S. banks are major risk transmitters.

Our results allow investors, banks, central banks, and policymakers to better detect the degree to which a bank contributes to the systemic risk of the banking system worldwide. These findings also help uncover the time-varying character of systemic risk. From a bank's perspective, this information is useful because it can help banks adjust their operations to reduce their risk reception from the system. From a central bank's perspective, this information is valuable because it allows them to adjust monetary policies of each systemically important bank, depending on whether it is a net risk transmitter or a net risk receiver. This information is also important to investors who engage in investment decisions that vary over time and crisis periods.

5. Conclusion

Using a sample of daily stock prices of the 83 largest banks from 24 countries over the 2003-2020 period, we propose a new systemic risk index while distinguishing among three major crisis periods (GFC, ESDC, and COVID-19). The cross-quantilogram method developed by Han et al. (2016) is the foundation of our new systemic risk index with the aim of estimating the directional predictability for each pair of banks at low quantiles of the return distribution related to downside risk spillover among banks within a network. After presenting the network based on directional predictability, the new systemic risk index is calculated as the sum of directional predictions of all pairs of banks in the network. The first main finding of our research is that systemic risk has never been as high as during the first wave of the COVID-19 pandemic in spring 2020, much higher than during the GFC. The second main finding indicates that U.S. banks are major risk transmitters, while Asian banks are major risk receivers. These main findings are proven to be robust when compared with alternative methods from Chen et al. (2019), Brownlees and Engle (2017) (SRISK), and Holló et al. (2012) (CISS).

The first main finding, related to the highest level of systemic risk during the COVID-19 pandemic, may be counterintuitive because the COVID-19 pandemic is not a financial crisis like the GFC. However, this finding may be explained by the fact that the economic crisis caused by the COVID-19 pandemic is more global than the GFC, as it affects all sectors of the economy and all countries. Therefore, the COVID-19 pandemic affects banks in a more global way than the GFC through liquidity, loan collections, capital positions, asset quality, earnings, and costs (Boru, 2020). Our second main finding relates to the difference between U.S. banks and Asian banks regarding their systemic risk profiles. Indeed, U.S. banks are the most important risk transmitters, while Asian banks are major risk receivers. This result may be due to the structural differences between U.S. banks and Asian banks regarding size, international operations, and monetary policy tools. Based on this finding, we suggest that regulators should consider monetary policies for capital requirements as a function of each bank's systemic risk profile. In addition, this result partly confirms that of Diem et al. (2020), following which the nature of the financial network matters and regulators should adopt policies based on this nature.

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Supplementary material

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 are multiplied by 100.

Table A.3: Topological properties – centrality measures (whole period, 2003-2020)

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 (normalised version, $2 \times \text{number of shortest paths} / (n \times n - 3n + 2)$, where n is the number of vertices), and ‘eigenvector centrality’ measures the connectedness to high scoring nodes (defined as values of the first eigenvector of the network adjacency matrix). In all cases, a high centrality score indicates a more prominent position and/or influence of a vertex in the network.