An evolution of global and regional banking networks: A focus on Japanese banks' international expansion*

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Abstract

The significant increase in cross-border lending of Japanese banks since the Great Financial Crisis of 2007-2009 is documented to have both a global and regional dimension. This paper investigates how this expansion affects domestic financial stability. Based, on a network-based approach we show that Japanese banks have a prominent role in the global banking network in providing liquidity via cross-border lending. We also apply the Spinglass methodology to detect communities formed within the network and show that Japan is highly connected and has a central role in the East-Asian regional banking network. As a further step in the analysis, we employ a novel spatial econometric approach, namely, a time-varying spatial autoregressive (SAR) model to analyze the evolution of the network's spillover effects over time. Our empirical analysis points to the positive spillover effects of banking stability arising from cross-border lending activities. However, the results suggest that the spillovers are more pronounced at the global level than regional. Furthermore, we find that the role of Japanese banks in the global banking network has more than doubled since 2014.

Keywords: banking networks; spillover effect; spatial autoregression

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1. Introduction

Japanese banks have undergone a significant international expansion since the Great Financial Crisis (GFC) of 2007-2009. Indeed, they are the leading global banks in cross-border lending, with their market share increasing from 7.6% in 2007 to nearly 15% in mid-2019, with a total of nearly $4.5 trillion of foreign claims. The reach of this expansion is documented to have both a global and regional dimension. In particular, there has been a surge in overseas activities in other Asian countries. The increasing international activities of banks offer important advantages such as risk-sharing and diversification (Allen et al., 2011, Navaretti et al., 2010) as well as profitability opportunities (Hattori and Suda 2007). However, the increased exposure and reliance on overseas activities renders Japanese banks more vulnerable to external shocks (Bruno and Shin 2015). This poses financial stability implications, as a crisis can be triggered by banks' international operations rather than domestic fundamentals via financial linkages. Therefore, one possible source of financial instability resides in the structure of Japanese banks' cross-border relationships.

The structure of interconnectedness between financial institutions may indeed play a key role in understanding how financial spillovers can be transmitted across borders through linkages in the banking sector. The GFC highlighted not only that crises can be transmitted to other countries by banking connections (Kalemli-Ozcan et al., 2013) but also revealed the intertwined nature of financial systems (Allen and Babus 2009). Since then, a growing number of studies have employed a network-based approach to analyze cross-border contagion and the transmission of shocks in intertwined banking systems (Haldane and May 2011; Hale 2012; Hale et al., 2016; Tonzer 2015). In particular, understanding the network structure in which banking systems are connected via cross-border financial claims is crucial for assessing financial stability (Allen and Babus 2009, Haldane 2009). From this perspective, when monitoring the financial stability of a given country that is characterized by an international banking system, consideration should also be given to the international dimension of its activities and its interconnections with other banking systems.

To this aim, our study adds to the growing literature on risk contagion[†] in international banking at the country level, focusing on the interconnectedness and role of the Japanese banking system in the international lending market. Although the vulnerability of international activities may stem from the side of both assets and liabilities, in this paper, we

[†] Similar to Tonzer (2015), contagion and spillover are used interchangeably to illustrate the transmission of financial distress (stability) between countries by banking linkages.

focus on asset vulnerabilities in line with the activities undertaken by Japanese banks, which, as suggested by Lam (2013), have increased their holdings of foreign assets while holding their short-term liabilities rather stable. We employ a network analysis approach using cross-border bilateral data from the BIS-consolidated international banking statistics. In addition, we apply a novel econometric analysis, a time-varying spatial autoregressive (SAR) technique, to measure the role and degree of influence of the network on the stability of connected countries via cross-border linkages.

To the best of our knowledge, there is no available study of risk contagion in international banking that employs a time-varying SAR technique. We further add to the originality of the analysis by not only assessing the dominant role of Japanese banks on the global banking network but also capturing their role within the East Asian regional network. The empirical analysis takes several steps. We first construct a global network of banks' cross-border claims consisting of 47 countries available from the BIS banking statistics database over the 2006-2017 period. The network here consists of nodes, which in this paper are country-level banking sectors that are connected via links by means of borrowing and lending to each other. The network topology results highlight the changing role of Japanese banks within the network over the sample time period. The relative importance and the level of connectedness, as well as the centrality of the Japanese banking system, have indeed increased in recent years.

From our constructed global banking network, we apply the Spinglass community detection algorithm to detect the clusters formed within the network. A community, or cluster, is a group of nodes with strong cross-border claims against each other relative to the claims to other parts of the network. We find that after 2007-2008, the Japanese banking system serves not only as a global hub but also as a regional hub. Here, we argue that Japanese banks not only play an important role in the regional network by providing liquidity to other East Asian countries but also act as a bridge to connect nodes in the network that are not directly related (Allen and Babus, 2009).

To empirically assess the role of the global banking network on the stability of countries' banking systems, we use a Bayesian estimation approach for the standard SAR model and further extend it to a time-varying SAR model. We first apply the methodology to a global network, which consists of 22 countries due to data availability, as well as the regional network, consisting of five countries. Our empirical results suggest that in the post-2013 period, there was not only an increase in cross-border lending by global banks but also an increase in the influence of the network on banking stability across countries. We also find positive spillover effects when the model is applied to the regional network. However, the empirical results also capture the negative spillover effects that arise during periods of financial distress, such as those during the GFC and the period of the sovereign debt crisis. The dynamic structure of the banking network, coupled with the role Japanese banks have on both global and regional networks, provides crucial insights for policymakers in maintaining (or monitoring) financial stability.

The paper is structured as follows. Section 2 reviews the relevant literature followed by the background and some stylized facts on the international activities of Japanese banks in Section 3. Section 4 provides a network analysis for both global and regional banking. Section 5 describes the model and reports the empirical results, including robustness checks. Section 6 provides a conclusion.

2. Literature Review

The international banking literature has widely explored the role global banks have in transmitting shocks to and across countries. Peek and Rosengren (1997, 2000) show how a shock originating in the Japanese domestic economy during the 1990s was transmitted overseas to the U.S. via the banking system. Using bank-level data, these studies suggest that the liquidity shock of the foreign affiliates of Japanese banks in the U.S. negatively affected real economic activity in the U.S. Furthermore, other studies provide evidence of how global shocks can be transmitted to individual countries. Schnabl (2012) shows how a liquidity shock resulting from the Russian default of 1998 was transmitted to Peru. Using a novel dataset on the interbank market, the study illustrates how the liquidity shock received by international banks led to a decline in lending to Peruvian banks. Consequently, this had a negative impact on credit provision to Peruvian firms. Alegria et al., (2017) document the spillover effect of the global liquidity shock, which emerged following the global financial crisis of 2007-2009, on the Chilean banking system. They show how the tightening of the international lending market led to Chilean banks that had relied on foreign funding to incur higher borrowing rates. Similarly, Aiyar (2012) shows how the global credit supply shock, due to the occurrence of the global financial crisis, had a negative impact on the UK domestic lending market. The contraction in domestic lending to firms and households was higher for banks that were more dependent upon foreign funding. Other studies have shown how the GFC (global shock) that originated in the U.S. was transmitted across countries by banking systems. Cetorelli and Goldberg (2011) study the channels by which global banks transmitted shocks to a number of emerging economies in Asia, Latin America and Europe during 2007-2009. The authors show that cross-border bank lending significantly declined in the region, resulting in a fall in the domestic loan supply in emerging markets.

These studies mainly focus on the role of global banks in transmitting shocks abroad; that is, spillovers to host market(s) arise via either the operations of foreign banks or the reliance of their domestic banks on foreign funding. In this way, the studies indicate the channels through which a financial shock, global or linked to an individual country, would dry up credit provision in the host economy when global banks operate. Kamber and Thoenissen (2013) examine the international transmission of financial shocks in an international real business cycle model. They develop a two-country real business cycle model, the UK and U.S., to analyze the transmission of shocks during the 2007-2009 financial crisis. They find that greater exposure to overseas economies by lending to foreign firms leads to greater spillover effects of foreign financial shocks being transmitted to the home economy. In contrast, Puri et al., (2010), in their study of the spillover of the 2007-2009 crisis to the German lending sector, find that after the onset of the crisis, one of the main German banks, Landsbanken, was directly exposed to subprime assets in the U.S., leading the bank to incur major losses. Puri et al., (2010) find that savings banks that were linked to Landsbanken reduced lending more than other saving banks with no exposure. Cao et al., (2017) show that a liquidity shock can be transmitted to the parent bank via exposure to countries in crisis via cross-border ownership bank linkages, with reference to the European sovereign debt crisis in 2010. Using subsidiary bank-level data to connect banks located in countries experiencing a crisis, such as Greece, Ireland, Italy and Portugal, with banks operating in all other European countries, they find that banks with higher ownership ties to those banks in the countries experiencing a crisis were associated with a lower growth lending rate during the crisis than banks with no exposure.

However, these studies examine shock transmission only via direct exposures and do not consider the characteristics of the wider network created by global banks in which contagions can spread. The financial network literature that studies the effect of network connections on financial stability highlights the role of banks with interlinked balance sheets in generating contagion. Earlier research by Allen and Galle (2000) and Freixas et al., (2000) suggest that the greater the connections formed—up to a complete network—in the interbank market, the more resilient the system is to the propagation of a shock. Neir et al., (2007) extend the model by Allen and Galle (2000) by conducting simulations in a random network. They find a nonmonotonic relationship between connectivity and contagion. Other studies have conducted a network analysis of global banks, analyzing the network characteristics of global banking networks. Minoui and Reyes (2013) use BIS locational data to construct a global network of the interbank market for the 1978-2009 period. They analyze the features of the network and find that connectivity is relatively unstable; it rises before a financial crisis and falls thereafter. A number of studies have analyzed the structure of the global financial market network (Cerutti and Zhou 2017; Chinazzi et al., 2013; Hale, 2012 and Hale et al., 2016)[‡] with reference to the 2007-2009 crisis and found similar results to those of Minoui and Reyes (2013). Cerutti and Zhou (2017; 2018), on the other hand, find that while connectivity through the global banking network declined following the crisis, some parts of the network became more regionally linked. In particular, Cerutti and Zhou (2018) find that the regionalization trend, for which connectivity has increased among noncore banking systems, has been driven by countries such as Australia, Canada, Hong Kong and Singapore. The study finds that the principal determinants of the observed regionalization trend in the global banking network are mainly the retrenchment of European banks and the role of regional factors, such as geographical and cultural factors. Considering these findings, the authors argue that the increased regionalization process may not be a transitional phenomenon. Therefore, the topology of the regional network could be vital to analyze in addition to the global banking network when assessing the vulnerability of cross-border linkages to financial stability. The literature on regional network analysis is very limited. Alves et al., (2013) construct a network of European interbank markets using the aggregate bilateral exposure among 53 large European banks. Peltonen et al., (2015) construct a macronetwork including both country banking linkages and sectorial-level linkages, by which each banking system is linked to the other sectors of the economy, for 14 European countries. However, to the best of our knowledge, there are no studies that construct a regional network that focuses on East Asia.

Another strand of literature on network analyses conducts country-specific studies to analyze financial contagion mainly using simulation techniques to examine the effect of the failure of an individual bank on financial stability. Upper and Warm (2004) study the German interbank market, Furfine (2003) studies the linkages of U.S. banks, Wells (2004) focuses on the UK interbank market, and Imakubo and Soejima (2006) study the Japanese interbank money market. However, these studies are restricted to an individual country and focus on

[‡] Chinazzi et al., (2013) use international portfolio investment flows to analyze the topology of the financial network. Hale (2012) and Hale et al., (2016) use syndicated loans to construct a yearly global network of interbank market, while Cerutti and Zhan (2017) use BIS consolidated data supplemented with bank level data.

country-level financial linkages and, hence, do not consider the contagion that may arise via cross-border banking linkages.

Cihak et al., (2011) study the effect of the international financial connectedness of an individual country's banking sector on domestic financial stability using both simulation and econometric techniques. They construct a global banking network using BIS locational data and estimate the likelihood of a banking crisis in a particular country, taking into account the interconnectedness of the country's banking sector in the network. Both methodologies suggest an "M"-shaped relationship between the interconnectedness of a country's banking sector and financial stability. In this study, the degree of interconnectedness used in the empirical estimations is a centrality measure obtained from the network analysis.

Tonzer (2015) also incorporates the network structure to study whether cross-border linkages facilitate spillovers within a network consisting of 18 country-level banking systems. The study uses a spatial econometric technique, including a spatial interaction term, to analyze the spillovers of instability of interconnected banking systems using confidential BIS locational data. The results suggest that there is a positive spillover effect for banking systems that are connected via cross-border linkages with countries that have stable banking systems, and vice versa. Therefore, the bilateral positions of cross-border linkages at the country level are an important indicator of financial stability.

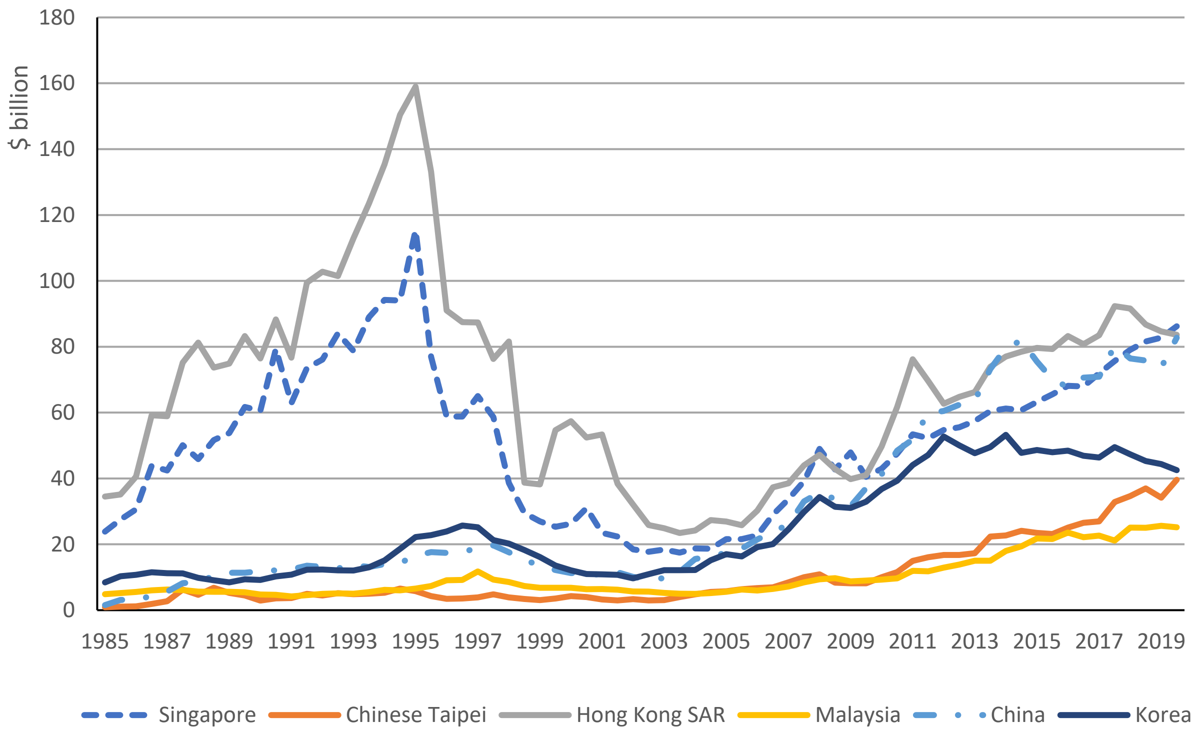
We build on these papers to provide empirical evidence of the role of the global banking network on the stability of the banking sectors within the network. The originality of our research stems mainly from three aspects. First, the empirical model we employ, to the best of our knowledge, has not been used in international banking to analyze network spillover effects. Second, we capture the prominent and increasing role of Japanese banks in the global banking network in providing liquidity. Third, we provide empirical evidence of the existence of an East Asian regional network and assess the role Japanese banks play.

3. Japanese banks international expansion background

During the 1980s, Japanese banks were among the largest in the world and dominated the international lending market. While their overseas activities were dispersed globally, such as in Southeast Asia, Latin America and Europe, their dominant presence was in the U.S. (Peek and Rosengren 1999). However, following the country's stock market crash in the early 1990s, Japanese banks faced major financial problems that reduced their ability to maintain their leading role in international markets. Indeed, Japanese banks had to withdraw from their international activities and significantly reduce their presence in the U.S. market. The implications of the substantial decline in loan provision activities of Japanese banks were far-reaching for the U.S. credit market and the real economy (Peek and Rosengren, 1997, 2000).

In the aftermath of the financial crisis that hit the Japanese economy and subsequently its banking sector, the country's main banks ceased their U.S. activities but expanded in the Asian market. Given the booming economic conditions in Asia during the mid-1990s, Japanese banks sought an opportunity that could help them revive their financial positions. However, in a dramatic turn of events, the Asian crisis in 1997 proved to be detrimental to the health of Japanese banks. These trends are evident in Figure 3.1, which shows the foreign claims of Japanese banks in a number of selected Asian countries. Hong Kong and Singapore were the largest countries in which Japanese banks had lent during the 1990s. Faced with an increasing number of nonperforming loans in the Asian market, Japanese banks had to again cease their international operations and return to the domestic market.

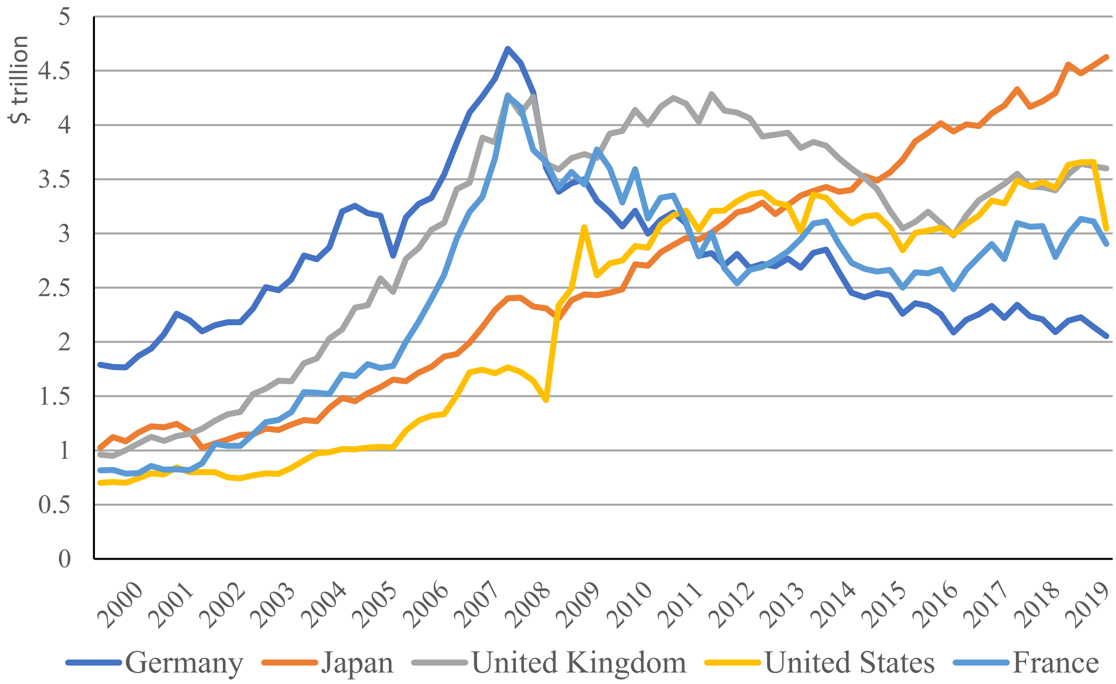
Figure 3.1: Japanese banks' cross-border exposure to selected Asian countries



Source: BIS Consolidated Banking Statistics

Following the retrenchment from foreign activities (markets) in the aftermath of the crisis, Japanese banks, which had become largely domestically oriented, had fully recovered by the mid-2000s. Moreover, financial health had improved considerably, so much so that during the GFC, it was the Japanese banks that came to the rescue of some of the world's largest banks (Shabani et al., 2016; IMF 2015). While the Japanese economy was indeed hit by the financial crisis of 2007-2009, mainly via exports, its banking sector proved to be resilient. In what followed, Japanese banks then revived their overall international position. Indeed, as seen from Figure 3.2, cross-border lending continued to grow, while other countries, such as the United Kingdom, France, the United States and Germany, reduced their lending, reflecting the aftermath of the crisis. In relation to regional activities, Japanese banks also increased their claims toward most Asian countries, such as Hong Kong, China and Singapore, as is evident in Figure 3.1.

Figure 3.2: Cross-border claims against all counterparties



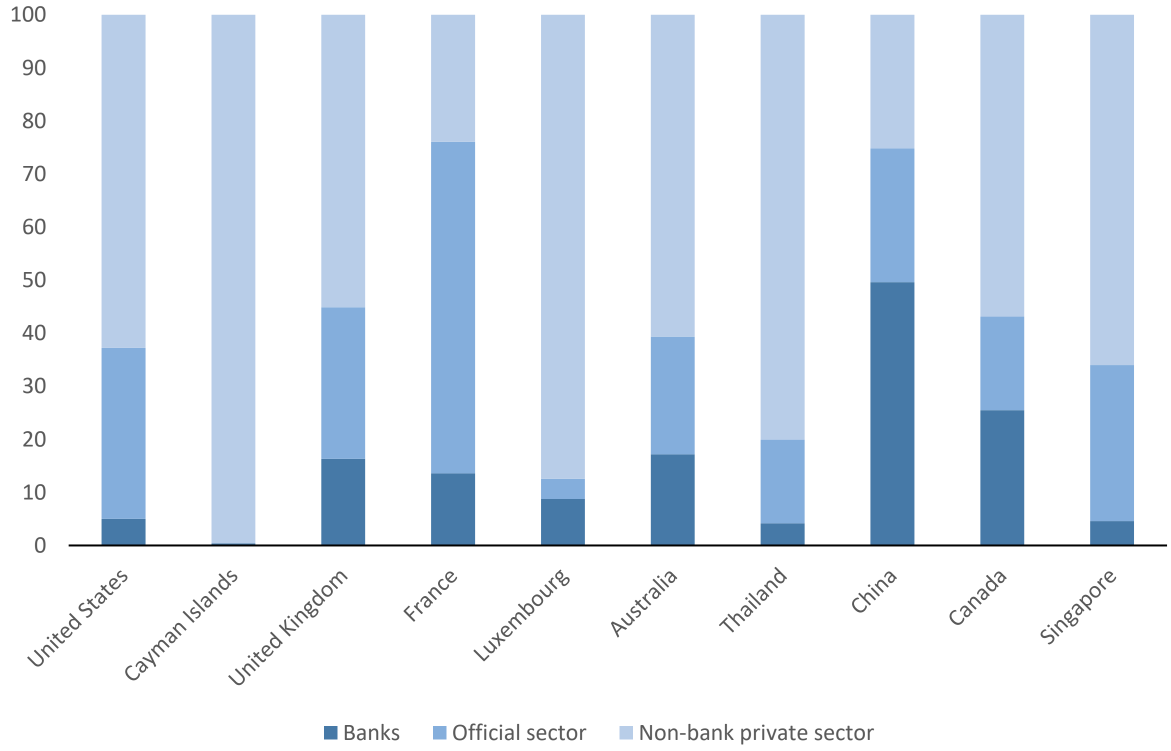
Source: BIS Consolidated Banking Statistics

Figure 3.3 shows the countries and sectors for which Japanese banks have the largest cross-border exposure, at the end of 2019. The U.S. remains the largest recipient of foreign claims of Japanese banks at a global level, with a total of $1.8 trillion. Approximately 62% of foreign claims are against the nonbank private sector, including nonbank financial institutions, households and nonfinancial corporations. However, positions with nonbank financial institutions account for approximately 25% of total foreign claims. In contrast, while Japanese banks also appear to have large claims, to the size of $618 billion, toward the Cayman Islands, more than 99% of the claims are against the nonbank private sector, including nonbank financial institutions[§]. Other countries that Japan holds claims against include some of the main European countries, including France, the UK, and Luxembourg, as well as Asian countries, such as China, Singapore, and Thailand. Furthermore, Canada and Australia both appear to be in the top 10 countries for which Japanese banks have sizable cross-border claims. Figure 3.3 also reveals that, overall, most of the Japanese cross-border

[§] Aldasoro et al.,(2020) suggest that the large claims that Japanese banks have toward the offshore nonbanking sector could reflect the banks' holdings of structured assets, namely, Collateral Loan Obligations (CLOs). According to FSA (2019) Japanese banks holdings of CLOs amounted to $107 billion, as of the end of 2018.

claims are held toward the nonbank private sector, with the exception of China, where the banking sector is the largest recipient sector.

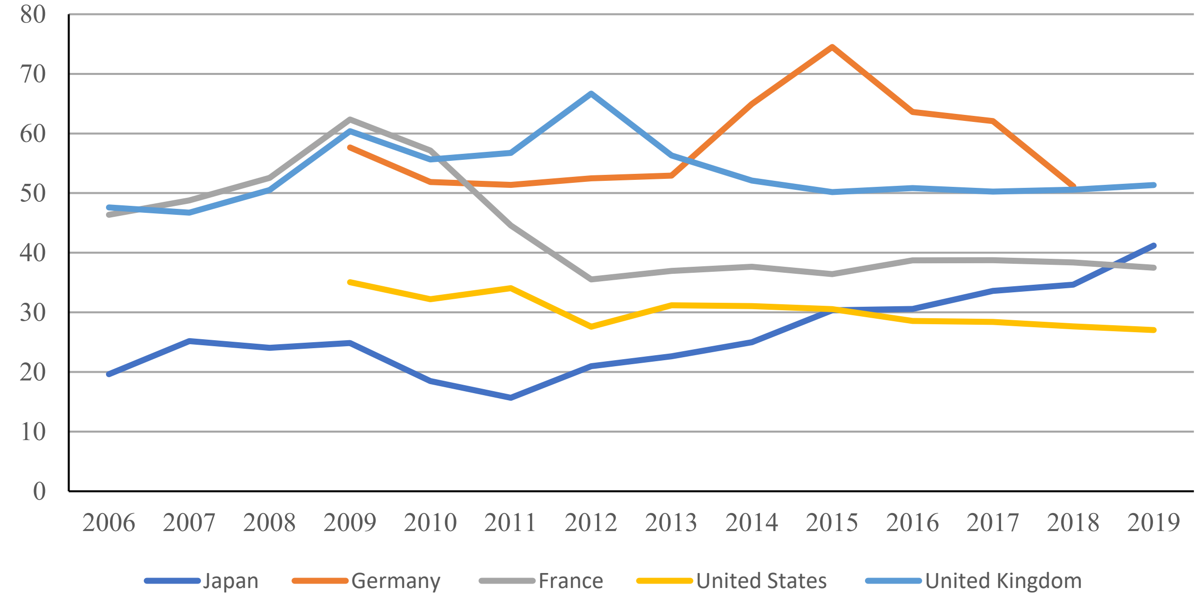
Figure 3.3 Consolidated foreign claims of Japanese banks, against counterparty country and sector, 2019.



Source: Authors' own calculations based on data from BIS, Consolidated Banking Statistic, Ultimate risk basis. Notes: Foreign claims are presented as a percentage of each sector to the total foreign claims. The figure includes the top 10 countries that have received the largest amount of cross-border lending from Japanese banks.

The international expansion of Japanese banks is also reflected in the revenue generated by these activities in proportion to the total revenue activities. Figure 3.4 depicts an increase in the overseas revenue generated by the country's largest three banks, namely, Mitsubishi UFJ, Mizuho and Sumitomo Mitsui. In addition to their resilience during the GFC and hence their strong financial position, other domestic factors may explain the surge of overseas activities by Japanese banks. Indeed, the lack of domestic growth opportunities (Lam 2013) coupled with the quantitative easing measures undertaken by the Bank of Japan, whereby lowering long-term interest rates and flattening the yield curve, gave banks more incentive to search for yield abroad. Another proposed argument in the literature is the retrenchment of European banks (Lam 2013, Cerutti and Zhou 2018), particularly from Asia, further adding to the incentives of Japanese banks to increase cross-border lending, especially in the region. The retrenchment of European banks is also captured in Figure 3.4, which shows that the share of overseas revenue declines in the aftermath of the 2009 financial crisis and the later European Sovereign Debt crisis.

Figure 3.4 Overseas revenue as a percentage of total revenue for main banks in selected countries



Source: Bloomberg, Authors' own calculations.
Notes: The share of overseas revenue to total revenue is calculated by using bank-level data for the largest banks in each country. For Japan, data for Mizuho, Mitsubishi and Sumitomo banks are used to construct the total overseas revenue generated by these banks to total revenue. Figures for 2006 represent data for only Mitsubishi and Sumitomo banks, as there are no data available for Mizuho bank. For Germany, due to data availability, only Commerzbank and Deutsche Bank are used in the calculations. Data for both banks are available only from 2009 to 2018. For France, data represent the revenue reported by Societe Generale, BNP Paribas and Credit Agricole. Data for Credit Agricole for 2009 are not available. For the United States, data on Bank of America, Citigroup and JPMorgan Chase are obtained and available from 2009. For the calculations of the United Kingdom, the share of overseas revenue data on Barclays, HSBC and Natwest Group were used. The figure for 2009 represents data for Barclays and HSBC only.

4. Network analysis

4.1 Data

Network representation of the international banking system requires cross-border bilateral claims that banking entities have on each other. While the scarcity of data that tracks the foreign activities of large global banks is well documented in the literature (see, for example, Cerutti et al., 2011; Hale et al., 2016), the BIS International Banking Statistics reports cross-border bilateral exposure for BIS reporting banks on an aggregate country basis. The BIS compiles and reports these data on both a locational and consolidated basis.

The Consolidated Banking Statistics (CBS) report consolidates gross foreign claims of global banks headquartered in 31 reporting BIS countries. Global banks can make cross-border loans directly via their headquarters in the home country, or they can set up deposits taking foreign affiliates in the form of subsidiaries or branches in various host countries across the globe. Therefore, foreign claims reported in the CBS consist of cross-border claims on unaffiliated foreigners (via headquarters) and local claims of foreign affiliates on borrowers in the country where the affiliate resides. The CBSs are published on an immediate borrower basis and an ultimate risk basis. The former identifies the location of the immediate counterparty, whereas the latter records where the ultimate risk lies in the instance that it does not rest with the immediate counterparty. For example, claims of a UK bank that are guaranteed by a Japanese bank are recorded as claims against the Japanese banks.

The Locational Banking Statistics (LBS), on the other hand, report cross-border claims of global banks on a residence basis. The dataset captures cross-border assets and liabilities of banks located in 47 reporting BIS countries vis-a-vis counterparties in more than 200 recipient countries. Indeed, data are recorded based on the residency of a reporting bank corresponding to the national accounts and balance of payment methodology[**]. In this way, the external positions of banking systems are unconsolidated, and hence, the intergroup positions are not netted out as in the CBS.

Both the CBS and LBS datasets are presented on an aggregate country level rather than at the individual bank level. Therefore, by "banking system", we refer to the cross-border positions, both asset and liabilities, of individual banks that are part of the banking system of the reporting country. However, the different methodologies used to collect both datasets can indeed help clarify what is meant by a "banking system." For example, the LBS records the bilateral cross-border lending of banks located in a BIS-reported country regardless of banks' nationality[††], in which case lending by a Japanese bank's subsidiary in New York would be included in the position of banks in the United States. Therefore, the LBS will include the positions of all banks that operate in the United States and hence are part of the U.S. banking system. However, in the CBS, the lending of the same Japanese affiliate located in New York will be consolidated and reported by the country where the parent entity is located and hence will be part of the Japanese banking system.

For our paper, the CBS dataset is more suitable mainly for two reasons. First, the CBS captures the exposure of global Japanese banks on a worldwide consolidated basis[‡‡], and, therefore, we can gauge the bilateral linkages created by the Japanese banking system. The

[**] For a more detail overview of the differences between the consolidated and locational banking statistics see McGuire and Tarashev (2008) and Avdjiev et al., (2015).
[††] The LBS do not provide information on the bilateral cross-border positions by nationality of reporting banks.
[‡‡] Although the intragroup position of banks are netted out, the data does include those of foreign subsidiaries, the majority of which or wholly owned (Avdjiev and Wooldridge, 2018).

dataset not only provides information on the foreign activities of Japanese banks,, which allows us to capture the exposure of the banking system to individual countries, but also the sectorial exposure, such as the public sector, banks and nonbanks, in that country. The foreign activities of Japanese banks, and thereby their foreign exposure, can have important implications for financial stability in the event of shocks being transmitted from foreign countries. Second, in an attempt to understand the drivers of bilateral linkages created by Japanese banks, data by bank nationality are needed given that key decisions are usually centralized at the headquarters level (Fender and McGuire 2010). Indeed, Schnabel (2012) illustrates the decisive role played by parent affiliates (i.e., headquarters) of foreign banks located in Peru during the 1998 Russian crisis.

4.2 Network Description

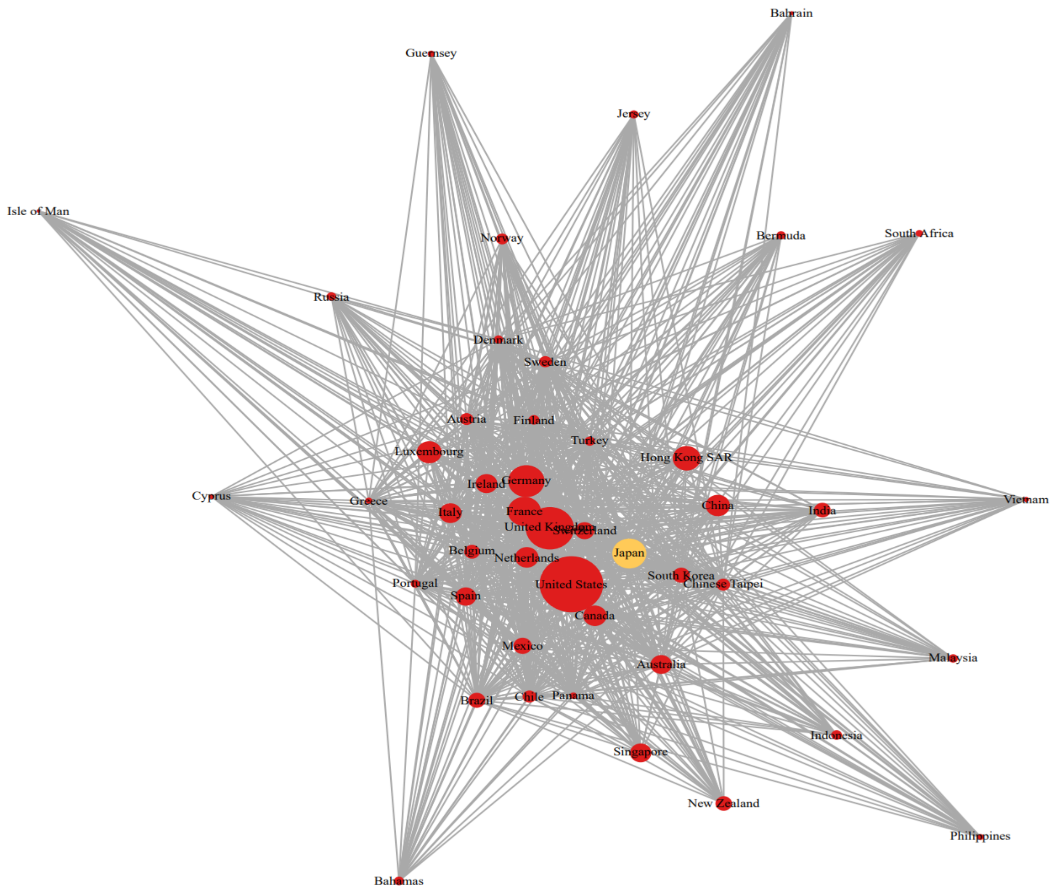
The intricate structure of cross-border linkages between banking systems can be best formalized using network analysis. We construct a global banking network for each quarter from the first quarter of 2006 to the fourth quarter of 2017. Each node in the graph represents the countries' banking system, with the edges of the network representing the cross-border lending and borrowing activities of their banking systems. In this way, the analysis is able to capture the cross-border exposure each banking system (node) has toward other banking systems included in the sample. An important feature of the network is the location of the nodes within the network. That is, the positions of the nodes relative to each other are determined by the weighted exposure to one another; hence, nodes that are plotted closer together have greater exposure to one another.

To best capture the position and prominence of nodes in the network, we use the total degree (also known as the Freeman degree) and eigenvector centrality (often referred to as the prestige score). The total degree counts the number of edges that connect to a particular node; therefore, it measures the connectivity of a given node within the network. However, because it only counts the direct connections it has with other nodes, the total degree measure best captures local importance (Allen et al., 2020; Zhou et al., 2017). In contrast, Eigenvector centrality can be used to capture the importance of a node throughout the network by assigning higher scores to those nodes that are connected to other important nodes in the network. Therefore, the importance of a node is determined by the importance of the nodes it has direct ties with. This, on the other hand, would suggest that a banking system that is well connected with another important banking system would be more vulnerable to the transmission of negative shocks. A high eigenvector centrality score is indicative of a "financial hub" and supports the concept of global core membership in the financial network (von Peter, 2007 and Minoiu and Reyes 2013).

Figure 4.1 offers a visual representation of the global banking network for the fourth quarter of 2017, consisting of 47 countries. This includes both BIS reporting and nonreporting countries[§§], which by way of construction identifies a core-periphery network structure (Cerutti and Zhou, 2018). A core-periphery banking network structure displays a central dense cluster surrounded by less connected nodes. Minoiu and Reyes (2013) argue that a great deal of instability within the network arises from the connections made to the highly concentrated and greatly exposed areas of the network[***].

[§§] Table 1A in the Appendix provides the list of countries included, which consists of 31 reporting countries and 16 nonreporting countries. It is worth noting that bilateral data can only be formed for BIS-reporting countries, which better captures the borrower/lender relationship/exposure of their representative banking system. However, this is not possible for nonreporting countries due to data limitation and hence the relationship is restricted to only the borrower counterparty in empirical analyses.

Figure 4.1: Network representation of the borrowing and lending of the banking systems of 47 countries.



Notes: The network is a representation of the cross-border lending and borrowing of 47 banking systems' countries for 2017 Q4. The nodes indicate the eigenvector centrality score that each banking system holds.

Countries that depict a higher degree of centrality are France, Spain, Switzerland, the UK and the U.S. at a value of 70 based on a Freeman degree, followed by Belgium, Denmark and Japan at a value of 69. Therefore, their banking systems are connected to approximately 34-35 other banking systems in the network sample via cross-border financial claims. The eigenvector centrality measure indicates that the U.S., UK, Germany and Japan are the most influential banking systems in the network. The prominent role of the U.S. reflects the exposure of its banking system to European countries, which are part of the core network. Japan, on the other hand, seems to be more exposed (connected) not only to core countries but also to noncore and offshore centers such as Bahrain, Hong Kong, Singapore and Panama. This can be observed from the visual depiction in Figure 4.1, as well as by the argument put forward in Section 2. Both measures discussed so far suggest that countries such as Japan, the U.S., Switzerland, the UK and other European countries such as France, Spain and Denmark fit well with the definition of "financial hub" proposed by von Peter (2007). Indeed, a banking hub is exposed to many other nodes, including other hubs, and will likely facilitate the distribution of liquidity across the network (von Peter, 2007). Furthermore, a banking hub may serve as an intermediary in the network by connecting nodes that are not directly connected.

Looking at the network over time, Table 1 reports snapshots of the ranking of countries that depict higher degrees of centrality for three different years, 2006, 2009 and 2013. Countries that seem to have maintained their influential position over time, are the U.S., the U.K., Germany, and France. It is notable that in both 2009 and 2013, Japan depicts a higher eigenvector degree centrality reflecting the increasing role of Japanese banks in the network over time.

Table 1: Top 10 countries by eigenvector centrality for selected years

2006		2009		2013	
Country	**Eigenvector Centrality**	**Country**	**Eigenvector Centrality**	**Country**	**Eigenvector Centrality**
United States	0.706	United States	0.692	United States	0.720
United Kingdom	0.550	United Kingdom	0.520	United Kingdom	0.507
Germany	0.218	Germany	0.262	Germany	0.234
France	0.173	France	0.185	France	0.198
Netherlands	0.127	Spain	0.150	Japan	0.155
Spain	0.125	Japan	0.145	Netherlands	0.131
Italy	0.125	Italy	0.135	Hong Kong SAR	0.120
Japan	0.099	Ireland	0.131	Spain	0.094
Ireland	0.098	Netherlands	0.120	Italy	0.092
Mexico	0.092	Canada	0.087	Luxembourg	0.086

Notes: The eigenvector centrality measure used in this table captures the importance of a country throughout the network by assigning higher scores to those banking systems that are connected to other important banking systems in the network.

The intermediary role of banking systems, which act as a bridge between unconnected banking systems via the shortest path, can be best captured by the betweenness measure. Higher values denote a greater scope for intermediation. Countries including France, Spain, Switzerland, the U.S. and the UK are associated with the highest betweenness score of 11.68. This is followed by Japan, scoring 10.01. The high ranking of the European countries is intuitive given their regional position. The finding on Japan, however, suggests that the country's banking system could indeed act as an intermediary in channeling funds between the core of the network and the East Asian region. This is also supported by the visual depiction of the network representation, Figure 4.1, in which Japan is clearly located between the East Asian region and the core members of the network.

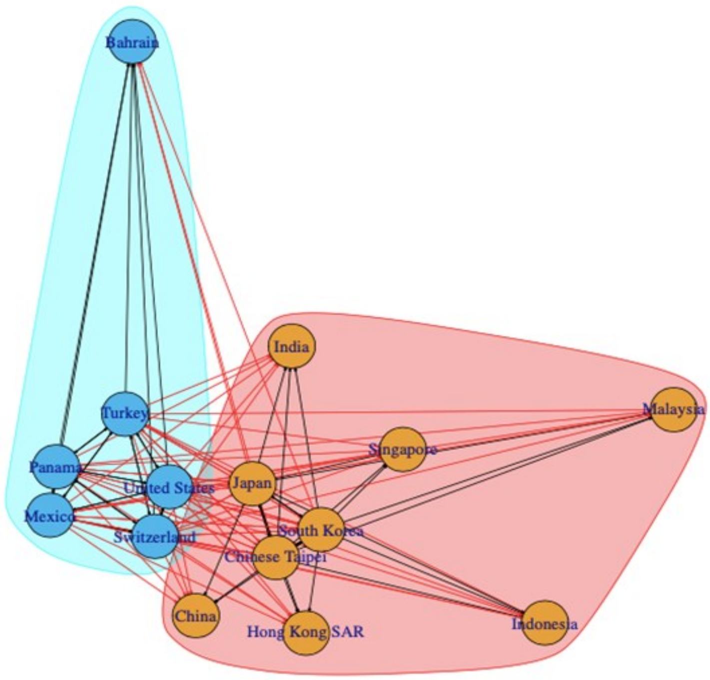
In addition, we also estimate the PageRank measure for the nodes in the network. This is a derivative of the eigenvector centrality measure, which takes into account the number of connections a node has as well as the prestige of the nodes to which it is connected. This produces a rankable measure, allowing the identification of the most important banking systems in the network (Korniyenko *et al*., 2018). The results of the ranking, presented in Table 1B in Appendix 1, reveal Japan to be the fifth most influential banking system in the global network as well as indicating that Japanese banks are strongly connected via cross border claim to other major financial centers. The findings are similar when the Integrated Value of Influence (IVI) measure is employed to capture the relative importance of each banking system in the global network. As discussed in Salavaty et al., (2020), the IVI algorithmic approach uses a combination of six network measures, including those already discussed above, to form a holistic view of a county's position and importance in the network. Table 1B in Appendix 1 also provides the results of the IVI method which reinforces the findings of Japanese banks playing a significant role in the global banking network. A further point to our analysis is the detection of communities in the constructed global banking network. Community, as well as the measures of centrality analyzed above, are indeed the most important components of network structure put forward in the literature (see Allen et al., 2020). Furthermore, from a financial stability perspective, it is necessary to examine communities within the network, as their increased density can be reflective of a concentrated pocket of systematic risk (Allen and Babus, 2009; Minoiu and Reyes, 2013, Garratt et al., 2011).

To achieve this, we run a community detection process[†††], in which a cluster is a group of nodes with strong financial claims against each other compared to claims to other parts of the network. We employ the Spinglass community detection process using a semi-supervised method to partition the graph by accounting for how potential clusters interact with adjacent clusters. Here the aim is to minimize edge betweenness between communities rather than splitting the graph into a predetermined number of clusters. (See Appendix 1 for a more detail on the detection process)

[†††] Cluster and communities are used interchangeably in this paper.

We detect six communities within our global banking network as of the last quarter of 2017, as shown in Figure 1A in the Appendix. Figure 4.2 illustrates the countries that are located in Community A, which includes core banking systems such as those of Japan, Switzerland and the U.S. as well as offshore centers such as Bahrain and Panama, together with a number of East Asian countries. Given the diverse nature and relatively large number of banking systems that are located within this cluster, 15 in total, the community might have a modular structure of its own. That is, a large cluster may contain several smaller clusters, and hence, we can identify those banking systems that are more connected via cross-border linkages within the same community.

Figure 4.2: Graphical representation of Community A



Notes: The above graph is a representation of cross-border claims of the banking systems that fall within Community A. The two shaded areas represent the two subcommunities detected using the Spinglass algorithm.

The results suggest that there are two subclusters in Community A, as illustrated by the two shaded clusters in Figure 4.2. Countries such as the U.S., Switzerland, Bahrain, Panama, Mexico and Turkey are located in the same subcluster, indicated by the blue-shaded node. Japan, India, Indonesia, Malaysia, Singapore, South Korea, Chinese Taipei, Hong Kong SAR and China are located in the same subcluster, denoted by the red-shaded area.

These findings are rather intuitive, in which regional factors are evident, especially in the case of Japan being most connected with and hence exposed to other East Asian countries. Therefore, this observation reinforces our argument derived from the visual depiction of the global network shown in Figure 4.1, which hints at the presence of a regional geographic community.

The estimated results support the regionalization argument put forward in the literature for which borrowing and lending relationships within the same region, especially toward noncore banking systems, have increased since the 2007-2009 financial crisis (Cerruti and Zhou (2017), IMF (2015)). In particular, our findings suggest that Japan, a core member of the global network, also has a prominent role within the regional banking network. Indeed, Japanese banks' overseas expansion, as measured here by the outstanding cross-border financial claims, is associated with the increase in regional interlinkages within the identified East Asian subcluster.

5. Empirical Analysis

5.1 The model

The global network created by means of banking systems forming international lending and borrowing relationships with each other could facilitate the transmission of shocks through the network. Indeed, given the intertwined nature of network creation, banking systems can be prone to both direct and indirect (stability spillover) effects. The banking stability of a country could therefore be threatened by the international exposure of its banking system via cross-border claims or by factors that affect the stability of the banking systems within the network rather than domestic fundamentals.

One of the most popular econometric models for network analysis that allows the capture of direct and indirect effects of financial spillovers is the spatial autoregressive (SAR) model (LeSage and Pace, 2009). Suppose we analyze some economic variables in a network of n countries over time $t = 1, \dots, T$. Define $\boldsymbol{y}_t$ as a $n \times 1$ vector of the dependent variable for n countries and $\boldsymbol{W}_t$ as a $n \times n$ weighting matrix. Then, a standard SAR model is formulated as

$$\boldsymbol{y}_t = \rho \boldsymbol{W}_t y_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\boldsymbol{X}_t$ is a $n \times k$ matrix of explanatory variables, $\boldsymbol{\beta}$ is a $k \times 1$ vector of coefficients, and $\boldsymbol{\varepsilon}_t$ is a $k \times 1$ vector of disturbances. We assume each of the disturbances $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{nt})'$ follows a normal distribution, $\varepsilon_{it} \sim N(0, \sigma^2)$, with a mutual independence between ε_{it} and

ε_{jt}, for simplicity. Then, equation (1) leads to the following formulation of the dependent variable for the i-th country:

$$y_{it} = \rho \boldsymbol{w}_{it} \boldsymbol{y}_t + \boldsymbol{x}_{it} \boldsymbol{\beta} + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma^2), \tag{2}$$

where $\boldsymbol{w}_{it}$ and $\boldsymbol{x}_{it}$ are the i-th row of $\boldsymbol{W}_t$ and $\boldsymbol{X}_t$, respectively.

In our analysis, y_{it} is a measure of banking stability proxied by the Z-score of country i at time t. For the weighting matrix, $\boldsymbol{W}_t$, the rows of the weighting matrix represent the outstanding cross-border claims of country i to country j at time t, and the columns represent the outstanding cross-border claims of country j on country i. $\boldsymbol{W}_t$ is row-normalized and hence measures the relative weight of cross-border claims between country i and j at time t. For the explanatory variable $\boldsymbol{X}_t$, to take into account a decline in the Z-score for most of the countries at the time of GFC, we use a GFC dummy variable that takes one at the fourth quarter in 2008 and zero for other periods.

The key parameter in the SAR model is the spatial parameter, denoted by ρ in equations (1) and (2). If $\rho \neq 0$, the network, the weighting matrix $\boldsymbol{W}_t$ affects the dependent variable $\boldsymbol{y}_t$. Therefore, a positive sign of ρ would reflect the stability of the banking system being positively related to the stability of the countries connected via cross-border linkages. The value of ρ reflects the degree of spatial dependence in banking stability across countries.

Given the dynamic structure of the global banking network, we extend the SAR model to a time-varying SAR model by allowing the spatial parameter ρ to vary over time:

$$\boldsymbol{y}_t = \rho_t \boldsymbol{W}_t \boldsymbol{y}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t, \tag{3}$$

where ρ_t follows the random-walk process:

$$\rho_{t+1} = \rho_t + \eta_t, \quad \eta_t \sim N(0, v^2). \tag{4}$$

The time-varying spatial parameter ρ_t measures the degree of influence of the network on the dependent variable $\boldsymbol{y}_t$. In the standard SAR model, nonzero ρ means that the network affects the dependent variable, and the increase in the weight on a specific country (say, Japan) over time implies that the country has a more key role in the international banking network, which affects the dependent variable more than in the past. Furthermore, if the time-varying version of the spatial parameter, ρ_t, has been increasing over time, it indicates that the influence of the network has generally become stronger; therefore, the country's role has become even more relevant. In other words, we can divide the increase in the country's role in the network into two factors: (i) the increase in the weighing matrix, and (ii) the increase in the influence of the network matrix in general (for all entities in the network), measured by changes in (i) the composition of the weighting matrix $\boldsymbol{W}_t$, and (ii) the time-varying coefficient ρ_t.

The standard SAR model is usually estimated by the maximum likelihood (ML) method or instrument variable (IV) method. However, the latent variables in the time-varying SAR model are high dimensional, which makes the use of ML and IV methods challenging. Therefore, we take a Bayesian estimation approach. The Bayesian approach for the standard SAR model is developed in, e.g., LeSage and Pace (2009) and Ohtsuka et al., (2010). We extend it for the time-varying SAR model (see Appendix 2 for a detail on the estimation method).

5.2 Results of the global banking network

As a first step in the analysis, we estimate (1) the standard (non-time-varying) SAR model. The model is estimated using sample data from 2006 Q1 to 2017 Q4. As discussed in section 3, W_t is a $n \times n$ matrix constructed using BIS consolidated banking statistics. Due to data limitations, we can only include 22 countries when estimating the model. The countries included in the analysis are Australia, Austria, Belgium, Brazil, Chile, Denmark, France, Germany, Greece, Ireland, Italy, Japan, Mexico, the Netherlands, Panama, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States. The dependent variable, y_{it}, is the bank Z-score, obtained from the Global Financial Development Database[‡‡‡], available from the World Bank. The bank Z-score variable measures the riskiness of a country's banking system, for which higher values indicate that the banking system is farther away from default.

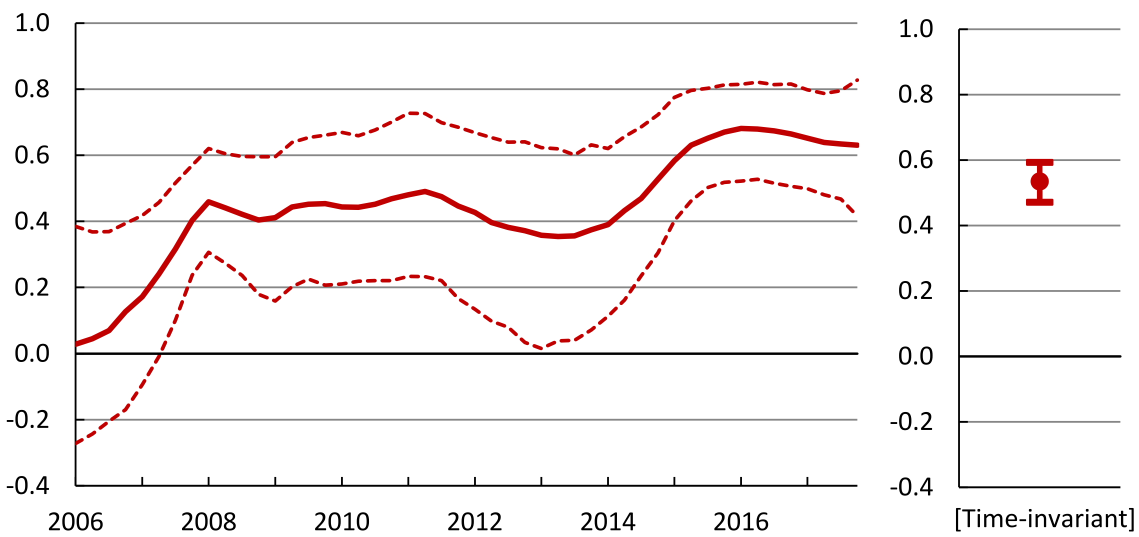
We first estimate the standard version of the SAR model described by equation (1). The estimated spatial parameter (ρ) is 0.535 with a 95% interval (0.471, 0.593). The statistically significant parameter indicates that banking stability across countries in the network is spatially dependent. That is, the value and sign of (ρ) is an indication of whether there is an amplification (a negative ρ) or stabilization (a positive ρ) effect on banking stability occurring in the event of a shock in the network. Hence, the stability of a banking system is positively related to the stability of the banking systems connected via cross-border claims

‡‡‡ Because the data are only available on an annual basis, the Z-score variable is linearly interpolated for the baseline model using quarterly series.

Next, we estimate the time-varying SAR model defined by equations (2) and (3). Figure 5.1 reports the results of the time-varying spatial parameter (ρ_t). The solid line indicates the mean estimate, and the dashed lines indicate the 95% interval. The figure also reports the estimated time-invariant spatial parameter from the standard SAR model for comparison. The estimated time-varying spatial correlation has increased over time and captures both the GFC and the European Sovereign Debt crisis. Indeed, the spatial parameter increased in the 2006 to 2008 period, then exhibited a relatively stable trend, and again increased around the 2015 to 2017 period. This finding points to relevant changes in spatial dependence in banking stability across countries over time. Indeed, a lower spatial parameter (ρ_t), evident during the financial crisis, is associated with a higher degree of instability (riskiness) of those banking systems that are connected via cross-border claims. In the post-2013 period, we observe that not only has there been an increase in the cross-border lending of international banks, associated with an increase in the weighing matrix, $W_{i,t}$, but also the influence of the network on banking stability (more prone to positive spillovers banking systems are) across countries has increased.

We conduct a formal statistical test to assess whether the spatial parameter in the first quarter of 2006 is different from the one in the fourth quarter of 2017. The test result indicates that the difference is statistically significant at five percent significance level, which proves that the time-varying parameter changed significantly.

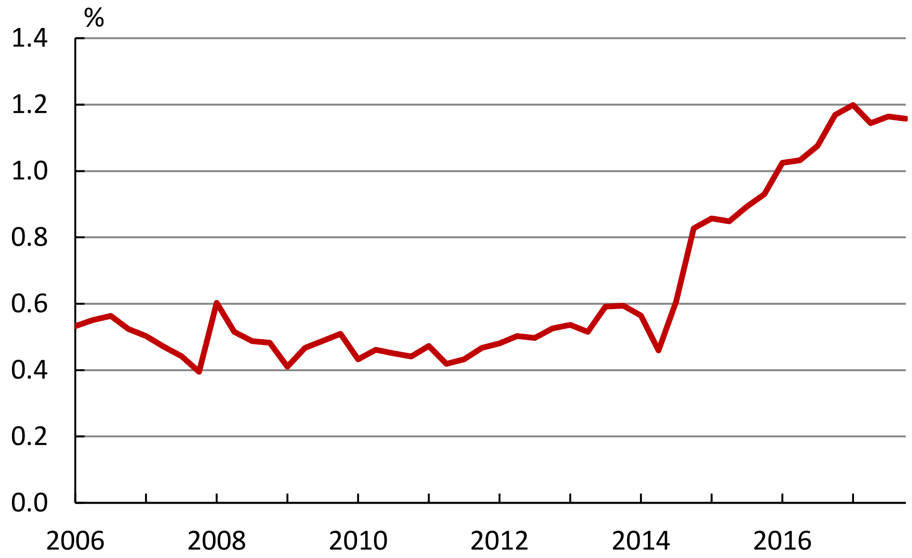
Figure 5.1: The estimated time-varying spatial parameter (ρ_t, left) in the time-varying SAR model and the time-invariant spatial parameter (ρ, right) in the standard SAR model for the quarterly series



Notes: The solid line and the diamond are mean estimates, and the dashed lines and bars are 95% intervals.

Furthermore, focusing on Japan's contribution in the network to banking stability, Figure 5.2 shows the sum of weights that Japan contributes to the other countries in the weighting matrix $W_{i,t}$. It is evident that the contribution slightly increases after the GFC and clearly hikes after 2014. As noted above, Japan's role in the network can be divided into two factors.[§§§] This finding indicates both increases in the weighting matrix and the influence of the network matrix measured by the time-varying spatial coefficient for Japan's increasing role in the network.

Figure 5.2: The sum of weights that Japan contributes to other countries in the weighting matrix.



5.3 Results of regional network

In this section, we present the results of the SAR models using a weighting matrix that represents the exposure of the regional (community) network identified in Section 3. In doing so, we attempt to capture any effects (spillover) on stability that could arise from such exposure. In other words, W_{it} here represents the outstanding cross-border claims of countries located in the regional network. We focus on the East Asian subcluster of Community A, and due to data limitations, the weighting matrix W_{it} captures only the claims of five East Asian countries, namely, Japan, Hong Kong, Korea, Singapore and

[§§§] Japan's contribution rises from 0.5% to approximately 1.2%. The 1.2% seems to be low, but the dataset includes 22 countries, which makes the number lower than the intuition. Indeed, the contribution increases more than doubly, which is important in this finding.

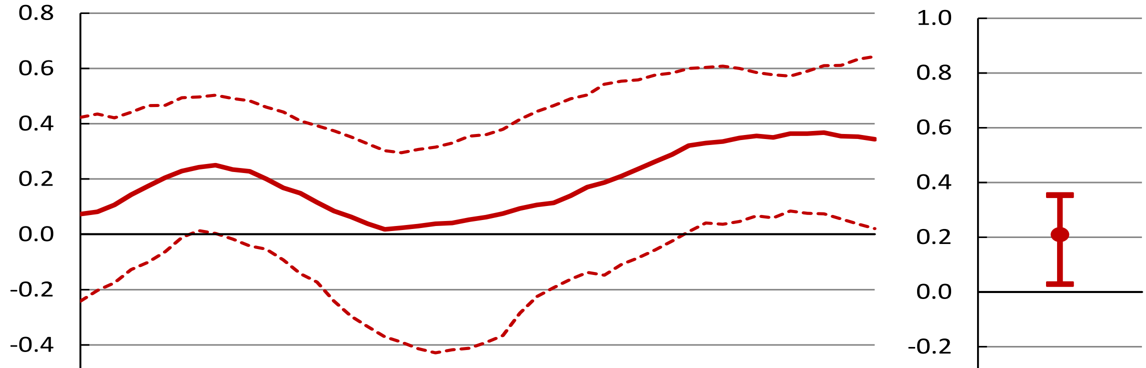
Chinese Taipei. Furthermore, data on cross-border claims used to construct the row standardized matrix, W_{it}, for the five countries are not complete, as reported in the BIS database. To construct a bilateral claims matrix for those quarters in which we have missing values, we use the mean of other nonmissing values in the same column in the matrix.

The estimated spatial parameter in the standard (time-invariant) SAR model using quarterly series is 0.210 with 95% intervals (0.029, 0.354), which indicates that the spatial parameter (ρ) is significant and positive for the regional network. This implies the positive stabilization effect the regional network has on banking stability across the region. However, the result of the time-invariant model suggests that the degree of spatial dependence is, on average, less in the case of the regional network.

When looking at the results of the time-varying estimates reported in Figure 5.3, it is evident that the spatial correlation (ρ_t) varies significantly over time. The degree of spatial dependence reflects the financial crisis during the period 2008 to 2009, for which banking instability in the region increased during this period. Notably, the spatial parameter increased until 2008 and then decreased until approximately 2011. However, thereafter, the spatial parameter increased significantly, with the trend becoming more pronounced, as depicted in the left panel of Figure 5.3.

The results confirm the argument put forward in this paper by providing empirical evidence not only of the increased regional interlinkages but also of the spatial effect these have on banking stability. The results suggest an overall positive spillover effect on banking stability, but they also capture the dynamics of the banking network. That is, during financial distress, such as the time period associated with the GFC and the sovereign debt crisis, the spillovers could have the reverse (and hence negative) feedback on home banking stability. Moreover, the increasing exposure and the influence of the regional network on Japanese banks could be an important aspect for policymakers. That is, regulatory policies and risk monitoring should take into account the increasing exposure and role of Japanese banks not only as leading global liquidity providers but also due to the crucial role they play in the region.

Figure 5.3: The estimated time-varying spatial parameter (ρ_t, left) in the time-varying SAR model and the time-invariant spatial parameter (ρ, right) in the standard SAR model for the regional network.



Notes: The solid line and the dot are mean estimates, and the dashed lines and bars are 95% intervals.

5.4. Robustness

In this section, we present the results of two robustness tests for the global banking network analysis[****]. We exclude Panama from the original dataset, which is an offshore financial center, as identified by the IMF (2000). Offshore financial centers are those in which financial services are mainly conducted vis-à-vis nonresident, i.e., borrowing and lending to nonresidents. The services offered by offshore centers are favorable given low or zero taxation (IMF, 2000). For this reason, in the first robustness test, we exclude Panama and estimate the model using the first quarterly series. The second robustness test examines an estimation using annual series to compare its result with the baseline estimation in which we use quarterly series with the originally annual series of Z-scores linearly interpolated[††††]. We estimate the annual model for both datasets, including and excluding Panama.

The results of the spatial correlation using quarterly series are presented in Figure 5.4 As evident, the spatial parameter ρ_t is statistically significant and positive in all specifications. Furthermore, the findings are in line with the results above, for which the degree of spatial dependence remains nearly within the same range. Looking at the estimated degree of spatial parameter ρ_t, it is evident that the role played by Panama in the network is rather minor.

[****] Hence, the robustness tests are based on a network consisting only 21 countries.

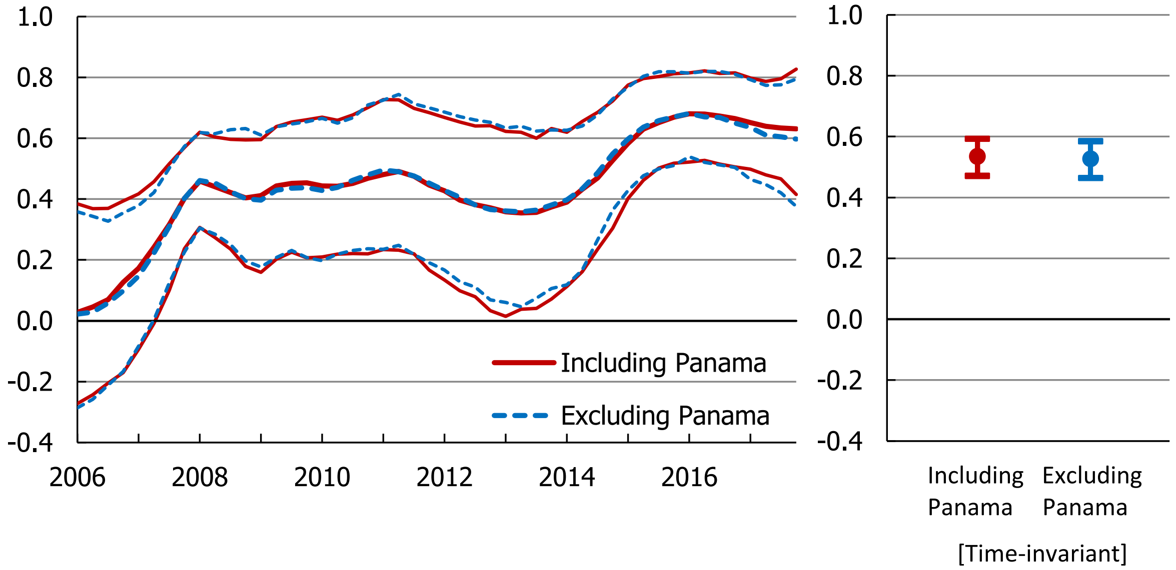
[††††] Let *x(t, q)* denote the quarterly Z-score series at the quarter *q* in year *t*, which we want to obtain. We first assign the annual Z-score in year *t* to the quarterly value of Z-score at the fourth quarter of year *t*, i.e., *x(t, 4)*. Then, we compute a linear interpolation for the quarterly value of Z-score from the first to the third quarter of each year as

$x(t, 1) = \{x(t-1, 4) * 3 + x(t, 4) * 1\} / 4,$

$x(t, 2) = \{x(t-2, 4) * 2 + x(t, 4) * 2\} / 4,$

$x(t, 3) = \{x(t-2, 4) * 1 + x(t, 4) * 3\} / 4.$

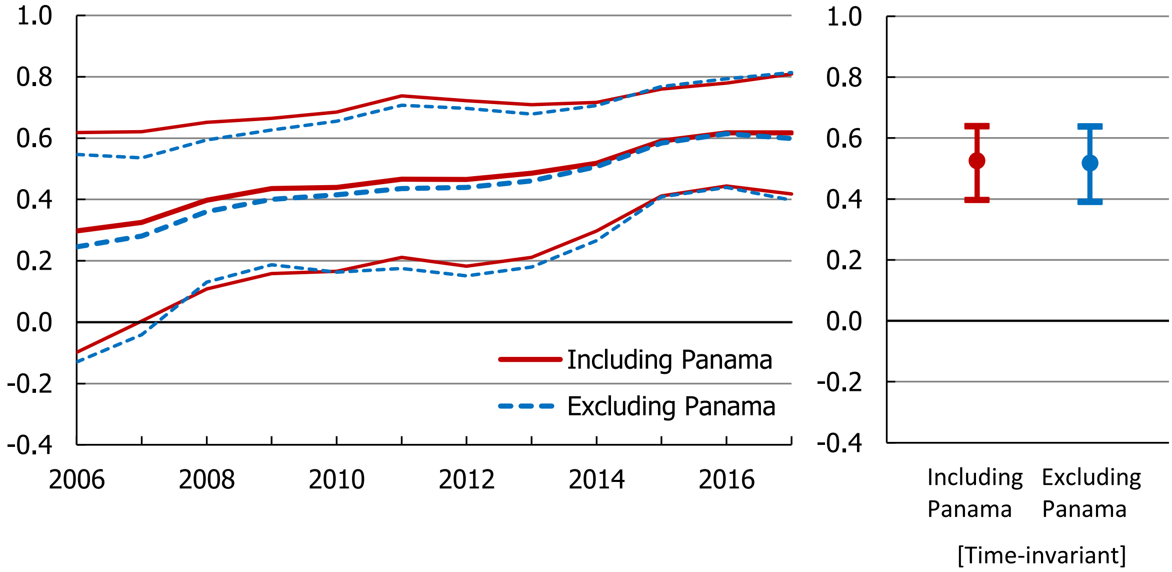
Figure 5.4: The estimated time-varying spatial parameter (ρ_t, left) in the time-varying SAR model and the time-invariant spatial parameter (ρ, right) in the standard SAR model for the quarterly series.



Notes: Solid lines show the mean estimate and 95% intervals for the dataset including Panama and dashed lines excluding Panama. Dots are mean estimate and bars 95% intervals.

Figure 5.5 presents the result for the annual series. As expected, the estimated time variance (ρ_t) does not reflect the same trend in fluctuations, but the degree of spatial dependence remains consistent. That is, the estimated statistical significance (ρ_t) is positive, pointing to the increased stability across countries and the positive influence the network has on stability.

Figure 5.5: The estimated time-varying spatial parameter (ρ_t, left) in the time-varying SAR model and the time-invariant spatial parameter (ρ, right) in the standard SAR model for the annual series.



Notes: Solid lines show the mean estimate and 95% intervals for the dataset including Panama and dashed lines excluding Panama. Dots are mean estimate and bars 95% intervals.

6. Conclusion

The international activities of global banks could have financial stability implications for both host and domestic economies via cross-border claims. While the existing literature provides some evidence on the financial spillover effects arising from the nature of highly interconnected banking systems (see, for example, Tonzer 2015), there is a lack of empirical evidence that takes into account the spatial dependence of banking stability in a time-varying setting. This paper fills this gap by focusing on the international lending of Japanese banks and attempts to capture the role of both the global and regional banking networks in explaining banking stability. We also provide empirical evidence of the prominent role Japanese banks have on the global banking network in providing liquidity via cross-border lending, thereby contributing to overall banking stability.

We use bilateral country-level bank data obtained from the BIS, and as a first step in the analysis, we employ a network analysis at both the global and regional levels. To this end, we construct global banking networks consisting of 47 countries. Our findings suggest that the level of connectedness and the centrality of the Japanese banking system have indeed increased in the last few years. From a network analysis perspective, the larger the connectedness of a particular banking system within the network is, the larger the risk of spillover effects borne by the network. We further find that Japan is part of a regional community that consists of a number of East Asian countries, such as Indonesia, Malaysia, Singapore, South Korea, Chinese Taipei, Hong Kong SAR and China. Employing the Spinglass community detection methodology, we provide empirical evidence of a rising regionalization trend, consistent with the argument put forward by Cerutti and Zhou (2017; 2018) and the IMF (2015).

Our overall results suggest that there are positive spillover effects of banking stability arising from cross-border lending activities within both global and regional networks. However, the coefficient associated with the estimated spatial parameter is of greater magnitude than in the regional analysis. This suggests that spillovers are more pronounced at the global level. However, when considering the spatial parameter over time for the regional network, we observed a steady increase after 2014, suggesting a more prominent role played by Japanese banks in the region. This, on the other hand, would mean that in the event of a financial crisis, the spillover effects would be negative, thereby increasing the instability of banking systems connected via cross-border claims.

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Appendix 1

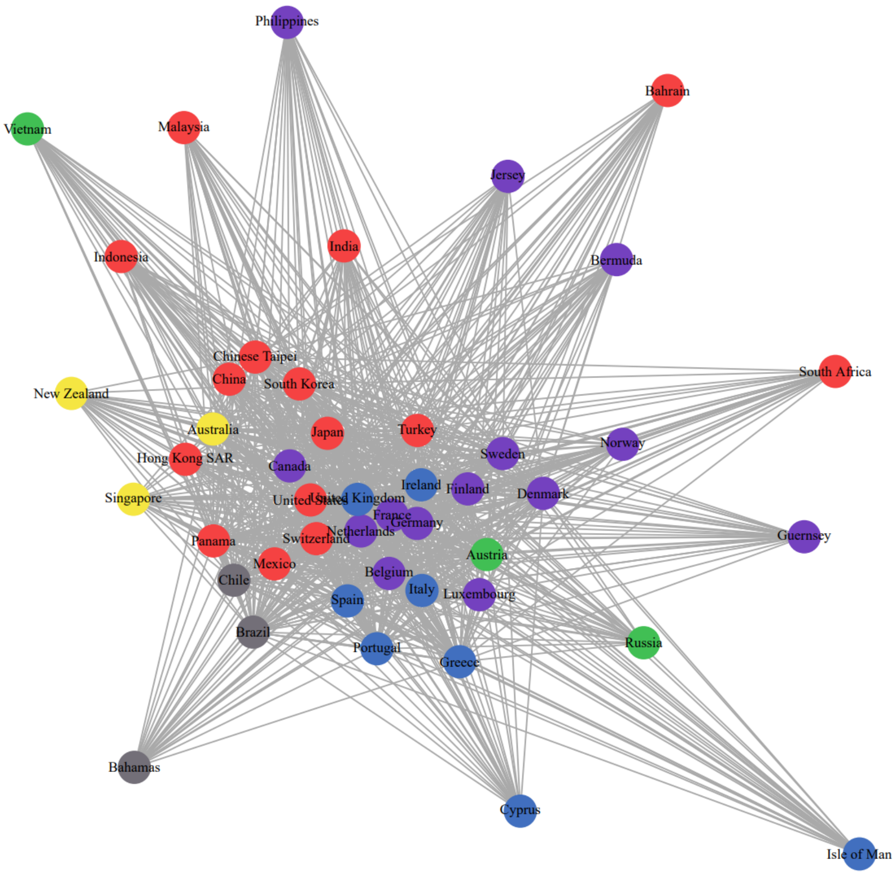
Table 1A: Countries included in the analysis and network measures for 2017 Q4

Country	Betweenness	Total Degree	Eigenvector Centrality	Community
Australia	8.67613	69	0.083889	B
Austria	7.364692	68	0.03332	C
Bahamas	0	20	0.01782	F
Bahrain	0	17	0.003659	A
Belgium	10.62777	69	0.045053	E
Bermuda	0	21	0.015592	E
Brazil	1.795391	53	0.052954	F
Canada	7.320074	59	0.099215	E
Chile	0.668814	46	0.034384	F
China	0	23	0.107666	A
Chinese Taipei	1.671883	60	0.034165	A
Cyprus	0	19	0.005577	D
Denmark	6.773865	68	0.015524	E
Finland	1.647942	43	0.021732	E
France	11.32823	70	0.200625	E
Germany	10.14715	68	0.24032	E
Greece	1.336554	56	0.009194	D
Guernsey	0	18	0.009199	E
Hong Kong SAR	0	24	0.141712	A
India	0	21	0.050995	A
Indonesia	0	22	0.021463	A
Ireland	6.532153	67	0.085599	D
Isle of Man	0	18	0.002379	D
Italy	4.101349	59	0.09151	D
Japan	**10.85329**	**69**	**0.211598**	**A**
Jersey	0	20	0.015475	E
Luxembourg	0	26	0.114402	E
Malaysia	0	19	0.016829	A
Mexico	0.379761	37	0.061721	A
Netherlands	6.844263	59	0.099646	E
New Zealand	0	18	0.049837	B
Norway	0	23	0.028045	E
Panama	2.255666	50	0.010039	A
Philippines	0	18	0.008299	E
Portugal	6.618665	63	0.014695	D
Russia	0	20	0.016651	C
Singapore	0	24	0.083363	B
South Africa	0	23	0.010449	A
South Korea	6.159334	64	0.053635	A
Spain	11.32823	70	0.07868	D
Sweden	5.194034	63	0.029943	E
Switzerland	11.32823	70	0.068304	A
Turkey	4.292351	58	0.019886	A
United Kingdom	11.32823	70	0.425286	D
United States	9.425963	69	0.738814	A
Vietnam	0	17	0.006152	C

Table 1B: Countries included in the analysis and ranking measures for 2017 Q4

Country	PageRank (Coefficient)	PageRank Rank	IVI (Coefficient)	IVI Rank
United States	0.22526	1	14075.70	15
United Kingdom	0.08308	2	24022.10	1
Germany	0.05198	3	21375.28	7
France	0.04337	4	23587.13	2
Japan	**0.03875**	**5**	**22687.84**	**5**
Hong Kong SAR	0.02876	6		
Luxembourg	0.02834	7		
Netherlands	0.02603	8	14699.17	12
China	0.02510	9		
Italy	0.02458	10	9372.84	19
Spain	0.02396	11	23351.03	3
Canada	0.02349	12	15619.56	10
Australia	0.02089	13	18225.36	9
Singapore	0.02061	14		
Switzerland	0.02017	15	23330.94	4
Mexico	0.01813	16	2087.76	26
Brazil	0.01753	17	4827.60	21
New Zealand	0.01690	18		
Chile	0.01603	19	2603.47	25
South Korea	0.01592	20	13288.99	16
Belgium	0.01581	21	21928.76	6
India	0.01564	22		
Norway	0.01534	23		
Sweden	0.01514	24	11373.19	17
Austria	0.01426	25	15587.37	11
Finland	0.01411	26	4471.67	23
Ireland	0.01373	27	20945.13	8
Chinese Taipei	0.01314	28	4559.10	22
Bahamas	0.01210	29		
Turkey	0.01189	30	9602.97	18
Indonesia	0.01184	31		
Denmark	0.01184	32	14409.00	13
Russia	0.01183	33		
Portugal	0.01132	34	14101.91	14
Cyprus	0.01123	35		
Malaysia	0.01092	36		
Bermuda	0.01085	37		
Jersey	0.01082	38		
Panama	0.01043	39	5632.65	20
Guernsey	0.01015	40		
Greece	0.01004	41	3857.52	24
South Africa	0.01003	42		
Philippines	0.00980	43		
Vietnam	0.00961	44		
Bahrain	0.00925	45		
Isle of Man	0.00904	46		

Figure 1A: Global banking network, by community color



Notes: The above graph is a representation of the bilateral cross-border claims of 47 banking systems' countries for 2017 Q4. We detect six communities within the global network, denoted by different shades of color.

Appendix 2

2.1: Integrated Value of Influence (IVI) Algorithm

The IVI approach takes a multidimensional approach to identify the most influential nodes within a network (Salavaty *et al.,* 2020); here we apply the method to the counterparty claims within a directed network of global baking centers. The algorithm is a combination of six network topology measures which are intended to capture the hubness and connectivity of individual nodes in relation to the wider network. These measures are:

I. Total Degree (TD)
II. Cluster Rank (CR)
III. LH Index (LH)
IV. Neighbourhood Connectivity (NC)
V. Betweenness Centrality (BC)
VI. Eigenvector Centrality (EC)

The IVI is calculated for each node:

$$IVI = (TD + LH) + (NC + CR)(BC + EC)$$

This creates a rankable value as shown in Appendix 1B. We do not calculate the IVI for the countries in the network which are counterparty only in the BIS dataset as the lack of two-way directionality makes it difficult to compare measure values and is not possible to obtain betweenness scores for these nodes.

2.2: Cluster Spinglass Community Detection Approach

We select the Spin-Glass community detection approach as this is best suited to the analysis of networks, where communities can overlap. Furthermore, this approach remedies a common deficit of the Newman and Girvan (2006) method, in that the latter often produced results with similar modularity scores but very different compositions (Eaton and Mansbach, 2012). The Spin-Glass approach allows for a semi-supervised approach; the number of selected spin states denotes the maximum number of regional communities which the algorithm is permitted partition the global network (a graph G) into. In our analysis, we set this value at six to reflect the six inhabited continents.

We consider a graph notation $G = (V, A)$, where $V = \{v_1, v_2, \dots, v_n\}$ are vertices representing BIS reporting and counterparty countries. A is an adjacency matrix which specifies the presence of claims (denoted by e_{ij}) between countries (v_i, v_j). Initially the approach follows the Newman-Girvan approach which seeks to minimise edge betweenness centrality and removes the highest valued edges to reveal communities within the network.

We define

$$m = \frac{1}{2}\sum_{i,j} A_{i,j},$$

and the modularity of the graph:

$$Q(C) = \frac{1}{2m}\sum_{i,j} \left(A_{ij} - P_{ij}\right)\delta\left(C_i, C_j\right),$$

where Q denotes the modularity of a pair of communities. Note that $\delta(C_i, C_j)$ takes on the value of one if v_i and v_j belong to the same community (such that $C_i = C_j$), and zero otherwise.

To identify modularity (Q) the Spin-Glass method takes on the approach found in the 'Potts Model,' which is a multi-spin approach over a range of possible values (equal to $2m$). These spins generate the probability values (such as A_{ij} in the above expression). Here the degree of each reporting country is given as: $d_i = \sum_j A_{ij}$, which substitutes into the following to give the probability values:

$$P_{ij} = \frac{d_i d_j}{2m}.$$

The Potts model allows for the estimation of up to k communities but supports natural identification of q communities such that $q \leq k$ (see Easton and Mansbach, 2012).

The Potts Model employs a Hamiltonian cycle to examine clusters (C) to which vertices (v_i, v_j) belong. This is obtained in probabilistic terms, within the Hamiltonian function. The functions ground state is:

$$H(C) = -\sum_{i \neq j} a_{ij} A_{ij} \delta(C_i, C_j) + \sum_{i \neq j} b_{ij} (1 - A_{ij}) \delta(C_i, C_j)$$

$$+ \sum_{i \neq j} c_{ij} A_{ij} \left(1 - \delta(C_i, C_j)\right) - \sum_{i \neq j} d_{ij} (1 - A_{ij}) \left(1 - \delta(C_i, C_j)\right).$$

Here the first line captures internal links within a community, the second captures missing links within a community, the third captures links outside the community and finally the fourth term reflects external missing links (Reichardt and Bornholdt, 2006). Over all this seeks to reward connections within communities and to minimise instances of connections outside of communities. When examining deviations from a global network, we employ a general probability function (γP_{ij}) to express the Hamiltonian function in the following reduced form:

$$H(C) = -\sum_{i \neq j} (A_{ij} - \gamma P_{ij}) \delta(C_i, C_j).$$

2.3: Bayesian Estimation Method for the Time-Varying SAR Model

For the estimation of the time-varying SAR model, we take the Bayesian estimation approach, because a likelihood of the model includes many integrals, which is computationally challenging to evaluate directly. We construct a Markov chain Monte Carlo (MCMC) algorithm, which has been a major strategy to estimate time-varying parameter models in econometrics (e.g., Koop, 2003). Under certain prior probability distributions, the MCMC algorithm produces the sample drawn from posterior distribution of parameters including unobserved latent variables, in our case the time-varying spatial parameter ρ_t.

We consider the posterior distribution given the data $\boldsymbol{y} = (\boldsymbol{y}_1, \dots, \boldsymbol{y}_T)$. Let $\boldsymbol{\rho} = (\rho_1, \dots, \rho_T)$. We set the prior probability density for $(\boldsymbol{\beta}, v)$. Given the data $\boldsymbol{y}$, we generate sample from the posterior distribution $\pi(\boldsymbol{\rho}, \boldsymbol{\beta}, v \mid \boldsymbol{y})$ using the MCMC method. We apply the following MCMC algorithm:

1. Initialize $(\boldsymbol{\rho}, \boldsymbol{\beta}, v)$.
2. Generate $\boldsymbol{\rho}$ conditional on $(\boldsymbol{\beta}, v)$.
3. Generate $\boldsymbol{\beta}$ conditional on $(\boldsymbol{\rho}, v)$.
4. Generate v conditional on $(\boldsymbol{\rho}, \boldsymbol{\beta})$.
5. Go to 2, until the MCMC converges.

We iterate this MCMC algorithm for 10,000 times in our analysis, after discarding 1,000 samples as a burn-in period.

In Step 2, we use a single-move sampler with the random-walk Metropolis-Hasting (MH) algorithm. Conditional on $(\boldsymbol{\beta}, v)$ and (ρ_{t-1}, ρ_{t+1}), we derive a posterior distribution of ρ_t. Because it forms a non-standard density function, we draw a candidate for the next sample ρ_t^*, as $\rho_t^* \sim N(\rho_t^0, q^2)$, where ρ_t^0 in the current state. Then, we accept ρ_t^* with a probability of the MH algorithm. If rejected, we use ρ_t^0 for the next sample. The variance q^2 of the proposal distribution is tuned as an acceptance ratio is roughly 30%. We apply this method for each of $\rho_1, \dots, \rho_T$, sequentially.

In Step 3, we set a prior distribution $\boldsymbol{\beta} \sim N(\boldsymbol{0}, \boldsymbol{I})$, and obtain the posterior distribution of $\boldsymbol{\beta}$, which forms a normal distribution given $(\boldsymbol{\rho}, v)$. In Step 4, we set a prior distribution $v^2 \sim IG(2, 0.02)$, where IG denotes an inverse gamma distribution, and obtain the posterior distribution of v^2, which also forms the inverse gamma distribution given $(\boldsymbol{\rho}, \boldsymbol{\beta})$.