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by Paul D McNelis and James Yetman

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Volatility spillovers and capital buffers among the G-SIBs

Paul D McNelis and James Yetman[1]

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Abstract

We assess the dynamics of volatility spillovers among global systemically important banks (G-SIBs). We measure spillovers using vector-autoregressive models of range volatility of the equity prices of G-SIBs, together with machine learning methods. We then compare the size of these spillovers with the degree of systemic importance measured by the Basel Committee on Banking Supervision's G-SIB bucket designations. We find a high positive correlation between the two. We also find that higher bank capital reduces volatility spillovers, especially for banks in higher G-SIB buckets. Our results suggest that requiring banks that are designated as being more systemically important globally to hold additional capital is likely to reduce volatility spillovers from them to other large banks.

Keywords: G-SIBs; contagion; connectedness; bank capital; cross validation.

JEL classifications: C58, F65, G21, G28.

Introduction

This paper examines volatility spillovers among global systemically important banks (G-SIBs), based on co-movements in equity price volatility at daily frequency.[2] A list of G-SIBs have been identified by the Financial Stability Board (FSB) in consultation with Basel Committee on Banking Supervision (BCBS) and national authorities each year since 2011.

Volatility spillovers are one way to assess the degree of connectedness among banks and is related to notions of contagion, although the latter typically refers to connectedness *in extremis*. When we think about banking-sector contagion effects, the focus was historically on runs on bank deposits (see eg Saunders and Wilson (1996), and Aharony and Swary (1983)). When one bank experiences problems, this can result in system-wide effects as depositors, with imperfect information, withdraw deposits from all banks, including those that are otherwise healthy.

More recently, volatility spillovers has been seen to depend more on interbank linkages on assets or on liabilities than the risk of depositor runs. Several measures have been proposed for assessing the systemic importance of banks in such an environment. To give a few examples, Zhou and Tarashev (2013) apply extreme value theory to credit default swaps and expected default probabilities to construct a price-based measure of systemic importance for 50 global banks for 2007–2011. Drehmann and Tarashev (2013) instead use simulations based on balance sheet data for 20 large banks to measure systemic importance as either i) the expected losses that a bank imposes on non-bank investors or ii) how much a bank contributes to the risk of other banks in systemic events.[3] Acharya et al (2009, 2017) instead use the average return on bank equities during the 5% worst days for market performance as a basis for measuring systemic risk. Finally, Adrian and Brunnermeier (2016) measure systemic risk of each institution as the change in the value at risk of the financial system as a whole conditional on the individual institution being in distress relative to its median state.[4]

Here, we take a complementary approach to assess the strength of inter-relationships between banks, focusing on the degree of volatility spillovers. We follow Demirer et al (2018) in using a market-based measure of the riskiness of banks, as reflected by equity price volatility, and look for commonality in that measure to examine connectedness.[5] A perception that a bank's riskiness is likely to spill over to other banks should be reflected in high levels of co-movement in their equity price volatility at high frequency, due to the implications of connectedness for bank profitability.

We first focus on the 20 G-SIBs that are listed on the New York Stock Exchange, including those listed via American Depository Receipts. We then extend the sample to 31 G-SIBs based on listings in their domestic markets.[6]

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[2]   A full list of the G-SIB banks for each year is given in Appendix Table A1. The process for designating benchmarks has evolved over time, and is summarised in BCBS (2011, 2013 and 2018).

[3]   See also Tarashev et al (2016) for related work.

[4]   For a survey of different measures of contagion, see Benoit et al (2017).

[5]   Our departures from Demirer et al (2018) include linking connectedness to bank capital and G-SIB designation by the BCBS.

[6]   In the case of the four Chinese banks in the larger sample, we use equity price data from their Hong Kong listing since capital controls may influence the equity price volatility of their Shanghai listings, especially at high frequency,

We measure risk using range volatility, based on an approximation for intra-day volatility. This is constructed using the logarithmic values of the opening, closing, high and low values of the daily bank share prices, following Garman and Klass (1980). We then apply the methods of Diebold and Yilmaz (2012) to assess how important each G-SIB is in influencing the equity price volatility of the other G-SIBs, measured by its outward connectedness.

Our sample runs from October 2007 to September 2018. Not surprisingly, the periods surrounding the Great Financial Crisis (GFC) saw volatility spillovers spike. But, even as these have moderated in subsequent periods, they have by no means disappeared.

The FSB first published a list of 29 banks designated as G-SIBs in November 2011. Starting with a wider list of large banks, they use twelve different proxies to measure five different aspects of systemic importance: the size of the bank, its interconnectedness, the availability of substitutes for the bank's services, the size of its cross-border lending and funding, and the complexity of its portfolio. These indicators are then normalised and combined to produce a single measure of systemic importance.[7] The number of designated banks has varied over time along with these indicators.

Since November 2012, G-SIBs have been further demarcated by the BCBS into buckets based on their relative systemic importance, with the list of banks and bucket allocations updated annually.[8] Then, beginning with the 2014 assessment, G-SIBs have been required to incrementally hold higher capital buffers in the form of Common Equity Tier 1 (CET1), with banks in higher buckets required to hold more, in reflection of their greater systemic importance. These requirements are phased in over time. Taking the 2014 cohort of G-SIBs as an example, provided they remained G-SIBs in subsequent years, their prescribed capital was increased in steps from 1 January 2016, with the full additional amount to be held by 1 January 2019.

Focusing on the period beginning November 2012, we find that outward connectedness – our measure of volatility spillovers – is strongly positively correlated with the G-SIB bucket categorisation of the BCBS, where higher bucket designations indicate greater outward volatility spillovers. We also find that a higher CET1 capital ratio reduces volatility spillovers, especially for banks in higher G-SIB buckets. Our results provide empirical support for current policy approaches: 1. banks that are designated more systemically important globally do exert greater influence on other banks' stock prices; and 2. the efficacy of higher capital in mitigating this influence supports these banks being required to meet higher capital requirements.

In related work, Goel et al (2019) assess the effectiveness of post-crisis regulatory reforms aimed at mitigating systemic risks from G-SIBs. They find that overall financial system risks have declined since the GFC, and that G-SIBs have tended to reduce their systemic importance. In part, this is because G-SIBs expanded their balance sheets less quickly than other large banks, and also shifted to less complex assets. In addition, as Neanidis (2019) has recently shown, the importance of effective banking regulation is crucial for mitigating the negative effects of volatile capital flows on economic growth for many countries and for various categories of capital flows.

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[7]   For more details, see BCBS (2013).

[8]   See http://www.fsb.org/work-of-the-fsb/policy-development/systematically-important-financial-institutions-sifis/global-systemically-important-financial-institutions-g-sifis/.

In the next section we describe the data set we use as well as the methodology for obtaining the realised daily range volatility measures for the banks. Section 2 describes our empirical methodology and reports the level of connectedness among G-SIBs listed in the US market. Section 3 analyses the relationships over time between connectedness, G-SIB designation, CET1 capital ratios and the home domicile of banks. Section 4 extends the results to a wider sample of G-SIBs based on their domestic listings. We then conclude in Section 5.

1. Data and measurement of risk and contagion

1.1 Data

We first consider twenty US listed G-SIBs. These banks represent around two-thirds of the G-SIB universe, but offer the advantage of sharing the same trading hours and trading days, so provide a clean environment to assess the drivers of spillovers.[9]

Table 1 gives the names of the banks. Four are foreign banks whose shares are traded in the US markets either through the American Depository Shares or American Depository Receipts. The data span the period from 18 October 2007 to 28 September 2018.

Globally systemically important banks: US listings[1]							Table 1
Code[2]	Name	Type[3]	Mean	Median	Std Dev	Min	Max
BAC	Bank of America		-1.111	-1.131	0.473	-2.711	0.004
BK	Bank of New York Mellon		-0.845	-0.888	0.340	-1.503	0.049
BCS	Barclays		-1.172	-1.123	0.376	-2.904	0.018
BBVA	BBVA		-0.263	-0.272	0.289	-0.935	0.280
C	Citigroup		-2.101	-2.205	0.553	-3.766	0.000
CS	Credit Suisse	ADS	-0.892	-0.883	0.436	-1.865	0.005
DB	Deutsche Bank		-1.224	-1.164	0.588	-2.462	0.046
GS	Goldman Sachs		-0.327	-0.309	0.281	-1.427	0.199
HSBC	HSBC		-0.681	-0.675	0.226	-1.438	0.025
ING	ING Bank		-1.254	-1.260	0.425	-2.680	0.000
JPM	JP Morgan Chase		0.132	0.064	0.369	-1.098	0.949
MS	Morgan Stanley		-0.996	-1.067	0.302	-1.473	0.049
MFG	Mizuho Financial Group	ADR	-0.776	-0.769	0.367	-1.953	0.021
RBC	Royal Bank of Canada		0.017	0.038	0.226	-0.994	0.431
RBS	Royal Bank of Scotland	ADS	-2.876	-3.004	0.803	-4.153	0.013
SAN	Santander		-0.873	-0.950	0.416	-1.703	0.088
STT	State Street		-0.630	-0.644	0.253	-1.058	0.203
SMFG	Sumitomo Mitsui FG	ADS	-0.234	-0.133	0.331	-1.548	0.413
UBS	UBS		-1.191	-1.201	0.273	-2.057	0.000
WFC	Wells Fargo		0.123	0.103	0.332	-1.361	0.670

Notes: [1] Changes in log bank share prices, in USD. [2] On the NYSE. [3] ADR: American Depository Receipt; ADS: American Depository Share. Otherwise conventional listing.

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[9]   We will later extend the sample to include all G-SIB banks.

To illustrate changes in bank share prices over the sample period, we first normalise each series by dividing by the first observation, and then take natural logarithms. The resulting series are summarised in Table 1. With the exception of JP Morgan, Royal Bank of Canada and Wells Fargo, we see that the mean and median values over this period are negative, ie the end of period share price is below the starting observation, in October 2007. In terms of volatility, the standard deviation is largest for the Royal Bank of Scotland and lowest for the Royal Bank of Canada.

The realised daily range volatility measure, denoted by σ_t^R, comes from an approximation based on difference between the daily opening (o) and closing (c), as well as maximum (h) and minimum (l) of the natural logarithmic values of the share prices observed each day, based on Garman and Klass (1980):

$$\sigma_t^R = .511(h - l)^2 - .019[(c - o)(h + l - 2o) - 2(h - o)(l - o)] - .383(c - o)^2. \qquad (1)$$

These authors found that range volatility closely approximated daily within sample realised volatility measures coming from very high-frequency data.

Graph 1 displays the median values across the 20 banks, through time, of the range volatility σ_t^R. The volatility around the time of the GFC dominates. However, while volatility diminished after 2010, it has by no means disappeared.

Median values of intra-day range volatility   Graph 1
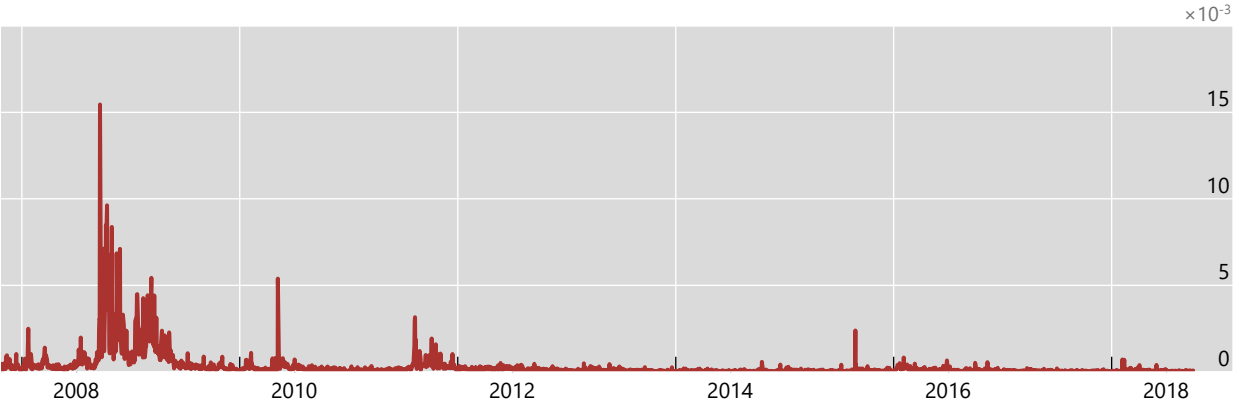
Source: authors' calculations

Graph 2 illustrates the median range volatility (in levels, at daily frequency) in two charts, with different scales, showing the range volatility before 2010 and after 2010. The period after 2010 displays distinct periods of high volatility across the banking sector: in late 2010, in 2011 and in 2015–2016. These are periods of high bank stock price volatility due to fears of contagion from the European sovereign debt crisis as well as the downgrading of the US credit rating from AAA to AA+ on 6 August 2011. In the 2015–2016 period, factors such as the Brexit vote, the fall in oil prices, the slowing of the Chinese economy and the election in the United States are plausible explanations for the spikes in the volatility measure.

We next model the connections between these volatility measures, focusing on how much of the volatility of each G-SIB can be explained by the volatility of each of the others. We work with the levels of the range volatility measures for our primary results, but have confirmed that they are robust to

using logarithmic transformations instead. We then check to see if more systemic banks have larger volatility spillovers on other banks, and whether higher capital adequacy will work to reduce this.

Range volatility: GFC and post-GFC

Graph 2
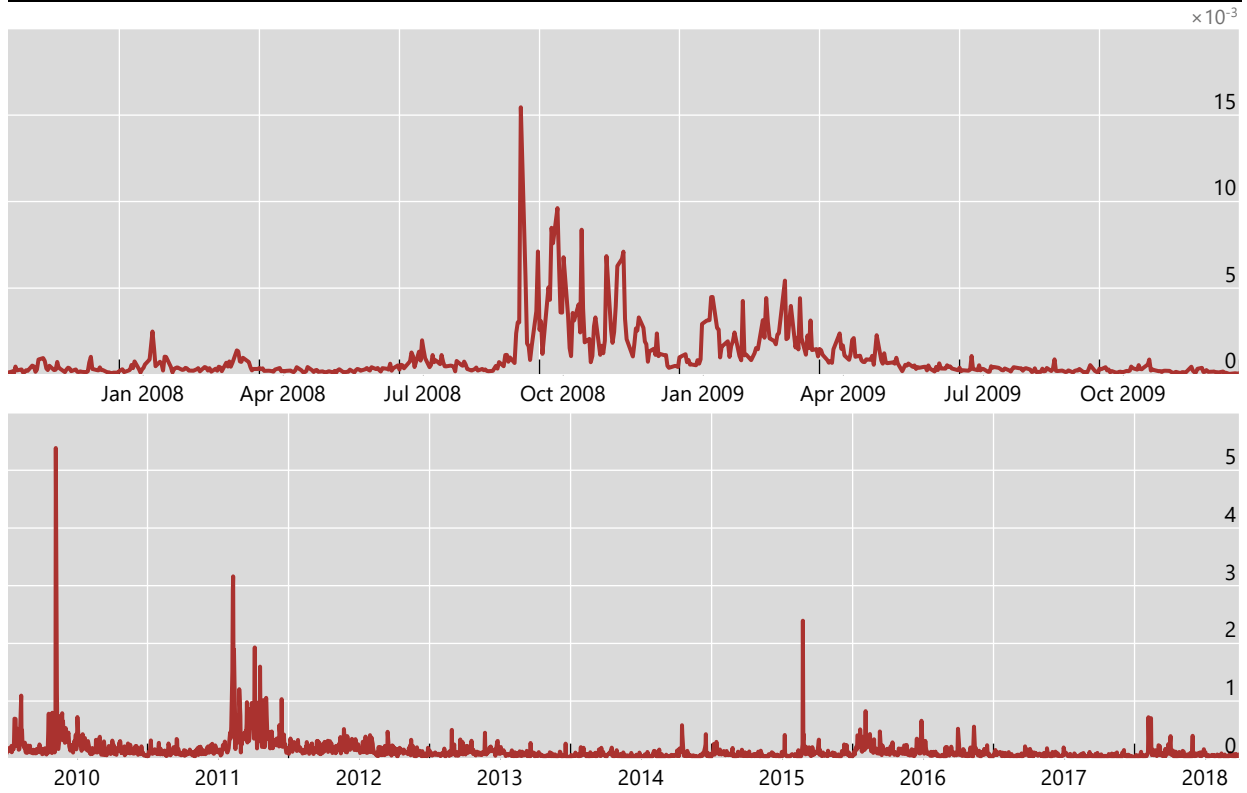
Source: Authors' calculations

1.2 Regularisation of a big VAR

Following a series of papers by Diebold and Yilmaz (2012), Diebold and Yilmaz (2013) and Yilmaz (2018), we examine the volatility measures, and also their evolving connectedness, through time. We estimate a vector autoregressive (VAR) model on the daily range volatility measures, first for the full sample and then based on a rolling window of 150 days, in order to estimate time-varying measures of volatility spillovers. We use a lag length of five trading days for our VAR.

Given that the VAR model is a relatively large one, with 100 parameters plus a constant term for each bank, our model requires regularisation. We use the elastic net estimator due to Zou and Hastie (2005) for parameter reduction:

$$\beta_{Enet} = \underset{\beta}{\text{argmin}}\{\sum_{t=1}^{T} (y_t - \sum_i \beta_i x_{it})^2 + \lambda \sum_{i=1}^{k} [\alpha|\beta_i| + (1-\alpha)\beta_i^2]\}. \tag{2}$$

As with other, familiar, criteria for reducing parameters, such as the Akaike (AIC), Schwartz (BIC) and Hannan-Quinn (HQIC) information criteria, the elastic net penalises models for having more parameters. With this net, the choices of α and λ are key. These control the degree of shrinkage and,

by extension, the variables that remain in the estimated model. In moderation, shrinkage can improve both prediction and interpretability of estimated models. However, excessive regularisation would result in important variables being left out of the model and can harm both predictive capacity and the inferences drawn about the system being studied.

The elastic net generalises many different estimators. The LASSO (Least Absolute Shrinkage Selection Operator) and Ridge penalty are both special cases, based on $\{\alpha, \lambda\}$ values of $\{1, +\}$ and $\{0, +\}$ respectively (Yilmaz 2018). With $\lambda = 0$, there is no penalty for the number of non-zero parameters, and the estimates are simply least-squares.

We set the parameter $\alpha = 0.5$, and estimate the coefficients of the model for alternative values of λ. As λ increases, more and more parameters go to zero. We choose λ based on the widely used machine learning algorithm called cross validation (CV).

Using this method, we select a grid of values for λ, ranging from the lowest, $\lambda = 0$, to the minimal value of λ for which $\beta_i = 0 \ \forall i, \lambda^*$. We then partition λ into a grid of 100 values over $[0, \lambda^*]$ and choose the λ that minimises the out-of-sample mean squared error based on a test set of withheld data. Once we have identified λ in this fashion, we then estimate β over the full sample. We thus effectively use the in-sample training-set data to select λ, but the full sample to estimate β. For the split between in-sample and out-of-sample, we divide the data into five equally sized time periods and withhold each of these in turn, with the λ chosen based on out-of-sample mean squared forecast errors across the five samples. We follow this same method of parameter reduction, or regularisation, both for full sample estimation and for each of the moving-window estimations based on rolling samples of 150 daily observations.

1.3 Variance decomposition and volatility spillovers

It is well known that the impulse-response paths and forecast error-variance decomposition measures are sensitive to the ordering of the variables in a VAR model. Following the approach of Diebold and Yilmaz (2012), we make use of the generalised method for obtaining forecast-error variance decomposition due to Pesaran and Shin (1998), which does not rely on orthogonal shocks and is invariant to ordering. In simple terms, this uses the historically observed correlation between shocks to tease out how much of the observed forecast error is attributable to shocks to the volatility of stock prices of each of the banks in the sample.

Our variance decomposition is of the 10 trading day-ahead forecast error. Each element of the resulting 20x20 matrix tells us how much of the equity price volatility of a bank can be explained by the shock to volatility of each bank. Excluding the diagonal elements, which reflect the equity price variance explained by its own shocks, summing along the rows of the matrix reveals the total inward connectedness of each of the banks, while summing along the columns reveals the total outward connectedness.

Diebold and Yilmaz (2014) argue that this way of measuring connectedness is closely related to measures of systemic risk. The inward-connectedness measure, they note, represents the exposures of individual banks to systematic shocks from the network as a whole, while the outward connectedness indicates the contribution of the individual bank to systemic network events. We would expect these measures to change through time, reflecting changes in banking regulations and increasing

globalisation of financial markets. For this reason, we report these measures of volatility spillovers both for the full sample and as time-varying measures based on rolling-window regressions.

| Full sample measures of connectedness | | | | Table 2 |
Code	Name	Net	Inward	Outward
BAC	Bank of America	2.818	0.255	3.074
BK	Bank of New York Mellon	1.602	0.858	2.460
BCS	Barclays	-0.101	0.718	0.617
BBVA	BBVA	-0.007	0.729	0.723
C	Citigroup	-0.213	0.776	0.563
CS	Credit Suisse	-0.824	0.993	0.169
DB	Deutsche Bank	-0.350	0.874	0.524
GS	Goldman Sachs	-0.550	0.833	0.283
HSBC	HSBC	-0.907	0.984	0.076
ING	ING Bank	-0.899	0.992	0.093
JPM	JP Morgan Chase	-0.507	0.819	0.313
MS	Morgan Stanley	1.484	0.558	2.042
MFG	Mizuho Financial Group	-0.754	0.959	0.206
RBC	Royal Bank of Canada	-0.222	0.770	0.547
RBS	Royal Bank of Scotland	-0.353	0.861	0.508
SAN	Santander	-0.795	0.970	0.175
STT	State Street	0.968	0.500	1.467
SMFG	Sumitomo Mitsui FG	0.501	0.482	0.983
UBS	UBS	-0.051	0.760	0.709
WFC	Wells Fargo	-0.841	0.974	0.132
Note: total spillover = 0.7834.				

2. Connectedness

2.1 Full sample connectedness: US listed banks

Table 2 gives the measures of outward, inward and net connectedness for the twenty banks listed on stock exchanges in the US, based on full-sample estimation of the forecast-error variance decomposition matrix. The inward-connectedness measure for each bank is the percentage of the total variance of the volatility which is due to spillovers from other banks. The outward-connectedness measure is the amount of the total variance of all of the banks' volatility explained by the specific bank.[10] The net connectedness measure is simply the outward less inward measure, indicating whether the bank is a net transmitter or a net receiver of volatility with respect to the G-SIBs as a whole.

For the overall sample estimation, we see that Bank America (BAC), Bank of New York Mellon (BK) and Morgan Stanley (MS) are the largest net transmitters of risk to the rest of the banking system. By

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[10]   In later results we will focus on outward connectedness, which we will normalise by the number of banks in the sample, to make it more comparable across the two samples that we examine. See the Table A2 for the full spillover matrix.

the same token, we see that Credit Suisse (CS), HSBC, ING Bank and Wells Fargo (WFC) are the banks with the greatest exposure to risk from the rest of the banking system.

The total spillover index is simply the sum of the off-diagonal elements of the variance-decomposition matrix relative to the total variance of the system as a whole divided by the number of banks. The index is 78.34 per cent, indicating that spillovers can explain almost 80% of the variation in total equity price volatility of the banks in our sample.

2.2 Time-varying connectedness: US listed banks

We next consider rolling regressions, with a window of 150 days, to see how connectedness has evolved over time. We obtain, using the same elastic net estimation, time-varying forecast-error variance decomposition matrices from which we extract the spillover effects as well as measures of overall connectedness for the banks. The sample starts on 22 May 2008 and ends on 28 September 2018.

Time-varying outward connectedness index[1]   Graph 3
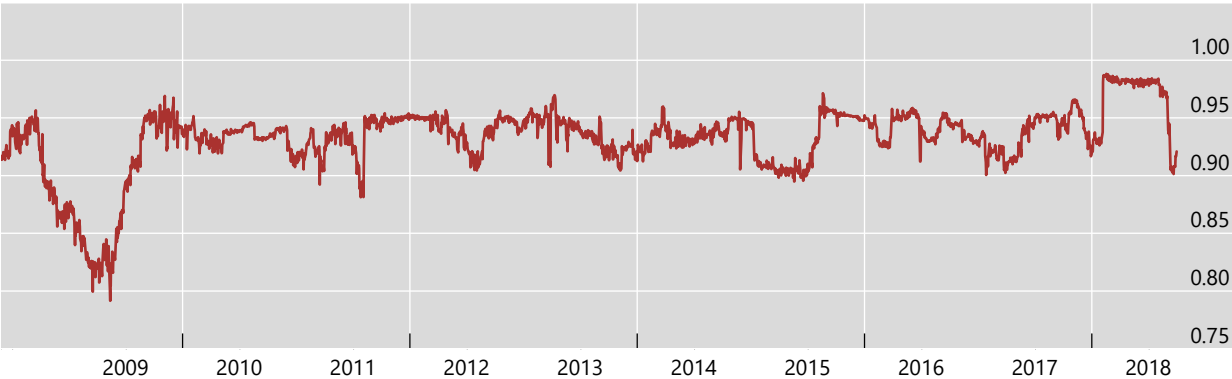
[1] Overall share of volatility explained by spillovers from other banks.
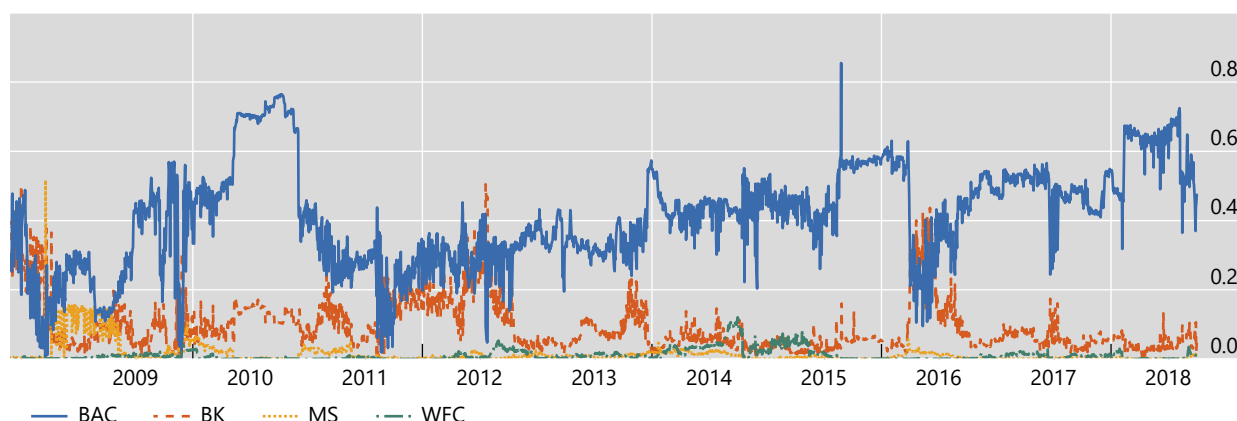
Source: Authors' calculations

Graph 3 displays the time-varying outward connectedness across the full sample of GSIBs. We see that the index is over 90% for most of the sample, indicating an even higher degree of outward connectedness than indicated by the full-sample estimation and demonstrating the importance of allowing for changes in spillovers between the banks over time. We note in passing that the use of regularisation, both for the full sample and for the rolling regressions, tends to bias the estimates toward less connectedness rather than more, since many of the coefficients from cross-lagged effects end up being set to zero. However, what is of interest is not the overall degree of inter-connectedness between banks, but the ways specific banks transmit risks to the system as a whole.

From our rolling regressions we also obtain the outward connectedness for each bank for each rolling sample, which we normalise by the number of banks in the sample. Table 3 gives summary statistics: the mean, median and maximum values as well as the standard deviations across the rolling samples. This table shows that BAC has the strongest contagion effect, reaching a maximum value of over 85% of the total variance of the banking system. However other banks, including BK, BCS, MS, MFG and UBS, at various times, account for as much as around 50 per cent of the total banking-sector risk.

Rolling sample outward connectedness: US listed					Table 3
Code	Name	Mean	Median	Max	Std dev
BAC	Bank of America	0.410	0.419	0.855	0.670
BK	Bank of New York Mellon	0.095	0.066	0.505	0.344
BCS	Barclays	0.091	0.071	0.475	0.313
BBVA	BBVA	0.043	0.035	0.410	0.152
C	Citigroup	0.033	0.019	0.249	0.163
CS	Credit Suisse	0.016	0.013	0.141	0.061
DB	Deutsche Bank	0.015	0.010	0.235	0.079
GS	Goldman Sachs	0.020	0.015	0.347	0.087
HSBC	HSBC	0.014	0.008	0.162	0.076
ING	ING Bank	0.011	0.006	0.175	0.072
JPM	JP Morgan Chase	0.016	0.011	0.267	0.094
MS	Morgan Stanley	0.016	0.005	0.517	0.139
MFG	Mizuho Financial Group	0.047	0.010	0.506	0.332
RBC	Royal Bank of Canada	0.018	0.009	0.346	0.118
RBS	Royal Bank of Scotland	0.012	0.005	0.140	0.069
SAN	Santander	0.009	0.004	0.134	0.071
STT	State Street	0.015	0.005	0.252	0.115
SMFG	Sumitomo Mitsui FG	0.026	0.007	0.374	0.199
UBS	UBS	0.014	0.001	0.489	0.158
WFC	Wells Fargo	0.011	0.005	0.121	0.072

To better understand the dynamics of banking sector contagion, Graph 4 shows the outward connectedness of three banks with high maximum levels of outward connectedness (BAC, BK and MS), as well as one with low levels for contrast (WFC), over time. We see that there are jumps in volatility spillovers at the beginning of the sample in late 2011 and in 2016, corresponding to the time of the downgrading of US debt and Brexit, respectively. However, these effects may also be affected by policy and regulation. For this reason, we next consider modelling banks' outward connectedness as an endogenous variable depending, in part, on G-SIB buckets and capital ratios.

Dynamics of outward connectedness: examples[1]   Graph 4

[1] Average size of spillovers to all G-SIBs

Source: authors' calculations

3. Explaining G-SIB volatility spillovers

Based on our rolling regressions, we have 20 banks x 2608 estimates of outward connectedness (one for each rolling sample). We now examine the relationships between these and G-SIB bucket designations, CET1 capital, G and the region of home domicile.

For G-SIB bucket, we use the designations published by the FSB annually, beginning in 2012 (see Appendix Table A1). Given the changing composition of the G-SIB list, there are some banks that were not G-SIBs for part of the sample. For these observations, we substitute a bucket designation of zero.[11]

For the CET1 capital ratio, we use the latest available capital measure divided by risk weighted assets at the time of each rolling sample. For banks where there are missing observations, we interpolate the ratio to obtain a quarterly series assuming a linear trend between available data.[12] We also include a trend (Year) and dummies for each of the three regions of the world represented in the dataset: Americas, Europe and Asia.

Our results are reported in Table 4. The coefficient on the G-SIB bucket is positive and highly statistically significant, indicating that the more systemically important a bank is – as identified by the BCBS – the stronger its outward connectedness with other G-SIBs is. The second and third explanatory variables are the CET1 capital ratio and the interaction between the G-SIB bucket and the CET1 capital ratio. The coefficient on the first of these is positive, while that on the second is around six times larger and negative. Given that most of our observations are for banks in a G-SIB bucket of one or higher, taken together, these estimates suggest that a higher CET1 capital ratio is associated with lower levels of volatility spillovers to other banks, and the effects of higher capital ratios on reducing this

[11]   We start using this as an ordinal variable, but will also consider dummies for each bucket later

[12]   There are some gaps in our series. However, reported results are robust to using the Tier 1 capital ratio (which is available for all banks in our sample for the full time series) in place of CET1.

connectedness are larger the higher the bank's designated G-SIB bucket is.[13] On the face of it, this result provides support for the idea that more systematically important banks should be subject to higher capital charges, in that higher capital adequacy lowers the spillovers: in addition to the fact that these banks are more connected, higher capital is especially effective at protecting other banks from negative volatility spillovers from them. The final regressors illustrate that overall outward contagion has a positive trend, and the effect is very similar whether a G-SIB bank's home jurisdiction is in the Americas, Europe or Asia.

Explaining outward connectedness of US listed G-SIBs			Table 4
Variable	Coefficient	t-statistic[1]	P-value
G-SIB bucket[2]	0.0856	27.9	0.000
CET1 capital ratio	0.000973	3.3	0.001
(G-SIB bucket) x (CET1 capital ratio)	-0.00607	-26.3	0.000
Year	0.00269	6.0	0.000
Americas	-5.38	-6.0	0.000
Europe	-5.43	-6.0	0.000
Asia	-5.42	-6.0	0.000
N=27,251; R^2=0.24			

[1] Based on robust standard errors. [2] This is included as an ordinal variable, with zero substituted in place of banks that were not on the G-SIB list in a given rolling sample.

It is possible that our explanatory variables are not fully independent from each other. In particular, by the end of the sample, banks in higher G-SIB buckets, which are more systematically important, are required to hold higher capital. However, to the extent that this is true it would strengthen our results since, once we control for the G-SIB bucket, more capital is associated with less outward connectedness. But if we drop the first and third variables above, so that there is no control for the bucket, the CET1 capital ratio continues to enter with a negative coefficient, which is larger and more statistically significant than with the bucket variables included. The implication is that banks in higher G-SIB buckets generally hold less capital, which highlights the importance of including the G-SIB bucket as a control variable.[14]

We consider a number of robustness checks, including replacing the "Year" variable with year dummies, replacing the G-SIB bucket variable with dummies for each bucket, adding measures of policy uncertainty to the regressions, dropping one bank at a time from the sample and using leads or lags of some variables. Except where otherwise stated, the results are robust.

When we include dummy variables for each of the G-SIB buckets, our estimates of outward connectedness – and their 95% confidence bands (relative to bucket zero, for banks that were not designated G-SIBs in a given year) – are given in Graph 5. They demonstrate that there is a highly statistically significant monotonic relationship between G-SIB bucket designation and outward connectedness. Also, the positive coefficient on the CET1 capital ratio is not robust: in some

[13]   The negative coefficient on CET1 may be partly due to the small number of observations in bucket zero in the sample: these are from only two banks and constitute less than 7% of the total sample.

[14]   Indeed, the unconditional mean of the CET1 capital ratio is highest for banks in the second bucket (13.0%), before falling for higher buckets (12.9% for bucket 3 and 11.8% for bucket 4, respectively).

specifications, it becomes statistically insignificant and/or changes sign. But in all cases, the general result still holds that for all except bucket zero, higher capital ratios reduce outward connectedness and by more the higher the designated bucket is. Similar results (available on request) are obtained if we replace CET1 capital with Tier 1 capital instead.

Outward connectedness by G-SIB bucket

Graph 5
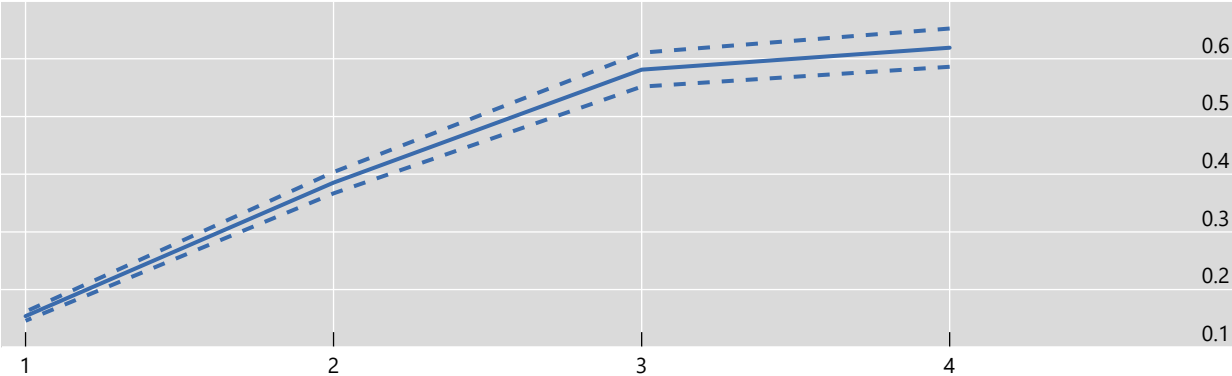
Estimated effect of G-SIB buckets (X axis) on outward connectedness (Y axis) relative to bucket zero (banks that were not designated G-SIBs at a given point in time). Solid line = estimated effect; dashed lines = 95% confidence bands.

Source: authors' calculations

Returning to the original specification, when we add year dummies, banks with a home domicile in the Americas become more important as a source of contagion than those from Europe or Asia. After controlling for other variables, the coefficient on the Americas, at 0.63, is positive and highly statistically significant, while the other regional dummies are negative but statistically insignificant from zero.

We also consider adding measures of uncertainty to the regressions. These include uncertainty regarding economic policy, monetary policy, fiscal policy, national security, regulation, financial regulation, trade and crises and are drawn from Baker et al (2016).[15] These do not change our main results. However, not surprisingly, the forms of uncertainty we examine are significant predictors of increased outward connectedness in their own right.

We also consider introducing leads of some of the explanatory variables, as additional robustness checks. Our measure of outward connectedness is based on rolling estimation over the previous 150 trading days of equity price data. By contrast, our measure of capital is lagged by between one and around 63 trading days (the average number of trading days in a quarter, given that it available only quarterly), and G-SIB buckets are based on bank data that is further lagged, and remains constant for a full year. To ensure that this asynchronicity is not driving our results, we consider replacing the bucket designation with that from three, six, nine or 12 months ahead. For the CET1 capital ratio, we consider a 63-day rolling average of our existing series, pushed forward by 63 days, which approximates the daily capital ratio if it were to follow a linear path between quarterly reporting. In all these cases, our results are qualitatively and quantitatively similar to those reported above.

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[15]   See http://www.policyuncertainty.com/

4. The full sample of G-SIBs

The above analysis is based only on those G-SIBs that are listed in US equity markets. Next we widen the sample to include all G-SIBs based on their domestic listing in the jurisdiction of their headquarters (see Appendix Table A1 for a list). This will allow us to confirm if our results carry over to the universe of G-SIBs, of which those that are US listed may not be a representative sample.[16]

Doing so, however, raises some challenges. First, there are four Chinese G-SIBs, and the short-term movements in their equity prices on the Shanghai Stock Exchange could be constrained by the effect of capital controls that limit financial flows to and from China. We therefore use listings in the Hong Kong Stock Exchange for each of these, since there are no capital controls on financial flows into and out of Hong Kong SAR.

Second, different markets are open for different periods each day, and our measures are based on data at daily frequency. On any given day, markets in Asia open first, followed by those in Europe and then the Americas. The trading days in Asia and Europe, and in Europe and the Americas, overlap, but markets in Asia are closed before those in the Americas open. This could matter if, for example, shocks affecting Japanese banks occur outside of Japanese trading hours: any spillover to US banks' equity prices could have already occurred before the Japanese markets open, and the source of the shock incorrectly attributed to US rather than Japanese banks. Or, information that primarily affects US banks, but is received by markets when US markets are closed but Japanese banks are open, may be misinterpreted as shocks originating from Japanese banks.

To ensure that our results are not driven by asynchronous trading days, we repeat the estimation in the following three different ways: based on calendar days for all jurisdictions; lag equity data for Asia by one day; and lag equity data for Asia and Europe by one day. We then compare the results across the three specifications to see if they are robust.

Third, different markets have slightly different trading calendars each year. This only relates to a few days per year for each market. We therefore simply repeat observations on σ_t^R from the previous day when they would otherwise be missing.

Finally, given the larger number of banks in the sample, there are potentially more parameters to be estimated. We therefore use a longer sample of 250 day rolling averages instead of the 150 days in the previous section to ensure sufficient degrees of freedom.

The results with no lags, analogous with Table 3 above, are presented in Table 5. These are broadly similar to those for the US listed banks, but with some differences. First, the most systemically important bank is less important in the larger sample: the average outward connectedness for Bank of America falls from 0.41 to 0.18. This is perhaps not surprising, given that the larger sample includes more banks that are geographically distant from the United States. Second, the magnitudes are generally smaller for all banks. This could reflect the more geographically diverse nature of the larger sample. Third, for those banks that are common to both samples, the decline is concentrated in banks listed in the Americas and Asia: on average, the median outward connectedness of Europe-based banks is little changed.

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[16] For example, 40% of the sample of US listed banks are US headquartered banks, but just 22% of the wider sample are.

Rolling sample outward connectedness: domestic listed; no lags		Mean	Median	Max	Std dev
Code	Name				Table 5
BAC	Bank of America	0.173	0.185	0.362	0.077
BK	Bank of New York Mellon	0.039	0.028	0.155	0.028
BCS	Barclays	0.074	0.043	0.439	0.090
BBVA	BBVA	0.039	0.039	0.131	0.024
C	Citigroup	0.022	0.015	0.097	0.019
CS	Credit Suisse	0.013	0.009	0.068	0.012
DB	Deutsche Bank	0.013	0.010	0.075	0.010
GS	Goldman Sachs	0.012	0.009	0.050	0.009
HSBC	HSBC	0.015	0.007	0.106	0.015
ING	ING Bank	0.011	0.007	0.057	0.009
JPM	JP Morgan Chase	0.028	0.008	0.231	0.047
MS	Morgan Stanley	0.007	0.005	0.033	0.005
MFG	Mizuho Financial Group	0.017	0.014	0.095	0.015
RBC	Royal Bank of Canada	0.013	0.005	0.276	0.024
RBS	Royal Bank of Scotland	0.029	0.014	0.271	0.047
SAN	Santander	0.004	0.003	0.029	0.004
STT	State Street	0.007	0.004	0.057	0.007
SMFG	Sumitomo Mitsui FG	0.005	0.002	0.032	0.006
UBS	UBS	0.009	0.006	0.053	0.008
WFC	Wells Fargo	0.007	0.003	0.066	0.010
ABC	Agricultural Bank of China	0.025	0.019	0.162	0.020
BOC	Bank of China	0.009	0.008	0.048	0.006
BNP	BNP Paribas	0.007	0.005	0.027	0.005
CCB	China Construction Bank	0.008	0.004	0.059	0.009
CASA	Groupe Crédit Agricole	0.011	0.007	0.062	0.012
ICBC	Industrial and Commercial Bank of China Ltd	0.005	0.003	0.028	0.003
MUFJ	Mitsubishi UFJ FG	0.006	0.003	0.029	0.006
NB	Nordea	0.007	0.003	0.051	0.010
GLE	Société Générale	0.018	0.008	0.138	0.025
SCP	Standard Chartered	0.013	0.009	0.083	0.013
UCG	Unicredit Group	0.017	0.013	0.115	0.014

When we look at the full sample, Agricultural Bank of China appears to be the most important bank among those added to the sample, with an average outward connectedness of 0.026. That ranks it the 7th most outwardly connected bank in our sample in terms of the average effect, and 5th in terms of its median effect.

Table 6 presents the median contagion effects for the three different lag specifications. On the whole, lagging the data makes little difference: the correlation between each pair of columns of median outward connectedness exceeds 0.99.

			Table 6
Rolling sample median outward connectedness: domestic listed; different lags			

Code	Name	No lags	Lag Asia	Lag Asia and Europe
BAC	Bank of America	0.185	0.252	0.253
BK	Bank of New York Mellon	0.028	0.041	0.041
BCS	Barclays	0.043	0.064	0.065
BBVA	BBVA	0.039	0.053	0.054
C	Citigroup	0.015	0.018	0.018
CS	Credit Suisse	0.009	0.015	0.015
DB	Deutsche Bank	0.010	0.018	0.018
GS	Goldman Sachs	0.009	0.011	0.011
HSBC	HSBC	0.007	0.015	0.014
ING	ING Bank	0.007	0.012	0.012
JPM	JP Morgan Chase	0.008	0.009	0.009
MS	Morgan Stanley	0.005	0.006	0.006
MFG	Mizuho Financial Group	0.014	0.023	0.023
RBC	Royal Bank of Canada	0.005	0.006	0.006
RBS	Royal Bank of Scotland	0.014	0.024	0.023
SAN	Santander	0.003	0.005	0.005
STT	State Street	0.004	0.005	0.005
SMFG	Sumitomo Mitsui FG	0.002	0.008	0.008
UBS	UBS	0.006	0.009	0.008
WFC	Wells Fargo	0.003	0.004	0.004
ABC	Agricultural Bank of China	0.019	0.019	0.019
BOC	Bank of China	0.008	0.008	0.008
BNP	BNP Paribas	0.005	0.005	0.005
CCB	China Construction Bank	0.004	0.004	0.004
CASA	Groupe Crédit Agricole	0.007	0.007	0.007
ICBC	Industrial and Commercial Bank of China Ltd	0.003	0.003	0.003
MUFJ	Mitsubishi UFJ FG	0.003	0.003	0.004
NB	Nordea	0.003	0.003	0.003
GLE	Société Générale	0.008	0.008	0.008
SCP	Standard Chartered	0.009	0.009	0.009
UCG	Unicredit Group	0.013	0.013	0.013

The more important test is whether the addition of non-US listed banks, and the timing assumptions, affects the second stage regressions – where we assess the effect of the G-SIB bucket, the CET1 capital ratio and the interaction between them affects outward connectedness. These results are given in Tables 7–9. The results are robust: in all three specifications, the G-SIB bucket is significantly positively correlated with outward connectedness, the CET1 capital ratio is small and statistically insignificant, while the interaction between them is larger and negative and highly significant. This indicates that higher capital is more effective in reducing volatility spillovers from G-SIBs the higher is the BCBS's designation of the bank's systemic importance. This is consistent with our previous results on US listed G-SIBs.

Explaining outward connectedness of domestic listed G-SIBs: no lags			Table 7
Variable	Coefficient	t-statistic	P-value
G-SIB bucket	0.0252	20.9	0.000
CET1 capital ratio	0.000128	1.1	0.281
(G-SIB bucket) x (CET1 capital ratio)	-0.00169	-18.1	0.000
Year	0.00130	8.9	0.000
Americas	-2.60	-8.8	0.000
Europe	-2.62	-8.9	0.000
Asia	-2.62	-8.9	0.000
N=41 304; R^2=0.29			

Explaining outward connectedness of domestic listed G-SIBs: lag Asia			Table 8
Variable	Coefficient	t-statistic	P-value
G-SIB bucket	0.0294	19.0	0.000
CET1 capital ratio	-0.000260	-1.7	0.084
(G-SIB bucket) x (CET1 capital ratio)	-0.00191	-15.8	0.000
Year	0.00154	8.0	0.000
Americas	-3.07	-7.9	0.000
Europe	-3.09	-7.9	0.000
Asia	-3.10	-7.9	0.000
N=41 304; R^2=0.28			

Explaining outward connectedness of domestic listed G-SIBs: lag Asia and Europe			Table 9
Variable	Coefficient	t-statistic	P-value
G-SIB bucket	0.0296	19.2	0.000
CET1 capital ratio	-0.000212	-1.4	0.159
(G-SIB bucket) x (CET1 capital ratio)	-0.00193	-16.0	0.000
Year	0.00156	8.1	0.000
Americas	-3.10	-8.0	0.000
Europe	-3.13	-8.0	0.000
Asia	-3.13	-8.0	0.000
N=41 304; R^2=0.28			

5. Conclusions

Beginning in 2011, the FSB began publishing a list of G-SIBs. From the following year, these were divided into buckets based on their degree of systemic importance globally. Following a phase-in period that began at the start of 2016, these banks have been required to satisfy higher capital

requirements in the form of CET1, the more so the higher the bucket that the bank is allocated to.[17] The rationale for higher loss absorbency requirements is to reduce the probability of failure, given the negative externalities associated with a G-SIB's collapse, which other current regulatory policies do not fully address.[18]

In this paper, we investigate the factors that drive volatility spillovers between G-SIBs. We measure these spillovers between banks based on co-movement in equity price volatility using the methods in Diebold and Yilmaz (2012). First, we find that banks in higher G-SIB buckets, and thus designated as being more systemically important by the BCBS, are the source of larger spillovers than those in lower buckets. Second, we find that a higher CET1 capital ratio helps to reduce the outward connectedness of G-SIBs with each other, especially for more systemically important banks: the higher a G-SIB's bucket designation is, the greater the marginal negative effect of a higher CET1 capital ratio on outward connectedness is. Taken together, our empirical evidence provides support for the effectiveness of higher capital standards in reducing spillovers, as measured by equity price volatility, among the G-SIBs.

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[17] The capital requirement increments – over and above those for non-G-SIBs – are 1% to the Common Equity Tier 1 ratio (as a percentage of risk-weighted assets) for bin 1, 1.5% for bin 2, 2% for bin 3, 2.5% for bin 4 and 3.5% for the (thus far empty) bin 5. See Table 2 in BCBS (2013).

[18] See, for example, the discussion in the introduction of BCBS (2011).

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G-SIB bucket designations										Table A1
Bank name	04.11.2011	01.11.2012	11.11.2013	06.11.2014	03.11.2015	21.11.2016	21.11.2017	16.11.2018	US listed sample	Domestic sample
Agricultural Bank of China				1	1	1	1	1		Y
Bank of America	*	2	2	2	2	3	3	2	Y	Y
Bank of China	*	1	1	1	1	1	2	2		Y
Bank of New York Mellon	*	2	1	1	1	1	1	1	Y	Y
Banque Populaire CdE	*									
Barclays	*	3	3	3	3	2	2	2	Y	Y
BBVA		1	1	1					Y	Y
BNP Paribas	*	3	3	3	3	3	2	2		Y
China Construction Bank					1	1	2	1		Y
Citigroup	*	4	3	3	3	4	3	3	Y	Y
Commerzbank	*									
Credit Suisse	*	2	2	2	2	2	1	1	Y	Y
Deutsche Bank	*	4	3	3	3	3	3	3	Y	Y
Dexia	*									
Goldman Sachs	*	2	2	2	2	2	2	2	Y	Y
Groupe BPCE		1	1	1	1	1		1		
Groupe Crédit Agricole	*	1	2	1	1	1	1	1		Y
HSBC	*	4	4	4	4	3	3	3	Y	Y
Industrial and Commercial Bank of China Limited			1	1	1	2	2	2		Y
ING Bank	*	1	1	1	1	1	1	1	Y	Y
JP Morgan Chase	*	4	4	4	4	4	4	4	Y	Y
Lloyds Banking Group	*									
Mitsubishi UFJ FG	*	2	2	2	2	2	2	2		Y
Mizuho FG	*	1	1	1	1	1	1	1	Y	Y
Morgan Stanley	*	2	2	2	2	1	1	1	Y	Y
Nordea	*	1	1	1	1	1	1			Y
Royal Bank of Canada							1	1	Y	Y
Royal Bank of Scotland	*	2	2	2	1	1	1		Y	Y
Santander	*	1	1	1	1	1	1	1	Y	Y
Société Générale	*	1	1	1	1	1	1	1		Y
Standard Chartered		1	1	1	1	1	1	1		Y
State Street	*	1	1	1	1	1	1	1	Y	Y
Sumitomo Mitsui FG	*	1	1	1	1	1	1	1	Y	Y
UBS	*	2	2	1	1	1	1	1	Y	Y
Unicredit Group	*	1	1	1	1	1	1	1		Y
Wells Fargo	*	1	1	1	1	2	2	2	Y	Y

Note: There were no bucket designations in 2011. For the Chinese banks (Agricultural Bank of China, Bank of China, China Construction Bank, Industrial and Commercial Bank of China Limited), we use listings in the Hong Kong Stock Exchange.

Full sample forecast error variance decomposition matrix: US listings

Table A2

	BAC	BK	BCS	BBVA	C	CS	DB	GS	HSBC	ING	JPM	MS	MFG	RBC	RBS	SAN	STT	SMFG	UBS	WFC	Inward
BAC	0.745	0.048	0.018	0.002	0.051	0.002	0.002	0.006	0.001	0.000	0.017	0.012	0.001	0.001	0.002	0.001	0.010	0.002	0.006	0.076	0.255
BK	0.021	0.142	0.017	0.007	0.010	0.005	0.006	0.027	0.000	0.001	0.006	0.250	0.001	0.003	0.026	0.001	0.370	0.020	0.087	0.002	0.858
BCS	0.087	0.118	0.282	0.001	0.012	0.003	0.003	0.005	0.001	0.001	0.007	0.212	0.002	0.001	0.049	0.001	0.191	0.006	0.006	0.014	0.718
BBVA	0.069	0.169	0.059	0.271	0.009	0.008	0.098	0.003	0.024	0.003	0.004	0.070	0.014	0.062	0.011	0.083	0.029	0.007	0.006	0.001	0.729
C	0.527	0.059	0.019	0.013	0.224	0.002	0.007	0.007	0.014	0.001	0.077	0.015	0.000	0.001	0.001	0.000	0.019	0.001	0.005	0.010	0.776
CS	0.060	0.161	0.037	0.027	0.011	0.007	0.017	0.012	0.003	0.011	0.009	0.093	0.022	0.090	0.078	0.001	0.078	0.235	0.047	0.001	0.993
DB	0.105	0.213	0.056	0.096	0.025	0.020	0.126	0.010	0.001	0.003	0.013	0.077	0.008	0.074	0.014	0.002	0.075	0.004	0.076	0.002	0.874
GS	0.066	0.146	0.021	0.031	0.014	0.011	0.017	0.167	0.001	0.001	0.014	0.098	0.003	0.011	0.006	0.001	0.057	0.130	0.204	0.001	0.833
HSBC	0.342	0.124	0.035	0.058	0.113	0.022	0.020	0.014	0.016	0.058	0.019	0.055	0.008	0.006	0.009	0.002	0.041	0.018	0.032	0.009	0.984
ING	0.294	0.185	0.036	0.059	0.008	0.040	0.014	0.007	0.004	0.008	0.006	0.037	0.057	0.038	0.039	0.000	0.008	0.148	0.008	0.003	0.992
JPM	0.323	0.119	0.038	0.036	0.173	0.005	0.028	0.016	0.003	0.001	0.181	0.020	0.001	0.007	0.003	0.003	0.017	0.001	0.022	0.004	0.819
MS	0.017	0.062	0.011	0.006	0.008	0.005	0.005	0.024	0.001	0.000	0.006	0.442	0.001	0.001	0.027	0.000	0.282	0.013	0.089	0.001	0.558
MFG	0.034	0.153	0.049	0.113	0.005	0.006	0.060	0.006	0.011	0.004	0.003	0.211	0.041	0.044	0.124	0.076	0.037	0.021	0.002	0.001	0.959
RBC	0.092	0.230	0.069	0.053	0.040	0.003	0.043	0.007	0.001	0.002	0.034	0.058	0.050	0.230	0.060	0.002	0.014	0.005	0.002	0.002	0.770
RBS	0.010	0.060	0.020	0.003	0.003	0.003	0.003	0.034	0.002	0.000	0.001	0.255	0.006	0.005	0.139	0.001	0.112	0.331	0.008	0.001	0.861
SAN	0.089	0.205	0.060	0.158	0.011	0.017	0.159	0.006	0.005	0.005	0.006	0.094	0.009	0.044	0.013	0.030	0.061	0.004	0.023	0.001	0.970
STT	0.013	0.074	0.009	0.005	0.008	0.004	0.004	0.018	0.000	0.000	0.005	0.271	0.001	0.001	0.013	0.000	0.500	0.003	0.069	0.001	0.500
SMFG	0.019	0.042	0.010	0.017	0.003	0.001	0.009	0.008	0.000	0.001	0.003	0.154	0.020	0.146	0.026	0.000	0.024	0.518	0.000	0.000	0.482
UBS	0.151	0.202	0.034	0.034	0.034	0.011	0.025	0.064	0.002	0.001	0.064	0.053	0.002	0.013	0.005	0.001	0.029	0.033	0.240	0.002	0.760
WFC	0.755	0.090	0.019	0.005	0.024	0.002	0.004	0.009	0.003	0.000	0.019	0.009	0.000	0.000	0.001	0.000	0.012	0.003	0.018	0.026	0.974
Outward	3.074	2.460	0.617	0.723	0.563	0.169	0.524	0.283	0.076	0.093	0.313	2.042	0.206	0.547	0.508	0.175	1.467	0.983	0.709	0.132	

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