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Financial Interconnectedness, Amplification, and Cross-Border Activity[*]

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Abstract

Interconnectedness is an essential feature of banks, but it can be a shock-amplifier. We explore changes in, and implications and underlying drivers of interconnectedness among major banks in the world, focusing on their stock market volatilities. The estimated vector autoregressive model reveals significant changes in interconnectedness between before and after the global financial crisis of 2007-09. Specifically, the estimation shows a significant increase in connectedness from foreign banks to Japanese banks. The impulse responses to a credit shock show that changes in the estimated interconnectedness can be an amplifier for Japanese banks in particular. A panel regression analysis suggests that Japanese banks' cross-border activity, especially lending, has likely driven an increase in connectedness from foreign banks.

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1. Introduction

Interconnectedness is at the heart of the activity of financial intermediaries, banks in particular. Banks borrow from and lend to each other in order to manage liquidity and funding. They trade market and credit instruments to manage risks. They have common exposures to, e.g., specific industries and regions, due to the similarities of their business models. However, financial interconnectedness can be an amplifier of shocks in the financial system, as has become evident in the global financial crisis (GFC) of 2007-09. In response, to build a more resilient financial system, policymakers have made considerable efforts to reduce financial interconnectedness since the crisis. The milestone of such efforts is the regulatory reforms including the Basel III reforms. The evidence suggests, albeit not conclusively, that these regulatory reforms and changes in market behaviors have contributed to a decrease in direct interconnectedness -- specific interconnectedness arising from direct contractual exposures -- among banks.[1]

However, there are still challenges facing policymakers. First, given that the post-crisis reforms are moving toward their implementation and evaluation phases, it is essential to assess the evolution of financial interconnectedness between before and after the GFC. Especially, interconnectedness as perceived by market participants is of particular interest. This is because it is such interconnectedness that invoked investors' uncertainty and fears about financial institutions, which drove their disruptive reactions (i.e., runs) and contagions in response to negative events such as the collapse of Lehman Brothers, making these events a trigger for the full-blown financial crisis.[2] Second, what is an implication of a change in financial interconnectedness between before and after the GFC, if any? Specifically, it should be assessed whether such a change in financial interconnectedness will be a stabilizer or an amplifier of stress in the financial system, because there are theories suggesting both possibilities.[3] Third, what has driven the evolution of financial interconnectedness? Addressing potential problems arising from financial interconnectedness requires an understanding of its underlying drivers.

In this paper, we tackle on these three challenges. Our contribution to the empirical literature on financial interconnectedness is the comprehensiveness of our analyses: we address the

[1] Liu, Quiet, and Roth (2015) report that direct interconnectedness through interbank credit exposures in the U.K. has declined since the GFC. Financial Stability Board (2018) documents that, on average, bank to non-bank interconnectedness has dropped from crisis peaks, but remains modestly above pre-crisis average levels. For an overview of policy measures to address financial interconnectedness, see Yellen (2013). For a supervisory framework for measuring and controlling large-exposure direct interconnectedness, see Basel Committee on Banking Supervision (2014).

[2] Scott (2012) argues that contagion was the main driving force of the U.S. financial crisis of 2007-09, not direct interconnectedness -- i.e., asset and liability interconnectedness -- itself.

[3] For models of financial interconnectedness, see, e.g., Allen and Gale (2000) and Gai, Haldane, and Kapadia (2011). See also Glasserman and Young (2016) for a survey.

measurement, implications, and underlying drivers of financial interconnectedness.

In doing so, we pay close attention to Japanese major banks as well as global systemically important banks (G-SIBs). In domestic markets, Japanese banks, both large and small, have been struggling with decreasing profitability amid the persistent decline in population and the number of firms as well as the prolonged low interest rate environment. In overseas markets, foreign banks, European banks in particular, have retreated since the GFC. Against these backgrounds both at home and abroad, Japanese major banks have significantly increased foreign lending, which promises higher profitability than domestic lending. Indeed, according to the BIS consolidated banking statistics, foreign claims by Japanese banks almost doubled during the period of 2009-18, while those by banks in major European countries decreased. Consequently, Japanese major banks' connectedness with foreign banks has likely increased possibly through an increase in common exposures with foreign banks. This paper sheds light on this source of potential vulnerabilities for Japanese major banks as well as foreign counterparts.

Our approach for addressing the three challenges -- measurement, implications, and underlying drivers of financial interconnectedness -- and the resulting findings can be summarized as follows. First, we estimate financial interconnectedness among G-SIBs and Japanese major banks by using a vector autoregressive (VAR) model for the pre-crisis period of 2003-06 and the post-crisis period of 2015-18. The variable of interest is banks' stock price volatilities, which capture investors' uncertainty and fears about banks.[4] The estimated financial interconnectedness summarizes the direction and intensity of the impact of one bank's volatility on other banks' volatilities. The model estimation and a comparison between before and after the GFC show that the measure of connectedness from banks in the same country/region has increased in the U.S., but decreased in Europe and Japan. However, the estimated changes in connectedness from foreign banks -- i.e., those outside the country/region -- are opposite: the measure of such connectedness has increased in Europe and Japan, but they have slightly decreased in the U.S.

Second, to explore the implications of changes in the estimated financial interconnectedness, we examine whether the impact of a negative shock, transmitted via the estimated financial interconnectedness, is amplified or stabilized. In this examination, we focus on the interest-rate snapback risk in U.S. credit markets. The U.S. corporate credit cycle appears to be at its record high in recent history (IMF, 2019). Potential re-pricing in the credit markets would stress indebted firms and could have ramifications to the financial system.

[4] Our approach to estimate financial interconnectedness is classified as an indirect interconnectedness approach. For other approaches and the taxonomy of studies on interconnectedness, see Kara, Tian, and Yellen (2015).

Our approach for examining the role of interconnectedness for the interest-rate snapback risk is as follows. We incorporate a U.S. credit spread into the VAR model of banks' stock price volatilities, which we used in estimating interconnectedness, and study impulse responses to a shock to the credit spread. The empirical results indicate that in response to an increase in the credit spread, the average stock price volatility of Japanese major banks increases more and such an increase lasts longer with the post-crisis interconnectedness than with the pre-crisis interconnectedness. In other words, the change in the interconnectedness amplifies the impact of such a negative shock for Japanese major banks. A decomposition of interconnectedness shows that it is an increase in the connectedness, from foreign banks to Japanese banks, that drives such amplification. However, for other banks such as U.S. and European banks, the effects of such an interest-rate snapback have decreased somewhat between before and after the GFC. This implies that the changes in interconnectedness during the period act as a stabilizer. For European banks, such changes are a decrease in connectedness from banks in the same country/region; for U.S. banks, such changes are a decrease in connectedness from foreign banks and a decrease in connectedness among foreign banks. These results show the complicated nature of how financial interconnectedness propagates or dampens shocks.

Third, to investigate the underlying drivers of the estimated financial interconnectedness, we explore the relationships between the estimated measure of such interconnectedness and potential drivers. In light of changes in the estimated financial interconnectedness and the developments in banks' cross-border activity after the GFC, we hypothesize that the two -- financial interconnectedness and banks' cross-border activity -- are related. We provide two findings that support this hypothesis. First, the estimated measure of connectedness from foreign banks shows a significant positive correlation with banks' *cross-jurisdictional activity*, which is one of the indicators constituting the G-SIB score.[5] Second, a panel regression analysis for Japanese major banks using bank-level data including foreign lending and funding during the period of 2004-18 shows that the ratio of foreign lending to total assets has a statistically significant impact on the estimated measure of connectedness from foreign banks. In addition, though the impact is smaller than foreign lending, a stable funding measure -- namely, the ratio of client-related deposits to the sum of foreign currency denominated loans and securities -- also has a statistically significant impact on the measure of connectedness. These results suggest that an expansion of banks' cross-border activity has led to an increase in connectedness from foreign banks since the GFC, possibly through changes in their asset and liability structure and changes in their common exposure.

[5] The indicators that constitute the G-SIB score measure the systemic importance of banks. For the indicators' definition and a summary of their recent developments, see Basel Committee on Banking Supervision (2019).

The methods used in our analyses to address these challenges are not necessarily new, but some of them are worth mentioning. First, our measure of financial interconnectedness is the lagged coefficients of a VAR model close in spirit to Billio et al. (2012) and Basu et al. (2017). Specifically, one-day lagged coefficients show how banks' stock price volatilities today are influenced by those yesterday. In addition, in estimating the VAR model to measure financial interconnectedness, the LASSO (least absolute shrinkage and selection operator) method is used. The LASSO method allows us to deal with problems associated with a large number of estimated parameters -- the so-called the curse of dimensionality -- in the VAR model. In addition, it allows us to extract important linkages from a statistical viewpoint, whereas weak linkages are forced out of the model. Second, in examining whether a change in the estimated interconnectedness between before and after the crisis amplifies a credit shock, generalized impulse responses in the framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) are used. This is in line with Diebold and Yilmaz (2014), who use generalized impulse responses to calculate variance decompositions for measuring financial interconnectedness. A caveat is that a credit shock is not identified, but the correlations of reduced-form shocks -- the residuals of the VAR model -- are taken into account in generalized impulse responses. Third, a rolling regression is used to estimate interconnectedness in exploring the underlying drivers of the estimated interconnectedness in the panel regression analysis. A rolling regression is also used by Billio et al. (2012) and Diebold and Yilmaz (2014), among others, to study the time-variation of interconnectedness. Rolling regression allows us to conduct a panel regression by increasing the number of observations in terms of the time horizon.

Related Literature

Our paper, as mentioned above, addresses three challenges regarding financial interconnectedness: measurement, implications, and underlying drivers. Most of the empirical literature on financial interconnectedness has focused on measurement. In this regard, our paper is closely related to Basu et al. (2017), who use a VAR model with a Granger causality test, which is an extension of a pair-wise Granger causality approach taken by Billio et al. (2012), and to Diebold and Yilmaz (2014), who use a VAR model with variance decomposition. Our connectedness measure is less restrictive than those of Basu et al. (2017) and Diebold and Yilmaz (2014) and can be regarded as lying between the two. On the one hand, unlike Diebold and Yilmaz (2014), our measure does not impose restrictions on simultaneous effects of shocks, because our measure, similar to that of Basu et al. (2017), is lagged coefficients of a VAR model, chosen to focus on lagged effects from one bank to other banks and their magnitudes. On the other hand, unlike Basu et al. (2017), our measure, similar to that of Diebold and Yilmaz (2014), does not impose Granger causality. Despite these differences between our measure and those of Basu et al. (2017) and Diebold and Yilmaz (2014), where possible, we use the latter two connectedness measures for robustness checks.

Our paper is also related to the empirical papers on financial interconnectedness, which employ the LASSO method or similar shrinkage methods to deal with the curse of dimensionality in estimating a relatively large network. These include Demirer et al. (2018), Basu et al. (2017), and Malik and Xu (2017).

Compared to the measurement of interconnectedness, its underlying drivers are less explored in the literature on indirect interconnectedness. On this topic, Billio et al. (2012) and Diebold and Yilmaz (2014) report that interconnectedness measured by stock prices tends to increase during financial stress. Candelon, Ferrara, and Joëts (2018) extend Diebold and Yilmaz (2014) by estimating a regime-switching VAR model and show that interconnectedness increases when market uncertainty is elevated. Malik and Xu (2017), using both time series and panel regression analyses, show that interconnectedness measures are affected by policy uncertainty, financial stress, U.S. long-term interest rates, and individual bank profitability. The present paper proposes a new factor -- cross-border activity, especially lending -- as a potential driver of inward connectedness from foreign banks.

Implications of interconnectedness for amplification are presumably the least understood area in indirect interconnectedness. The theoretical literature suggests that interconnectedness can be an amplifier or a dampener of a shock, depending on the nature of the interconnectedness and the type of the shock. However, the empirical literature on whether interconnectedness amplifies or dampens a shock is limited. The present paper contributes to this literature by studying how a shock to credit markets is transmitted to the global banking system via the estimated interconnectedness, including its segments such as the connectedness from abroad.

Broadly, this paper contributes to policymakers' agenda to address financial interconnectedness as an amplifier of negative shocks and a disrupter to the financial system. For discussion of policymakers' focus since the GFC, see Haldane (2009), IMF (2010), Yellen (2013), and Arregui et al. (2013).

The remainder of the paper is organized as follows. Section 2 is on the measurement of interconnectedness. It estimates global financial interconnectedness before and after the crisis and presents the results by visualizing them as a network graph and by introducing some metrics of the degree of interconnectedness. Section 3 is on the implications of the interconnectedness, estimated in Section 2, for amplification. It estimates the VAR with a credit shock and examines how the changes in the estimated interconnectedness in different segments of the network between before and after the crisis amplify or stabilize the impact of a snapback of credit spreads.

Section 4 is on the driving forces of the estimated interconnectedness. It explores what lies behind the changes in financial interconnectedness before and after the crisis by focusing on G-SIB scores and foreign lending and funding by Japanese banks. Section 5 concludes.

2. Measuring Interconnectedness

Financial interconnectedness, especially that perceived by market participants, inevitably involves unobservable components. Yet, despite being unobservable, such interconnectedness could drive market participants' disruptive reactions in a stress event, such as runs on financial institutions, as in the GFC. In this section, we estimate such interconnectedness implied by asset prices among the G-SIBs and Japanese major banks, and present the result in two ways: as a network graphical representation and as metrics of the degree of interconnectedness. The network graphical representation allows us to visualize the estimated networks before and after the crisis and highlight the contrast between the two. Using interconnectedness metrics allows us to assess changes in the degree of interconnectedness quantitatively. The metrics will also be used for further analyses in a subsequent section.

2.1. Econometric Approach

We estimate interconnectedness across major banks in the world simultaneously. As in a standard network approach, interconnectedness can be summarized by a connection matrix, given by

$$\boldsymbol{B} = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1n} \\ \vdots & \ddots & \vdots \\ \beta_{n1} & \cdots & \beta_{nn} \end{bmatrix},$$

where β_{ij} is the strength of the linkage from bank j to bank i. Let $\boldsymbol{y}_t \equiv [y_{1t} \quad \cdots \quad y_{nt}]'$ denote an $n \times 1$ vector of a financial variable of interest, where y_{it} is such a variable for bank i in period t. Similar in spirit to Diebold and Yilmaz (2014), a connection matrix $\boldsymbol{B}$ can be estimated by the following VAR(1):

$$\boldsymbol{y}_t = \boldsymbol{B}\boldsymbol{y}_{t-1} + \boldsymbol{e}_t, \tag{1}$$

where $\boldsymbol{e}_t \sim \text{i.i.d.}\, N(0, \boldsymbol{\Sigma})$. As is clear from equation (1), our interconnectedness of interest is linkages from financial variables in the previous period to those in the current period, that is, one-period-lag influences. In principle, $\boldsymbol{y}_t$ can follow VAR(p), but we focus on VAR(1) for simplicity as in Basu et al. (2017). VAR(1) is also chosen for the study on the basis of the AIC.

Another useful measure of interconnectedness within the VAR approach is variance decomposition, as studied by Diebold and Yilmaz (2014). The variance decomposition metrics take into account the contemporaneous linkages summarized by the variance-covariance matrix $\mathbf{\Sigma}$ in addition to one-period-lagged linkages summarized by the VAR coefficient matrix $\boldsymbol{B}$. We use this measure for robustness checks for some analyses, but we primarily focus on interconnectedness measured by $\boldsymbol{B}$ for three reasons. First, the coefficient matrix $\boldsymbol{B}$ reflects the direct effect from each bank to other banks. The variance-covariance matrix $\mathbf{\Sigma}$ captures the correlation of shocks, but it is not obvious whether such correlation accurately reflects causality. Second, the coefficient matrix $\boldsymbol{B}$ tells us the absolute strength of interconnectedness, but the variance decomposition metrics provide only the relative strength of interconnectedness among banks. Information on the absolute strength is critical in analyzing the implications and underlying drivers of interconnectedness in later sections. Third, as mentioned in the Introduction, the coefficient matrix $\boldsymbol{B}$ is estimated using the LASSO method so that the estimated $\boldsymbol{B}$ is sparse, i.e., the values of many elements of $\boldsymbol{B}$ are zero. Unlike the variance decomposition metrics, which are not sparse in general, the sparse matrix $\boldsymbol{B}$ allows us to highlight the linkages that play a significant role for interconnectedness. This advantage will become clear when the estimated $\boldsymbol{B}$ is visualized using network graphical representation.

We estimate equation (1) by using a LASSO method as mentioned earlier. A LASSO method or similar shrinkage methods have gained popularity in estimating financial interconnectedness (see, e.g., Demirer et al., 2018, Basu et al., 2017, and Malik and Xu, 2017) because such methods generate sharp predictions for a regression with many coefficients relative to the sample size. In our case, such methods are useful for dealing with the large number of banks, i.e., the large size of the matrix $\boldsymbol{B}$, in estimating equation (1) with a relatively small sample size in time dimension $t = 1,2,\dots,T$. Specifically, we use the square-root LASSO, which is an extended version of the standard LASSO, following Belloni, Chernozhukov, and Wang (2011), as its estimators have some desirable properties.[6] For the i-th equation of (1), the coefficients $\boldsymbol{\beta}_{i\cdot} \equiv [\beta_{i1} \quad \cdots \quad \beta_{in}]$ -- linkages from banks $j = 1,\dots,n$ to bank i -- are estimated using the square-root LASSO as follows:

$$\widehat{\boldsymbol{\beta}}_{i\cdot} = \operatorname{argmin}\left\{\sum_{t=1}^{T}(y_{it} - \boldsymbol{\beta}_{i\cdot}\boldsymbol{y}_{t-1})^2\right\}^{\frac{1}{2}} + \lambda\sum_{j=1}^{n}|\beta_{ij}| \tag{2}$$

where $\lambda \geq 0$ is a penalty parameter. In the case of $\lambda > 0$, the method penalizes the non-zero values of coefficients in $\boldsymbol{B}$ as shown in the second term of the right-hand-side of (2), making the estimated network $\widehat{\boldsymbol{B}}$ sparse by assigning zero to the coefficients that are less important in

[6] Belloni, Chernozhukov, and Wang (2011) show that the squared-root LASSO achieves near-oracle performance without information on the standard deviation of error terms even if error terms are non-Gaussian.

explaining the dynamics of $\boldsymbol{y}_t$ than the other (non-zero) coefficients. If $\lambda = 0$, then the estimator reduces to the OLS, which in general assigns non-zero values to all coefficients with a significant degree of uncertainty, especially when n is relatively large compared to T. The penalty parameter λ with respect to the non-zero coefficients is set following Javanmard and Montanari (2014).[7]

The LASSO method provides sharp prediction for interconnectedness, meaning each pair of banks either has or does not have a linkage, but this prediction should be interpreted carefully. For example, if two banks, say, banks 1 and 2, affect bank 3 equally but in a slightly different way, then the LASSO method may identify the linkage only from one of the two banks, say bank 1, and attach zero value to the linkage from the other bank, bank 2. Hence, pairwise linkages estimated by the LASSO method may not be so robust to small perturbations. However, what appears to be relatively robust is the overall impact from banks 1 and 2 on bank 3: the estimated linkage from bank 1 would reflect the true linkages from banks 1 and 2. Hence, in interpreting estimated interconnectedness, we pay attention to overall linkages rather than individual linkages. For discussion on the LASSO method and its interpretations, see Belloni, Chernozhukov, and Hansen (2014).

For better understanding of what we intend to estimate using the LASSO method, it is useful to recall that estimating (1) using the standard LASSO method is equivalent to Bayesian estimation with Laplace priors.[8] In other words, as econometricians, in such an estimation, we attach Laplace priors on coefficients to reflect our view that the significant linkages, which we aim to estimate, are relatively sparse and thereby sharp. We do not try to estimate all possible linkages but only the significant ones that survive in spite of the penalty included in (2).

We use the square-root LASSO method as our benchmark in estimating interconnectedness, but we also include other methods within the class of LASSO for robustness checks of our main results. Such methods include the variance decomposition with the graphical LASSO, the Granger causality method, and the adaptive elastic net (Zou and Zhang, 2009), the last of which combines the LASSO penalty and the ridge penalty.[9]

[7] In the main results shown in this paper, we set $\lambda = \sqrt{(\Phi^{-1}(1-0.1/\mathrm{n})/\mathrm{T}}$, where Φ denotes a cumulative standard normal distribution function This is the default value in *SSLASSO,* an R function provided by Javanmard and Montanari (2014) and available at https://web.stanford.edu/~montanar/sslasso/code.html. In addition, to check the robustness of the results, we also use $\lambda = 1.1 \times \Phi^{-1}(1-0.1/\mathrm{n})/T$, following Belloni, Chernozhukov, and Wang (2011). Furthermore, we estimate the model by using an elastic net with the penalty parameter λ chosen based on the cross-validation. Our main results in this paper do not change qualitatively with alternative values for λ. The results for robustness mentioned in this paper are available upon request.

[8] For details, see Park and Casella (2008).

[9] For applications of estimating financial interconnectedness, see Basu et al. (2012) for the Granger causality method and Demirer et al. (2018) for the adaptive net.

2.2. Financial Variables of Interest and Data

Our focus is on the interconnectedness of the daily volatilities of stock prices among G-SIBs and Japanese major banks. Our sample covers about 30 banks.[10]

Similar to the VIX -- the Chicago Board Option Exchange Volatility Index, which is often touted as an "investor fear gauge" -- the volatility of a bank stock price reflects investors' uncertainty and fears about the bank. What we are interested in is the interconnectedness of such uncertainty and fears among banks, which may reflect not only fundamentals such as direct lending/borrowing exposures but also other factors such as common exposures, and complexity and opacity of the financial linkages. As became evident in the GFC, it was investors' perception and their resulting reactions that pushed the whole financial system to the brink of collapse.

The frequency of volatilities used for estimation is daily for two reasons. First, our interest lies in how market participants would react through their perceived financial interconnectedness. Thus, the shorter the frequency of data, the better such reactions can be captured by the estimation. Second, using high-frequency data allows us to estimate interconnectedness with a lag, even within a short period of time. Interconnectedness $\boldsymbol{B}$ does not take into account the contemporaneous connectedness reflected in $\boldsymbol{\Sigma}$ in equation (1), but, as the frequency of the data becomes shorter, both $\boldsymbol{B}$ and $\boldsymbol{\Sigma}$ would involve less noise and especially $\boldsymbol{B}$ would more capture lagged but immediate responses of bank stock price volatilities.[11]

Following Demirer et al. (2018), the stock price volatility for bank i in period t is calculated as follows:

$$\tilde{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})] \\ - 0.383(C_{it} - O_{it})^2 \tag{3}$$

[10] The list of sample banks consists of JP Morgan Chase; Citigroup; Bank of America; Goldman Sachs; Morgan Stanley; Bank of NY Mellon; State Street; Wells Fargo; Royal Bank of Canada; Credit Suisse; UBS; BNP Paribas; Deutsche Bank; Credit Agricole; ING; Banco Santander; Societe Generale; Unicredit Group; Barclays; HSBC; Standard Chartered; Agricultural Bank of China; Bank of China; Industrial and Commercial Bank of China; China Construction Bank; Mizuho; MUFG; Sumitomo Mitsui; Resona; Shinsei; Aozora; Sumitomo Mitsui Trust Bank; Mizuho Trust Bank; Sumitomo Trust Bank.

[11] In estimating the VAR specification (1) with daily data, time differences may matter. Specifically, we use calendar dates for the daily data, and given the fact that the stock market opens first in Japan, followed by Europe and the U.S. for a given calendar date, one-day lag effects captured by $\boldsymbol{B}$ in (1) are more likely to be estimated for the direction from the U.S. or Europe to Japan than vice versa. To address this potential problem and for robustness, we also estimate (1) using the same data but with data on Japanese banks moved one-day forward. In this data formulation, the stock market opens first in Europe, followed by the U.S. and Japan for a given model date. The main results in this paper are robust to the use of this alternate data formulation.

where H_{it}, L_{it}, O_{it}, and C_{it} are respectively the logs of daily high, low, opening, and closing prices for bank stock i on day t. The data source is Bloomberg. In our estimation, the square root of the volatility calculated by (3) is standardized so that it has mean zero and standard deviation unity. By doing so, the strength of interconnectedness represented by $\boldsymbol{B}$ in equation (1) becomes comparable among banks. For example, the β_{ij}'s can be compared or summed.[12]

2.3. Estimated Interconnectedness

To address the question of what change, if any, there is in global financial interconnectedness between before and after the crisis, the VAR specification given by equation (1) is estimated using daily volatility data over a three-year horizon for the pre-crisis period of 2003-06 and the recent post-crisis period of 2015-18.[13] To highlight the contrast between the interconnectedness between before and after the crisis, in the following, the estimated networks are presented using interconnectedness metrics and a graphical representation.

Number of links

A simple metric of connectedness for the estimated network $\widehat{\boldsymbol{B}}$ is the number of links in the network. There is a link, i.e., an edge, from bank j to bank i if and only if $\hat{\beta}_{ij} \neq 0$. We focus on a change in the number of links between before and after the GFC for three major countries/regions: the U.S., Europe, and Japan. Specifically, three types of links are considered: (i) within-links -- links from one country/region to itself; (ii) in-links -- inward links to one country/region from other countries/regions; and (iii) out-links -- outward links from one country/region to other countries/regions. Outside-links are defined similarly to links among other countries/regions, but we do not consider such links here, because they are reflected in the within-links of other countries/regions. Using the estimated network $\widehat{\boldsymbol{B}}$, the numbers of these types of links, e.g., for the U.S., are given by

$$N_{\mathrm{US}}^{\mathrm{within}} = \sum_{i \in \{\text{U.S. banks}\}}^{n} \sum_{j \in \{\text{U.S. banks}\}}^{n} \mathbf{1}_{\{\hat{\beta}_{ij} \neq 0\}}$$

$$N_{\mathrm{US}}^{\mathrm{in}} = \sum_{i \in \{\text{U.S. banks}\}}^{n} \sum_{j \in \{\text{non U.S. banks}\}}^{n} \mathbf{1}_{\{\hat{\beta}_{ij} \neq 0\}}$$

[12] Taking the natural logarithm of the volatility as in Diebold and Yilmaz (2014) before standardizing it does not affect our main results significantly.

[13] In the three-year horizon, there are 27 and 32 banks in the pre-crisis period and the post-crisis period, respectively. Focusing on the same banks between the pre-crisis and post-crisis periods does not affect our main results. Moreover, our main results also hold for a five-year horizon: the pre-crisis period of 2001-06 and the recent post-crisis period of 2013-18.

$$N_{\text{US}}^{\text{out}} = \sum_{i \in \{\text{non U.S. banks}\}}^{n} \sum_{j \in \{\text{U.S. banks}\}}^{n} \mathbf{1}_{\{\hat{\beta}_{ij} \neq 0\}}$$

where $N_{\text{US}}^{\text{within}}$, $N_{\text{US}}^{\text{in}}$, and $N_{\text{US}}^{\text{out}}$ denote respectively the numbers of within-links, in-links, and out-links for the U.S. and $\mathbf{1}\ \{\hat{\beta}_{ij} \neq 0\}$ is an indicator variable, taking value 1 if $\hat{\beta}_{ij} \neq 0$. These numbers are defined similarly for Europe and Japan.

Figure 1 shows changes in the numbers of within-links, in-links, and out-links between before and after the GFC for the U.S., Europe, and Japan. Notable changes are observed for in-links and out-links. Specifically, the number of in-links increases for Japan, and the numbers of both in-links and out-links increase for Europe, implying that Japanese and European banks have become more affected by foreign banks and additionally that European banks have become more influential for foreign banks. In contrast, the number of in-links decreases for the U.S., implying that U.S. banks have become less affected by foreign banks. A close look at the relationship between Japanese and European banks shows that the number of links from European banks to Japanese banks increases, implying that the degree of connectedness from European banks to Japanese banks has increased between before and after the crisis.

A graphical representation of the estimated network $\hat{\boldsymbol{B}}$ is also useful for understanding changes in the networks between before and after the crisis. Figure 2 shows such a graph, where each vertex represents a bank and each edge represents the effect of one bank on another bank. For example, if $\beta_{ij} \neq 0$, then an edge is drawn from bank j to bank i. Red, light-blue, and white vertices denote Japanese, U.S., and European and other banks, respectively. To highlight the contrast in the number of in-links for Japan between before and after the crisis, edges directed to Japanese banks are colored red.

Two observations are made from Figure 2. First, although the estimated network $\hat{\boldsymbol{B}}$'s become sparse and thus easier to see than otherwise would be the case, they are still highly complex. The network for the pre-crisis period with 27 banks has 9.4 edges per bank and 255 edges in total, and that for the post-crisis period with 32 banks, the corresponding numbers are 10.2 and 325, respectively. Second, the number of edges to Japanese banks, highlighted in red, is much greater in the post-crisis period than in the pre-crisis period. These networks visualize the observation confirmed in Figure 1(b) that the number of banks that affect Japanese banks has increased significantly since the crisis.

Intensity of links

In order to go beyond the number of links as a quantification of the degree of intensity of connectedness, let us define the intensities of within-links, in-links, and out-links, e.g., for the U.S., denoted by $I_{\text{US}}^{\text{within}}$, $I_{\text{US}}^{\text{in}}$, and $I_{\text{US}}^{\text{out}}$, respectively, as follows:

$$I_{\text{US}}^{\text{within}} = \sum_{i\in\{\text{U.S. banks}\}}^{n} \sum_{j\in\{\text{U.S. banks}\}}^{n} \hat{\beta}_{ij}$$

$$I_{\text{US}}^{\text{in}} = \sum_{i\in\{\text{U.S. banks}\}}^{n} \sum_{j\in\{\text{non U.S. banks}\}}^{n} \hat{\beta}_{ij}$$

$$I_{\text{US}}^{\text{out}} = \sum_{i\in\{\text{non U.S. banks}\}}^{n} \sum_{j\in\{\text{U.S. banks}\}}^{n} \hat{\beta}_{ij}$$

These indicators are defined as simple summations of the estimated VAR coefficients. Summing the coefficients makes sense because a positive coefficient implies a volatility amplifier: an increase in volatility of one bank today increases other banks' volatility tomorrow. As can be expected, the sign of almost all the estimated coefficients is positive.

Figure 3 shows changes in the intensities of within-links, in-links, and out-links between before and after the GFC for the U.S., Europe, and Japan. The main observation regarding the numbers of links shown in Figure 1 applies to this intensity metric. That is, the intensity of in-links increases for Japan and Europe and that of out-links increases for Europe, implying that Japanese and European banks have become more affected by foreign banks and European banks have become more influential for foreign banks. In addition, the changes in the number and intensity metrics suggest that U.S. banks have become less affected by foreign banks. However, some changes in the intensities of links differ in direction from those in the number of links. For example, the changes in the intensity of within-links have different signs from those in the number of within-links for the U.S. and Europe.

These differences point to the complexity of interconnectedness: simple metrics such as the number or intensity of links can be useful, but they shed light on only one aspect of complex interconnectedness. Such differences in measured changes in interconnectedness make it difficult for us to infer the implications of changes in interconnectedness for banks and the financial system. Implications need to be derived directly from the $\hat{\boldsymbol{B}}$'s (the estimated network matrices) before and after the crisis, not from simple metrics based on them. This will be explored in the next section.

3. Interconnectedness as an Amplifier or a Stabilizer

Theory suggests that interconnectedness can destabilize or stabilize the financial system. Thus, we would like to know whether the changes in interconnectedness estimated in the previous section amplify or stabilize disruptions to the global banking system. Given some shock to the system, according to our VAR specification (1), the shock affects banks today, and then from the next period, the affected banks interact with each other through the network and drive their stock price volatilities. What we are after is how a change in the network $\widehat{\boldsymbol{B}}$'s before and after the crisis affects bank stock price volatilities, which capture investors' uncertainty and fears. Thus, our specific question is as follows: Does the post-crisis network amplify or stabilize volatilities relative to the pre-crisis network?

To address this question, we consider a shock to a U.S. corporate bond yield spread, reflecting its importance in driving the economy[14] and policymakers' recent focus on the so-called interest-rate snapback risk.[15] Ideally, such a shock should be identified, but we take an agnostic view and consider generalized impulse responses, in the framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), to a reduced-form shock to the credit spread, close in spirit to the variance decomposition used by Diebold and Yilmaz (2014).[16] The credit spread used for the estimation is the daily U.S. high-yield corporate bond spread. The data source is Bloomberg.

To analyze how a shock to the credit spread is transmitted through the network estimated in Section 2, the credit spread is incorporated into the original VAR specification (1) as follows:

$$\begin{bmatrix} CS_t \\ \boldsymbol{y}_t \end{bmatrix} = \begin{bmatrix} \rho & \boldsymbol{A}_1' \\ \boldsymbol{A}_2 & \boldsymbol{B} \end{bmatrix} \begin{bmatrix} CS_{t-1} \\ \boldsymbol{y}_{t-1} \end{bmatrix} + \boldsymbol{u}_t, \tag{4}$$

where $\boldsymbol{u}_t \sim N(0, \boldsymbol{\Omega})$ and CS_t is the credit spread. In principle, the VAR in equation (4) should be estimated jointly. However, to fix the network $\boldsymbol{B}$ at $\widehat{\boldsymbol{B}}$ estimated by (1) for coherency with the previous analysis, the remaining coefficients are estimated sequentially as follows. The $n \times 1$ vector $\boldsymbol{A}_2$ is estimated by regressing $\hat{e}_{it} = y_{it} - \widehat{\boldsymbol{\beta}}_{i\cdot}\boldsymbol{y}_{t-1}$ on CS_{t-1} for each i using the OLS. The autoregressive coefficient ρ is estimated by regressing CS_t on CS_{t-1} using the OLS, and the $n \times 1$ vector $\boldsymbol{A}_1$ is estimated by regressing the residual on $\boldsymbol{y}_{t-1}$ using the square-root LASSO.[17]

[14] See, e.g., Gilchrist and Zakrajšek (2012).

[15] See, e.g., Committee on the Global Financial System (2018).

[16] For checking the suitability of using generalized impulse responses, we also use the same VAR specification (2) but with monthly data and identify a credit shock using the excess bond premium, calculated by Favara et al. (2016), as an instrumental variable as in Stock and Watson (2012). We confirm that the signs of the responses to an identified credit shock are consistent with those of the generalized impulse responses reported in this section for the U.S., Europe, and Japan. For details, see the appendix.

[17] For robustness checks, we also estimated the specification (4) using the square-root LASSO without fixing coefficients $\boldsymbol{B}$ and confirmed that the estimation results did not affect our main results significantly.

Figure 4 plots the generalized impulse responses to a 200 bps increase in the credit spread for the U.S., Europe, and Japan. In each panel, the solid line corresponds to the response of the average volatility among banks in the country/region in the post-crisis period and the dashed line corresponds to that in the counterfactual scenario in which only the network $\widehat{\boldsymbol{\beta}}_{i\cdot}$ -- the effects of other banks on bank i -- is replaced with that estimated for the pre-crisis period for all i that exist both in the pre-crisis and post-crisis periods.[18] Thus, the dashed line labeled "Before the crisis" in Figure 4 represents counterfactual impulse responses. Comparing the estimated impulse responses after the crisis and the counterfactual ones before the crisis allows us to isolate the impact of the estimated change in interconnectedness arising as an effect of the credit shock on bank volatilities.

As shown in Figure 4, for the U.S. and especially for Europe, the impulse responses with the post-crisis interconnectedness are less amplified than those with the pre-crisis interconnectedness. This implies that the overall changes in the interconnectedness between before and after the crisis have stabilized the impact of the credit shock. However, for Japan, the impulse responses show the opposite: impulse responses with the post-crisis interconnectedness are more amplified than those with the pre-crisis interconnectedness, albeit their levels are still less than those for the U.S. and Europe. This implies that a change in the interconnectedness acts as an amplifier for Japan.

This raises the question of which part of interconnectedness -- within-links, in-links, out-links, or other links -- drives the changes in the impulse responses. To address this question, the change in the impulse responses, decomposed into various types of links according to whether they are within-links, in-links, or out-links, is shown in Figure 5.[19]

The decomposition in Figure 5 shines a light on the impacts of the different parts of interconnectedness for the U.S., Europe, and Japan. For U.S. banks, the overall change in the interconnectedness acts somewhat as a stabilizer, but the decomposition shows that the change in the within-links (dark blue bars in the figure) amplifies the responses, whereas the changes in the in-links (light blue) and the outside-links (white) dampen the responses (Figure 5(a)). The

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[18] In replacing $\widehat{\boldsymbol{\beta}}_{i\cdot}$ for simulating a counterfactual scenario, if bank j did not exist in the pre-crisis period, then $\hat{\beta}_{ij}$ is set to zero. Also, $\widehat{\boldsymbol{\beta}}_{i\cdot}$ is replaced only if bank i exists in both the pre-crisis and post-crisis periods.

[19] The decomposition is conducted as follows. First, starting from the post-crisis interconnectedness, the interconnectedness is replaced by the pre-crisis interconnectedness one part at a time. The order of the replacement is in-links, outside-links, within-links, out-links, credit-spread-in-links, and credit-spread-out-links, where credit-spread-in-links refers to links directed from the credit spread to banks in the country/region and credit-spread-out-links refers to links directed from the credit spread to banks outside the country/region. Second, for each step of the replacement, impulse responses to the credit shock are calculated. Third, the difference between the impulse responses between each pair of adjacent steps is calculated and defined as the contribution of a change in the interconnectedness between that pair of steps. The results from this decomposition are not necessarily free from the effects of the order of the replacement of interconnectedness, but we have confirmed that changes in the order do not affect our main results significantly.

implications of the within-links and the in-links -- amplifying and dampening, respectively -- coincide with the directional changes in the intensity metrics of those links -- an increase and a decrease, respectively -- as shown in Figure 3.

For European banks, similar to U.S. banks, the overall change in the interconnectedness plays the role of a stabilizer. The decomposition shows that the dampening effect of the change in the within-links (dark blue) dominates the amplifying effect of the change in the in-links (light blue) (Figure 5(b)). Again, similar to U.S. banks, the implications of the within-links and the in-links match the directional changes in the intensity metrics of those links: the intensity of the within-links decreases but that of the in-links increases as shown in Figure 3. However, from the changes in the intensity metrics, which are similar in size between within-links and in-links, it is not obvious whether the effect of one type of links dominates that of the other. The impulse responses and the decomposition of their changes each bring unique information on the impact of different parts of interconnectedness on banks.

For Japanese banks, unlike U.S. and European banks, the overall change in the interconnectedness acts as an amplifier. What drives such amplification is the change in the in-links -- the connectedness from foreign banks to Japanese banks (Figure 5(c)). The amplifying effect of the change in the in-links dominates the dampening effect of the change in the within-links, increasing the post-crisis responses of Japanese banks' volatilities to the credit shock originating in the U.S. The change in the in-links as an amplifier for Japanese banks is consistent with the observation that the intensity of the in-links increases.

4. Underlying Drivers of Interconnectedness

Finally we address the question of what drives the change in the financial interconnectedness between before and after the crisis. The networks estimated in Section 2 may reflect direct interconnectedness, e.g., direct lending and borrowing, and/or other factors such as common exposure and business model similarities, but the estimated networks are silent about the actual underlying drivers of their formation.

This section investigates what lies behind a change in the financial interconnectedness. As a first step, it examines a potential relationship between the estimated interconnectedness and the G-SIB-score indicators, which measure the systemic importance of banks. Next, motivated by the finding of the amplifying effect of the in-links for Japanese banks, a panel regression analysis is conducted for Japanese banks to examine cross-border activity as a potential driver of interconnectedness.

4.1. G-SIB-Score Indicators

The indicators that constitute G-SIB scores measure the systemic importance of banks and thereby may be related to the interconnectedness estimated in Section 2. These indicators are classified into five categories: size, interconnectedness, substitutability/financial institution infrastructure, complexity, and cross-jurisdictional activity.[20] For each category, a simple average of indicators within the category is calculated.[21] The constructed indicator for each category represents systemic importance relative to other G-SIBs and thus may have some implications for the estimated interconnectedness.

For each indicator, we mechanically check whether the indicator is correlated with the intensity of within-links, in-links, or out-links among G-SIBs. We find that among the various pairs of the G-SIB-score indicators and the metrics of estimated links, only the intensity of the in-links for individual banks -- the degree of connectedness from foreign banks to individual banks -- in the post-crisis period of 2015-2018 has a positive correlation with the cross-jurisdictional activity indicator in 2017 at a 1 percent level of statistical significance.[22] The cross-jurisdictional activity indicator aims to capture banks' global footprint and measures the bank's activities outside its home (headquarter) jurisdiction relative to the overall activity of other banks in the sample: cross-jurisdictional claims such as foreign lending and cross-jurisdictional liabilities including foreign currency funding outside its home. The simple but statistically significant correlation shown in Figure 6 suggests that it may be foreign exposure of assets and liabilities, notably foreign lending and the associated funding from foreign banks, as well as the resulting common exposure and vulnerability to foreign banks, that lies behind the degree of connectedness from foreign banks, measured by the intensity of in-links.

4.2. Panel Analysis

Motivated by the finding illustrated in Figure 6, we explore the role of foreign exposure as a potential driver of the change in the estimated interconnectedness, especially with respect to in-links, before and after the crisis. In particular, we focus on Japanese banks, for three reasons. First, as observed in Section 2, the number and intensity of in-links have increased significantly between the pre-crisis and post-crisis periods for Japanese banks. Second, Japanese banks have massively expanded their foreign operations since the crisis, unlike U.S. and European banks, as indicated by, e.g., Van Rixtel and Slee (2013). Third, quarterly data on foreign

[20] The G-SIB indicators are updated annually and available from 2014. For a summary of their recent developments, see Basel Committee on Banking Supervision (2019).

[21] Simple averaging within each category is consistent with the way indicators are aggregated into a G-SIB score.

[22] This result is robust to the use of 2015-2017 averages for the G-SIB-score indicators.

exposure, among others, are available for Japanese banks from the pre-crisis period.

To take advantage of quarterly data for individual Japanese banks, the intensity of in-links is calculated quarterly using a rolling regression of the VAR specification (1). Estimated quarterly intensity metrics are then used as an independent variable for a panel analysis. The rolling window is set to 200 days, similar to Malik and Xu (2017).

With quarterly data including the intensity of in-links at hand, we consider the following fixed-effect panel regression:

$$I_{jt}^{\mathrm{in}} = \delta_j + \gamma_1 \mathrm{FL}_{jt} + \gamma_2 \mathrm{FS}_{jt} + \boldsymbol{\gamma}_3' \boldsymbol{X}_{jt} + \boldsymbol{\gamma}_4' \boldsymbol{Z}_t + \varepsilon_{jt} \tag{5}$$

where I_{jt}^{in} is the intensity of in-links for bank j, δ_j is the fixed-effect, FL_{jt} is the share of foreign lending to the total lending for bank j, and FS_{jt} is a measure of funding stability, given by client-related deposits divided by the sum of foreign currency denominated loans and securities. The vector $\boldsymbol{X}_{jt}$ includes other bank-specific variables such as the ratio of foreign securities to total assets and the share of foreign investors, as measured by the ratio of the amount of stocks held by foreign institutional investors to total shares. The share of foreign investors is introduced to control potential impacts from stockholdings by foreign investors, which may drive co-movements among stock prices for Japanese major banks. The vector $\boldsymbol{Z}_t$ includes time-specific variables such as VIX and the economic policy uncertainty index. These time-specific variables are included to reflect the findings by Diebold and Yilmaz (2014), Demirer et al. (2018), and Malik and Xu (2018) that connectedness measures based on stock prices tend to increase during financial stress and heightened policy uncertainty. This is possibly because investors tend to become more sensitive to their perceived connectedness among banks especially under stress events and severe policy uncertainty. The summary statistic for each variable is shown in Table 1.[23]

We consider six specifications within the regression form (5) and report the results in Table 2. Six observations can be made from the results. First, for all the specifications, the share of foreign lending has statistically significant positive effects. That is, the intensity of in-links -- the degree of connectedness from foreign banks -- tends to increase as the foreign exposure increases. Specifications (a)-(d) include period fixed effects so that the significance of the foreign lending share stems mainly from its cross-sectional variations. These results suggest that an increase in foreign lending during the post-crisis period could be one of the main underlying drivers of an increase in the estimated connectedness from foreign banks to Japanese banks. Second, the share of foreign securities -- another type of exposure in the asset side of bank balance sheets --

[23] The data sources are Nikkei, "NEEDS" for the share of foreign investors, Bloomberg for the VIX, PolicyUncertainty.com for the economic policy uncertainty index, and the Bank of Japan for other variables.

has no significant effects for specifications (b)-(f). These first two results suggest that it is overseas lending rather than foreign securities investment that is most likely to have driven the estimated connectedness from foreign banks. Third, the measure of funding stability -- a stability measure in the liability side of bank balance sheets -- has statistically significant negative effects for specifications (c)-(f). Admittedly, the values of the estimated coefficients are relatively small. Judged from these values and their statistical significance, overseas lending is likely to have larger impacts on the estimated connectedness from foreign banks than funding stability.[24] Nevertheless, this result still implies that Japanese banks with less stable funding bases are more likely to be affected by foreign banks' behavior, which is consistent with the fact that Japanese banks rely on U.S. and European counterparts for raising U.S. dollars through FX and currency swaps. Fourth, the share of foreign investors does not have any significant effects, as shown for specifications (d)-(f). The results on the roles of foreign lending and funding stability are robust to adding the share of foreign investors.

The last two observations pertain to time-specific variables. First, VIX has a statistically significant positive sign, as shown for specifications (e) and (f). This result is consistent with previous studies, such as Diebold and Yilmaz (2014), Demirer et al. (2018), and Candelon, Ferrara, and Joëts (2018), which suggest that connectedness measures based on stock prices tend to increase in times of stress and uncertainty. Second, following the study of Malik and Xu (2017), specification (f) incorporates the economic policy uncertainty index, but the economic policy uncertainty index has no significant effects on the estimated connectedness from foreign banks.

To summarize, the analyses in this section indicate that banks' cross-border activities, represented by overseas lending and its funding stability, appear to be one of the underlying drivers of the estimated connectedness from foreign banks to domestic banks and its changes from the pre-crisis period to the post-crisis period.

5. Conclusion

Among the many factors contributing to the global financial crisis of 2007-09, the role of the interconnectedness of the global financial system is perhaps the least understood, as mentioned by Glasserman and Young (2016). Similarly, among the many potential risks currently facing the

[24] For example, in specifications (e) and (f), the coefficients of the share of overseas lending and funding stability are about 0.8 and -0.01, respectively. Given the standard deviations of about 0.1 and 1.0 for the share of overseas lending and funding stability, respectively, as shown in Table 1, the impact of one-standard-deviation changes in the two variables can be simply calculated as 0.08 (0.8 times 0.1) and -0.01 (1.0 times -0.01), respectively. Hence, in absolute terms, the impact of foreign lending is about eight times as large as that of funding stability.

global financial system, the role of the interconnectedness is perhaps the least understood. Against this background, this paper has explored the measurement, implications, and underlying drivers of the interconnectedness. Specifically, it has focused on the interconnectedness perceived by market participants and has examined the interconnectedness of stock price volatilities for G-SIBs and Japanese major banks, as such volatilities reflect investors' uncertainty and fears about the banks.

The present paper's findings and arguments regarding interconnectedness can be summarized in terms of the following three aspects: measurement, implications, and underlying drivers. First, regarding measurement, our estimation reveals some patterns of changes in the interconnectedness between before and after the crisis. Specifically, it was observed that Japanese and European banks have become more affected by foreign banks, whereas U.S. banks have become less affected by foreign banks. Conversely, European banks have become more influential for foreign banks.

Second, regarding implications, our analysis implies that changes in connectedness as a whole can amplify or stabilize the impact of a snapback of credit yields on bank volatilities, depending on the country/region; in addition, depending on the type of connectedness, changes of some type of connectedness can amplify or stabilize the impact of the snapback within the same country/region. In particular, consistent with the findings on measurement, the impact of the snapback has increased for Japanese banks, mainly through an increase in the connectedness from foreign banks, whereas for European banks, whose estimated connectedness from foreign banks has also increased, the impact of the snapback has attenuated. The latter is because the change in connectedness within European banks has a dampening effect which dominates the amplifying effect exerted from the increase in connectedness from foreign banks. These somewhat complicated results suggest that the quantitative implications of interconnectedness should be explored using all interconnectedness information rather than just using summary metrics, though such metrics are useful for getting an overall grasp of the interconnectedness.

Third, regarding underlying drivers, this paper has argued that banks' cross-border activity can be one of the driving forces of interconnectedness. The supporting evidence is two-fold: (i) the positive relationship between the estimated connectedness from foreign banks and the G-SIB indicators on cross-border activities and (ii) the panel regression results for Japanese banks. Specifically, the panel regression results imply that foreign lending and foreign currency funding stability have statistically significant effects on the degree of connectedness from foreign banks.

We conclude the paper by mentioning some future challenges. In deriving the implications of the estimated interconnectedness, the paper has focused on a snapback of credit yields, but this is just one of many potential shocks that could disrupt the financial system. Other shocks, such as monetary policy shocks, policy uncertainty shocks, and bank-specific shocks, also warrant analysis. Also, the paper examines cross-border activities as a potential driver of the connectedness from foreign banks, but there could be other factors that affect it. Decomposing cross-border activity into its asset side and liability side and identifying their impacts on the interconnectedness is another challenge. Our panel regression results suggest that overseas lending -- the asset side -- is likely to have bigger impacts on the estimated connectedness from foreign banks than does foreign currency funding stability -- the liability side. However, more granular factors within cross-border activities deserve analysis. In addition, potential driving factors have remained unexplored for other types of interconnectedness, such as linkages among banks within a country/region and linkages from banks in a country/region to those in other countries/regions. Notwithstanding these remaining challenges and caveats, we believe that this paper represents a contribution toward promoting understanding of global financial interconnectedness.

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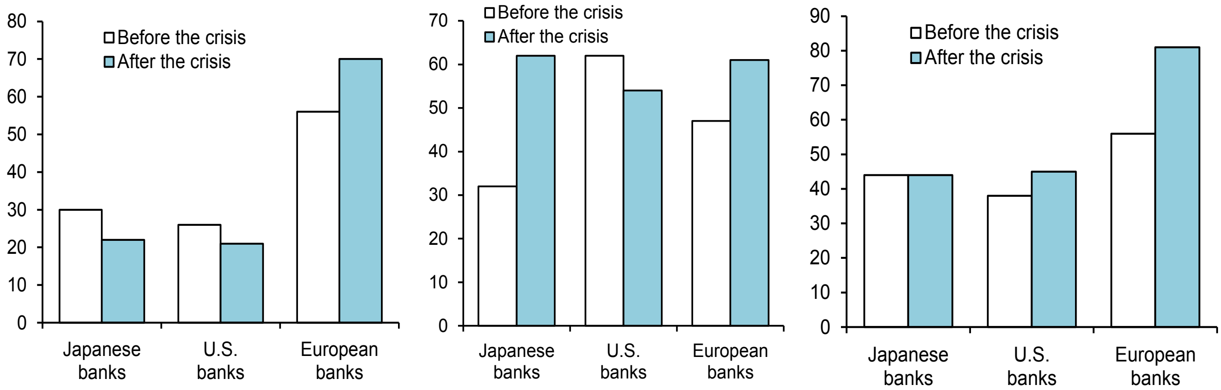
Figures and Tables

Figure 1: Numbers of links

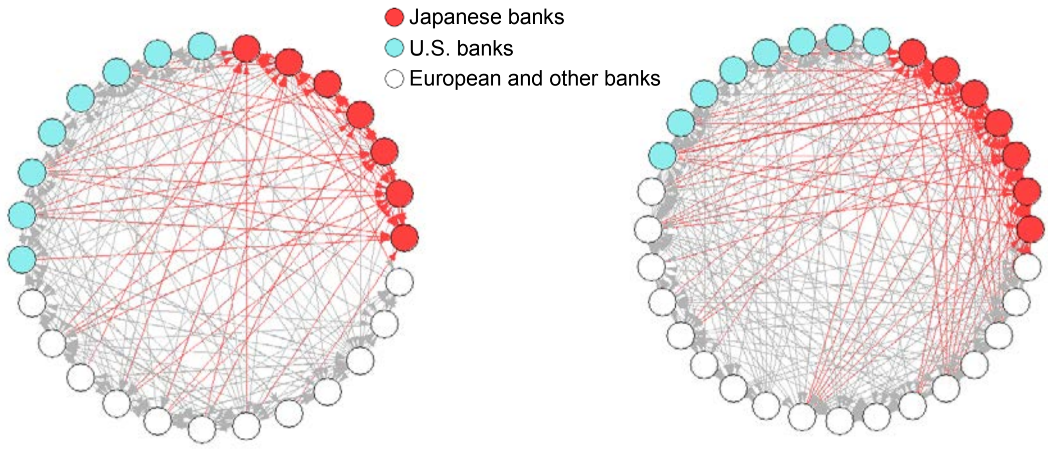
(a) Within-links N^{within} (b) In-links N^{in} (c) Out-links N^{out}



Note: The number of links is counted for all the banks in the sample for both the pre-crisis period and the post-crisis period. Within-links are links among the same country/region. In-links are links to a country/region from outside the region/country. Out-links are links from a country/region to outside the country/region.

Figure 2: Graphical representation of the estimated networks

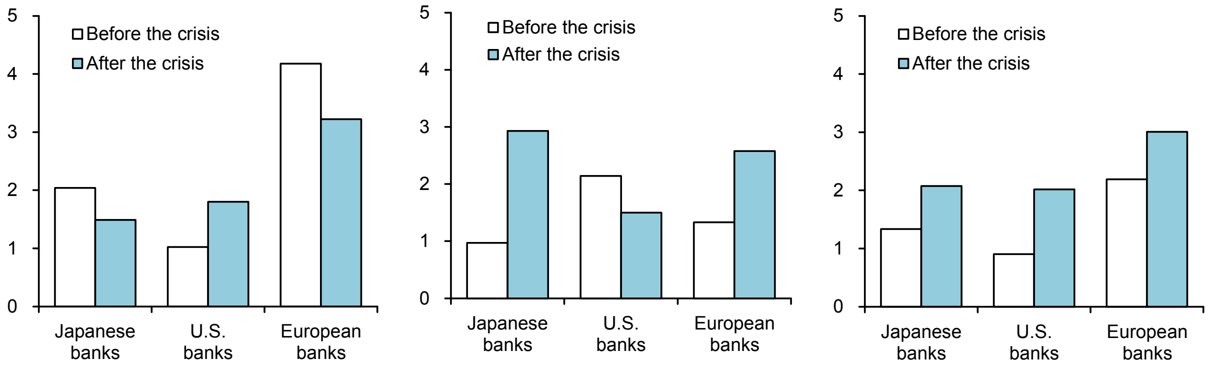
(a) Before the crisis (b) After the crisis



Note: The red lines are the links directed to Japanese major banks. Edge widths are proportional to the size of the coefficient.

Figure 3: Intensities of links

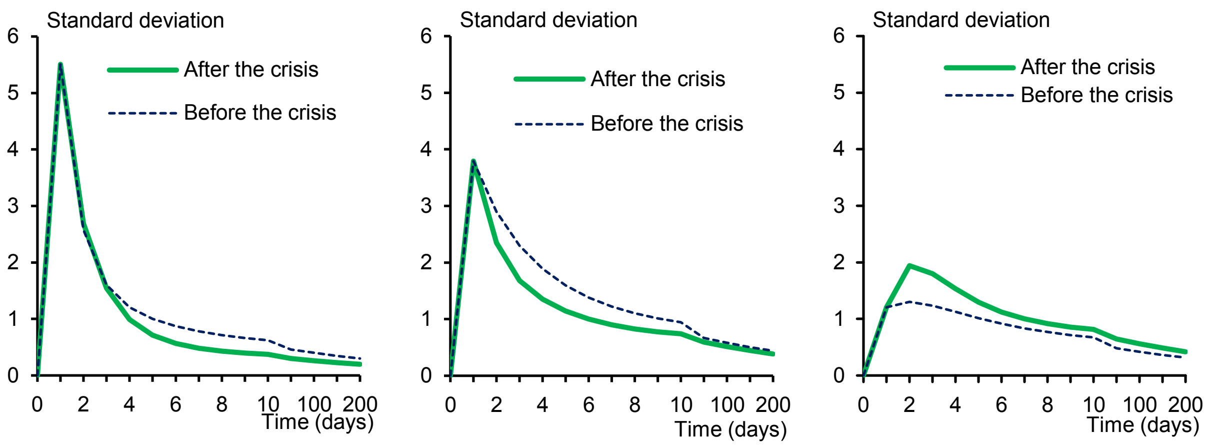
(a) Within-links I^{within} (b) In-links I^{in} (c) Out-links I^{out}



Note: The intensity of links is calculated for all the banks in the sample for both the pre-crisis period and the post-crisis period. Within-links are links among the same country/region. In-links are links to a country/region from outside the region/country. Out-links are links from a country/region to outside the country/region.

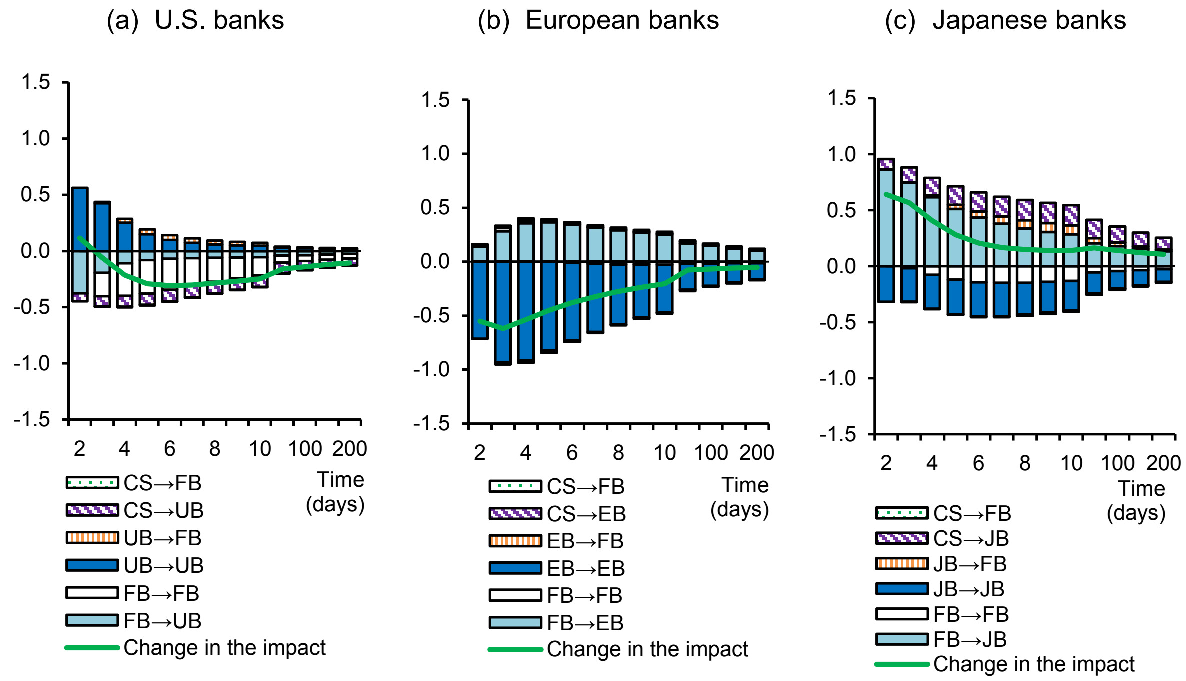
Figure 4: Impulse responses to an increase in the credit spread

(a) U.S. banks (b) European banks (c) Japanese banks



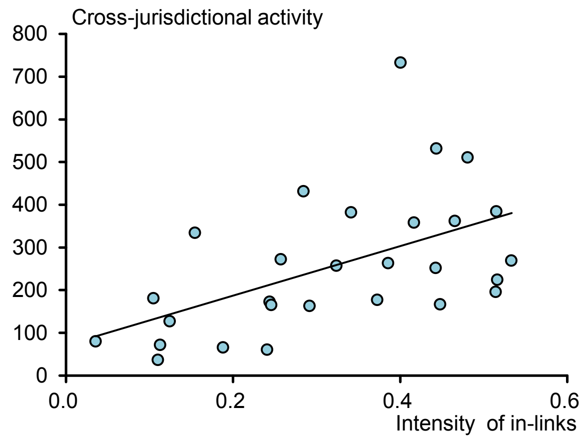
Note: The vertical axis represents the standard deviation for banks in each country/region. The responses are averages of the impact on the banks for which data are available both before and after the crisis. "Before the crisis" is calculated by replacing the coefficients estimated for the period after the crisis with the ones estimated for the period before the crisis.

Figure 5: Decomposition of the changes in the impulse responses



Note: An arrow → indicates a link and its direction. "FB" indicates foreign banks, "JB" indicates Japanese banks, "UB" indicates U.S. banks, "EB" indicates European banks, and "CS" indicates credit spreads on U.S. high-yield bonds.

Figure 6: Cross-jurisdictional activity versus intensity of in-links



Note: "Cross-jurisdictional activity" is the simple average of two G-SIB score indicators, cross-jurisdictional claims and cross-jurisdictional liabilities, in 2017. The intensity of in-links is calculated from the estimated post-crisis interconnectedness.

Table 1: Summary statistics of variables for the panel analysis

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Intensity of in-links	0.193	0.175	0.785	0.000	0.148	394
Share of overseas lending	0.130	0.107	0.383	0.002	0.102	413
Share of foreign securities	0.058	0.052	0.188	0.001	0.036	413
Funding stability	0.609	0.410	7.828	0.006	0.997	413
Share of foreign investors	0.161	0.111	0.663	0.008	0.144	408
VIX	18.648	15.950	54.920	9.190	8.744	59
Policy Uncertainty	103.853	99.518	175.575	58.822	30.101	59

Table 2: Panel regression results

	(a)	(b)	(c)	(d)	(e)	(f)
Share of overseas lending	0.264 **	0.285 **	0.325 ***	0.324 **	0.779 ***	0.809 ***
	(0.118)	(0.125)	(0.115)	(0.134)	(0.137)	(0.157)
Share of foreign securities		-0.138	-0.214	-0.219	0.166	0.137
		(0.210)	(0.201)	(0.259)	(0.227)	(0.212)
Funding stability			-0.011 ***	-0.011 **	-0.010 *	-0.010 *
			(0.003)	(0.005)	(0.005)	(0.005)
Share of foreign investor				-0.003	0.030	0.037
				(0.069)	(0.102)	(0.105)
VIX					0.004 ***	0.005 ***
					(0.001)	(0.001)
Policy uncertainty						-0.0002
						(0.000)
Bank fixed effect	YES	YES	YES	YES	YES	YES
Period fixed effect	YES	YES	YES	YES	NO	NO
Observation	394	394	394	394	394	394
Adjusted R-squared	0.696	0.696	0.698	0.697	0.148	0.147

Note: *, ** and *** indicate statistical significance at the 1, 5, and 10 percent levels, respectively. Standard errors are given in parentheses. The estimation is based on 7 Japanese major banks. The estimation period is from 2004Q1 to 2018Q3

Appendix

In this appendix, we estimate the VAR specification (4) and identify a shock to the credit spread by using an instrumental variable method. By doing so, we aim to complement our main result in Section 3, which is based on an analysis using generalized impulse responses.

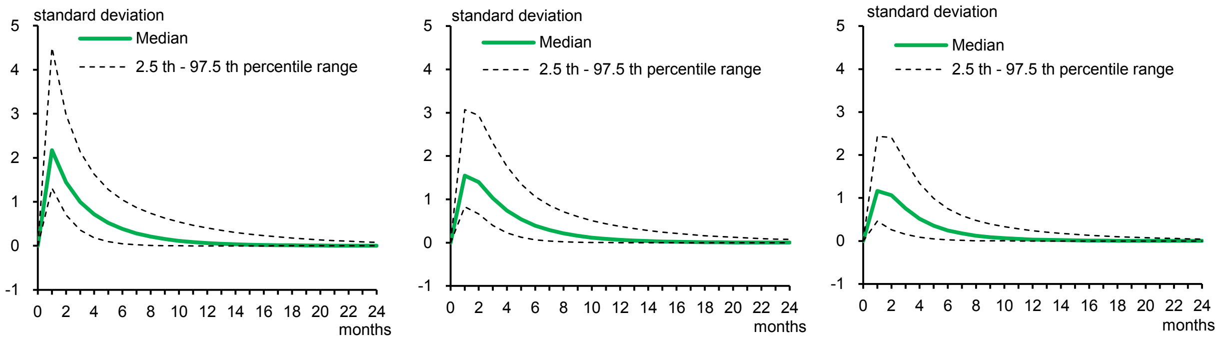
Following Stock and Watson (2012), we use the excess bond premium (EBP), which is a financial indicator introduced by Gilchrist and Zakrajšek (2012) (though we used the version updated by Favara et al., 2016), as an instrumental variable to identify a shock to the credit spread. Because the frequency of the EBP is monthly, we use monthly data for bank stock price volatilities, estimate the VAR specification using the square-root LASSO, and identify a credit spread shock using the EBP as an instrument. Due to the limited sample size, we use the sample of 2004Q1-2018Q3, which covers both the pre-crisis and post-crisis periods.

Figure A1 presents the estimated impulse responses to a 200 bps increase in the credit spread. These responses differ from the generalized impulse responses reported in Figure 4, reflecting differences in the estimation methods, the data frequencies, and the sample periods. However, there are also some similarities. Specifically, the signs of the responses are the same between the two types of impulse responses for the U.S., Europe, and Japan. In addition, the average values of the first 30 days of the generalized impulse responses are not far from those of the first month of the impulse responses estimated by an instrumental variable method for the U.S., Europe, and Japan. These results suggest that although a shock is not identified in the generalized impulse responses, such responses are still useful for considering responses to a credit shock.

Figure A1: Impulse responses to an increase in the credit spread:

Estimation based on an instrumental variable method

(a) U.S. banks (b) European banks (c) Japanese banks



Note: The confidence intervals are computed by a recursive wild bootstrap using 10,000 replications, as in Mertens and Ravn (2013).