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Identifying Systemically Important Banks: A Transfer Entropy Approach

Identifikácia systémovo významných bánk: Metóda transferovej entropie

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Abstract: In recent years, the banking sector has been exposed to several negative shocks, leading to higher interconnectedness and increased systemic risk. The aim of this study is to examine the structure of the global banking sector and identify systemically important banking institutions in the context of risk transmission. Using daily stock price data from 77 global banks from November 2015 to December 2025, we apply the transfer entropy method to construct a TE-weighted network. The results confirm a high degree of interconnectedness within the banking sector. Banks such as BoCom, Goldman Sachs, Industrial Bank, KB Financial Group, and HDFC Bank are identified as the most systemically important banks. These banks primarily act as receivers of risk, which they may subsequently transmit to other parts of the system. In contrast, banks such as Deutsche Bank, PNC, and Hua Xia Bank represent key sources of risk transmission within the banking sector.

Key words: *Systemic risk. Banking sector. SIFIs. Transfer entropy.*

JEL Classification: G01. G28. G31.

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Introduction

In the financial system, financial institutions do not operate in isolation but are closely interconnected through various contracts and international agreements. In general, the largest financial institutions tend to be the most interconnected. Therefore, the failure or financial distress of one or more of these institutions can spread to other institutions, which may negatively affect the stability of the overall financial system (Rodríguez-Moreno and Peña, 2013; Silva et al., 2018). Financial contagion can be considered one of the primary sources of systemic risk, the importance of which has increased due to growing deregulation, financial innovations, and the increasing interconnectedness of banks in the global financial market (Black et al., 2016; Härdle et al., 2016; Demirer et al., 2018; Hué et al., 2019).

In the banking sector, which plays a crucial role in financing households and businesses, banking institutions are highly interconnected not only through cross-border banking activities but also through their linkages with capital markets, other financial institutions, and common regulatory frameworks (Glasserman & Young, 2016). Given the high degree of interconnectedness in the banking sector, not all banking institutions contribute equally to systemic risk. Some banks, which are larger, more systemically important, and more connected to other banks, namely systemically important institutions, have a greater impact on vulnerability and systemic risk in the banking sector (Borri & Giorgio, 2021; Atasoy et al., 2024; Foglia et al., 2024). Systemic risk can be measured using several methods; however, in recent years, as the banking sector has been exposed to several negative shocks, the transfer entropy method has gained increasing attention. Transfer entropy, unlike traditional econometric methods, such as correlation and Granger causality, can capture not only linear but also nonlinear and asymmetric relationships between variables, which are particularly relevant during periods of heightened financial stress. For this reason, transfer entropy has been increasingly applied in recent years, especially in the analysis of banking networks, the study of financial contagion, and the identification of systemically important financial institutions (Li et al., 2013; Wang et al., 2023; Yijun et al., 2023; Zhao et al., 2024).

The main goal of this study is therefore to apply the transfer entropy method to analyse the structure of the global banking sector and to identify systemically important banking institutions in the context of risk transmission across the network. To achieve this goal, the study focuses on two research questions: first, which banks can be considered systemically important, and second, whether these banks also act as key sources of risk transmission or, if not, which institutions can be identified as the key sources.

The structure of the paper is organized as follows: Following the Introduction, Chapter 1 provides the theoretical background necessary to understand the issue of systemic risk and its transmission within the banking sector. Chapter 2 presents the data and a detailed description of the methodology. Chapter 3 presents the results, and the final chapter offers concluding remarks and suggestions for further research.

1 Theoretical background

Systemic risk has become an important topic in academic research, primarily due to its potential to destabilize the entire financial system. The International Monetary Fund (2009) and the European Central Bank (2010) define systemic risk as the risk of financial instability caused by the failure of all or part of the financial system, with negative effects on the real economy. In the literature (Rodríguez-Moreno and Peña, 2013; Silva et al., 2018; Baumöhl et al., 2020), a common feature across various definitions of systemic risk is that, due to the high interconnectedness of financial institutions, the failure or distress of one or more institutions can spread to others and lead to their failure. Additionally, Torri et al. (2021) highlight that measuring interconnectedness in the banking system is crucial for maintaining financial stability, as it helps identify potential channels of risk transmission and the most systemically important institutions. Regulators have increasingly focused on systemically important institutions, as distress in these institutions can spread far beyond their national markets, thereby highlighting their crucial role in the global financial network (Tlemsani et al., 2024).

Systemic risk is difficult to capture within a single framework. Therefore, a wide range of indicators has been proposed in the academic literature with the aim of identifying and capturing its main characteristics (Hansen, 2013). Systemic risk can be measured based on the probability of default of a financial institution or the financial system as a whole (Option-iPoD, JPoD, BSI, DiDe, and PCE), the level of expected losses (CoVaR, SES, SRISK, DIP, and Systemic CCA), financial contagion (CoRisk, PCA, Granger causality, and network analysis), and financial stress (SWARCH, CISS, and RAMSI) (Kleinow and Moreira, 2016). Indicators such as the Cs indicator (Thomson, 2009), SIFI, CISS (Hollo et al., 2012), and spillover-to-others and spillover-from-others (Diebold & Yilmaz, 2014) also help assess the systemic importance of financial institutions. Most of these systemic risk indicators, such as CoVaR, MES, and SRISK, use market-based data, including stock prices, returns, volatility, and credit default swap spreads. This is because these data are frequently available and easily accessible. Stock prices are often used to represent the financial health of institutions, making them crucial inputs for systemic risk models. Their importance is further supported by research showing a positive

relationship between stock price volatility and bank risk (Jizi & Dixon, 2017; Garel et al., 2020; Sun et al., 2020).

Alongside traditional methods, there has been a growing need in recent years to apply more advanced approaches for assessing systemic risk, such as machine learning techniques, graph theory, and network analysis (Chen et al., 2019; Kou et al., 2019; Zhang, 2019; Baumöhl et al., 2020). Among more recent and increasingly used approaches, the transfer entropy method can also be included. This method enables the analysis of both the direction and intensity of risk transmission between financial institutions, which is particularly important in the study of systemic risk. Unlike traditional econometric approaches, such as correlation analysis or Granger causality, transfer entropy can capture not only linear but also nonlinear and asymmetric relationships between variables, which are especially relevant during periods of heightened financial stress. For this reason, transfer entropy has been increasingly applied in recent years, particularly in the analysis of banking networks, the study of financial contagion, and the identification of systemically important financial institutions (Li et al., 2013; Wang et al., 2023; Yijun et al., 2023; Zhao et al., 2024).

2 Methodology

In line with the main goal of this study, we apply the transfer entropy method and subsequently construct the TE-weighted network to analyse the structure of the banking sector and to identify systemically important banking institutions. In the first step of the implementation of the TE method, we calculate logarithmic returns $r_{i,t}$ from the daily closing stock prices of individual banks, defined as:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \quad (1)$$

where $P_{i,t}$ denotes the closing price of bank i at time t . As a proxy for each bank's risk level, the standard deviation of logarithmic returns within a 28-day rolling window, with a step size of 20 days, is used (Wang et al., 2023). The risk indicator for each bank is therefore defined as follows:

$$\sigma_{i,t'} = \sqrt{\frac{1}{T} \sum_{t'}^{t'+T} (r_{i,t} - \bar{r}_i)^2} \quad (2)$$

where T represents the window size, t' denotes the starting point of the rolling window, and \bar{r}_i is the mean of logarithmic returns of bank i calculated within the given rolling window. By applying this process, we obtain a time series of rolling standard deviations for each bank,

representing the evolution of risk over time. As a robustness check, we calculate the risk indicator using alternative parameter settings; however, the results were almost unchanged, especially the ranking of banking institutions, suggesting that the parameter settings do not bias the analysis. Subsequently, these values are normalized using min–max normalization, where the minimum and maximum are computed for each bank’s risk indicator across all windows:

$$\sigma_{i,t}^{norm} = \frac{\sigma_{i,t} - \min(\sigma_i)}{\max(\sigma_i) - \min(\sigma_i)} \quad (3)$$

These normalized values are subsequently transformed into three symbolic states using empirical quantiles $q_{0.2}$ and $q_{0.8}$ as thresholds, ensuring a discretization suitable for transfer entropy estimation (Li & Niu, 2018; Caserini & Pagnottoni, 2022):

$$s_{i,t} = \begin{cases} 0.2 & \text{if } r_{i,t}^{norm} < q_{0.2} \\ 0.6 & \text{if } q_{0.2} \leq r_{i,t}^{norm} \leq q_{0.8} \\ 0.8 & \text{if } r_{i,t}^{norm} > q_{0.8} \end{cases} \quad (4)$$

Based on the discretized values, we estimate transfer entropy, which captures the directional flow of information between time series. In this context, the information flow can be interpreted as risk transmission between banking institutions. From a conceptual perspective, transfer entropy can be defined as the conditional mutual information between the future value of a time series Y and the past values of another time series X , while simultaneously accounting for the past values of time series Y itself. Formally, transfer entropy is defined as:

$$TE_{X \rightarrow Y} = \sum p(y_{t+1}, y_t^{(k)}, x_t^{(l)}) \log \left(\frac{p(y_{t+1} | y_t^{(k)}, x_t^{(l)})}{p(y_{t+1} | y_t^{(k)})} \right) \quad (5)$$

where $x_t^{(l)}$ and $y_t^{(k)}$ represent the l and k past values of the source and target time series, respectively. In line with empirical practice, we set the lag length to one period for both the source and target time series ($k = 1 = l$), which corresponds to the assumption of a first-order Markov process. This lag specification represents a practical simplification that stabilizes the estimation of transfer entropy (Bollt, 2012; Lee et al., 2012; Kissler et al., 2020; Caserini & Pagnottoni, 2022). The statistical significance is assessed via surrogate testing: for each pair, the source time series is permuted 100 times, and a null distribution of transfer entropy (TE) values is constructed using 300 bootstrap replications. The observed TE is then compared with this distribution to obtain a p-value (Barnett et al., 2009), ensuring that only statistically robust directional dependencies are considered meaningful. Given that this process is performed for all ordered pairs of banks ($n \times n$), a multiple testing problem arises, which may lead to false positives. To address this issue, the Benjamini–Hochberg false discovery rate (FDR) correction is applied, controlling for the expected proportion of false positives.

Based on the estimated transfer entropy values, we construct a TE-weighted directed network to analyse the structure of the global banking sector. In this network, nodes represent individual banking institutions, while edges capture the direction and intensity of risk transmission between them, and edge weights are determined by the corresponding transfer entropy values. To further analyse the position of banks within the network, the following network characteristics are computed:

- Strength (in/out): Represents the sum of the weights of incoming and outgoing edges, reflecting the overall magnitude of risk absorbed or transmitted by a bank.
- Betweenness centrality: Measures how often a node lies on the shortest paths between other nodes, thereby identifying key intermediaries in risk transmission.
- Closeness centrality: Is based on the average shortest-path distance to all other nodes in the network and reflects how quickly a node can reach other nodes.
- Eigenvector centrality and PageRank: Assess a bank's systemic importance by considering not only the number and strength of its connections but also the importance of the connected institutions.
- Hub and Authority scores: Are derived from the HITS algorithm and distinguish between banks acting as transmitters and receivers of risk; the hub score identifies key transmitters of risk, while the authority score identifies key receivers of risk.

To assess the structure of the overall banking sector, we analyse a sample of 77 of the world's largest banking institutions headquartered in America, Europe, and Asia. The sample is constructed based on an international ranking published by the analytical platform TABInsights, which annually identifies the world's largest banks according to their total assets. Within this ranking, we focus on the top 100 banks; however, the final sample is limited by the availability of market data required for the construction of the risk indicator. Consequently, only those banks whose shares are publicly traded and for which sufficiently long and continuous time series of market data are available are included. The list of selected institutions, together with their total assets, country of headquarters, region, and ticker symbol, is presented in Appendix A (Table A1).

Daily closing prices for these banking institutions were obtained from the publicly available Yahoo Finance database over the period from November 16, 2016 to December 30, 2025. For each bank, we use the home market primary listing (the most liquid share class), and stock prices are retained in local currencies. No currency conversion is applied, as logarithmic returns are not directly affected by the currency denomination. Moreover, converting prices into

a common currency might bias the analysis due to exchange rate fluctuations. Potential bias could also be caused by differences in trading hours and trading days across exchanges. To avoid issues related to non-synchronous trading hours, we compute daily logarithmic returns and then the 28-day rolling standard deviation, sampled every 20 trading days (Equation 2). In the case of non-synchronous trading days across exchanges, we use the last available closing price for banks that were not traded on a given day. This approach may mitigate potential bias caused by missing observations.

3 Results and discussion

Based on the results of transfer entropy, we can identify significant channels of risk transmission between banking institutions. In general, higher values indicate more intensive risk transmission. The highest transfer entropy was observed between Morgan Stanley and BNP Paribas, where Morgan Stanley represents the source of risk transmission. Morgan Stanley also transmits risk to BBVA and NatWest Group, but the intensity of its transmission is lower. Significant linkages were also identified between Societe Generale and Bank of Nanjing, Capital One Financial Corp. and BMO, as well as between Deutsche Bank and Goldman Sachs, representing important channels of risk transmission (Appendix B – Figure B1).

These findings are also supported by the network visualization in Figure 1, where each node represents a ranking institution, and each directed edge is weighted by the corresponding TE value, reflecting the intensity and direction of risk transmission. To improve clarity, this visualization displays the most significant linkages, specifically the top 15% of the strongest connections based on transfer entropy values. Based on the network visualization, we can observe that the banks located in the core of the network are more interconnected with other banks compared to those situated on the periphery. Therefore, the most interconnected banks include, for example, CaixaBank, Goldman Sachs, BoCom, BOC, Bank of Beijing, HDFC Bank, KB Financial Group, and Societe Generale. In contrast, banks such as KBC Bank, Raiffeisen Gruppe, BOCHK, DBS, China Everbright Bank, Mizuho, NBC, and Danske Bank can be considered less interconnected.

Focusing on the position of parent institutions of banks operating in Slovakia, which are highlighted in Figure 1, differences in their level of interconnectedness can be observed. Erste Group Bank, the parent company of Slovenská sporiteľňa, is located in a relatively central position, indicating a higher degree of interconnectedness with other global banking institutions within the network. In contrast, banking groups such as KBC Bank (ČSOB) and Raiffeisen Gruppe (Tatra banka) are located on the periphery of the network, suggesting a lower level of

interconnectedness and a more regionally concentrated structure. UniCredit and Intesa Sanpaolo (VÚB banka) are also positioned towards the periphery; however, they exhibit a

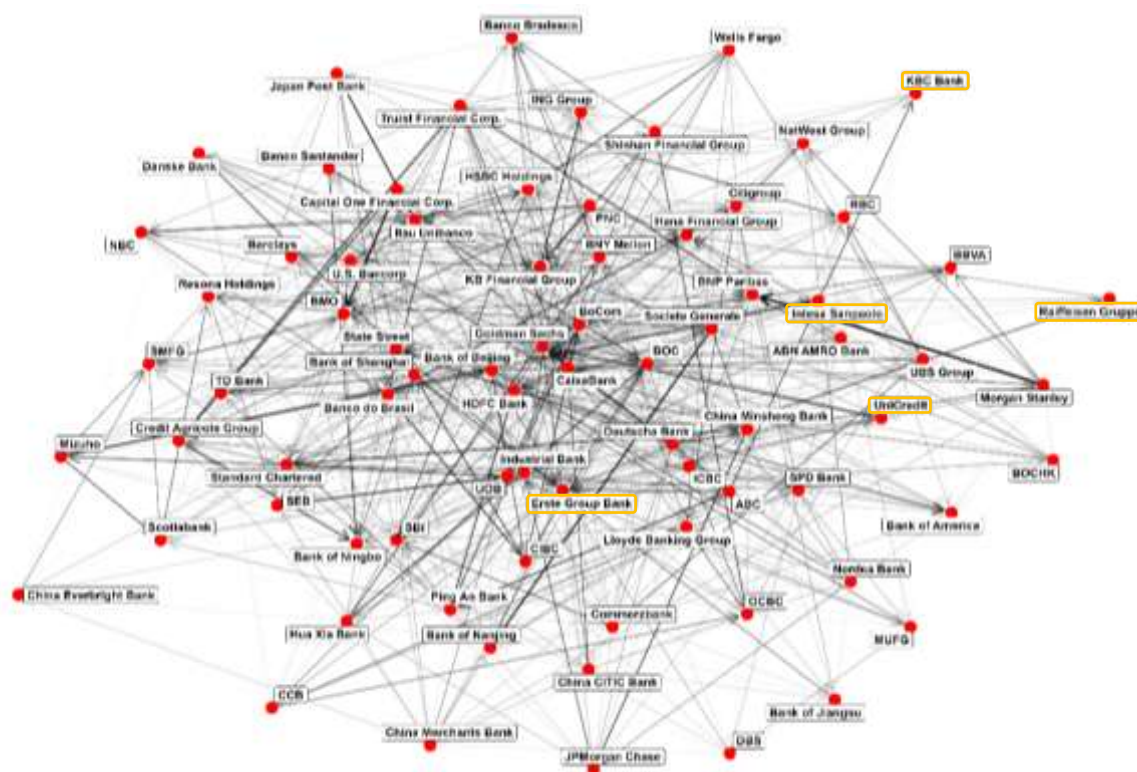


Figure 1 Global banking network
Source: own elaboration in R

higher level of interconnectedness compared to KBC Bank and Raiffeisen Gruppe.

As mentioned above, the visualization includes only the top 15% strongest linkages, and therefore, for a more detailed analysis of the network structure and the positions of individual banking institutions, the network characteristics are computed based on all linkages in the network, as shown in Table 1.

Table 1 Network characteristics of banking institutions

| Bank | S_IN | S_OUT | BTW | CLS | EIG | PR | HUBS | AUTH |
|--------------------|--------|--------|-----|--------|--------|--------|--------|--------|
| BoCom | 7,6072 | 5,7757 | 57 | 0,0010 | 1,0000 | 0,0162 | 0,7594 | 0,9846 |
| Goldman Sachs | 7,6809 | 5,6185 | 61 | 0,0010 | 0,9982 | 0,0161 | 0,7499 | 1,0000 |
| Industrial Bank | 7,6183 | 6,1710 | 106 | 0,0011 | 0,9951 | 0,0161 | 0,7989 | 0,9868 |
| KB Financial Group | 7,6461 | 5,8853 | 70 | 0,0010 | 0,9904 | 0,0160 | 0,7712 | 0,9920 |
| HDFC Bank | 7,5228 | 6,2078 | 80 | 0,0011 | 0,9801 | 0,0159 | 0,8137 | 0,9736 |
| Banco do Brasil | 7,4140 | 6,0240 | 77 | 0,0010 | 0,9592 | 0,0157 | 0,7866 | 0,9582 |
| BOC | 7,3670 | 6,4707 | 113 | 0,0011 | 0,9585 | 0,0156 | 0,8428 | 0,9549 |
| Erste Group Bank | 7,3713 | 6,1043 | 117 | 0,0011 | 0,9557 | 0,0156 | 0,8068 | 0,9527 |
| State Street | 7,4008 | 5,6004 | 30 | 0,0010 | 0,9646 | 0,0156 | 0,7411 | 0,9618 |

| Bank | S_IN | S_OUT | BTW | CLS | EIG | PR | HUBS | AUTH |
|-------------------------|-------------|--------------|------------|------------|------------|-----------|-------------|-------------|
| CaixaBank | 7,3536 | 6,4930 | 81 | 0,0011 | 0,9486 | 0,0155 | 0,8567 | 0,9539 |
| Hana Financial Group | 7,1971 | 6,0121 | 72 | 0,0011 | 0,9279 | 0,0152 | 0,7978 | 0,9296 |
| Bank of Ningbo | 7,0454 | 5,2041 | 10 | 0,0009 | 0,9244 | 0,0151 | 0,6796 | 0,9129 |
| Bank of Shanghai | 6,6658 | 6,3181 | 44 | 0,0011 | 0,8729 | 0,0144 | 0,8306 | 0,8632 |
| Itau Unibanco | 6,7917 | 6,5053 | 57 | 0,0011 | 0,8790 | 0,0144 | 0,8574 | 0,8846 |
| SBI | 6,5753 | 6,2871 | 55 | 0,0011 | 0,8568 | 0,0142 | 0,8236 | 0,8431 |
| BNP Paribas | 6,6128 | 6,0496 | 32 | 0,0011 | 0,8603 | 0,0141 | 0,8030 | 0,8628 |
| ICBC | 6,5618 | 5,8722 | 29 | 0,0010 | 0,8524 | 0,0141 | 0,7756 | 0,8499 |
| UOB | 6,4307 | 5,8374 | 46 | 0,0011 | 0,8379 | 0,0140 | 0,7812 | 0,8244 |
| BMO | 6,5028 | 6,4298 | 41 | 0,0011 | 0,8466 | 0,0139 | 0,8459 | 0,8529 |
| Societe Generale | 6,3904 | 6,2910 | 48 | 0,0011 | 0,8354 | 0,0139 | 0,8342 | 0,8244 |
| Bank of Beijing | 6,3966 | 6,5045 | 66 | 0,0011 | 0,8320 | 0,0138 | 0,8508 | 0,8272 |
| Credit Agricole Group | 6,3737 | 5,6232 | 19 | 0,0010 | 0,8310 | 0,0137 | 0,7447 | 0,8313 |
| Lloyds Banking Group | 6,3650 | 6,0121 | 30 | 0,0010 | 0,8257 | 0,0137 | 0,7869 | 0,8235 |
| OCBC | 6,2855 | 5,6259 | 37 | 0,0010 | 0,8210 | 0,0137 | 0,7425 | 0,8082 |
| SPD Bank | 6,2956 | 5,4437 | 34 | 0,0010 | 0,8236 | 0,0137 | 0,7142 | 0,8104 |
| Scotiabank | 6,3650 | 5,5125 | 13 | 0,0010 | 0,8215 | 0,0137 | 0,7320 | 0,8240 |
| TD Bank | 6,3400 | 5,8541 | 32 | 0,0010 | 0,8215 | 0,0137 | 0,7764 | 0,8182 |
| China Minsheng Bank | 6,1195 | 6,0211 | 40 | 0,0011 | 0,8107 | 0,0135 | 0,7957 | 0,7902 |
| HSBC Holdings | 6,2612 | 6,3369 | 60 | 0,0011 | 0,8197 | 0,0135 | 0,8302 | 0,8158 |
| Resona Holdings | 6,0640 | 6,0762 | 17 | 0,0010 | 0,7942 | 0,0133 | 0,8093 | 0,7835 |
| BNY Mellon | 6,0872 | 6,3600 | 23 | 0,0011 | 0,7981 | 0,0132 | 0,8393 | 0,7916 |
| SEB | 5,9808 | 5,9555 | 16 | 0,0011 | 0,7889 | 0,0132 | 0,7922 | 0,7725 |
| Bank of America | 6,0050 | 5,3887 | 1 | 0,0010 | 0,7885 | 0,0131 | 0,7184 | 0,7826 |
| CIBC | 5,9814 | 6,1631 | 29 | 0,0011 | 0,7855 | 0,0131 | 0,8206 | 0,7773 |
| NatWest Group | 5,9938 | 5,5470 | 9 | 0,0010 | 0,7862 | 0,0131 | 0,7323 | 0,7784 |
| Standard Chartered | 6,0760 | 5,9720 | 21 | 0,0010 | 0,7882 | 0,0131 | 0,7909 | 0,7926 |
| Banco Bradesco | 5,9897 | 5,4303 | 8 | 0,0010 | 0,7803 | 0,0130 | 0,7236 | 0,7775 |
| Commerzbank | 5,9472 | 6,1148 | 16 | 0,0011 | 0,7810 | 0,0130 | 0,8097 | 0,7734 |
| Shinhan Financial Group | 5,9290 | 5,5439 | 22 | 0,0010 | 0,7788 | 0,0130 | 0,7297 | 0,7698 |
| ABC | 5,9355 | 6,1022 | 35 | 0,0011 | 0,7784 | 0,0130 | 0,8054 | 0,7662 |
| ING Group | 5,9112 | 6,1403 | 11 | 0,0011 | 0,7710 | 0,0129 | 0,8135 | 0,7689 |
| Nordea Bank | 5,8615 | 6,1637 | 28 | 0,0011 | 0,7719 | 0,0129 | 0,8162 | 0,7596 |
| Barclays | 5,8723 | 5,8391 | 2 | 0,0010 | 0,7666 | 0,0128 | 0,7763 | 0,7656 |
| Japan Post Bank | 5,8112 | 5,5621 | 12 | 0,0010 | 0,7611 | 0,0127 | 0,7279 | 0,7579 |
| SMFG | 5,7563 | 5,6749 | 23 | 0,0010 | 0,7491 | 0,0127 | 0,7588 | 0,7417 |
| Ping An Bank | 5,7059 | 5,4343 | 29 | 0,0010 | 0,7544 | 0,0126 | 0,7150 | 0,7393 |
| UniCredit | 5,7246 | 5,7300 | 8 | 0,0010 | 0,7489 | 0,0126 | 0,7620 | 0,7441 |
| Deutsche Bank | 5,5378 | 7,5976 | 71 | 0,0013 | 0,7270 | 0,0123 | 1,0000 | 0,7127 |
| JPMorgan Chase | 5,6063 | 5,6210 | 5 | 0,0010 | 0,7336 | 0,0123 | 0,7487 | 0,7274 |
| Wells Fargo | 5,6278 | 5,9513 | 18 | 0,0011 | 0,7298 | 0,0123 | 0,7931 | 0,7341 |
| Citigroup | 5,6080 | 5,8016 | 23 | 0,0010 | 0,7316 | 0,0122 | 0,7711 | 0,7354 |
| Intesa Sanpaolo | 5,5332 | 5,8570 | 11 | 0,0010 | 0,7217 | 0,0122 | 0,7774 | 0,7155 |
| PNC | 5,5199 | 6,9052 | 24 | 0,0012 | 0,7223 | 0,0122 | 0,9255 | 0,7181 |

| Bank | S_IN | S_OUT | BTW | CLS | EIG | PR | HUBS | AUTH |
|-----------------------------|-------------|--------------|------------|------------|------------|-----------|-------------|-------------|
| Morgan Stanley | 5,4744 | 6,1566 | 20 | 0,0011 | 0,7157 | 0,0121 | 0,8074 | 0,7111 |
| BOCHK | 5,4001 | 5,8372 | 3 | 0,0010 | 0,7069 | 0,0120 | 0,7706 | 0,7015 |
| Bank of Jiangsu | 5,3959 | 5,0869 | 2 | 0,0009 | 0,7071 | 0,0120 | 0,6749 | 0,6957 |
| MUFG | 5,3520 | 5,4999 | 11 | 0,0010 | 0,7027 | 0,0120 | 0,7278 | 0,6841 |
| BBVA | 5,4312 | 5,6304 | 8 | 0,0010 | 0,7092 | 0,0119 | 0,7508 | 0,7089 |
| RBC | 5,4418 | 5,6087 | 3 | 0,0010 | 0,7056 | 0,0119 | 0,7426 | 0,7144 |
| Bank of Nanjing | 5,2733 | 5,8157 | 20 | 0,0010 | 0,6913 | 0,0118 | 0,7677 | 0,6816 |
| China Merchants Bank | 5,2457 | 5,1450 | 18 | 0,0010 | 0,6914 | 0,0118 | 0,6729 | 0,6789 |
| NBC | 5,3937 | 5,2839 | 8 | 0,0010 | 0,6974 | 0,0118 | 0,7060 | 0,7019 |
| KBC Bank | 5,2484 | 5,5245 | 7 | 0,0010 | 0,6878 | 0,0117 | 0,7359 | 0,6840 |
| Hua Xia Bank | 5,0443 | 6,6776 | 12 | 0,0011 | 0,6675 | 0,0115 | 0,8835 | 0,6467 |
| Raiffeisen Gruppe | 5,1333 | 5,4056 | 3 | 0,0010 | 0,6746 | 0,0115 | 0,7091 | 0,6686 |
| China CITIC Bank | 5,0083 | 5,7035 | 4 | 0,0010 | 0,6590 | 0,0113 | 0,7540 | 0,6449 |
| Mizuho | 4,9347 | 5,9741 | 13 | 0,0011 | 0,6469 | 0,0112 | 0,7958 | 0,6359 |
| China Everbright Bank | 4,8630 | 4,8181 | 4 | 0,0009 | 0,6438 | 0,0110 | 0,6348 | 0,6316 |
| Danske Bank | 4,7362 | 5,9670 | 1 | 0,0010 | 0,6275 | 0,0108 | 0,7949 | 0,6145 |
| U.S. Bancorp | 4,7379 | 6,8725 | 19 | 0,0011 | 0,6199 | 0,0108 | 0,9186 | 0,6099 |
| DBS | 4,6860 | 5,2264 | 5 | 0,0010 | 0,6118 | 0,0107 | 0,6891 | 0,6021 |
| UBS Group | 4,6379 | 6,5826 | 11 | 0,0011 | 0,6044 | 0,0105 | 0,8719 | 0,6044 |
| ABN AMRO Bank | 4,4894 | 6,2345 | 5 | 0,0011 | 0,5862 | 0,0103 | 0,8228 | 0,5810 |
| Banco Santander | 4,5041 | 6,2570 | 2 | 0,0011 | 0,5932 | 0,0103 | 0,8361 | 0,5842 |
| Capital One Financial Corp. | 4,5080 | 7,0600 | 2 | 0,0012 | 0,5906 | 0,0103 | 0,9409 | 0,5874 |
| CCB | 4,4323 | 5,4369 | 3 | 0,0010 | 0,5801 | 0,0102 | 0,7215 | 0,5736 |
| Truist Financial Corp. | 4,0708 | 7,2388 | 23 | 0,0012 | 0,5346 | 0,0096 | 0,9588 | 0,5242 |

Source: own elaboration

Based on the PageRank indicator, banks such as BoCom, Goldman Sachs, Industrial Bank, KB Financial Group, and HDFC Bank can be identified as the most systemically important banking institutions within the global banking network. When considering other network-based indicators, substantial heterogeneity in their positions can be observed, particularly in terms of their ability to transmit, mediate, or absorb risk.

Industrial Bank exhibits a high value of betweenness centrality (106), indicating its significant role as an intermediary in the transmission of risk among banks within the network. At the same time, the bank records a higher value of the Strength-in indicator (7.6183) compared to Strength-out (6.1710), along with a high Authority score (0.9868), suggesting that it also acts as an important receiver of risk. Although some banks in the network, such as BOC (113) and Erste Group Bank (117), record even higher betweenness centrality values, highlighting their significant role in risk transmission, their relatively lower PageRank and eigenvector centrality values suggest that their overall systemic importance is slightly lower compared to Industrial Bank. In the case of both of these banks, similarly to Industrial Bank,

higher values of Strength-in and the Authority score predominate over those of Strength-out and the Hub score, suggesting that they also play a crucial role as receivers of risk. These results further indicate that systemically important banks are highly interconnected with other systemically important institutions, thereby forming the core of the banking network. Within this core, the banks often act as receivers of risk, which they may subsequently transmit to other parts of the system through their intermediary role.

In contrast, to identify the most important sources of risk transmission, we focus on the Hub score indicator, which captures a bank's ability to propagate risk shocks to other entities. For this purpose, banks are ranked based on this indicator in descending order, with particular attention given to the top 15 banking institutions with the highest scores (Table 2).

Table 2 Top 15 banks as sources of risk transmission

| Bank | S_IN | S_OUT | BTW | CLS | EIG | PR | HUBS | AUTH |
|-----------------------------|--------|--------|-----|--------|--------|--------|--------|--------|
| Deutsche Bank | 5,5378 | 7,5976 | 71 | 0,0013 | 0,7270 | 0,0123 | 1,0000 | 0,7127 |
| Truist Financial Corp. | 4,0708 | 7,2388 | 23 | 0,0012 | 0,5346 | 0,0096 | 0,9588 | 0,5242 |
| Capital One Financial Corp. | 4,5080 | 7,0600 | 2 | 0,0012 | 0,5906 | 0,0103 | 0,9409 | 0,5874 |
| PNC | 5,5199 | 6,9052 | 24 | 0,0012 | 0,7223 | 0,0122 | 0,9255 | 0,7181 |
| U.S. Bancorp | 4,7379 | 6,8725 | 19 | 0,0011 | 0,6199 | 0,0108 | 0,9186 | 0,6099 |
| Hua Xia Bank | 5,0443 | 6,6776 | 12 | 0,0011 | 0,6675 | 0,0115 | 0,8835 | 0,6467 |
| UBS Group | 4,6379 | 6,5826 | 11 | 0,0011 | 0,6044 | 0,0105 | 0,8719 | 0,6044 |
| Itau Unibanco | 6,7917 | 6,5053 | 57 | 0,0011 | 0,8790 | 0,0144 | 0,8574 | 0,8846 |
| CaixaBank | 7,3536 | 6,4930 | 81 | 0,0011 | 0,9486 | 0,0155 | 0,8567 | 0,9539 |
| Bank of Beijing | 6,3966 | 6,5045 | 66 | 0,0011 | 0,8320 | 0,0138 | 0,8508 | 0,8272 |
| BMO | 6,5028 | 6,4298 | 41 | 0,0011 | 0,8466 | 0,0139 | 0,8459 | 0,8529 |
| BOC | 7,3670 | 6,4707 | 113 | 0,0011 | 0,9585 | 0,0156 | 0,8428 | 0,9549 |
| BNY Mellon | 6,0872 | 6,3600 | 23 | 0,0011 | 0,7981 | 0,0132 | 0,8393 | 0,7916 |
| Banco Santander | 4,5041 | 6,2570 | 2 | 0,0011 | 0,5932 | 0,0103 | 0,8361 | 0,5842 |
| Societe Generale | 6,3904 | 6,2910 | 48 | 0,0011 | 0,8354 | 0,0139 | 0,8342 | 0,8244 |

Source: own elaboration

Based on the Hub score, banks such as Deutsche Bank, Truist Financial Corp., Capital One Financial Corp., PNC, U.S. Bancorp, and Hua Xia Bank can be identified as the most significant sources of risk transmission. When interpreting this indicator, it is important to also consider the systemic importance of these institutions within the network and to assess it in combination with other indicators.

Among the mentioned banks, Deutsche Bank can be considered the most significant source of risk transmission, as it not only records the highest values of the Hub score (1.0000) and Strength-out (7.5976), but also shows relatively high values of eigenvector centrality (0.7270) and PageRank (0.0123). These results suggest that Deutsche Bank not only transmits risk

shocks to other institutions, but is also strongly interconnected with systemically important banks, which increases its potential to destabilize the entire banking system. In the case of Truist Financial Corp. and Capital One Financial Corp., although the values of the Hub score (0.9588 and 0.9409) and Strength-out (7.2388 and 7.0600) are relatively high, their lower values of eigenvector centrality (0.5346 and 0.5906) and PageRank (0.0096 and 0.0103) indicate weaker interconnectedness with systemically important banks. As a result, their ability to transmit risk is likely more localized and limited to peripheral parts of the network. In contrast, banks such as PNC and Hua Xia Bank record slightly lower values of the Hub score (0.9255 and 0.8355) and Strength-out (6.9052 and 6.6776), but, compared to Truist Financial Corp. and Capital One Financial Corp., they show higher values of eigenvector centrality (0.7223 and 0.6675) and PageRank (0.0122 and 0.0115). Therefore, they can be considered more significant sources of risk transmission from the perspective of the overall structure of the banking network.

Based on the presented results and their comparison with existing research, the research questions can be addressed as follows. In line with the first research question, systemically important banking institutions were identified using the PageRank indicator, which, similarly to eigenvector centrality, captures the importance of a bank based on its connections to other important banks (Yun et al., 2019; Gao et al., 2024; Chen et al., 2025). In this context, BoCom, Goldman Sachs, Industrial Bank, KB Financial Group, and HDFC Bank can be considered the most systemically important banks. The network characteristics of these institutions confirm, in line with existing literature, that systemically important banks are highly interconnected with other systemically important institutions, thereby forming the core of the banking network (Eboli, 2024; Lie et al., 2025). The results confirm that these banks primarily act as receivers of risk, which may subsequently be transmitted to other parts of the network through their intermediary role. To answer the second question, the Hub score indicator was used. Based on its results, banks such as Deutsche Bank, Truist Financial Corp., Capital One Financial Corp., PNC, U.S. Bancorp, and Hua Xia Bank can be identified as crucial sources of risk transmission. However, the results highlight that a bank's ability to transmit risk, as captured by the Hub score and Strength-out indicators, does not necessarily reflect high systemic importance (Acemoglu et al., 2015; Glasserman & Young, 2015; Franch et al., 2024). Banks that combine a strong ability to transmit risk with high interconnectedness with other systemically important banks, as captured by eigenvector centrality and PageRank, represent the most significant sources of systemic risk (Battiston et al., 2012; Li et al., 2025). Therefore, it is important to distinguish between local and systemically important sources of risk transmission. While banks such as Truist Financial Corp. and Capital One Financial Corp. can be considered local sources

of risk transmission, banks such as Deutsche Bank, PNC, and Hua Xia Bank represent systemically important sources of risk transmission with the potential to affect the entire banking sector. Overall, the results highlight the importance of considering not only the intensity of risk transmission, but also the structure of interconnections within the banking network, which plays a key role in identifying systemically important banks.

Focusing on the Slovak banking sector, the results indicate that the parent institutions of banks operating in Slovakia hold different positions within the global banking network. In particular, Erste Group Bank, the parent company of Slovenská sporiteľňa, can be considered the most interconnected institution, which is consistent with its ranking among the top systemically important banks. In contrast, banking groups such as KBC Bank (ČSOB) and Raiffeisen Gruppe (Tatra banka) are located on the periphery of the network, suggesting a lower level of interconnectedness. These findings suggest that the Slovak banking sector may, through its interconnected parent institutions, contribute to risk transmission and increase the overall level of risk in the banking sector (Anginer et al., 2017; Fiala, 2017).

Conclusion

The main objective of this study was to examine the structure of the global banking sector and identify systemically important banking institutions. The results obtained from the TE-weighted network confirm a high degree of interconnectedness among banking institutions at the global level. In general, banks located in the core of the network are more interconnected with other institutions than those situated on the periphery. Therefore, banks such as CaixaBank, Goldman Sachs, BoCom, BOC, Bank of Beijing, HDFC Bank, KB Financial Group, and Societe Generale can be identified as the most interconnected institutions. In contrast, banks such as KBC Bank, Raiffeisen Gruppe, BOCHK, DBS, China Everbright Bank, Mizuho, NBC, and Danske Bank can be considered less interconnected institutions. Focusing on the Slovak banking sector, Erste Group Bank, the parent institution of Slovenská sporiteľňa, is identified as the most interconnected institution, while KBC Bank (VÚB banka) and Raiffeisen Gruppe (Tatra banka) are positioned on the periphery of the network, indicating lower interconnectedness.

Based on the network characteristics, banks such as BoCom, Goldman Sachs, Industrial Bank, KB Financial Group, and HDFC Bank are identified as systemically important banks forming the core of the network. These banks primarily act as receivers of risk, which may subsequently be transmitted to other parts of the network through their intermediary role. In contrast, banks such as Deutsche Bank, PNC, and Hua Xia Bank can be considered systemically

important transmitters of risk, while Truist Financial Corp. and Capital One Financial Corp. represent local sources of risk transmission. These findings highlight that the ability to transmit risk does not necessarily reflect high systemic importance. Therefore, key risk transmitters should be considered in combination with their level of interconnectedness and position within the network.

This paper provides useful insights for regulators and policymakers, as the proposed approach offers a potential framework for identifying systemically important institutions based on transfer entropy in combination with a network-based approach. It allows the identification of key channels of risk transmission and institutions that play a crucial role in this process. This is particularly important for the design of macroprudential policies, as it may help regulators to focus on monitoring systemically important institutions and better target policy measures. Future research could benefit from applying this methodology to alternative samples of financial institutions and could focus on analysing the determinants that cause the different positions of individual banking institutions within the network.

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APPENDIX A

Table A1 List of analysed banks

| Bank | Total assets (USD mil.) | Country | Region | Ticker |
|-----------------|-------------------------|---------|---------|-----------|
| ICBC | 6 688 735 | China | Asia | 601398.SS |
| ABC | 5 923 763 | China | Asia | 601288.SS |
| CCB | 5 558 377 | China | Asia | 601939.SS |
| BOC | 4 803 510 | China | Asia | 601988.SS |
| JPMorgan Chase | 4 002 814 | USA | America | JPM |
| Bank of America | 3 261 519 | USA | America | BAC |
| HSBC Holdings | 3 017 048 | UK | Europe | HSBA.L |

| Bank | Total assets (USD mil.) | Country | Region | Ticker |
|-----------------------|--------------------------------|----------------|---------------|---------------|
| BNP Paribas | 2 800 402 | France | Europe | BNP.PA |
| MUFG | 2 758 725 | Japan | Asia | 8306.T |
| Credit Agricole Group | 2 693 578 | France | Europe | ACA.PA |
| Citigroup | 2 352 945 | USA | America | C |
| SMFG | 2 045 316 | Japan | Asia | 8316.T |
| BoCom | 2 041 446 | China | Asia | 601328.SS |
| Wells Fargo | 1 929 845 | USA | America | WFC |
| Banco Santander | 1 901 935 | Spain | Europe | SAN.MC |
| Barclays | 1 900 675 | UK | Europe | BARC.L |
| Mizuho | 1 891 981 | Japan | Asia | 8411.T |
| Goldman Sachs | 1 675 972 | USA | America | GS |
| China Merchants Bank | 1 664 868 | China | Asia | 600036.SS |
| Societe Generale | 1 629 097 | France | Europe | GLE.PA |
| UBS Group | 1 565 028 | Switzerland | Europe | UBSG.SW |
| Japan Post Bank | 1 559 964 | Japan | Asia | 7182.T |
| RBC | 1 558 365 | Canada | America | RY.TO |
| TD Bank | 1 479 549 | Canada | America | TD.TO |
| Industrial Bank | 1 439 616 | China | Asia | 601166.SS |
| Deutsche Bank | 1 436 150 | Germany | Europe | DBK.DE |
| China CITIC Bank | 1 306 013 | China | Asia | 601998.SS |
| SPD Bank | 1 296 308 | China | Asia | 600000.SS |
| Morgan Stanley | 1 215 071 | USA | America | MS |
| Lloyds Banking Group | 1 135 116 | UK | Europe | LLOY.L |
| China Minsheng Bank | 1 070 676 | China | Asia | 600016.SS |
| ING Group | 1 056 574 | Netherlands | Europe | INGA.AS |
| Scotiabank | 1 013 295 | Canada | America | BNS.TO |
| BMO | 1 011 587 | Canada | America | BMO.TO |
| Intesa Sanpaolo | 966 234 | Italy | Europe | ISP.MI |
| China Everbright Bank | 953 408 | China | Asia | 601818.SS |
| NatWest Group | 886 344 | UK | Europe | NWG.L |
| SBI | 855 994 | India | Asia | SBIN.NS |
| Standard Chartered | 849 668 | UK | Europe | STAN.L |
| UniCredit | 811 682 | Italy | Europe | UCG.MI |
| BBVA | 799 671 | Spain | Europe | BBVA.MC |
| Ping An Bank | 790 408 | China | Asia | 000001.SZ |
| CIBC | 747 747 | Canada | America | CM.TO |
| U.S. Bancorp | 678 318 | USA | America | USB |
| CaixaBank | 653 280 | Spain | Europe | CABK.MC |
| Nordea Bank | 645 362 | Finland | Europe | NDA-FI.HE |
| DBS | 606 132 | Singapore | Asia | D05.SI |
| Hua Xia Bank | 599 593 | China | Asia | 600015.SS |
| Bank of Beijing | 578 365 | China | Asia | 601169.SS |
| Commerzbank | 574 227 | Germany | Europe | CBK.DE |
| PNC | 560 038 | USA | America | PNC |

| Bank | Total assets (USD mil.) | Country | Region | Ticker |
|-----------------------------|--------------------------------|----------------|---------------|---------------|
| Bank of Jiangsu | 541 442 | China | Asia | 600919.SS |
| Truist Financial Corp. | 531 176 | USA | America | TFC |
| Resona Holdings | 516 673 | Japan | Asia | 8308.T |
| BOCHK | 516 422 | Hong Kong | Asia | 2388.HK |
| Danske Bank | 515 869 | Denmark | Europe | DANSKE.CO |
| HDFC Bank | 514 053 | India | Asia | HDFCBANK.NS |
| KB Financial Group | 513 011 | South Korea | Asia | 105560.KS |
| Shinhan Financial Group | 500 771 | South Korea | Asia | 055550.KS |
| Capital One Financial Corp. | 490 144 | USA | America | COF |
| Itau Unibanco | 461 523 | Brazil | America | ITUB4.SA |
| OCBC | 457 996 | Singapore | Asia | O39.SI |
| Bank of Shanghai | 442 062 | China | Asia | 601229.SS |
| Hana Financial Group | 431 780 | South Korea | Asia | 086790.KS |
| Bank of Ningbo | 428 167 | China | Asia | 002142.SZ |
| BNY Mellon | 416 064 | USA | America | BK |
| ABN AMRO Bank | 398 641 | Netherlands | Europe | ABN.AS |
| UOB | 393 965 | Singapore | Asia | U11.SI |
| Banco do Brasil | 387 835 | Brazil | America | BBAS3.SA |
| Erste Group Bank | 366 224 | Austria | Európa | EBS.VI |
| Bank of Nanjing | 355 030 | China | Asia | 601009.SS |
| State Street | 353 240 | USA | America | STT |
| KBC Bank | 347 478 | Belgium | Europe | KBC.BR |
| SEB | 339 590 | Sweden | Europe | SEB-A.ST |
| Raiffeisen Gruppe | 337 252 | Switzerland | Europe | RBI.VI |
| Banco Bradesco | 334 603 | Brazil | America | BBDC4.SA |
| NBC | 331 701 | Canada | America | NA.TO |

Source: own elaboration based on TABInsights (2025)

Note: Total assets are based on banks' financial statements for 2024, typically as of December 31, 2024.

APPENDIX B

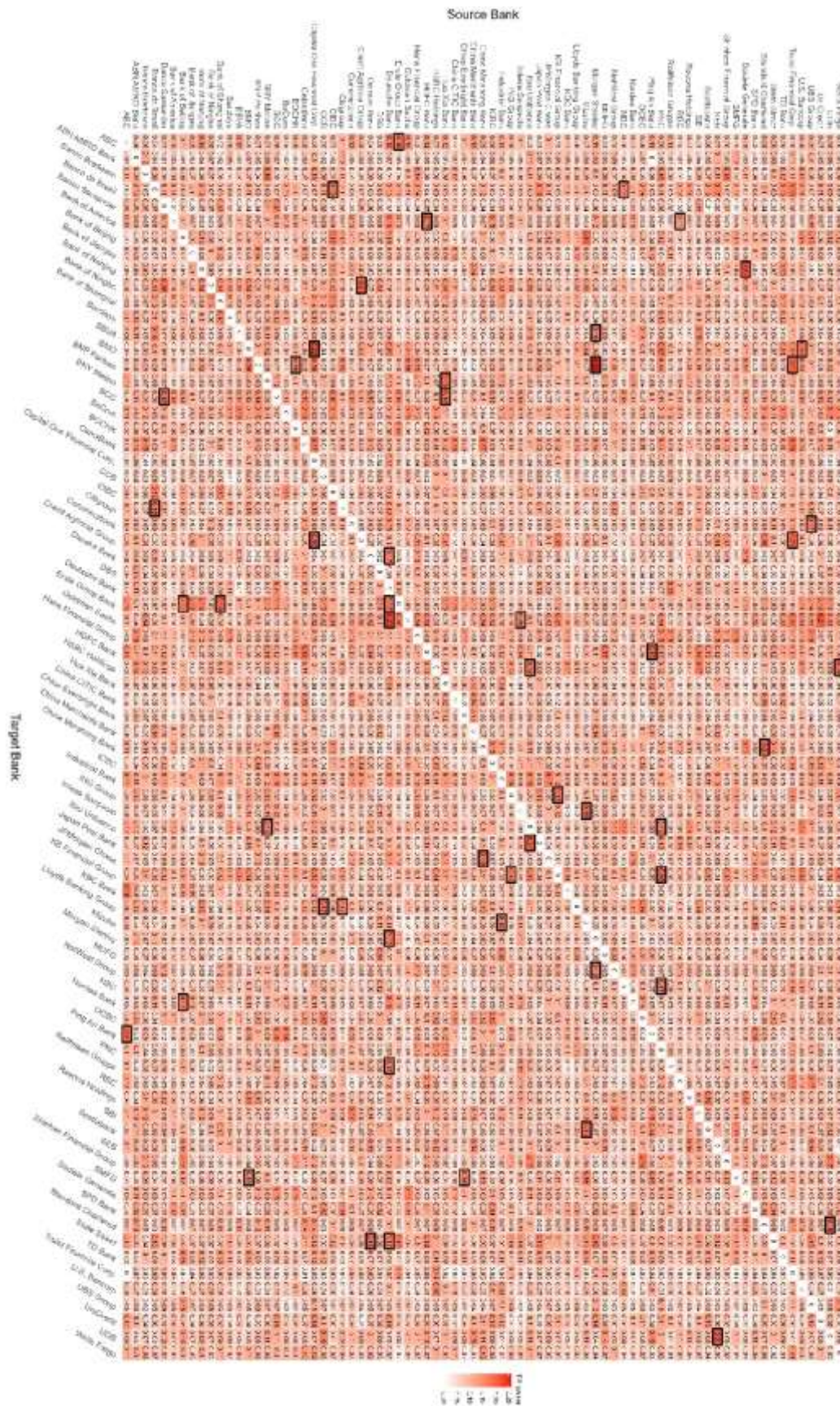


Figure B1 Transfer entropy matrix (after FDR Correction)
Source: own elaboration in R