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The network and own effects of global-systemically-important-bank designations ☆

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This paper considers the network structure of listed depository institutions around the globe through volatility spillovers to assess the network and own effects from Global Systemically Important Bank (GSIB) designations as done by the Financial Stability Board (FSB). Different from previous studies, after considering the (network) spillover effects of GSIB designations in the model, we cannot reject the null hypothesis that the direct effects of GSIB designations are zero for the cumulative abnormal returns of the targeted institutions. However, we unveil unintended heterogeneous spillover effects of these designations, which depend on the profitability and riskiness of the involved institutions in the network. Finally, we find evidence that the GSIB designations increase GSIBs' resilience to external shocks, but they also induce volatility spillovers from GSIBs to other banks in the network. The intended change of the volatility-spillover intensity of GSIBs mitigates the unintended effects to some extent, but it does not offset them.

1. Introduction

In the new millennium, we were already twice reminded of the importance of systemic risk and associated spillovers as a consequence of large degree of interdependencies of the global financial system and spillovers between its players. In the first quarter of 2023, the failure of Silicon Valley Bank triggered a turmoil which led to global rippling effects that in Switzerland induced the takeover of Credit Suisse by UBS, leading to one of the largest financial institutions worldwide. Events like this attract the interest of the public and academics alike. Important goals of academic work on systemic risk of the financial industry are the derivation of accurate indicators and the identification of systemically important financial institutions (SIFIs), specifically, systemically important banks (SIBs), as adverse shocks from as well as on these core intermediaries can have devastating aggregate economic effects (Elliott, Golub, and Jackson, 2014).

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Earlier global shocks and the associated literature on systemic risk led to new financial regulations, e.g., through the new Basel III agreement and the Financial Stability Board (FSB) mandate, that explicitly designate SIFI status globally and/or domestically and put measures in place to mitigate systemic risk in the global and domestic financial industry. The latter measures include requirements of a greater loss absorbency and of higher supervisory expectations for risk management functions, data aggregation capabilities, risk governance, and internal controls for SIFIs (see FSB, 2012).

While these policy measures may help reducing contagion risks when failures occur in the financial system, they are not a panacea and they cannot possibly eliminate contagion in the system. Prior studies provide both theoretical and empirical evidence in support of this point of view. For instance, based on evidence for 61 countries in 1980–1997, Demirgüç-Kunt and Detragiache (2002) find that the presence of an explicit deposit insurance (as a form of government guarantee) is associated with less financial stability. Eichberger and Summer (2005) develop a model to study the impact of capital adequacy on contagious defaults arising from heterogeneous banks' mutual credit relations in the interbank market and find that systemic risk might increase as a consequence of imposing capital constraints on banks. Hence, even after the new Basel III agreement and the inception of the FSB, shocks may propagate – and thereby get amplified – in the global financial system, and individual financial institutions are heterogeneous in the propensity to be affected by these shocks.

The current literature sheds some light on the potential impact of SIFI designations on both SIFIs and non-SIFIs. Among others, leading examples include O'Hara and Shaw (1990), Moenninghoff, Ongena, and Wieandt (2015), and Dewenter and Riddick (2018). However, most of the related studies do not distinguish between direct and indirect or spillover effects of SIFI designations. A SIFI designation will impose direct effects on the designated financial institution, according to earlier work. However, as SIFIs – and, in particular, Global SIFIs – are systemically important, such a designation should by design trigger indirect effects on other financial institutions (both other SIFIs and non-SIFIs) through the linkages in the financial network. A proper identification of SIFI designations on other SIFIs and non-SIFIs requires a holistic consideration of the global financial system because of the network linkages present in that system. Omitting relevant players in that system may lead to measurement of effects which is biased and/or misattribute some effects to institutions which are not responsible for them. Understanding how the effects of SIFI designation affect the SIFI network and quantifying the heterogeneity of these effects should be of special interest not only to academic scholars but also to regulators whose goal is to better identify the vulnerabilities of the financial system.

The present paper aims at contributing to this discussion by exploring the direct and spillover effects of the FSB's Global Systemically Important Bank (GSIB) designations using the largest-possible data set on the global banking industry, covering 1,215 different banks in 89 economies and 9 years between 2012 and 2020. Specifically, we include all depository institutions in Datastream (i.e., institutions whose two-digit SIC code is 60), for which daily data are relatively comprehensively available. We focus on outcome effects in the period 2012–2020, as from 2012 onwards the FSB publishes a list of GSIBs in each year that are required to hold additional capital of 1.0–2.5% of Common Equity Tier 1,[1] depending on the individual institution's systemic relevance as measured by an indicator-based approach.

We capture the network linkages between the 1,215 banks. This is done by relying on recent techniques to quantify connectedness in high-dimensional networks, as proposed and developed in a series of papers that include Diebold and Yilmaz (2009, 2012, 2014), Demirer, Diebold, Liu, and Yilmaz (2018), and Gross and Siklos (2020). For this approach we use data on the volatility measured by daily-high and daily-low stock-market prices of the banks in a vector-autoregression for the system of all banks. Based on the decomposition of the forecast error variance of volatility, a directed spillover matrix for interbank shock transmission is established. We use the latter to represent the (estimated) network structure among the banks in a model of bank-specific abnormal returns as a function of not only own but network-weighted other banks' additional loss-absorbency requirements.

Specific findings of our study are the following. In contrast to earlier work (e.g., Moenninghoff, Ongena, and Wieandt, 2015), the direct effect of GSIB designation is statistically insignificant, suggesting that the significant positive effects observed by earlier work might be caused by the omitted indirect effects transmitted from other banks in the network.

In terms of the indirect (spillover) effects, addressing the potential endogeneity of the measure of bank connectedness through a control-function approach, the spillover effects of GSIB designation on sample banks' cumulative abnormal returns are significantly negative. In addition, when we decompose the volatility spillover matrix based on the volatility transmitter and recipient's profitability and riskiness, we find significantly negative spillover effects of GSIB designation in particular in two cases: when the GSIB volatility transmitter and its volatility recipient are (i) more and less profitable, respectively; and (ii) more and less risky, respectively. This finding aligns with the research of Yang and Zhou (2013), who documented similar volatility spillover effects among financial institutions, showing that these effects are contingent upon the riskiness of the institutions involved. [2]Consequently, the heterogeneities in the consequences of GSIB designation on other banks may be

[1] As defined by the Basel III framework, Common Equity Tier 1 is a component of Tier 1 capital that consists qualifying common stock and related surplus, retained earnings, accumulated other comprehensive income and other disclosed reserves, qualifying common shares issued by consolidated subsidiaries of the bank and held by minority interest, and other regulatory adjustments. For more detailed information, we refer the readers to https://www.bis.org/basel_framework/standard/CAP.htm.

[2] Specifically, they find that the leverage ratio and, particularly, the short-term debt ratio are significant determinants of credit-risk transfers among financial institutions. As the stock-return volatility is a major determinant of CDS (credit default swap) spread of the firm, our findings can be viewed to be consistent with theirs.

important for the determination of the GSIB status, as indirect adverse consequences on third parties appear to be typically ignored when designating the status.

The just-mentioned effects are clearly all unintended by the FSB in designating GSIB status. What the FSB intends to do is reducing the magnitude of spillovers from GSIBs (and, eventually, the effects of spillovers to them). We find evidence of such an intended effect of GSIB designations, that GSIB designation reduces the magnitude of spillovers to GSIBs themselves, but it is relatively small. Overall, the effect on mitigating volatility spillovers to GSIBs reduces the overall effect of designations in the network only to a minor extent in the average event window of GSIB designations considered.

Using this empirical framework, we contribute to the literature in the following ways. First, we offer a network-based framework to allow for and document the spillover effect of GSIB designations on all banks in the global financial system. In contrast to previous studies that treated financial institutions in the system as independent, we explicitly acknowledge the global network interdependence of banks whereby, apart from direct treatment effects, GSIB treatment may induce indirect, spillover effects on other banks in the system with a magnitude that depends on the treated and untreated banks' position in the network. Relative to other studies which did pay attention to network interdependencies, we include a larger number of significant institutions. This is important as omitting relevant units in the system may lead to biased effect estimates and a misattribution of effects to units which are not responsible for them.[3]

Second, we contribute to the wider discussion of the potency of the too-big-to-fail doctrine by decomposing the spillover effects of systemic risk reflected in GSIB designations and by alluding to their heterogeneity in the banking sector. Some potentially important policy implications flow from this analysis. E.g., it reveals which spillover recipients benefit the most from the mitigation of shock cascades resulting from GSIB designations. Ultimately, the approach could even provide an empirically-informed decision tool to rank large banks in terms of the predicted ensuing benefits from GSIB status to the global banking network.

The remainder of the paper is organized as follows. In the next section, we discuss the related literature. In Section 3, we outline the empirical strategy applied to identifying direct and indirect effects flowing from the designation of GSIB status. In Section 4, we describe the data and their sources. Section 5 contains a discussion of the main empirical results. Section 6 is devoted to several extensions. The last section concludes with a brief summary.

2. Related literature

The present study is placed at the interface of two literatures: the one on systemic risk measurement and the one on effects of too-big-to-fail status of banks and, more generally, SIB or SIFI policies. This section highlights work we particularly relate to in these literatures.

2.1. Systemic risk measurement

The measurement of relevant systemic risk is paramount to identifying the vulnerabilities of the financial system and maintaining financial stability. Key approaches proposed in earlier work to such measurement are the following: the conditional value at risk (CoVaR) approach of Adrian and Brunnermeier (2016); the marginal expected shortfall (MES) approach and the systemic expected shortfall (SES) approach of Acharya, Pedersen, Philippon, and Richardson (2017); the systemic risk measure (SRISK) of Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2016); the CatFin measure of Allen, Bali, and Tang (2012), the principal component and Granger-causality-network approaches of Billio, Getmansky, Lo, and Pelizzon (2012), and the variance decomposition approach in a series of studies including Diebold and Yilmaz (2009, 2012, 2014), Yang and Zhou (2013), Demirer, Diebold, Liu, and Yilmaz (2018), and Gross and Siklos (2020).[4] The latter approach represents a directional aggregation of forecast volatility in a high-dimensional network, and it is closely related to the CoVaR and MES measures. All three measures rely on some directional aggregation of network links.

In this study, we employ the variance-decomposition approach of Diebold and Yilmaz (2009, 2012, 2014), Demirer, Diebold, Liu, and Yilmaz (2018), and Gross and Siklos (2020). It uses information at the pairwise covariance level of forecast volatility of all banks in the data and, as applied in this study, provides for a time-specific network matrix which permits aggregating characteristics of other banks as determinants for a given bank at a given time.

2.2. The effect of a too-big-to-fail government guarantees as a SIFI and SIB policy measure

It is well acknowledged in the literature that a too-big-to-fail (TBTF) government guarantee will trigger moral hazard problems: such a guarantee reduces depositors' and creditors' incentives to monitor treated institutions, and it encourages

[3] To better illustrate this point, let us assume that there are three banks in the system, i.e., Bank A, Bank B, and Bank C. Let us also assume that Bank A is highly connected with both Bank B and Bank C, which makes Bank A systemically important, while on the other hand, Banks B and C are not connected at all. If we do not include Bank A in our sample when estimating the network linkages, we might come to the wrong conclusion that Banks B and C are highly connected and systemically important, despite the fact that the high connectedness is solely induced by the systemically importance of Bank A. This is very similar to the omitted variable bias problem in econometric analysis.

[4] For a more comprehensive discussion of the applied work on systemic risk measurement, we refer the readers to the survey of Bisias, Flood, Lo, and Valavanis (2012) and Benoit, Colliard, Hurlin, and Pérignon (2017).

TBTF institutions to take excess risks (Demirgüç-Kunt and Kane, 2002; Stern and Feldman, 2004). At the same time, TBTF guarantees provide the treated institutions with competitive advantages in terms of cost of funding and risk premia (Bigus and Prigge, 2005). The benefits associated with TBTF status even motivate financial institutions to dedicate resources to growing beyond their socially optimal size (Kane, 2000; Penas and Unal, 2004).

At the macro level, TBTF guarantees not only induce a redistribution from well-capitalized, conservatively run banks to large and risky banks (Kane, 1985), but they also increase treated banks' shareholder value at the cost of taxpayers, and in times of financial crisis bank bailouts transfer taxpayer wealth directly to bank creditors (Moenninghoff, Ongena, and Wieandt, 2015). Using a "bounding" approach, Boyd and Heitz (2016) find that overall, the social costs of TBTF banks tend to substantially exceed the benefits.[5]

However, there exists little conclusive empirical evidence on the systemic effects of TBTF guarantees (Boyd and Heitz, 2016). A key approach towards the latter is the event study approach, which assesses the immediate stock market responses to the designation (both officially and unofficially) of banks as TBTF. Examples include O'Hara and Shaw (1990), Abreu and Gulamhussen (2013), Moenninghoff, Ongena, and Wieandt (2015), and Dewenter and Riddick (2018). By treating the TBTF and non-TBTF banks as independent entities, a main finding in most of the aforementioned studies is that while TBTF designation leads to positive abnormal returns for TBTF banks, it leads to negative abnormal returns for other banks, which suggests that the TBTF status creates value for treated banks' shareholders and negative externalities to untreated banks.

Beyond the potential impact of the TBTF policy on the equity market, previous studies also considered effects on the bond market (Morgan and Stiroh, 2005; Balasubramnian and Cyree, 2011), the credit-default-swap market (Völz and Wedow, 2011; Demirgüç-Kunt and Huizinga, 2013), the option market (Kelly, Lustig, and Van Nieuwerburgh, 2016), banks' risk-taking behavior (Völz and Wedow, 2011; Gropp, Gruendl, and Guettler, 2013; Cubillas, Fernández, and González, 2017), and mergers and acquisitions between financial institutions (Brewer and Jagtiani, 2013).

3. Methodology

In what follows, we will make use of indices $\{i,j\}$ for banks and t for time (days or dates). It is useful to refer to the number and the set of banks in the data at time t by N_t and Ξ_t, respectively.

Apart from t we will use e to denote a specific event date among t and N_e and Ξ_e to denote the number and set of firms belonging to the data subsample around event date e. In the subsequent analysis, an event date e will correspond to one specific publication date of the FSB regarding the GSIB status of banks. For estimation, we will require the data to be balanced within an event window. Since the data will generally be unbalanced across event dates $e = 1,\ldots,E$ covered, the unique number and set of firms throughout the data-set will be $N \geq N_e$ and $\Xi = \Xi_1 \cup \ldots \cup \Xi_E$, respectively.

The approach we adopt will involve the following steps.

Step 1: Measuring daily stock return volatility and estimating the corresponding directional inter-bank spillovers.

We measure the volatility of daily stock returns by following the approach of Parkinson (1980) and Diebold and Yilmaz (2012) who focused on stock indexes rather than individual stocks. Specifically, we determine the annualized daily return volatility of a bank's stock as

$$x_{it} = 100\sqrt{365 \times 0.361\left(p_{it}^{max} - p_{it}^{min}\right)^2} \tag{1}$$

where p_{it}^{max} and p_{it}^{min} measure the maximum and the minimum, respectively, of the log of the price stock i is traded at on day t and 0.361 is a scaling factor. Stacking the data on x_{it} for all firms at day t obtains the $N_t \times 1$ vector $\boldsymbol{x_t}$ which will be used below.

To measure inter-bank risk spillovers, we use the connectedness measure based on variance decompositions as proposed and developed in Diebold and Yilmaz (2009, 2012, 2014) and Demirer, Diebold, Liu, and Yilmaz (2018). This measure captures how much of entity i's future uncertainty (at horizon H) is due to shocks arising not with entity i, but rather with entity j (Demirer, Diebold, Liu, and Yilmaz 2018).

To measure the pair-wise connectedness between banks i and j around event date e, we conduct the variance decomposition of $\boldsymbol{x_t}$ in a vector autoregression of order p, VAR(p), which can be formulated as $\boldsymbol{x}_{e,t} = \sum_{i=1}^{p}\Phi_{e,i}\boldsymbol{x}_{e,t-i} + \boldsymbol{\varepsilon}_{e,t}$ for a generic day, where $\boldsymbol{\varepsilon}_{e,t}\ N(0,\Sigma_e)$ is the error vector and $\Sigma_e = E\left(\boldsymbol{\varepsilon}_{e,t}\boldsymbol{\varepsilon}_{e,t}'\right)$ is the variance–covariance matrix pertaining to event date e. In what follows, we will use the orders $p = 1$ and $p = 2$ for the VAR. The reason for Σ_e being e-indexed here is the unbalancedness of the underlying data across event windows as well as the estimation for each event window separately. The diagonal element of Σ_e pertaining to observation $\{e,ii\}$ will be $\sigma_{e,ii}^2$. The moving-average representation of this model is $\boldsymbol{x}_{e,t} = \sum_{i=0}^{\infty}\boldsymbol{A}_{e,i}\boldsymbol{\varepsilon}_{e,t-i}$, where the $N_e \times N_e$ coefficient matrices $\boldsymbol{A}_{e,i}$ obey the recursion $\boldsymbol{A}_{e,i} = \sum_{k=1}^{p}\Phi_{e,k}\boldsymbol{A}_{e,i-k}$ with $\boldsymbol{A}_{e,0}$ being an $N_e \times N_e$ identity matrix and $\boldsymbol{A}_{e,i} = 0$ for $i < 0$. We follow Diebold and Yilmaz (2012) and Demirer, Diebold, Liu, and Yilmaz (2018) to use the "generalized identification" framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), which produces variance decompositions that are invariant to ordering of the data.

Firm j's contribution to firm i's H-step-ahead generalized forecast-error variance, is

[5] For a more comprehensive discussion of the consequences of TBTF policy, refer to the excellent review of Strahan (2013).

$$\theta^{g}_{e,ij}(H) = \frac{\sigma^{-1}_{e,jj}\sum_{h=0}^{H-1}\left(\boldsymbol{e}'_{e,i}\boldsymbol{A}_{e,h}\Sigma_{e}\boldsymbol{e}_{e,j}\right)^{2}}{\sum_{h=0}^{H-1}\left(\boldsymbol{e}'_{e,i}\boldsymbol{A}_{e,h}\Sigma_{e}\boldsymbol{A}'_{e,h}\boldsymbol{e}_{e,i}\right)}, H = 1, 2, \cdots, \tag{2}$$

where with $H \leq 10$ we follow Koop, Pesaran, and Potter (1996), Pesaran and Shin (1998), and Gross and Siklos (2020) to consider up to 10 days for the forecast error, $\sigma_{e,jj}$ is the square root of $\sigma^{2}_{e,jj}$, and $\boldsymbol{e}_{e,i}$ is an $N_e \times 1$ selection vector with unitary entry for the ith element and zeros otherwise.

Finally, since $\sum_{j\in\Xi_{e}}\theta^{g}_{e,ij}(H)\neq 1$ and we will use another dependent variable to capture the direct impact of GSIB designation on the designated bank's own value in our later analysis, we replace $\theta^{g}_{e,ij}(H)$ with zero when $i = j$ and then normalize each entry ij (where $i\neq j$) of the generalized variance decomposition matrix by the respective row sum to ensure that the variance shares sum up to unity. In what follows, we will refer to the H-step-ahead inter-bank spillovers in x_{it} in a ten-year time window up until event date e by $s_{e,ij}$ and define it as

$$s_{e,ij} = \frac{\theta^{g}_{e,ij}(H)}{\sum_{j\in\Xi_{e}}\theta^{g}_{e,ij}(H)}, i\neq j \tag{3}$$

where $\sum_{j\in\Xi_{e}} s_{e,ij} = 1$ and $\sum_{i,j\in\Xi_{e}} s_{e,ij} = N_e$.

Step 2: Decomposing directional inter-bank spillovers into their predicted (exogenous) and unpredicted (endogenous) components.

Since the dependent variable in this study (i.e., the cumulative abnormal returns, CARs) and the inter-bank spillovers are both constructed using stock-price data, the explanatory variable that captures the spillover effects of GSIB designation (constructed using the inter-bank spillovers) is endogenous. To address this problem, we rely on a set of instrumental variables (IVs), which help to decompose the directional inter-bank spillovers into their predicted (exogenous) and unpredicted (endogenous) components. The set of IVs relate to the specialization distance and geographic distance between banks i and j, respectively.

For the specialization distance between banks i and j on event date e, we will make use of an $SN_e \times 1$ vector of asset shares, $\boldsymbol{h}_{SNe}$, where a typical element states the share of total assets of bank i's product segment s relative to bank i's total assets on event date e, and an $SN_e \times 1$ vector of ones, $\boldsymbol{\iota}_{SNe}$. Here N_e indicates the number of banks on event date e and S indicates the number of product segments that the N_e banks together operate in, and SN_e is just the number of banks times the number of product segments. Based on these two vectors, we define the matrix

$$\widetilde{\boldsymbol{H}}_{e} = \boldsymbol{h}_{SNe}\boldsymbol{\iota}'_{SNe} \tag{4}$$

and the $SN_e \times SN_e$ bank-product segment-to-bank-product segment distance matrix

$$\boldsymbol{D_e} = |\widetilde{\boldsymbol{H}}_{e} - \widetilde{\boldsymbol{H}}'_{e}| \tag{5}$$

After defining an $SN_e \times N_e$ matrix $\boldsymbol{L}_{SNe}$ where a typical element in the i's column states the share of total assets of bank i's product segment s relative to bank i's total assets on event date e, we obtain the $N_e \times N_e$ bank-to-bank weighted specialization distance matrix

$$\boldsymbol{SPEDIS}_{Ne} = \boldsymbol{L}'_{SNe}\boldsymbol{D_e}\boldsymbol{L}_{SNe} \tag{6}$$

where a typical element $SPEDIS_{e,ij}$ $(i \neq j)$ measures the asset-share weighted specialization distance between banks i and j on event date e. And when $i = j$, we replace $SPEDIS_{e,ij}$ with zero.

For the geographic distance between banks i and j on event date e, we will make use of a $CN_e \times CN_e$ matrix, $\boldsymbol{G_e}$, where a typical element states the distance between the capital cities of the countries where the banks' geographic segments locate in. C indicates the number of geographic segments that the N_e banks together operate in, and CN_e is just the number of banks times the number of geographic segments on event date e.

Similarly, after defining an $CN_e \times N_e$ matrix $\boldsymbol{K}_{CNe}$ where a typical element in the i's column states the share of total assets of bank i's geographic segment c relative to bank i's total assets on event date e, we obtain the $N_e \times N_e$ bank-to-bank weighted geographic distance matrix

$$\boldsymbol{GEODIS}_{Ne} = \boldsymbol{K}'_{CNe}\boldsymbol{G_e}\boldsymbol{K}_{CNe} \tag{7}$$

where a typical element $GEODIS_{e,ij}$ $(i \neq j)$ measures the (log of) asset-share weighted geographic distance between banks i and j on event date e. And when $i = j$, we replace $GEODIS_{e,ij}$ with zero.

Thus, we decompose the directional inter-bank spillovers $s_{e,ij}$ into their predicted (exogenous) and unpredicted (endogenous) components using the following equation:

$$s_{e,ij} = \alpha_0 + \alpha_1 SPEDIS_{e,ij} + \alpha_2 SPEDIS^{2}_{e,ij} + \alpha_3 GEODIS_{e,ij} + \alpha_4 GEODIS^{2}_{e,ij} + \alpha_5 SPEDIS_{e,ij} \times GEODIS_{e,ij} + \boldsymbol{\alpha}_{ij} + \boldsymbol{\gamma}_{e} + \varepsilon_{e,ij} \tag{8}$$

The predicted value of the spillover measure from the above equation, $\widehat{s}_{e,ij}$, captures the exogenous component and the residual, $\breve{s}_{e,ij}$, captures the endogenous component.

Step 3: Measuring banks' cumulative abnormal returns (CARs).

We are particularly interested in estimating the direct as well as the indirect, transmitted (from other banks) effect of additional levels of required loss absorbency on cumulative abnormal returns. We will use the mnemotechnic labels $CAR_{e,iw}$ to denote bank i's cumulative abnormal returns measured on (meaning, in a window up until) day w. To calculate $CAR_{e,iw}$ we first decompose daily stock market returns of each bank around the date of GSIB designations into their systematic and their idiosyncratic components. Let us use $BankReturn_{e,it}$ to denote the stock-market returns of bank i on day t for event e. We follow Moser and Rose (2014) in our benchmark analysis and focus on days 395 to 29 prior to event date e. This is done to avoid an influence of the respective GSIB-designation event on $BankReturn_{e,it}$ in the estimation window. Denoting the date or day at which event e happened by T_e, this means that t takes on values between T_e-395 and T_e-29. Moreover, we follow the same authors to specify the "normal" or systematic returns of a firm as an additive function of two components, a firm-event-specific constant (average), $\alpha_{e,i}$, and the return on the MSCI ((Morgan Stanley Capital International) market index at the end of day t before event e, $MarketReturn_{e,it}$. Formally, we estimate the following regression equation:

$$BankReturn_{e,it} = \alpha_{e,i} + \beta_{e,i} MarketReturn_{e,t} + \varepsilon_{e,it} \text{ over } t = [Te - 395, Te - 29] \tag{9}$$

where the estimated prediction of $\alpha_{e,i} + \beta_{e,i} MarketReturn_{e,t}$ obtains the systematic component of the one-day return $BankReturn_{e,it}$, and $\varepsilon_{e,it}$ is the idiosyncratic component. The expectations about the mean and the variance of $\varepsilon_{e,it}$ are $E(\varepsilon_{e,it}) = 0$ and $E\left(\varepsilon^2_{e,it}\right) = \sigma^2_{e,i}$. Subsequently, will refer to the latter as abnormal returns and define

$$AR_{e,it} = BankReturn_{e,it} - \left(\widehat{\alpha}_{e,i} + \widehat{\beta}_{e,i} MarketReturn_{e,t}\right) = \widehat{\varepsilon}_{e,it} \tag{10}$$

where a hat indicates regression estimates. For a stock to be included in the regression, we require that the minimum number of observations (days) for the estimation window is 90. Hence, stocks with observations in the estimation window with less than 90 days are excluded.

While the estimation of the parameters ($\alpha_{e,i}$, $\beta_{e,i}$) uses data from the time window T_e-395 to T_e-29, we use the estimates thereof to compute $AR_{e,it}$ for a time period closer to the event. Let us use the value of post-event days w={1,3,5,7,10}. Then, we can define cumulative abnormal returns for bank i, day w, and event e as the dependent variable for the final step:

$$CAR_{e,iw} = \sum_{t=T_e-1}^{T_e+w} AR_{e,it} \text{ for } w = \{1,3,5,7,10\}. \tag{11}$$

Since w = 10 requires data from one day before T_e up until 10 days after T_e, we use 12 day-data points for this window. For the ease of comparison of estimates, we therefore only include firms in the final step regarding event e, for which stock-market data in all 12 days from $T_e - 1$ to $T_e + 10$ are available. Hence, stocks with observations in the post-event window with less than 12 days are excluded generally in the final step.

Step 4: Estimating the direct and transmitted effects of GSIB designation along with additional levels of required loss absorbency on GSIBs.

In the final step, $CAR_{e,iw}$ is used to learn about its responses to the direct as well as the indirect effect of additional levels of required loss absorbency related to GSIB designation. We will use information on the additional levels of required loss absorbency which are administered for banks that are deemed globally systemically important, and we refer to those levels as $LOSSABSORB_{e,i}$. We will make use of the latter as a determinant of $CAR_{e,iw}$ in two ways: first, the parameter on $LOSSABSORB_{e,i}$ reflects the direct (own) effect of additional levels of required loss absorbency on bank i on event date e; second, $\overline{LOSSABSORB}_{e,i}$ measures the indirect, transmitted effect of other, closely connected banks' additional levels of required loss absorbency on bank i on event date e. The latter is defined as

$$\overline{LOSSABSORB}_{e,i} = \sum_{j \neq i} s_{e,ij} LOSSABSORB_{e,j} \tag{12}$$

As we may be concerned that interbank interdependence of bank i with other banks may be correlated with time shocks in the stochastic part of CAR, we use a control-function (or IV) approach (Wooldridge, 2015) to address potential endogeneity problems. Using the estimated spillover from equation (8) above, $\widehat{s}_{e,ij}$, we may define $\breve{\overline{LOSSABSORB}}_{e,i}$ as the residual of the following regression

$$\overline{LOSSABSORB}_{e,i} = \gamma_0 + \gamma_1 \sum_{j \neq i} \widehat{s}_{e,ij} LOSSABSORB_{e,j} + \varepsilon_{e,i} \tag{13}$$

so that $\breve{\overline{LOSSABSORB}}_{e,i} = \hat{\varepsilon}_{e,i}$. We will use this variable as an additional control in the regression below:

$$CAR_{e,iw} = \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 \overline{LOSSABSORB}_{e,i} + \theta_3 \breve{\overline{LOSSABSORB}}_{e,i} + \boldsymbol{\mu}_i + \boldsymbol{\gamma}_e + \varepsilon_{e,iw} \tag{14}$$

where μ_i captures a firm-fixed effect, and γ_e captures an event-window-fixed effect.

4. Data

In general, we intend to include data on all listed depository institutions (which belong to the 2-digit US SIC sector 60) around the globe in our analysis. At the heart of the analysis are stock-market data as well as GSIB-related additional levels of required loss absorbency. We will devote separate subsections to each of these data.

4.1. Stock-market data

We use daily stock-market data around each GSIB designation event from Datastream. We initially consider 10 event dates in this estimation, including: Nov. 4, 2011, Nov. 1, 2012, Nov.11, 2013, Nov. 6, 2014, Nov. 3, 2015, Nov. 21, 2016, Nov. 21, 2017, Nov. 16, 2018, Nov. 22, 2019, and Nov. 11, 2020.

To calculate CARs, we retrieve stock return data on active banks around the globe from Datastream. These data underly the dependent variable *BankReturn* above. For market returns (referred to as *MarketReturn* in the above equations), we use MSCI global index retrieved from Datastream.

To calculate dynamic volatility spillovers between banks, we rely on a 10-year rolling window for each event date of GSIB designation. For example, for the event of Nov.1, 2012, we use a window from Jan. 1, 2003 to Dec. 31, 2012 to construct the spillover matrix; for the event of Nov.11, 2013, we use a window from Jan. 1, 2004 to Dec. 31, 2013 to construct the spillover matrix, etc. We retrieve daily high and low stock prices on active banks around the globe from Datastream.

4.2. Data on additional levels of required loss absorbency

We obtain the lists of banks in each year of 2011–2020 that are designated as GSIBs by the FSB and the related additional levels of required loss absorbency for the GSIBs from FSB's official website. Since for the event date of Nov. 4, 2011 the FSB did not provide additional levels of required loss absorbency, data on 2011 are eliminated in the final step of the analysis. For the present research purpose, only listed depository institutions in the lists are considered, i.e., unlisted depository institutions and non-depository institutions are excluded. Appendix A provides the list of GSIBs along with the corresponding additional levels of required loss absorbency for each year.

The final dataset for the estimation of Step 4 covers 1,215 different banks in 89 economies (See Appendix B for the economy list) and 9 years between 2012 and 2020.

4.3. Data on other variables

Data on the other variables used in the analysis are retrieved from the following sources: data on the geographic distance between the capital cities of the countries that banks' geographic segments are located in are retrieved from the CEPII GeoDist database; data on banks' total assets, return on assets (ROA), capital-asset ratio, the ratio of non-performing loans to total loans, and assets on product and geographic segments are retrieved from Datastream.

4.4. Descriptive statistics

Table 1 reports on the number and total assets of banks by continent and year. From Table 1 we find the following. First, the number of GSIBs features heterogeneity at the continental level: approximately half of the GSIBs are in Europe, 30% in Asia, and 20% in North America. Second, the ratio of the number (total assets) of GSIBs to the number (total assets) of other banks in each continent also exhibits heterogeneity: it is approximately 5% (145%) for Europe, 2% (63%) for Asia, 1% (129%) for North America. And apparently, although the number of GSIBs is relatively small (about 2% of the total number of the banks), the total assets of GSIBs comprises a big portion of the total sample asset, which is on average 45% between year 2011 and 2020.

To provide a broad picture of the volatility spillovers in the banking industry around the globe, we follow previous aforementioned studies and further introduce three spillover concepts. First, the total directional spillovers (connectedness) to bank i from all other banks j on event date e is measured by:

$$s_{e,i\cdot} = \frac{\sum_{j \in \Xi_e, j \neq i} s_{e,ij}}{\sum_{i,j \in \Xi_e} s_{e,ij}} = \frac{\sum_{j \in \Xi_e, j \neq i} s_{e,ij}}{N_e} \tag{15}$$

Second, the total directional spillovers from (connectedness of) bank i to all other banks j on event date e is measured by:

$$s_{e,\cdot i} = \frac{\sum_{j \in \Xi_e, j \neq i} s_{e,ji}}{\sum_{i,j \in \Xi_e} s_{e,ij}} = \frac{\sum_{j \in \Xi_e, j \neq i} s_{e,ji}}{N_e} \tag{16}$$

Third, the system-wide spillovers (connectedness) on event date e are measured by:

$$s_t = \frac{\sum_{i,j \in \Xi_e, j \neq i} s_{e,ij}}{\sum_{i,j \in \Xi_e} s_{e,ij}} = \frac{\sum_{i,j \in \Xi_e, j \neq i} s_{e,ij}}{N_e} \tag{17}$$

Table 1
Number and total assets of banks by year, continent, 2011–2020.

Continent	Bank Type	Panel A. Number of banks									
		Year									
		2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Africa	GSIBs	0	0	0	0	0	0	0	0	0	0
	Other banks	67	68	71	72	75	75	77	77	76	76
Asia	GSIBs	5	5	6	7	8	8	8	8	8	8
	Other banks	377	386	392	394	400	420	437	447	444	454
Europe	GSIBs	12	12	12	12	11	11	11	9	9	9
	Other banks	162	168	171	174	176	189	197	208	211	215
N. America	GSIBs	4	4	4	4	4	4	5	5	6	6
	Other banks	302	306	311	314	323	334	346	363	370	372
Oceania	GSIBs	0	0	0	0	0	0	0	0	0	0
	Other banks	7	7	7	7	7	7	7	7	7	7
S. America	GSIBs	0	0	0	0	0	0	0	0	0	0
	Other banks	39	40	38	38	38	39	38	38	39	39
Continent	Bank Type	Panel B. Total assets of banks									
		Year									
		2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Africa	GSIBs	0	0	0	0	0	0	0	0	0	0
	Other banks	884	842	839	892	813	811	820	842	882	931
Asia	GSIBs	11,000	11,300	13,800	16,800	19,500	21,600	22,200	22,800	24,000	26,600
	Other banks	23,100	25,300	24,100	24,700	23,000	31,500	34,100	35,400	38,000	41,900
Europe	GSIBs	23,700	19,400	18,200	19,400	15,000	14,800	14,700	12,900	12,900	15,000
	Other banks	10,500	10,500	10,700	11,300	10,300	10,900	11,700	13,000	13,200	15,700
N. America	GSIBs	7,500	7,820	7,840	8,130	7,940	8,330	9,530	9,770	11,100	12,900
	Other banks	5,630	6,170	6,330	6,730	6,950	7,590	7,200	7,590	7,320	8,430
Oceania	GSIBs	0	0	0	0	0	0	0	0	0	0
	Other banks	2,900	3,020	2,780	3,100	2,670	2,730	2,880	2,720	2,600	2,840
S. America	GSIBs	0	0	0	0	0	0	0	0	0	0
	Other banks	1,440	1,450	1,400	1,640	1,380	1,260	1,300	2,880	1,280	1,220

Notes: Panel A of this table reports the number of GSIBs and other banks by continent and year and Panel B of this table reports total assets (in billions of U. S. dollars) of GSIBs and other banks by continent and year.

In Table 2 we summarize yearly averages of each of the above volatility spillover measures for the GSIBs and other banks in six continents in the world. Panels A and B report results estimated from a VAR(1) model and a VAR(2) model, respectively. For banks other than the GSIBs the spillover measures are summarized at the continental level due to space limitations. The main elements are the sum of the directional spillovers in the corresponding group, the row sums labeled "from others" are the yearly average of total directional spillovers from others defined in Equation (15), the column sums labeled "to others" are the yearly average of total directional spillovers to others defined in Equation (16), and the lower right element is the yearly average of system-wide spillover defined in Equation (17).

As results from the VAR(1) and the VAR(2) model are similar, for simplicity we focus on Panel A. Through direct comparisons, we have the following observations. First, we find that North America, Europe, and Asia are the main risk transmitters and recipients in the sample period. However, the total directional volatility spillover from/to other groups is lower in Europe than Asia and North America. This might be due to the fact that the total number of banks in Europe is approximately half of the total number of banks in Asia and North America.

Second, for banks in Asia and North America, the "within-continent/group" directional volatility spillovers are significantly larger than the "cross-continent/group" directional volatility spillovers, suggesting that banks in Asia and North America established a closer "within continent/group" connection between each other than banks in other groups.

Third, we find that in total the GSIBs contribute about 6% (3%) of the spillovers to (from) others, which is not as high as expected considering their relative size. One possible reason is that the inclusion of too many small financial institutions for which the speed of information absorption into stock prices/returns is much slower than large ones, which could lead to an underestimation of the spillovers to small banks.[6] We therefore use a subsample of the 200 biggest banks in terms of their average annual total assets, and in Table 3 we report the volatility spillovers among these 200 banks estimated from a VAR (1) model.

We find that in total the GSIBs contribute about 15% (9%) of the spillovers to (from) others, which is comparable with the contributions of the whole continents of Asia, Europe, and North America. Therefore, in later estimations we will focus both on the full sample and the subsample to assess the robustness of our results.

[6] We thank an anonymous reviewer for this insightful comment.

Table 2
Yearly averages of directional bank volatility spillovers (in %), GSIB and six-continent aggregation.

Panel A. Estimates from VAR(1)

	GSIB	Africa	Asia	Europe	N. America	Oceania	S. America	***From others***
GSIB	0.24	0.04	0.58	0.39	0.81	0.02	0.03	1.86
Africa	0.17	0.81	2.41	1.20	1.98	0.05	0.20	6.01
Asia	1.11	1.67	21.11	4.69	8.92	0.21	0.82	17.41
Europe	0.93	0.86	4.83	4.37	5.74	0.12	0.47	12.95
N. America	1.10	0.88	5.30	3.20	19.87	0.13	0.51	11.11
Oceania	0.04	0.02	0.16	0.11	0.25	0.06	0.01	0.59
S. America	0.09	0.20	1.21	0.61	1.21	0.03	0.25	3.35
To others	3.45	3.68	14.49	10.20	18.90	0.55	2.04	53.29

Panel B. Estimates from VAR(2)

	GSIB	Africa	Asia	Europe	N. America	Oceania	S. America	***From others***
GSIB	0.16	0.09	0.67	0.41	0.71	0.02	0.05	1.94
Africa	0.15	0.56	2.55	1.20	2.09	0.04	0.23	6.26
Asia	0.90	2.28	17.51	5.93	10.50	0.23	1.17	21.01
Europe	0.59	1.09	6.06	3.48	5.42	0.12	0.56	13.84
N. America	0.91	1.55	8.72	4.38	14.47	0.16	0.80	16.52
Oceania	0.02	0.04	0.21	0.12	0.22	0.03	0.02	0.63
S. America	0.08	0.24	1.34	0.62	1.14	0.02	0.16	3.44
To others	2.66	5.28	19.54	12.65	20.08	0.60	2.83	63.64

Notes: This table reports descriptive statistics on the yearly average of volatility spillovers among listed depository institutions for GSIBs and other banks in the six continents of the world. Panels A and B report results estimated from a VAR(1) model and a VAR(2) model, respectively. The main elements are the yearly average of the sum of the directional spillovers in the corresponding group, the row sums labeled "from others" are the total directional spillovers from others defined in Equation (15), the column sums labeled "to others" are the total directional spillovers to others defined in Equation (16), and the lower right element is the system-wide spillover defined in Equation (17).

Table 3
Yearly averages of directional bank volatility spillovers (in %) of a subsample of 200 largest banks, GSIB and a six-continent aggregation.

	GSIB	Africa	Asia	Europe	N. America	Oceania	S. America	***From others***
GSIB	3.18	0.15	3.71	2.90	2.11	0.19	0.08	9.14
Africa	0.50	0.52	0.58	0.57	0.46	0.07	0.04	2.23
Asia	6.30	0.64	34.54	5.18	4.37	0.69	0.60	17.78
Europe	4.71	0.28	3.05	7.04	2.27	0.24	0.20	10.75
N. America	2.26	0.15	1.82	1.66	3.72	0.15	0.12	6.17
Oceania	0.40	0.04	0.59	0.35	0.40	0.38	0.03	1.82
S. America	0.39	0.08	1.10	0.56	0.39	0.05	0.17	2.57
To others	14.57	1.36	10.86	11.23	10.01	1.39	1.06	50.46

Notes: This table reports descriptive statistics on the yearly average of volatility spillovers among the 200 largest listed depository institutions (in terms of average annual total assets) in the six continents of the world. The results are estimated from a VAR(1) model. The rest of the setup is identical to Table 2.

In Table 4 we summarize descriptive statistics on the average CARs for the GSIBs and other banks on each continent. From an inspection of this table, we find the following. First, for the GSIBs, the average CARs are significantly different from zero in Asia, Europe, and North America. Second, for the other banks, significant CARs mainly come from Asia, Europe, and North America. Third, while average CARs of both GSIBs and other banks on most continents are significantly different from zero in Asia, Europe, and North America, the signs on them are quite different in different continents. For example, average CARs for both types of banks are significantly positive in Asia and North America, but significantly negative in Europe. A natural question then follows from this observation: Why are GSIB designations negative news for an average bank in Europe but good news for an average bank in Asia and North America? Through pure visual inspection it would be difficult to answer this question. In the next section, we will rely on regression results to shed light on this question and offer a possible answer.

5. Empirical results

5.1. Baseline results

Table 5 reports the first-stage IV estimation results. The following key findings can be identified from this analysis. First, all the IVs are statistically significant. Second, the impact of specialization distance on network links between banks is negative, i.e., the increase in specialization distance reduces volatility spillovers between banks, and the negative effect becomes stronger as the distance further increases. third, the relation between geographic distance and volatility spillover is U-shaped, and the impact of its interaction with specialization distance on network links is significantly negative.

Table 4
Average CARs for the GSIBs and other banks in each continent.

Panel A. GSIBs

Continent	Africa	Asia	Europe	N. America	Oceania	S. America
(-1,1)	/	0.0066**	−0.0103***	0.0055*	/	/
	/	(0.024)	(0.026)	(0.020)	/	/
(-1,3)	/	0.0083**	−0.0150***	0.0080*	/	/
	/	(0.029)	(0.036)	(0.028)	/	/
(-1,5)	/	0.0109**	−0.0112**	0.0087*	/	/
	/	(0.037)	(0.045)	(0.035)	/	/
(-1,7)	/	0.0096**	−0.0119***	0.0138**	/	/
	/	(0.036)	(0.045)	(0.041)	/	/
(-1,10)	/	0.0073	0.0018	0.0238***	/	/
	/	(0.044)	(0.061)	(0.058)	/	/
No. of Obs.	/	71	108	46	/	/

Panel B. Other banks

Continent	Africa	Asia	Europe	N. America	Oceania	S. America
(-1,1)	−0.0001	0.0011	−0.0066***	0.0045***	−0.0048	0.0019
	(0.056)	(0.047)	(0.076)	(0.032)	(0.026)	(0.061)
(-1,3)	−0.0055***	0.0006	−0.0074***	0.0094***	−0.0033	−0.0042
	(0.049)	(0.055)	(0.095)	(0.040)	(0.036)	(0.071)
(-1,5)	−0.0030	0.0026***	−0.0024	0.0103***	0.0029	0.0017
	(0.070)	(0.063)	(0.142)	(0.048)	(0.051)	(0.085)
(-1,7)	−0.0031	0.0033***	−0.0017	0.0089***	0.0097	0.0060
	(0.071)	(0.070)	(0.149)	(0.051)	(0.058)	(0.102)
(-1,10)	−0.0092	0.0019	0.0015	0.0142***	0.0058	0.0149**
	(0.161)	(0.084)	(0.164)	(0.062)	(0.076)	(0.128)
No. of Obs.	734	4,151	1,871	3,341	70	386

Notes: Panels A and B of this table report average CARs for the GSIBs and other banks in each continent, respectively. Standard errors are in the parentheses. Average CARs significantly different from zero at the 10%, 5%, and 1% levels are marked *, **, and ***, respectively.

Table 6 reports the estimation results of GSIB designations on CARs as in Equation (14) using the full sample. The weighted variables are constructed using volatility spillovers estimated from a VAR(1) model.[7] We find that the direct impact of GSIB designation (along with additional levels of required loss absorbency) is statistically insignificant across all windows, suggesting that the gains of being a GSIB do not significantly outweigh the associated losses, and the significant positive effects observed by earlier work might be caused by omitted indirect effects transmitted from other banks in the network.

On the other hand, the indirect (transmitted) effect of GSIB designation on recipient banks is significantly negative across all the event windows. In addition, except for the event windows (-1,7) and (-1,10), the coefficients on $\overline{\breve{LOSSABSORB}}_{e,i}$ are statistically significant, suggesting that the strength of interbank network link is indeed endogenous, given the chosen IVs.

In Panel A of Table 7 we report results on a subsample which includes banks in Asia, Europe, and North America only, as countries in the other continents do not have GSIBs and they are quite far from countries that have GSIBs. In Panel B we report results on the subsample of the 200 largest banks in terms of their average annual total assets.[8] The results in both panels are qualitatively similar to those of Table 6.

However, results based on the full sample can only provide a coarse picture of the story, as they ignore the potential heterogeneity of the effects. For example, as we are talking about all the listed depository institutions around the globe, they are very likely potential competitors to each other. And if the recipient is a competitor to GSIBs, GSIB designations might have either a positive indirect impact on the recipient, because of additional levels of required loss absorbency along with other administrative, legal, and operational costs faced by GSIBs, or a negative indirect impact on the recipient, because of the moral hazard problems of the GSIBs triggered by obtaining GSIB status. Estimating the indirect effect of GSIB designation using the full sample, hence, will merely give us an average effect but cannot address the potentially important heterogeneity. In the next subsection we will decompose the spillover matrix to explore some possible channels through which GSIB designations indirectly affect the global banking industry.

5.2. Results based on decomposed spillover matrices

In this subsection we explicitly consider heterogeneous effects of GSIB designation based on firm characteristics and the network structure from two dimensions, including bank performance and bank risk.

[7] Results on variables estimated from the VAR(2) model are very similar to those from the VAR(1) model. Due to space limitations the results are not reported here, but they are available upon request.

[8] Note that for the subsample of top 200 banks we re-estimate the volatility spillovers instead of using the same measurement from the full sample, while for the subsample of Asia, Europe, and North America we use the same measurement as before.

Table 5
First-stage regression results (Step 2).

Regressors	(1)	(2)
SPEDIS	−0.4352***	−0.1808***
	(0.013)	(0.006)
SPEDIS2	−28.7427***	−10.6011***
	(6.537)	(2.383)
GEODIS	−0.1368***	−0.0621***
	(0.003)	(0.002)
GEODIS2	4.5706***	2.0885***
	(0.218)	(0.100)
SPEDIS × GEODIS	45.4265***	19.6110***
	(1.936)	(0.874)
Bank-pair-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
Observations	11,672,218	11,672,218
R-squared	0.025	0.026

Notes: The table reports the estimation results from the following model: $s_{e,ij} = \alpha_0 + \alpha_1 SPEDIS_{e,ij} + \alpha_2 SPEDIS^2_{e,ij} + \alpha_3 GEODIS_{e,ij} + \alpha_4 GEODIS^2_{e,ij} + \alpha_5 SPEDIS_{e,ij} \times GEODIS_{e,ij} + \boldsymbol{\alpha}_{ij} + \gamma_e + \varepsilon_{e,ij}$.
$s_{e,ij}$ in Columns (1) and (2) measures the volatility spillover from bank j to bank i on event date e estimated from a VAR(1) model and a VAR(2) model, respectively, $SPEDIS_{e,ij}$ (scaled by 10^{-3}) measures the weighted specialization distance between banks i and j on event date e, $GEODIS_{e,ij}$ (scaled by 10^{-6}) measures the weighted geographic distance between banks i and j on event date e. The sample spans from 2011-2020. White (1980) robust standard errors adjusted for heteroskedasticity are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5%, and 1% levels are marked *, **, and ***, respectively.

To explore the potentially heterogenous effects, we decompose the $N_e \times N_e$ directional volatility spillover matrix on each event date e, $\boldsymbol{W}_e$, based on firm characteristics or the network structure under discussion. To illustrate the decomposing technique based on firm characteristic, we use bank performance as an example. Therefore, the spillover matrix $\boldsymbol{W}_e$ is decomposed into four matrices based on bank performance measured by ROA:

$$\boldsymbol{W}_e = \boldsymbol{Perform}_{e,LL} + \boldsymbol{Perform}_{e,HL} + \boldsymbol{Perform}_{e,LH} + \boldsymbol{Perform}_{e,HH} \tag{18}$$

where

$$\boldsymbol{Perform}_{e,LL} = \boldsymbol{Z}_{e,L} \cdot \boldsymbol{Z}'_{e,L} \circ \boldsymbol{W}_e$$

$$\boldsymbol{Perform}_{e,HL} = \boldsymbol{Z}_{e,H} \cdot \boldsymbol{Z}'_{e,L} \circ \boldsymbol{W}_e$$

$\boldsymbol{Perform}_{e,LH} = \boldsymbol{Z}_{e,L} \cdot \boldsymbol{Z}'_{e,H} \circ \boldsymbol{W}_e$, and

$$\boldsymbol{Perform}_{e,HH} = \boldsymbol{Z}_{e,H} \cdot \boldsymbol{Z}'_{e,H} \circ \boldsymbol{W}_e$$

and $\boldsymbol{Z}_{e,L}$ is a $N_e \times 1$ vector with the ith entry ($i \in \{1,..., N_e\}$) equaling one if the ROA of bank i are below the sample median and zero otherwise and $\boldsymbol{Z}_{e,H}$ is an $N_e \times 1$ vector with the ith entry ($i \in \{1,..., N_e\}$) equaling one if the ROA of bank i are above or equal to the sample median and zero otherwise, i.e., $\boldsymbol{Z}_{e,H} = \boldsymbol{\iota}_t - \boldsymbol{Z}_{e,L}$, with $\boldsymbol{\iota}_t$ being an $N_e \times 1$ vector of ones. Finally, $\circ$ indicates the Hadamard product. In this way, $\boldsymbol{Perform}_{e,LL}$, $\boldsymbol{Perform}_{e,HL}$, $\boldsymbol{Perform}_{e,LH}$, and $\boldsymbol{Perform}_{e,HH}$ measure the volatility spillovers from less profitable banks to less profitable banks, less profitable banks to more profitable banks, more profitable banks to less profitable banks, and more profitable banks banks to more profitable banks, respectively. We also decompose $\boldsymbol{W}_e$ based on bank risk measured by the Z-score (proposed by Mergaerts and Vander Vennet, 2016, which equals the log of the ratio of ROA plus the capital-asset ratio to the standard deviation of ROA) and the ratio of non-performing loans to total loans in a similar way.

After the decomposition of the spillover matrix, we reconstruct the network-weighted other banks' additional loss-absorbency requirements in the same way as before using each decomposed matrix and estimate the heterogeneous effects using the control-function approach.[9]

Tables 8-10 report the estimation results when the spillover matrix is decomposed based on firm characteristics. We find that bank performance and bank risk do contribute to the heterogeneity of the spillover effects. For the sake of brevity, we focus on the effects on the CAR for the event window (-1,10) hereafter.

Table 8 reports the estimation results when the spillover matrix is decomposed based on bank performance measured by ROA. We find that the significant negative impact of GSIB designation mainly comes from spillovers from (the designations of) GSIBs that have high ROA to recipients that have low ROA. This is reasonable as for GSIBs with better performance, higher

[9] With E endogenous variables, we always also have E control-function terms.

Table 6
Second-stage regressions (Step 4): Full sample.

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0022	−0.0037	−0.0031	−0.0005	0.0023
	(0.004)	(0.006)	(0.006)	(0.008)	(0.010)
$\overline{\text{LOSSABSORB}}$	−0.3187**	−0.5208***	−0.6176***	−0.5805***	−0.6534**
	(0.135)	(0.150)	(0.176)	(0.207)	(0.257)
$\breve{\text{LOSSABSORB}}$	0.2863**	0.3497**	0.2897*	0.2038	0.2237
	(0.135)	(0.149)	(0.168)	(0.201)	(0.242)
Constant	0.0202**	0.0296***	0.0360***	0.0316**	0.0348**
	(0.008)	(0.010)	(0.011)	(0.013)	(0.016)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	9,803	9,803	9,803	9,803	9,803
R-squared	0.0186	0.0344	0.0304	0.0295	0.0373
No. of banks	1,215	1,215	1,215	1,215	1,215

Notes: This table reports the estimation results for the following model:
$CAR_{e,iw} = \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 \overline{LOSSABSORB}_{e,i} + \theta_3 \overline{LOSSABSORB}_{e,i} + \boldsymbol{\mu}_i + \boldsymbol{\gamma}_e + \varepsilon_{e,iw}$.
$CAR_{e,iw}$, $w \in \{1,3,5,7,10\}$, is the cumulative abnormal return for bank i from one day before the event up until 10 days after the event. $LOSSABSORB_{e,i}$ is the additional level of required loss absorbency (%) for bank i, $\overline{LOSSABSORB}_{e,i}$ is the indirect spillovers of additional levels of required loss absorbency from other banks to bank i, and $\breve{LOSSABSORB}_{e,i}$ is the residuals of the indirect spillovers from Equation (13). The weighted variables are constructed using volatility spillovers estimated from a VAR model of order 1. All the variables are on an annual basis. The sample spans from 2012 to 2020. White (1980) robust standard errors adjusted for heteroskedasticity and firm-level clustering are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5%, and 1% levels are marked *, **, and ***, respectively.

Table 7
Second-stage regressions (Step 4): Subsample results.

Panel A: Banks in Asia, Europe, and North America only					
	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0024	−0.0035	−0.0023	0.0003	0.003
	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)
$\overline{\text{LOSSABSORB}}$	−0.3435**	−0.5502***	−0.6299***	−0.5560**	−0.7076**
	(0.160)	(0.178)	(0.202)	(0.240)	(0.286)
$\breve{\text{LOSSABSORB}}$	0.3043*	0.3763**	0.2757	0.1494	0.2466
	(0.160)	(0.179)	(0.202)	(0.242)	(0.282)
Constant	0.0231**	0.0325***	0.0362***	0.0290*	0.0370**
	(0.010)	(0.011)	(0.013)	(0.015)	(0.018)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	8,726	8,726	8,726	8,726	8,726
R-squared	0.0158	0.0366	0.031	0.0301	0.044
No. of banks	1,082	1,082	1,082	1,082	1,082
Panel B: Top 200 banks in terms of average annual total assets					
	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0043	−0.0032	−0.0039	−0.0015	−0.0004
	(0.005)	(0.007)	(0.007)	(0.010)	(0.012)
$\overline{\text{LOSSABSORB}}$	−0.1654*	−0.2220**	−0.2589**	−0.3660***	−0.3079*
	(0.099)	(0.108)	(0.112)	(0.140)	(0.185)
$\breve{\text{LOSSABSORB}}$	0.0975	0.0572	0.0012	0.0668	−0.0242
	(0.104)	(0.110)	(0.107)	(0.142)	(0.192)
Constant	0.0496*	0.0622**	0.0815***	0.1040***	0.0939*
	(0.027)	(0.030)	(0.029)	(0.036)	(0.048)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,665	1,665	1,665	1,665	1,665
R-squared	0.1205	0.1663	0.0515	0.0522	0.0657
No. of banks	200	200	200	200	200

Notes: Panel A of this table reports the estimation results for the subsample of banks in Asia, Europe, and North America only. Panel B of this table reports the estimation results for the subsample of 200 largest banks in terms of average annual total assets. The rest of the setup is identical to Table 6.

regulation costs associated with the GSIB status may reduce profit, but it does not outweigh the competitive advantage (entailed by the status) to low performance banks.

However, for GSIB volatility transmitters and non-GSIB recipients that are both in the high-ROA group, the competitive advantage entailed by the status for the high-ROA GSIBs might be relatively small with respect to the regulation costs. Therefore, we observe a significantly positive effect in this group, suggesting that the high-ROA recipients benefit from GSIB designations. And similar argument can be applied to the low-ROA-to-low-ROA group.

Table 8
Second-stage regressions: Spillover matrix decomposition based on bank performance.

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	−0.0004	−0.005	−0.0086	−0.0081	−0.0096
	(0.004)	(0.007)	(0.007)	(0.010)	(0.011)
$\overline{LOSSABSORB}$_LL_ROA	0.6004	1.4609***	1.6519**	1.4659**	2.2808**
	(0.428)	(0.433)	(0.731)	(0.722)	(0.927)
$\overline{LOSSABSORB}$_HL_ROA	0.7639	8.5945	9.2299	2.6454	3.6347
	(5.285)	(6.008)	(8.745)	(8.636)	(10.304)
$\overline{LOSSABSORB}$_LH_ROA	−24.6429	−104.9548***	−130.1122***	−91.1446**	−145.1914**
	(30.249)	(32.206)	(44.408)	(45.857)	(56.590)
$\overline{LOSSABSORB}$_HH_ROA	−0.6304	36.6493***	67.9022***	59.5244***	102.2711***
	(10.784)	(13.388)	(19.985)	(20.154)	(25.344)
Control functions	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7,963	7,963	7,963	7,963	7,963
R-squared	0.0249	0.0513	0.037	0.0347	0.0456
No. of banks	1,154	1,154	1,154	1,154	1,154

Notes: This table reports the estimation results for the following model: $CAR_{e,iw} = \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 \overline{LOSSABSORB}\_LL\_ROA_{e,i} + \theta_3 \overline{LOSSABSORB}\_HL\_ROA_{e,i} + \theta_4 \overline{LOSSABSORB}\_LH\_ROA_{e,i} + \theta_5 \overline{LOSSABSORB}\_HH\_ROA_{e,i} + \theta_6 \overline{LOSSABSORB}\_LL\_ROA_{e,i} + \theta_7 \overline{LOSSABSORB}\_HL\_ROA_{e,i} + \theta_8 \overline{LOSSABSORB}\_LH\_ROA_{e,i} + \theta_9 \overline{LOSSABSORB}\_HH\_ROA_{e,i} + \boldsymbol{\mu}_i + \boldsymbol{\gamma}_e + \varepsilon_{e,iw}$.
$\overline{LOSSABSORB}\_LL\_ROA_{e,i}$, $\overline{LOSSABSORB}\_HL\_ROA_{e,i}$, $\overline{LOSSABSORB}\_LH\_ROA_{e,i}$, and $\overline{LOSSABSORB}\_HH\_ROA_{e,i}$ measure indirect spillovers of additional levels of required loss absorbency from banks with ROA below the sample median to a bank *i* with ROA below the sample median, from banks with ROA below the sample median to a bank *i* with ROA above the sample median, from banks with ROA above the sample median to a bank *i* with ROA below the sample median, and from banks with ROA above the sample median to a bank *i* with ROA above the sample median, respectively. The rest of the setup is identical to Table 6.

Table 9
Second-stage regressions: Spillover matrix decomposition based on bank risk (Z-score).

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	−0.0035	−0.0056	−0.0114*	−0.0131	−0.0175*
	(0.004)	(0.007)	(0.007)	(0.009)	(0.011)
$\overline{LOSSABSORB}$_LL_ZSCORE	28.9680**	42.1005***	78.1416***	60.6824***	106.5663***
	(11.879)	(12.047)	(16.026)	(15.440)	(21.116)
$\overline{LOSSABSORB}$_HL_ZSCORE	−45.8597***	−72.6091***	−115.9190***	−89.7641***	−150.9987***
	(17.707)	(17.543)	(23.085)	(22.696)	(30.874)
$\overline{LOSSABSORB}$_LH_ZSCORE	−7.3974	3.3249	−1.3125	−13.1854	−25.176
	(9.313)	(9.445)	(14.335)	(13.917)	(17.172)
$\overline{LOSSABSORB}$_HH_ZSCORE	14.8705**	14.9321**	26.1018***	27.9462***	48.0026***
	(6.132)	(6.280)	(9.618)	(9.322)	(12.415)
Control functions	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7,691	7,691	7,691	7,691	7,691
R-squared	0.0263	0.0513	0.0358	0.0334	0.0463
No. of banks	1,121	1,121	1,121	1,121	1,121

Notes: This table reports the estimation results for the following model: $CAR_{e,iw} = \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 \overline{LOSSABSORB}\_LL\_ZSCORE_{e,i} + \theta_3 \overline{LOSSABSORB}\_HL\_ZSCORE_{e,i} + \theta_4 \overline{LOSSABSORB}\_LH\_ZSCORE_{e,i} + \theta_5 \overline{LOSSABSORB}\_HH\_ZSCORE_{e,i} + \theta_6 \overline{LOSSABSORB}\_LL\_ZSCORE_{e,i} + \theta_7 \overline{LOSSABSORB}\_HL\_ZSCORE_{e,i} + \theta_8 \overline{LOSSABSORB}\_LH\_ZSCORE_{e,i} + \theta_9 \overline{LOSSABSORB}\_HH\_ZSCORE_{e,i} + \boldsymbol{\mu}_i + \boldsymbol{\gamma}_e + \varepsilon_{e,iw}$.
$\overline{LOSSABSORB}\_LL\_ZSCORE_{e,i}$, $\overline{LOSSABSORB}\_HL\_ZSCORE_{e,i}$, $\overline{LOSSABSORB}\_LH\_ZSCORE_{e,i}$, and $\overline{LOSSABSORB}\_HH\_ZSCORE_{e,i}$ measure indirect spillovers of additional levels of required loss absorbency from more risky banks (with Z-score below the sample median) to a more risky bank *i*, from more risky banks to a less risky bank *i* (with Z-score above the sample median), from less risky banks to a more risky bank *i*, and from less risky banks to a less risky bank *i*, respectively. The rest of the setup is identical to Table 6.

This line of reasoning can also be applied to the volatility transmitters and recipients that are in the same riskiness group. When the transmitter and recipient have similar risk profiles, they tend to face more intensive competition between each other and the GSIB status cannot bring enough competitive advantage to outweigh additional regulation costs, which is advantageous for the non-GSIB competitors. Tables 9 and 10 report the estimation results when the spillover matrix is decomposed based on bank risk measured by Z-score and non-performing-loan ratio, respectively.

Table 10
Second-stage regressions (Step 4): Spillover matrix decomposition based on bank risk (the ratio of non-performing loans to total loans).

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0047	−0.0078	−0.0188***	−0.011	−0.0144
	(0.006)	(0.007)	(0.007)	(0.009)	(0.011)
$\overline{LOSSABSORB}$ _LL_NPER	13.7224	61.1441*	243.9627***	152.2096***	222.9407***
	(46.063)	(34.067)	(49.160)	(52.630)	(60.638)
$\overline{LOSSABSORB}$ _HL_NPER	−24.7325	−15.6354	−2.2963	14.0724	54.9122
	(37.157)	(39.976)	(43.433)	(42.917)	(56.893)
$\overline{LOSSABSORB}$ _LH_NPER	1.5984	−15.0043***	−39.0397***	−26.1440***	−35.4501***
	(7.736)	(5.247)	(7.646)	(8.480)	(10.139)
$\overline{LOSSABSORB}$ _HH_NPER	−4.0561	0.6581	−7.8195	−3.5162	−6.0392
	(3.833)	(4.187)	(5.919)	(6.089)	(6.863)
Control functions	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7,661	7,661	7,661	7,661	7,661
R-squared	0.0244	0.0574	0.047	0.0424	0.0589
No. of banks	1,038	1,038	1,038	1,038	1,038

Notes: This table reports the estimation results for the following model: $\smile CAR_{e,iw} = \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 \overline{LOSSABSORB}\_LL\_NPER_{e,i} + \theta_3 \overline{LOSSABSORB}\_HL\_NPER_{e,i} + \theta_4 \overline{LOSSABSORB}\_LH\_NPER_{e,i} + \theta_5 \overline{LOSSABSORB}\_HH\_NPER_{e,i} + \theta_6 \overline{LOSSABSORB}\ \_LL\_NPER_{e,i} + \theta_7 \overline{LOSSABSORB}\ \_HL\_NPER_{e,i} + \theta_8 \overline{LOSSABSORB}\ \_LH\_NPER_{e,i} + \theta_9 \overline{LOSSABSORB}\ \_HH\_NPER_{e,i} + \boldsymbol{\mu}_i + \boldsymbol{\gamma}_e + \varepsilon_{e,iw}$.
$\overline{LOSSABSORB}\ \_LL\_NPER_{e,i}$, $\overline{LOSSABSORB}\_HL\_NPER_{e,i}$, $\overline{LOSSABSORB}\_LH\_NPER_{e,i}$, and $\overline{LOSSABSORB}\_HH\_NPER_{e,i}$ measure indirect spillovers of additional levels of required loss absorbency from less risky banks (with the ratio of non-performing loans to total loans below the sample median) to a less risky bank *i*, from less risky banks to a more risky bank *i* (with the ratio of non-performing loans to total loans above the sample median), from more risky banks to a less risky bank *i*, and from more risky banks to a more risky bank *i*, respectively. The rest of the setup is identical to Table 6.

Table 11
Average values of firm characteristics by continent.

	ROA (%)	Z-score	Non-performing-loan ratio (%)
Africa	2.191	66.375	6.806
Asia	1.098	125.069	4.346
Europe	0.682	182.402	7.547
N. America	1.063	114.667	1.237
Oceania	1.032	149.442	1.727
S. America	3.052	55.495	3.114

Notes: The table reports average values of ROA, Z-score, and the ratio of non-performing loans to total loans for banks by continent.

Aligned with our expectations, we find that the significant negative impact of GSIB designation mainly comes from spillovers from the GSIBs that are relatively riskier to banks that are less risky (i.e., low Z-score-to-high Z-score group in Table 9 and high-to-low non-performing-loan ratio group in Table 10). In contrast, the effect of the more risky-to-more risky component in Table 9 (i.e., $\overline{LOSSABSORB}\ \_LL\_ZSCORE$) and the effect of the less risky-to-less risky component in both tables (i.e., $\overline{LOSSABSORB}\ \_HH\_ZSCORE$ and $\overline{LOSSABSORB}\ \_LL\_NPER$) are significantly positive.

The findings in Tables 8-10 suggest that the competitive advantages banks gain from GSIB designation outweigh the regulation costs associated with the status only when the volatility transmitter and recipient are not of the same (riskiness or performance) type. In Table 8 we find that the high ROA-to-low ROA component has a significantly negative impact on recipients' CARs. As risk and return are positively correlated, better performance is associated with more risk of banks' assets. Therefore, similar to the negative effect of the high ROA-to-low ROA component in Table 8, the more risky-to-less risky components in Tables 9 and 10 also have a negative impact on recipient banks' CARs.

Finally, results of Tables 8-10 can help explain why GSIB designations are negative news for an average bank in Europe but good news for an average bank in Asia and North America. Results in Tables 8-10 suggest that recipient banks with relatively low ROA and/or high Z-score will experience significantly negative spillover effects in CARs, and vice versa. And recipient banks with a relatively low non-performing-loan ratio will experience significantly positive spillover effects in CARs. If we look at the within-continent means of the above three variables in Table 11, it is clear that on average, banks in Europe have lower ROA, higher Z-score, and higher non-performing-loan ratio compared to those in Asia and North America. Together, these patterns suggest that recipient banks in Europe are more likely to experience significantly negative CARs and recipient banks in Asia and North America are more likely to experience significantly positive CARs.

Table 12
Robustness checks.

Panel A: CARs estimated by the Fama-French five-factor model

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.004	−0.0009	0.0014	0.0032	0.0054
	(0.004)	(0.006)	(0.007)	(0.008)	(0.010)
LOSSABSORB	−0.3044**	−0.4135***	−0.4079**	−0.4481**	−0.4966*
	0.004	−0.0009	0.0014	0.0032	0.0054
Observations	9,803	9,803	9,803	9,803	9,803
R-squared	0.0073	0.0047	0.0027	0.0041	0.0048
No. of banks	1,215	1,215	1,215	1,215	1,215

Panel B: An alternative volatility measurement based on Diebold and Yilmaz (2009)

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0027	−0.0068	−0.0085	−0.007	−0.0066
	(0.005)	(0.007)	(0.008)	(0.010)	(0.011)
LOSSABSORB	−0.2295*	−0.2587*	−0.4208**	−0.5574**	−0.4705*
	(0.134)	(0.132)	(0.192)	(0.225)	(0.266)
Observations	1,656	1,656	1,656	1,656	1,656
R-squared	0.1295	0.1683	0.0604	0.0599	0.0689
No. of banks	199	199	199	199	199

Panel C: An alternative volatility spillover estimated by DAG-SVAR model

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0051	−0.0018	0.0007	0.0012	0.0047
	(0.005)	(0.007)	(0.007)	(0.009)	(0.011)
LOSSABSORB	−0.081	−0.074	−0.0533	−0.1402*	−0.0851
	(0.080)	(0.084)	(0.072)	(0.084)	(0.127)
Observations	1,665	1,665	1,665	1,665	1,665
R-squared	0.0945	0.0504	0.0143	0.0163	0.0169
No. of banks	200	200	200	200	200

Notes: Panel A of this table reports the estimation results when CARs are estimated using the Fama-French five-factor model. Panel B of this table reports the estimation results when the volatilities are measured based on Diebold and Yilmaz (2009). Panel C of this table report estimation results when CARs are estimated using the Fama-French five-factor model and the volatility spillovers are measured using the DAG-SVAR model. Due to space limitations only the coefficients on LOSSABSORB and LOSSABSORB are reported. White (1980) robust standard errors adjusted for heteroskedasticity and firm-level clustering are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5%, and 1% levels are marked *, **, and ***, respectively.

5.3. Robustness checks

In this subsection we conduct some further robustness checks. First, as an alternative to the market model for calculating CAR, we use the Fama-French five-factor model.[10] As we can see from Panel A of Table 12, the results based on this model are qualitatively and quantitatively similar to the baseline results.

Second, following Diebold and Yilmaz (2009), we include weekly high, low, opening and closing prices to measure volatilities. Although this measurement assumes that volatility is fixed within weeks, it includes additional information on stock prices as compared to our original measure. The weekly stock return volatility is measured as follows:

$$vol_{it}^2 = 0.511\left(p_{it}^{max} - p_{it}^{min}\right)^2 - 0.019\left[\left(p_{it}^{close} - p_{it}^{open}\right)\left(p_{it}^{max} + p_{it}^{min} - 2p_{it}^{open}\right) - 2\left(p_{it}^{max} - p_{it}^{open}\right)\left(p_{it}^{min} - p_{it}^{open}\right)\right] - 0.383\left(p_{it}^{close} - p_{it}^{open}\right)^2 \tag{19}$$

where p_{it}^{max} is the Monday-to-Friday high, p_{it}^{min} is the Monday-to-Friday low, p_{it}^{open} is the Monday open and p_{it}^{close} is the Friday close (all in natural logarithms).[11] Since now the volatilities are on a weekly basis, to have enough degrees of freedom in the estimation we only use the subsample of top 200 banks in terms of average annual total assets. The estimation results are reported in Panel B of Table 12 and are qualitatively and quantitatively similar to the baseline results.

Third, the GVAR-based spillover measurement as such is not able to provide structural or economic interpretations of the VAR innovations. This may result in an ambiguity in the interpretation of the forecast error variance decomposition according to Yang, Tong and Yu (2021). We follow these authors to use a structural VAR framework based on a directed acyclic graph (DAG) to identify the volatility spillovers among the included financial institutions. Ideally, the DAG analysis can provide a structure of causality among VAR innovations in contemporaneous time and provide guidance for the subsequent structural VAR estimation.[12] For computational reasons as well as for reasons of complexity regarding the ordering of the vari-

[10] We retrieve data on the Fama-French five factors from Kenneth R. French's online data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Since data on the five factors for emerging markets are only available on a monthly basis, we use the five factors of developed economies as proxies for them.

[11] We annualized the weekly volatilities before estimation.

[12] For detailed discussions of the DAG-based SVAR model, see Yang and Zhou (2013) and Yang, Tong and Yu (2021), among others.

Table 13
The effects of GSIB designations on pair-wise volatility spillovers.

Regressors	(1)	(2)
$LOSSABSORB_i$	−0.0048***	−0.0022***
	(0.0003)	(0.0002)
$LOSSABSORB_j$	0.0471***	0.0220***
	(0.0004)	(0.0002)
SPEDIS	−0.4510***	−0.1882***
	(0.013)	(0.006)
SPEDIS2	−30.0511***	−11.2126***
	(6.795)	(2.503)
GEODIS	−0.1358***	−0.0616***
	(0.003)	(0.002)
GEODIS2	4.5607***	2.0839***
	(0.218)	(0.100)
SPEDIS × GEODIS	46.0500***	19.9024***
	(1.941)	(0.876)
Bank-pair-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
Observations	11,672,218	11,672,218
R-squared	0.0274	0.0287

Notes: The table reports the estimation results from the following model: $s_{e,ij} = \alpha_0 + \varphi_1 LOSSABSORB_{e,i} + \varphi_2 LOSSABSORB_{e,j} + \alpha_1 SPEDIS_{e,ij} + \alpha_2 SPEDIS^2_{e,ij} + \alpha_3 GEODIS_{e,ij} + \alpha_4 GEODIS^2_{e,ij} + \alpha_5 SPEDIS_{e,ij} \times GEODIS_{e,ij} + \boldsymbol{\alpha}_{ij} + \boldsymbol{\gamma}_e + \varepsilon_{e,ij}$. $s_{e,ij}$ in Columns (1) and (2) measures the volatility spillover from bank j to bank i on event date e estimated from a VAR (1) model and a VAR(2) model, respectively, $LOSSABSORB_{e,i}$ and $LOSSABSORB_{e,j}$ are the additional levels of required loss absorbency for banks i (the shock recipient) and j (the shock transmitter), respectively. The rest of the setup is identical to Table 5.

Table 14
Mediation effects of GSIB designations.

	(-1,1)	(-1,3)	(-1,5)	(-1,7)	(-1,10)
LOSSABSORB	0.0361	−0.0336	0.0756	0.0201	−0.0137
	(0.033)	(0.039)	(0.054)	(0.059)	(0.082)
LOSSABSORB_GSIB1	0.1859	−0.3836	0.1918	−0.2449	−0.5451
	(0.218)	(0.259)	(0.352)	(0.388)	(0.544)
LOSSABSORB_GSIB2	−0.0652	−0.2362***	−0.4055***	−0.4571***	−0.5430***
	(0.040)	(0.049)	(0.101)	(0.108)	(0.119)
LOSSABSORB_REST	−0.0421	−0.1837***	−0.3370***	−0.3836***	−0.4378***
	(0.042)	(0.050)	(0.104)	(0.111)	(0.122)
Constant	0.0591***	0.1361***	0.1850***	0.1982***	0.2776***
	(0.010)	(0.011)	(0.014)	(0.015)	(0.017)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	9,803	9,803	9,803	9,803	9,803
R-squared	0.0181	0.0338	0.0302	0.0294	0.0372
No. of banks	1,215	1,215	1,215	1,215	1,215

Notes: This table reports the OLS estimation results for the following model: $CAR_{e,iw} = \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 LOSSABSORB\_GSIB1_{e,i} + \theta_3 LOSSABSORB\_GSIB2_{e,i} + \theta_4 LOSSABSORB\_REST_{e,i} + \boldsymbol{\mu}_i + \boldsymbol{\gamma}_e + \varepsilon_{e,iw}$.
$CAR_{e,iw}$, $w \in \{1,3,5,7,10\}$, is the cumulative abnormal return for bank i from one day before the event up until 10 days after the event. $LOSSABSORB_{e,i}$ is the additional level of required loss absorbency (%) for bank i, $LOSSABSORB\_GSIB1_{e,i}$ is the indirect spillovers of additional levels of required loss absorbency to bank i mediated by the GSIB designation of bank i, $LOSSABSORB\_GSIB2_{e,i}$ is the indirect spillovers of additional levels of required loss absorbency to bank i mediated by the GSIB designation of all the other volatility transmitting banks, and $LOSSABSORB\_REST_{e,i}$ is rest of the spillovers of additional levels of required loss absorbency from GSIBs to bank i. The weighted variables are constructed using volatility spillovers estimated from a VAR model of order 1. The rest of the setup is identical to Table 6.

ables in the structural VAR, we have to limit the analysis to the subsample of the 200 largest banks to estimate the volatility spillovers in this case.

The DAG-SVAR-based results are reported in Panel C of Table 12. We find that the spillover effect of GSIB designations is still negative across all the event windows. However, the effect is estimated to be statistically significant only in the (-1,7) event window. Note that the lower statistical significance may stem from the large number of institutions and the numerous undirected edges resulted from the utilization of the PC algorithm in DAG analysis, in spite of a restriction to the 200 largest ones. As a result, even with this subsample, the ordering of the banks in terms of the causality among the VAR innovations (which is suggested by the DAG analysis) is very difficult and not possible without ambiguity. In our analysis, we decided to order the banks based on the difference between the number of times banks appear as a cause (the origin) in the relation of VAR innovations and the number of times they appear as the recipient (as suggested by the DAG) as well as their size.[13] However, this ordering is not perfect, as a reverse direction of influence may coexist, which makes the subsequent Cholesky decomposition problematic.

However, we should bear in mind that in spite of some concerns raised vis à vis the GVAR approach in the literature, we use instrumental-variable (IV) estimation throughout. The latter does not only address the potential endogeneity of the spillover measures, but it should also alleviate concerns regarding the ambiguity of the interpretation of the forecast error variance decomposition. Nevertheless, this issue presents challenges and underscores the necessity for improvement in the analysis of financial networks. We believe that investigating this aspect further deserves attention in future research.

6. Extensions

6.1. Mediation effects of GSIB designations through changes in volatility spillovers

In the analysis above, we focused on immediate (direct) and spillover effects from GSIB designations. However, we need to acknowledge that all the spillover effects are unintended by the FSB when designating GSIB status. The FSB's intentions are different: it designates the GSIB status if a bank is critical in the volatility-spillover network. Hence, the FSB aims at reducing the spillovers from and to depository institutions which have a critically central position in the spillover network. In the analysis above, we held the network (i.e., all elements $s_{e,ij}$) fixed at its value around event e. In this section, we want to acknowledge that part of the overall effects of GSIB designations is mediated through volatility-spillover network changes which are induced by the designations themselves. For this argument, note that we can write

$$s_{e,ij} = s_{e-1,ij} + \left(s_{e,ij} - s_{e-1,ij}\right) \tag{20}$$

where $s_{e-1,ij}$ is the state of the volatility-spillover network prior to (or without) the GSIB designations associated with event e. Using the latter in the definition of weighted loss absorbency of other banks in event window e, we can write

$$\overline{LOSSABSORB}_{e,i} = \overline{LOSSABSORB}_{e-1,i} + \Delta\overline{LOSSABSORB}_{e,i} \tag{21}$$

where

$$\Delta\,\overline{LOSSABSORB}_{e,i} = \sum_{j\neq i}\left(s_{e,ij} - s_{e-1,ij}\right)LOSSABSORB_{e,j}$$

Note that $\left(s_{e,ij} - s_{e-1,ij}\right)$ can be estimated in a slightly modified first-stage regression, where GSIB designations of banks i and j are included as two separate regressors (to discern effects of the designation on transmitters and recipients of volatility spillovers). The associated modified first-stage regression relative to Equation (8) reads:

$$\begin{aligned} s_{e,ij} = {} & \alpha_0 + \varphi_1 LOSSABSORB_{e,i} + \varphi_2 LOSSABSORB_{e,j} + \alpha_1 SPEDIS_{e,ij} + \alpha_2 SPEDIS^2_{e,ij} + \alpha_3 GEODIS_{ij} + \alpha_4 GEODIS^2_{ij} \\ & + \alpha_5 SPEDIS_{e,ij} \times GEODIS_{ij} + \boldsymbol{\alpha}_{ij} + \boldsymbol{\gamma}_e + \varepsilon_{e,ij} \end{aligned} \tag{22}$$

Then, we can define the estimate (indicated by hats)

$$\widehat{\left(s_{e,ij} - s_{e-1,ij}\right)} = \widehat{\varphi}_1 LOSSABSORB_{e,i} + \widehat{\varphi}_2 LOSSABSORB_{e,j} \tag{23}$$

We can now use the latter to define an estimate of $\Delta\overline{LOSSABSORB}_{e,i}$, which captures the effect of GSIB designations from volatility-spillover network changes due to GSIB designations only.

Table 13 reports first-stage regression results of Equation (22). The coefficients on the IVs are still statistically significant. More importantly, effects of GSIB designations on the transmitter and recipient are both statistically significant, but of opposite signs: while the GSIB designation of the recipient reduces volatility spillovers from other banks to the designated bank, the GSIB designation of the transmitter increases volatility spillovers from the designated bank to other banks, and the magnitude of the latter effect is much larger than the former one. Hence, we may state that the GSIB designations increase GSIBs' resilience to external shocks, which is intended by the FSB, but they also induce volatility spillovers from GSIBs to other banks in the network. The intended change of the volatility-spillover intensity of GSIBs mitigates the unintended effects to some extent, but it does not offset them.

Table 14 reports OLS estimation results with the weighted loss-absorbency variables constructed using the estimated components of $\Delta\overline{LOSSABSORB}_{e,i}$ in Equation (23). Specifically, the following regression model is estimated:

$$\begin{aligned} CAR_{e,iw} = {} & \theta_0 + \theta_1 LOSSABSORB_{e,i} + \theta_2 \overline{LOSSABSORB\_GSIB1}_{e,i} + \theta_3 \overline{LOSSABSORB\_GSIB2}_{e,i} + \theta_4 \overline{LOSSABSORB\_REST}_{e,i} + \boldsymbol{\mu}_i \\ & + \boldsymbol{\gamma}_e + \varepsilon_{e,iw} \end{aligned} \tag{24}$$

where $\overline{LOSSABSORB\_GSIB1}_{e,i}$ is the indirect spillover term of additional levels of required loss absorbency to bank i mediated by the GSIB designation of bank i, which is measured using $\widehat{\varphi}_1 LOSSABSORB_{e,i}$ in Equation (23), $\overline{LOSSABSORB\_GSIB2}_{e,i}$ is the indirect spillover term of additional levels of required loss absorbency to bank i mediated by the GSIB designations of all the other volatility transmitting banks, which is measured using $\widehat{\varphi}_2 LOSSABSORB_{e,j}$ in Equation (23), and $\overline{LOSSABSORB\_REST}_{e,i}$ is rest of the spillovers of additional levels of required loss absorbency from GSIBs to bank i.

Two issues are important from the table. First, the GSIB designation of the (volatility) transmitters has a significantly negative mediation effect on recipient banks' CARs. However, there is no mediation effect of the recipient's GSIB designation on its own CARs. Second, the mediation effect of GSIB designation is partial. A considerable amount of spillover effects comes from the network linkages inherited in the network structure before the designations are made.

7. Conclusions

Depository institutions are linked by interbank loans, the activity in common markets, the exposure to common regulatory standards, and through other channels. Some of these links establish a network structure among depository institutions which result in spillovers, inter alia, of shocks to individual institutions. Such spillovers work as amplifiers of idiosyncratic shocks. Since the Economic and Financial Crisis of 2008, significant national as well as supranational efforts have been made to mitigate the amplification of shocks through the network by identifying the key nodes -- referred to as Global Systemically Important Banks -- in the global network of depository institutions and to increase their resilience to shocks so that a larger extent of shocks could be absorbed by these key players in the network. A set of regulations for these players includes higher capital buffer, Total Loss-Absorbing Capacity (TLAC) requirements, group-wide resolution planning and regular resolvability assessments, higher supervisory expectations, etc.

The present paper focuses on GSIBs as designated by the Financial Stability Board (FSB) every year since 2011 with publication of a specific set of regulations since 2012. We consider listed depository institutions around the globe and investigate how the very designation of GSIBs and related regulations themselves induce spillover effects in the network of depository institutions. Clearly, in an existing network, regulations on specific nodes (here, specific institutions) are just one example of shocks that will have direct effects on the targeted institutions but also ones on third, un-targeted ones.

We document that when accounting for the indirect or spillover effects in the overall network, we cannot reject the null hypothesis that the direct effects of GSIB designations are zero for the cumulative abnormal returns of the targeted institutions -- which should be very much aligned with the interest of the FSB, whose goal is not to change the profitability of designated versus other institutions. However, we find unintended indirect effects from GSIB designations on other institutions which have clear patterns with regard to the profitability and riskiness of the involved institutions.

As indicated above, we find that GSIB designations do have some intended, positive effects beyond the just-mentioned unintended ones. We provide evidence that, at least to a minor extent, they reduce the volatility spillovers to GSIBs and, in turn, this mitigates shocks, including unintended effects of GSIB designations themselves.

For future research, we believe that a focus on the multiplex network interdependencies between financial institutions can bear important fruits in the analysis of shock transmissions in the system. For instance, network links as measured by volatility spillovers may look alike for different channels establishing such links (e.g., geographical neighborliness, similarity in specialization, etc.), but specific shocks may still travel at different intensities depending on the channel establishing the links. Such scrutiny might help gaining more precise knowledge about key players in the network depending on types of shocks the network may be exposed to.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A. List of GSIBs in the study and the corresponding additional levels of required loss absorbency (%).

Company name	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Bank of America	0	1.5	1.5	1.5	1.5	2	2	1.5	1.5	1.5
Bank of China	0	1	1	1	1	1	1.5	1.5	1.5	1.5
Barclays	0	2	2	2	2	1.5	1.5	1.5	1.5	1.5
BNP Paribas	0	2	2	2	2	2	1.5	1.5	1.5	1.5
Citigroup	0	2.5	2	2	2	2.5	2	2	2	2
Commerzbank	0	/	/	/	/	/	/	/	/	/
Deutsche Bank	0	2.5	2	2	2	2	2	2	1.5	1.5
Groupe Crédit Agricole	0	1	1.5	1	1	1	1	1	1	1
HSBC	0	2.5	2.5	2.5	2.5	2	2	2	2	2
ING Bank	0	1	1	1	1	1	1	1	1	1
JP Morgan Chase	0	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2
Lloyds	0	/	/	/	/	/	/	/	/	/
Mitsubishi UFJ FG	0	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Mizuho FG	0	1	1	1	1	1	1	1	1	1
Nordea	0	1	1	1	1	1	1	/	/	/
Royal Bank of Scotland	0	1.5	1.5	1.5	1	1	1	/	/	/
Santander	0	1	1	1	1	1	1	1	1	1
Société Générale	0	1	1	1	1	1	1	1	1	1
Sumitomo Mitsui FG	0	1	1	1	1	1	1	1	1	1
Unicredit Group	0	1	1	1	1	1	1	1	1	1
Wells Fargo	0	1	1	1	1	1.5	1.5	1.5	1.5	1
BBVA	/	1	1	1	/	/	/	/	/	/
Standard Chartered	/	1	1	1	1	1	1	1	1	1
Industrial and Commercial Bank of China Limited	/	/	1	1	1	1.5	1.5	1.5	1.5	1.5
Agricultural Bank of China	/	/	/	1	1	1	1	1	1	1
China Construction Bank	/	/	/	/	1	1	1.5	1	1	1.5
Royal Bank of Canada	/	/	/	/	/	/	1	1	1	1
Toronto-Dominion Bank	/	/	/	/	/	/	/	/	1	1

Note: The numbers (in percent) are the required level of additional common equity loss absorbency as a percentage of risk-weighted assets. For year 2011 the FSB did not provide additional levels of required loss absorbency. Entries with a "/" indicate that the bank is not designated as a GSIB in the corresponding year.

Appendix B. List of economies included in the final step

Argentina	Ireland	Qatar
Australia	Israel	Romania
Austria	Italy	Russia
Bahrain	Ivory Coast / Cote d'Ivoire	Rwanda
Bangladesh	Jamaica	Saudi Arabia
Belgium	Japan	Serbia
Bosnia and Herzegovina	Jordan	Singapore
Brazil	Kazakhstan	Slovakia
Bulgaria	Kenya	Slovenia
Canada	Kuwait	South Africa
Chile	Lebanon	South Korea
China, mainland	Lithuania	Spain
Colombia	Malawi	Sri Lanka
Croatia	Malaysia	Sweden
Cyprus	Malta	Switzerland

(*continued on next page*)

Appendix B (*continued*)

Argentina	Ireland	Qatar
Czech Republic	Mauritius	Syria
Denmark	Mexico	Taiwan, China
Ecuador	Montenegro	Tanzania
Egypt	Morocco	Thailand
Estonia	Namibia	Tunisia
Finland	Netherlands	Turkey
France	Nigeria	Uganda
Germany	North Macedonia	Ukraine
Ghana	Norway	United Arab Emirates
Greece	Oman	United Kingdom
Hong Kong, China	Pakistan	United States
Hungary	Peru	Venezuela
Iceland	Philippines	Vietnam
India	Poland	Zambia
Indonesia	Portugal	

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