Transparent Systemic-Risk Scoring[*]

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Abstract

Regulatory data used to identify Systemically Important Financial Institutions (SIFIs) have gradually become public since 2014. Exploiting this transparency shock, we show that the methodology implemented by the Basel Committee on Banking Supervision is biased and can create wrong incentives for regulated banks. Using regulatory data for 106 US and international banks, we show that the economic magnitude of the bias turns out to be important as the regulatory capital of some banks is reduced by more than EUR 12 billion or around 9% of their Tier 1 capital. The banks that benefit the most from the bias are US global and custodian banks. We then propose a modified methodology that corrects for the bias.

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1 Introduction

SIFIs, the acronym for Systemically Important Financial Institutions, is a palindrome as it reads the same backward or forward. While the way you read it does not matter, the way you rank financial firms is of utmost importance. Under Basel III, only the 30 most risky firms are typically designated as SIFIs and must hold additional regulatory capital. Moreover, the exact position of a firm within the SIFI list also matters as firms are allocated into risk buckets based on their *systemic-risk scores*. Indeed, being in the fifth risk bucket implies facing an additional 3.5% requirement in regulatory capital compared to 1% in the first risk bucket. Compared to the standard 8% Cooke Ratio in place since the first Basel Accord, the systemic-risk surcharge appears sizable. As a result, dropping from the list or switching across buckets leads to substantial changes in regulatory capital.

The systemic-risk scoring methodology currently implemented by the Basel Committee on Banking Supervision (BCBS) and the Financial Stability Board (FSB) is both simple and intuitive (BCBS (2013) and BCBS (2014b)). It aggregates information about five broad categories of systemic importance: size, interconnectedness, substitutability/financial institution infrastructure, complexity, and cross-jurisdictional activity. In order not to favor any particular facet of systemic risk, the BCBS computes an equally-weighted average of all categories.[1]

However, it is well known that such an aggregation process produces scores that are mechanically dominated by the categories that exhibit the highest cross-sectional variability. When variables are aggregated in absence of any form of standardization, they are effectively weighted by their standard deviation. As a result, the resulting systemic-risk scores, the ranking of banks, and in turn, their extra capital buffers are driven by a subset of variables

[1]There exists similar methodologies to compute systemic-risk scores for insurance companies (IAIS (2013)) and for non-bank non-insurance financial institutions (FSB-IOSCO (2015)).

only, which seems inconsistent with the original intention to give equal weight to each category. The BCBS (2013) itself acknowledges that some categories have an abnormally high influence on the value of the systemic-risk scores. On page 6, one can read that: "*The Committee has analysed the application of the scoring methodology described above to three years of data supplied by banks. It has found that, relative to the other categories that make up the G-SIB framework, the substitutability category has a greater impact on the assessment of systemic importance than the Committee intended for banks that are dominant in the provision of payment, underwriting and asset custody services.*"

In practice, there are two ways to correct for this statistical bias. One is to standardize each category prior to aggregation by subtracting the mean of the variable and scaling it by its cross-sectional volatility. Such a standardization, called z-transform, forces each distribution of observations to a mean of zero and a standard deviation of one while maintaining the integrity of the banks' unique pattern across categories. This technique has been routinely implemented since the 1970's in research in education to aggregate students' scores and in psychology to combine patients' attributes (see Guilford and Fruchter (1973) and Gardner and Erdle (1984)).

Another way to reduce the level of heterogeneity in the data is to trim outliers by capping some of the categories. Extreme values can either be discarded or set equal to a given percentile, a procedure known as winsorizing. While removing outliers can be seen as an ad hoc way of reducing the influence of the most volatile variables, it does help to alleviate the aforementioned statistical bias. However, central to this method is the choice of the cap: which categories to cap and at which level? When computing extra capital charges for systemic risk, the BCBS implements the latter strategy and applies a 5% cap to the substitutability category of each sample bank and no cap to the other categories.

In this paper, we provide empirical evidence about the distorting effects of capping systemic-risk categories. Using regulatory data for a sample of 106 global banks from 20 countries, we demonstrate that the number of categories actually capped and the ad hoc level of the cap have first-order effects on the list of SIFIs, and in turn on the regulatory capital of global banks. We show that slightly changing the capping scheme causes significant changes in the composition of the risk buckets. For instance, the current situation which consists in capping the substitutability category for four banks leads two banks to switch risk buckets and an aggregate change in regulatory capital of more than EUR 17 billion.[2] For some alternative caps considered in our study, the change in aggregate regulatory capital is as high as EUR 137 billion, which represents more than 50% of the extra capital due to systemic-risk regulation.

Alternatively, computing systemic-risk scores using standardized categories does not need any arbitrary choice to be made. Interestingly, this novel approach identifies the same 30 SIFIs as with the current methodology but allocates them differently across buckets. As a result, both the aggregate level of regulatory capital and the allocation of the capital across firms would differ with respect to the current situation.

This paper contributes to the literature on systemic-risk measurement. As shown by Benoit *et al.* (2016), there are two main families of systemic-risk measures: those that aggregate low-frequency regulatory data (like the BCBS approach) and those that are based on higher-frequency market data on banks' security prices. Four prominent examples of market-data based measures are the Marginal Expected Shortfall and the Systemic Expected Shortfall of Acharya *et al.* (2010), the SRISK of Acharya, Engle, and Richardson (2012) and Brownlees

[2]We follow the BCBS practice and convert all regulatory capital figures in EUR.

and Engle (2015), and the ΔCoVaR of Adrian and Brunnermeier (2016). The key advantage of the market-data based measures is that they can easily be implemented, compared, and backtested as their implementation only requires public data. Differently, the empirical performance of the regulatory approach could not be readily assessed because the necessary data were not in the public domain. It is only since 2014 that data have become available for most global banks, although the first SIFI list was published in 2011 using data from year-end end 2009. As a result, until very recently, academics were not in a position to conduct any empirical evaluation of this key policy tool.

The contribution of this paper is to show theoretically and empirically that the official methodology to set capital surcharges for global banks is biased. In particular, the current systemic-risk scoring methodology is not microfounded: it sometimes create incentives for the most risky banks to *increase* risk-taking. We also suggest a modification of the methodology to correct the bias and to uniquely identify SIFIs. Our modified scoring technique can readily be used to compute extra regulatory capital or to compute a systemic-risk tax on the banks that contribute the most to the risk of the financial system.[3] While there remains significant disagreement over the risk indicators to be included in the computation of an ideal systemic-risk score, this particular choice is beyond the scope of this paper. However, the aggregation process proposed in this paper remains valid for any set of risk indicators.

We believe that recognizing the ad-hoc and unstable nature of the regulatory tool currently used to regulate systemic risk should be of general interest. While our analysis is mainly motivated by some statistical arguments, it carries several important economic messages. First, recent findings in the literature on the real effects of capital requirements suggest that

[3] For instance in France, financial institutions with a regulatory capital greater than EUR 500 million must pay a tax of 0.5% of their regulatory capital (http://bofip.impots.gouv.fr/bofip/6632-PGP). Alternatively, such a systemic-risk tax could be based on the systemic-risk score proposed in this paper.

the capital misallocation reported in this paper is likely to distort the distribution of credit and risk-taking of large banks. Second, we show that the current systemic-risk regulatory framework is likely to lead to poor regulatory efficiency because it distorts incentives to lower systemic risk and fails to fully internalize the negative externalities created by the SIFIs. For instance, banks will have stronger incentives to reduce risk-taking in an area where there is greater cross-sectional variability because such risk indicator will mechanically carry more weight in the final score. Alternatively, a bank has no incentives to reduce risk once the cap is exceeded. Indeed, being at the cap or exceeding it by a large margin result in the same final score.

The rest of this paper is structured as follows. We discuss in Section 2 the rationale for regulating systemic risk. In Section 3, we present the scoring methodology currently in use by banking regulators, explain the origin of its bias, and suggest a way to correct it. In Section 4, we conduct an empirical analysis based on actual regulatory data. We summarize and conclude this paper in Section 5.

2 Why Regulate Systemic Risk

Equity capital provides loss absorption capacity to banks and protects their creditors. In practice, bankers claim that they maintain a low level of capital, or equivalently a high leverage, to boost their return on equity.[4] However, with little capital, even a small drop in asset value can make the bank insolvent, i.e., with a negative value of its equity capital. From the regulator's perspective, an optimal level of capital for the bank may not be socially optimal because of negative externalities due to a bank failure. First, when the deposit insurance

[4] This argument is sometimes referred to as the ROE fallacy argument because boosting leverage also increases the riskiness of equity and the associated risk premium (see DeMarzo and Berk (2014, page 497)).

premium paid by the banks is not risk-based or fairly priced, banks are tempted to take too much risk. Second, financial institutions connected to the failing bank can be either directly (counterparty risk and cross-holdings) or indirectly (fire sales and other contagion effects) affected by the bank failure. Another concern with low capital ratio is risk shifting. Indeed, having little “skin in the game” can incite banks to increase risk-taking. Furthermore, an aggravating factor is moral hazard as banks increase their risk exposures when the probability of being bailed out by the Government is high.

To increase financial stability and save taxpayers’ money, regulators impose minimum capital requirements to banks. Over the years, the level of the regulatory capital has been based on banks’ risk exposures to various sources of risk: credit risk (1988), market risk (1996), and operational risk (2005). Nowadays, the Basel III regulation does not only consider financial institutions in isolation but also ties capital requirements to systemic risk. The rationale for increasing the regulatory capital of the financial institutions that contribute the most to the risk of the system is to force such banks to internalize the externalities they inflict on the system and to create some incentives for them to reduce such externalities. However, regulators face a complex trade-off between maintaining high capital requirements to improve financial stability and low capital requirements to boost lending to firms and households and promote economic growth.

In practice, regulators need to quantify the contribution of a given bank to the risk of the system. Various econometric techniques are based on the market price of banks’ financial securities (see Acharya, Engle, and Richardson (2012) and Adrian and Brunnermeier (2016)). These bank-level measures are by nature global as they do not specifically target any particular risk channel. Furthermore, they can be easily computed at a daily frequency and as such are more reactive than risk measures computed on accounting data.

An alternative route is to compute a systemic-risk score for each bank by aggregating various systemic-risk categories. Ideally, these categories should capture all the main sources of systemic risk identified in the academic literature, such as (1) systemic risk-taking, or why financial institutions take large risk exposures and why they choose to be exposed to similar risks; (2) contagion between financial institutions, or how losses in one financial institution spillover to other institutions; and (3) amplification mechanisms, or why relatively small shocks can lead to large aggregate impacts (see Benoit *et al.* (2016) for more details and references). Once the categories are identified, regulators are free to put more weight on some of them depending on the regulators' risk tolerance with respect to a given category. If regulators have no economic reasons to favor any particular source of systemic risk, they should then give equal weight to all categories.

According to the Modigliani-Miller view, the level of capital should have little impact on the bank's cost of capital and lending policy (Admati and Hellwig (2013)). Alternatively, in presence of information asymmetry and agency costs, raising equity to meet capital requirements is expensive for banks and can force them to cut lending. Various empirical studies show that regulatory capital materially affects loan supply (Behn, Haselmann, and Wachtel (2016) and Jiménez *et al.* (2015)) and risk-taking (Becker and Opp (2014)). As a result, the choices of (1) the categories used to compute the systemic score and of (2) the aggregation process can have real effects. In the eventuality when the scoring methodology is biased towards a subset of categories, both the distributions of credit and risk-taking in the economy can be distorted.

An important feature of a sound systemic-risk regulation is to provide incentives to firms to reduce their systemic-risk contribution. In that context, capping a given category removes such incentives because the firms scoring very high on a capped category have no incentive whatsoever to reduce risk. As an example, consider a bank with a score of 17% on a given category, which is capped at 5%. Reducing this category anywhere between 17% and 5% will not reduce the score of the firm. An even more detrimental consequence of capping is that the bank will not be penalized in terms of systemic-risk score if it further increases the level of this category (e.g., to 20%). Capping categories also removes in some states of the world the positive link between the value of any category and the resulting capital surcharge. Beyond the cap, the regulatory tool does not force banks anymore to internalize the externalities they generate.

Finally, one last potential pernicious effect of allowing some categories to be capped is making lobbying more likely. Indeed, when capping is an option, all banks scoring particularly high on a given category have strong incentives to lobby the regulators and ask them to impose a cap on this particular category.

3 Measuring Systemic Risk

3.1 BCBS Methodology

The BCBS methodology is currently based on 12 systemic-risk indicators which are combined into five main systemic-risk categories: size, interconnectedness, substitutability/financial institution infrastructure, complexity, and the cross-jurisdictional activity of the bank (see Panel A in Appendix 1 and BCBS (2014b)).

Maybe the most natural dimension of systemic risk, *size*, is proxied by the measure of total exposures used in the Basel III leverage ratio (BCBS (2014a)). It corresponds to the sum of the bank's total assets, the gross value of securities financing transactions, credit derivatives and counterparty risk exposures, as well as some off-balance-sheet commitments. The maximum values of total exposures in our sample is for ICBC and is equal to EUR 3,106 billion. The *interconnectedness* category is made of three indicators: bank's total assets on financial system, its total liabilities to the financial system, and its total amount of securities outstanding. This category aims to capture the expected impact of the failure of a bank on its business partners. The *substitutability* category describes the potential difficulties that the bank's customers would face to replace the services provided by a failed bank. The three related indicators are the bank's payment activity, assets under custody held by the bank, and its total underwriting transactions both in debt and equity markets. The *complexity* category merges three indicators based on over-the-counter derivatives, trading and available-for-sale securities, as well as illiquid and hard-to-value assets, known as Level 3 assets. The greater the bank complexity, the higher the costs and the time needed to resolve a failing bank. Finally, the *cross-jurisdictional* category combines two indicators on cross-jurisdictional claims and liabilities. The rationale for accounting for cross-jurisdictional activities is that banks with international activities allow shocks to be transmitted throughout the financial system.

Formally, each bank i, for $i = 1, ..., N$, is characterized by K systemic-risk categories denoted $x_{i1}, ..., x_{iK}$. Each category x_{ij} is obtained by aggregating F_j indicators (X_{ijf}) associated with category j, scaled by their sample totals:

$$x_{ij} = \frac{1}{F_j} \sum_{f=1}^{F_j} \frac{X_{ijf}}{\sum_{i=1}^{N} X_{ijf}} \times 10,000. \tag{1}$$

The systemic-risk score for bank i, denoted S_i, is then defined as a weighted sum of these K categories:

$$S_i = \sum_{j=1}^{K} w_j \times x_{ij}, \tag{2}$$

where w_j corresponds to the weight (common to all banks) of category j in the systemic-risk score. Note that all x_{ij}, for $j = 1, ..., K$, have the same mean.

In order to give the same importance to each category, the BCBS considers an equally weighted index with $w_j = 1/K$. Under this assumption, an increase of 10% of a given category can be offset by a decrease of 10% of another category. In addition, the BCBS applies a 5% cap to the substitutability category and no cap to the other categories. Accordingly, the systemic-risk score is given by:

$$\bar{S}_i = \sum_{j=1}^{K} w_j \times \min(x_{ij}, cap_j), \tag{3}$$

with $cap_j = 5\%$ for the substitutability category and $cap_j = 100\%$ for the other categories.

Once the systemic-risk scores of all financial institutions have been computed, those with a score higher than a given threshold are qualified as SIFIs.[5] Then, following a bucketing approach, all SIFIs are allocated into four risk buckets of size 100 and an additional empty bucket (bucket 5) is appended to the top. All banks included in a given bucket face an extra capital surcharge that is added over and above existing capital requirements. The magnitude of the capital surcharge goes from 1% in bucket 1 to 3.5% in bucket 5.

Computing a systemic-risk score by means of an equally-weighted average (as in Equation 2) becomes problematic when the cross-sectional variances of the categories are different. In such a case, a 10% increase of a given category does not represent the same signal if the factor has a variance of 1 or a variance of 100. One implication of this situation is that the ranking issued from the systemic-risk score will be mainly driven by the most volatile categories (see Appendix 2 for a numerical illustration).

The bias will increase with the cross-sectional variation of any systemic-risk indicator. For

[5] This cut-off score has been set to 130 since the end-2012 exercise.

instance, between 2000 and 2007, the leverage of many global banks increased dramatically (Adrian and Shin (2010) and Adrian and Shin (2011)) which could have significantly distorted the distribution of the total exposure indicator across banks. Swings in the distribution of an indicator, and in particular in its volatility, mechanically affect the value of the systemic-risk scores and the resulting regulatory capital allocation.

3.2 How to Correct for the Bias

We show in this section how to remove the statistical bias that plagues the current systemic-risk scoring methodology. A simple correction consists in standardizing by their volatility all categories that enter into the definition of the score (see Benoit *et al.* (2016)). Note that there is no need to subtract the mean of the x_{ij} as it is equal to $10,000/N$ for each category.[6] In that case, the systemic-risk score becomes:

$$\widetilde{S}_i = \sum_{j=1}^{K} w_j \times \frac{x_{ij}}{\sigma_j}, \tag{4}$$

where $\sigma_j^2 = (x_{ij})$ corresponds to the cross-sectional variance of category j. Note that the rest of the formula remains unchanged. In particular the weight of each category is still equal to $w_j = 1/K$.

In order to scale the risk indicators in Equation 4, the cross-sectional variance of each category needs to be known. This is a realistic assumption as the values of all risk categories are now publicly disclosed. In practice, it would also be feasible to compute the variance of each category on a subset of banks only if some banks disclose their data with a lag.

[6] Replacing x_{ij} by $x_{ij} - \mathrm{E}(x_j)$ would mechanically lead to the same final ranking.

4 Empirical Analysis

The aim of this empirical analysis is to study the sensitivity of the official systemic-risk scoring methodology with respect to the number and values of the caps using actual regulatory data. We find that the capping scheme has a first order impact on the ranking of the SIFIs. In contrast, we show that standardization by mean of a z-transform leads to a robust, unique set of SIFIs which can readily be used to set bank-specific capital surcharges for systemic risk or to levy a tax on systemic risk.

4.1 Data and the Official SIFI List

We focus on the same two samples of international banks currently used by the BCBS. First, the main sample includes the largest 75 banks in the world as determined by the Basel III leverage ratio exposure measure, along with any bank that were designated as a SIFI in the previous year but are not otherwise part of the top 75. Second, the additional sample is made of an extra 15 banks including all banks with a leverage ratio exposure in excess of EUR 200 billion that are not included in the main sample. In addition, the additional sample also includes a set of 23 large banks that are under the supervision of national authorities. The two samples jointly include 114 banks in total (see Appendix 3).

For each sample bank, we collect the value of the 12 indicators required to compute the five systemic-risk categories as of fiscal year-end 2014 (see Appendix 1).[7] While most of these regulatory data are typically confidential data (e.g., cross-jurisdictional claims, intra-financial system liabilities), the BCBS now requires all banks with a Basel III leverage ratio exceeding EUR 200 billion, as well as banks that have been classified as a SIFI in the previous year, to

[7]Most sample banks have their fiscal year-end on December 31 but some sample banks have their fiscal year-end in October 31 (Canada) and in March 31 (Japan and India).

make publicly available the 12 indicators.

We collect our systemic-risk data from three different sources. First, the European Banking Authority website gathers data on leading European banks. Second, the Banking Organization Systemic Risk Report (FR Y-15) includes data from large US bank holding companies to monitor systemic risk as requested by the Dodd-Frank Act.[8] Third, for sample banks outside the EU and the US, we collect regulatory data directly from their individual websites. In total, we obtained all the requested data for 106 sample banks as eight banks do not fully comply with the systemic-risk disclosure requirement yet.[9] In order to compare reporting values expressed in different currencies, we follow the BCBS and convert all figures in Euro using spot rates as of December 31, 2014.

We start by scaling each bank-level indicator by the sum of this indicator across the 75 banks from the main sample and by displaying their probability distribution in Appendix 4.[10] A key result for this analysis is the fact that the various indicators exhibit strong heterogeneity in terms of volatility. For instance, the volatility for assets under custody (283) is more than three times larger than for securities outstanding (91). Furthermore, we see that all distributions are right-skewed which points to the dominant role played by a handful of global financial institutions. For instance, the market share of some financial institutions is close to 10% on the OTC derivatives market, more than 10% for payments activity, and even more

[8] 37 banks are currently monitoring by the European Banking Authority and their data can be obtained at http://www.eba.europa.eu/risk-analysis-and-data/global-systemically-important-institutions/2014. 33 bank holding companies are currently monitored by the Federal Reserve since their total assets is greater than $50 billion, and their FR Y-15 reports are available at http://www.ffiec.gov/nicpubweb/nicweb/Y15SnapShot.aspx.

[9] The missing banks are Australian banks (ANZ, Commonwealth, National Australia Bank, and Westpac) and Brazilian banks (Banco Bradesco, Banco do Brasil, Caixa, and Itaú Unibanco). None of the missing banks have ever been qualified as SIFI by the BCBS.

[10] Denominators are publicly available at http://www.bis.org/bcbs/gsib/denominators.htm. We notice that the means of all scaled indicators are always close to 10,000/106 but not exactly 10,000/106 as we sum indicators across 75 banks and not across all sample banks.

than 15% for assets under custody (with a skewness coefficient of 4.5). We provide more summary statistics in the Panel A of Table 1 as well as Panel B in Appendix 1.

[Insert Table 1]

We then combine the 12 indicators into five systemic-risk categories as described in Equation 1. We display the probability distributions of each category in Figure 1, along with some summary statistics in the Panel B of Table 1. Even after data have been aggregated, the distributions of the systemic-risk categories remain skewed (with a skewness coefficient of 3.6 for the substitutability category) with strong differences in the volatility of the categories. On average, the interconnectedness (respectively substitutability) category is the most (least) correlated with the other categories as reported in Table 2.

[Insert Figure 1 and Table 2]

We start our empirical analysis by replicating the list of SIFIs published in November 2015 by the FSB. To do so, we implement the official methodology described in Section 3.1. One of the categories, substitutability, needs to be capped at 5% (500 basis points), which affects four sample banks: JP Morgan Chase, Citigroup, Bank of New York Mellon, and State Street. The first two banks are US global banks whereas the last two are leaders in custodian activities. As shown in Figure 1 and in the Panel B of Table 1, winsorizing the highest four values mechanically reduces the volatility of the substitutability category: its standard deviation drops from 183 to 124. As a result, the effect of capping is to reduce the relative importance of the three components of the substitutability indicator, namely payment activity, assets under custody, and underwriting activity. Underweight these vital functions of the financial market may come as a surprise, especially given the fact that there were a major source of concern during the Lehman Brothers crisis.

Using Equation 3, we then compute the official systemic-risk score for all sample banks. We display the scores in descending order in Figure 2, and gives the identity and scores of the top 30 banks in Table 3. Using the cut-off scores provided by the BCBS, we allocate the top 30 banks into five risk buckets.[11] We obtain exactly the same list of SIFIs and the same bucket composition as the FSB. However, replicating the official methodology provides us with additional information compared to the list publicly disclosed by the FSB. Within each bucket, we rank banks in descending order and not like in the FSB list by alphabetical order.

Within each risk bucket, banks are equally-spread and show no sign of bunching below each cut-off values. Systematic bunching would indicate that SIFIs strategically manage the value of some of their indicators to lower their systemic score by one notch, which would allow them to save one or half a percentage point in regulatory capital (i.e. more than EUR 10 billion for the largest SIFIs).

By zooming in on the 130 cut-off value that divides SIFIs and non-SIFIs, we see that a small score difference can have a material impact on the regulatory capital. As shown in Figure 2, the score of the SIFI with the lowest systemic-risk score is exactly equal to the cut-off (Nordea, rank = 30, and score = 130). The non-SIFI with the highest score lies just below the cut-off (Royal Bank of Canada, rank = 31, and score = 123) whereas the non-SIFI with the second highest score is at safe distance from the cut-off (Commerzbank, rank = 32,

[11] The score range for Bucket 1 is [130-229], [230-329] for Bucket 2, [330-429] for Bucket 3, [430-529] for Bucket 4, and [530-629] for Bucket 5. These cut-off values have remained fixed since 2013 (end-2012 exercise). The rationale for not changing the cut-off values is that banks can only lower their systemic-risk surcharge by lowering their score and not by hoping that other banks' scores will increase or that cut-off values will be adjusted upwards.

and score = 108).

[Insert Figure 2 and Table 3]

4.2 Why Capping Inputs Leads to an Unstable SIFI List

We compare the lists of SIFIs with and without a cap on the substitutability category in Table 3. In the BCBS methodology, winsorizing categories reduces the score of the banks affected by the cap but does not affect the score of the other banks – the reason being that bank indicators are scaled by the pre-cap sum of the indicators. As a result, only the scores of the four banks with a substitutability category greater than 5% are modified. Without any cap, the score of JP Morgan Chase goes to 629, and similarly to 495 for Citigroup, to 225 for Bank of New York Mellon, and to 168 for State Street.

These new scores call for several changes in the composition of the buckets. We see that two out of the 30 banks switch buckets because of the cap. JP Morgan Chase switches from bucket 5 to bucket 4 (saving one percentage point in regulatory capital) whereas Citigroup drops from bucket 4 to bucket 3 (saving half a percentage point). Given the risk-weighted assets, as of year-end 2014, of JP Morgan Chase (EUR 1,213 billion), this means that JP Morgan Chase is able to reduce its regulatory capital by EUR 12.13 billion or 8.94% of its Tier 1 capital.[12] Similarly, the reduction in capital for Citigroup is 0.5% $\times$ 998 = EUR 4.99 billion or 3.63% of its Tier 1 capital. In total, the aggregate reduction is EUR 17.12 billion or 6.6% of the total extra regulatory capital due to the systemic-risk regulation (EUR 259.13 billion).

It is important to recognize that capping the substitutability category of four banks is

[12]Risk-weighted assets for all sample banks are obtained from Bankscope. Throughout this paper, we call Tier 1 capital the Core Equity Tier 1 capital.

a special case. One could indeed cap the substitutability category of two banks only, or the complexity category of 10 banks, or alternatively to trim the two highest values for all categories, etc. To see whether the choice made about caps leads to different outcomes, we report in Figure 3 the number of bucket changes (blue line, left axis) and the changes in aggregate regulatory capital (red line, right axis) of changing the number of banks affected by the cap on substitutability from n=0 to n=20. The reference point, indicated by a red dot, represents the current situation (i.e., capping the four highest substitutability values). We clearly see that the type of cap radically changes the composition of the various buckets and, in turn, the allocation of the regulatory capital across banks.

We generalize this analysis by contrasting the no-cap benchmark situation with scenarios in which we cap the n highest values of all five categories and reconstruct the buckets. Results in Figure 4 indicate that capping 20 banks triggers (1) 30 bucket changes and (2) a reduction of regulatory capital close to EUR 140 billion. This corresponds to more than 50% of the total extra regulatory capital due to the systemic-risk regulation.

[Insert Figures 3, and 4]

4.3 Systemic-Risk Scoring with Standardized Categories

We now turn to the computation of the systemic-risk scores based on standardized categories discussed in Section 3.2. As highlighted in Column 6 of Table 3, systemic-risk scores based on standardized categories identify the exact same top 30 banks as the FSB.[13] In Figure 5, we display all scores based on standardized categories in descending order.

[Insert Figure 5]

[13]This is not always the case. For instance, we show in Section 4.4 that for the year 2014, only 26 banks are identified as SIFIs by the two methodologies.

When allocating the identified SIFIs into the various risk buckets, we cannot use the cut-off scores provided by the BCBC because the units of measurement are not the same (recall that all categories are now scaled by their volatility). However, following standard classification methods, we define new buckets by setting our own thresholds to significant discontinuities in systemic-risk score - the cut-off values are 102, 183, 223, and 400. Keeping the top bucket empty, we end up with JP Morgan Chase only in bucket 4, six banks in bucket 3 since HSBC and Bank of America migrate to this bucket from buckets 4 and 2, respectively, four banks in bucket 2, and 19 remains in bucket 1. Based on this new bucket scheme, the total extra capital requirement would be different (EUR 265.83 billion) from the current level (EUR 259.13 billion). On the one hand, Bank of America and ICBC should increase their regulatory capital by EUR 5.20 billion (4.06% of Tier 1 capital) and EUR 8.40 billion (4.20% of Tier 1 capital), respectively. On the other hand, HSBC and Morgan Stanley should reduce their regulatory capital by EUR 5.02 billion (4.58% of Tier 1 capital) and EUR 1.88 billion (3.98% of Tier 1 capital), respectively.

4.4 Robustness Check

We replicate the analysis conducted for the year 2015 using data for the year 2014 (i.e., fiscal year-end 2013). As fewer banks have disclosed their data for this year, we end up with a cross-section of 97 banks only, instead of 106 banks in the main analysis. We display in Appendix 5 the top 30 banks based on their systemic-risk scores with a 5% cap on substitutability. Interestingly, we see that two banks identified as SIFIs by the FSB, namely Nordea (rank = 32, and score = 121) and BBVA (rank = 36, and score = 93), have a score below the 130 cut-off value that divides SIFIs and non-SIFIs. Thus, only 28 banks are identified as SIFIs in 2014 based on their systemic-risk score and two are so based on supervisory judgement.

The cap on substitutability affects the score of five banks, the same four banks as in 2015 plus Deutsche Bank. As a consequence, JP Morgan Chase, Citigroup, and Deutsche Bank move downward by one bucket, which allows them to collectively reduce their regulatory capital by EUR 15.56 billion or 7.26% of the total extra regulatory capital.[14]

With standardized-category based scores, we allocate SIFIs into risk buckets using the same cut-off values as in 2015. China Construction Bank becomes SIFIs under the standardization scheme whereas Standard Chartered and State Street are not SIFIs anymore.[15] We end up with 29 SIFIs: JP Morgan Chase in bucket 4, six banks in bucket 3 since HSBC and Bank of America migrate to this bucket from buckets 4 and 2, respectively, three banks in bucket 2, and 19 on bucket 1 since Goldman Sachs and Royal Bank of Scotland migrate to this bucket from bucket 2. Based on this new bucket scheme, the total extra capital requirement is higher (EUR 221.72 billion) than the level required by the FSB in 2014 (EUR 214.39 billion). We see that switching to standardized categories allows some banks to decrease their regulatory capital (HSBC, Goldman Sachs, Royal Bank of Scotland, Standard Chartered, and State Street) and forces others to increase their regulatory capital (Bank of America and China Construction Bank). Overall, only 26 banks are identified as SIFIs both by the systemic-risk scores based on standardized categories and by the official methodology.

5 Conclusion

Within less than ten years, the systemic-risk area has developed from an underexplored, mainly theoretical field of academic research into a high-priority regulatory issue. Actively regulating systemic risk requires policy tools such as the bank-level score studied in this paper.

[14]The reduction is decomposed as follows: EUR 10.06 billion for JP Morgan Chase (8.38% of Tier 1 capital), EUR 4 billion for Citigroup (3.50% of Tier 1 capital), and EUR 1.50 billion for Deutsche Bank (3.90% of Tier 1 capital).

[15]We keep Nordea and BBVA in the SIFI list because we follow the supervisory judgement of the FSB.

Using recently disclose data on the various facets of systemic risk, we show that the official methodology currently used to identify SIFIs and compute their regulatory capital is both biased and ad hoc. An important implication of this bias is to distort incentives for regulated banks to lower systemic risk and to fully internalize the negative externalities created by the SIFIs. For instance, banks will have stronger incentives to reduce risk-taking in an area where there is greater cross-sectional variability because such risk indicator will mechanically carry more weight in the final score. Alternatively, a bank has no incentives to reduce risk once the cap is exceeded. We show that the documented bias (1) leads to a severe misallocation of capital among banks (up to 9% of some banks' Tier 1 capital) and (2) is easy to fix.

Overall, our study points toward the importance of having regulatory tools that are micro-founded and create incentives for regulated banks to reduce their contribution to the risk of the system. It also calls for more regulatory data to be publicly disclosed in order to allow academic researchers to backtest regulatory tools. Making systemic-risk regulation more transparent would enrich the regulatory debate and ultimately improve financial stability.

While the focus in this paper is on banking regulation, our findings also resonate well with the current debate on the regulation of systemic risk in the insurance industry and the asset management industry. Indeed, the current process for identifying systemically-important insurance companies or asset management firms is very much inspired by the one developed for banks and, as such, shares some of its shortcomings.

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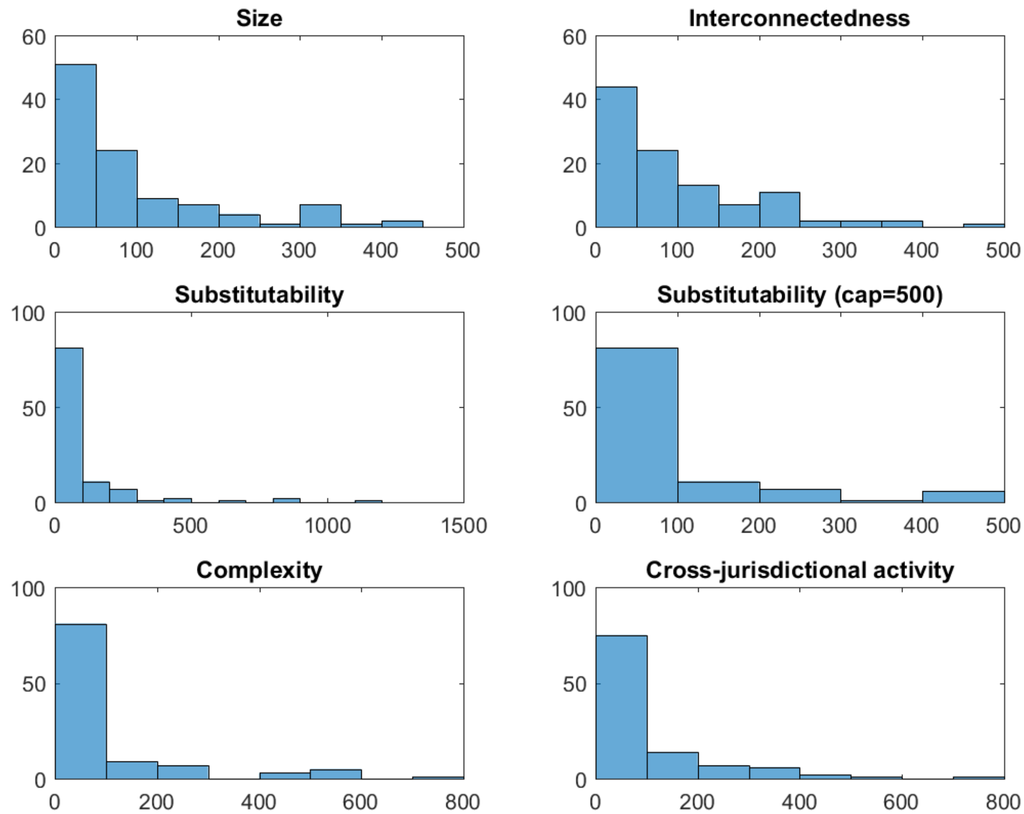


Figure 1: Distributions of the systemic-risk categories

The six histograms show the categories scores distributions of the 106 sample banks' size, interconnectedness, substitutability, substitutability capped at 5%, complexity, and cross-jurisdictional activity, respectively.

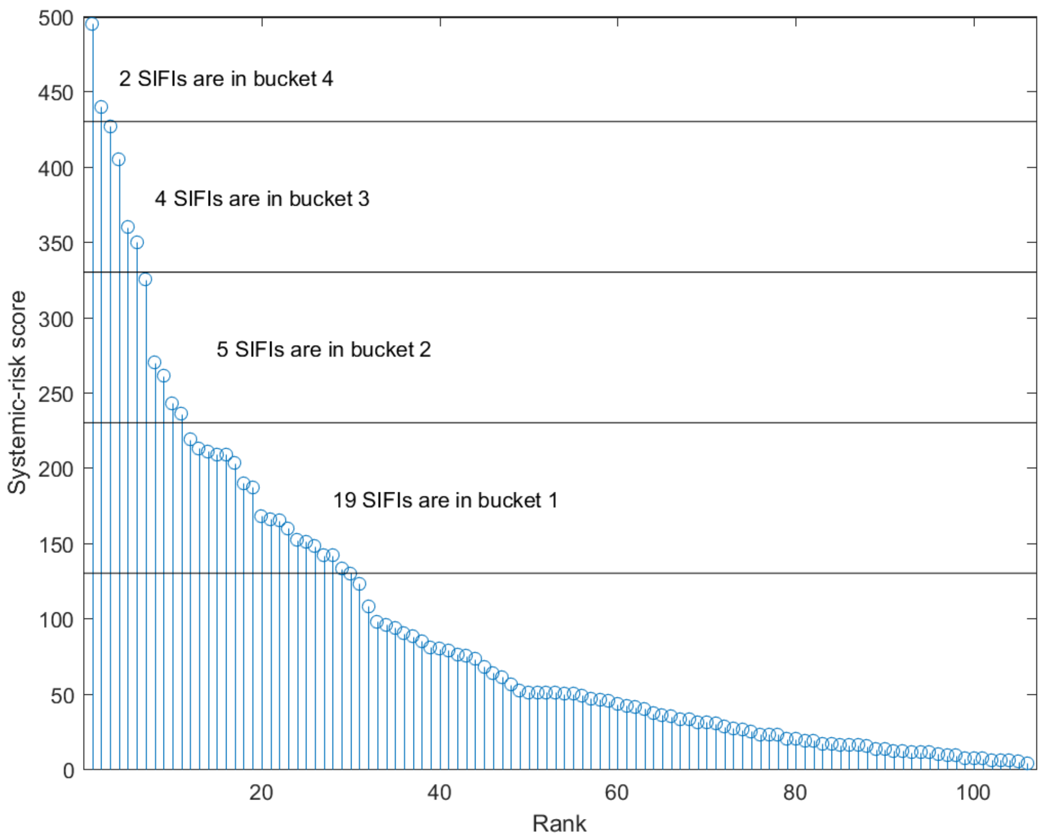


Figure 2: SIFI ranking based on the BCBS methodology

This figure displays the systemic-risk score based on the BCBS methodology for the 106 sample banks in descending order. Each circle represents a bank and solid lines allow to allocate banks into four systemic-risk buckets by applying cut-off scores provided by the BCBS. Cut-off values are 130, 230, 330, and 430.

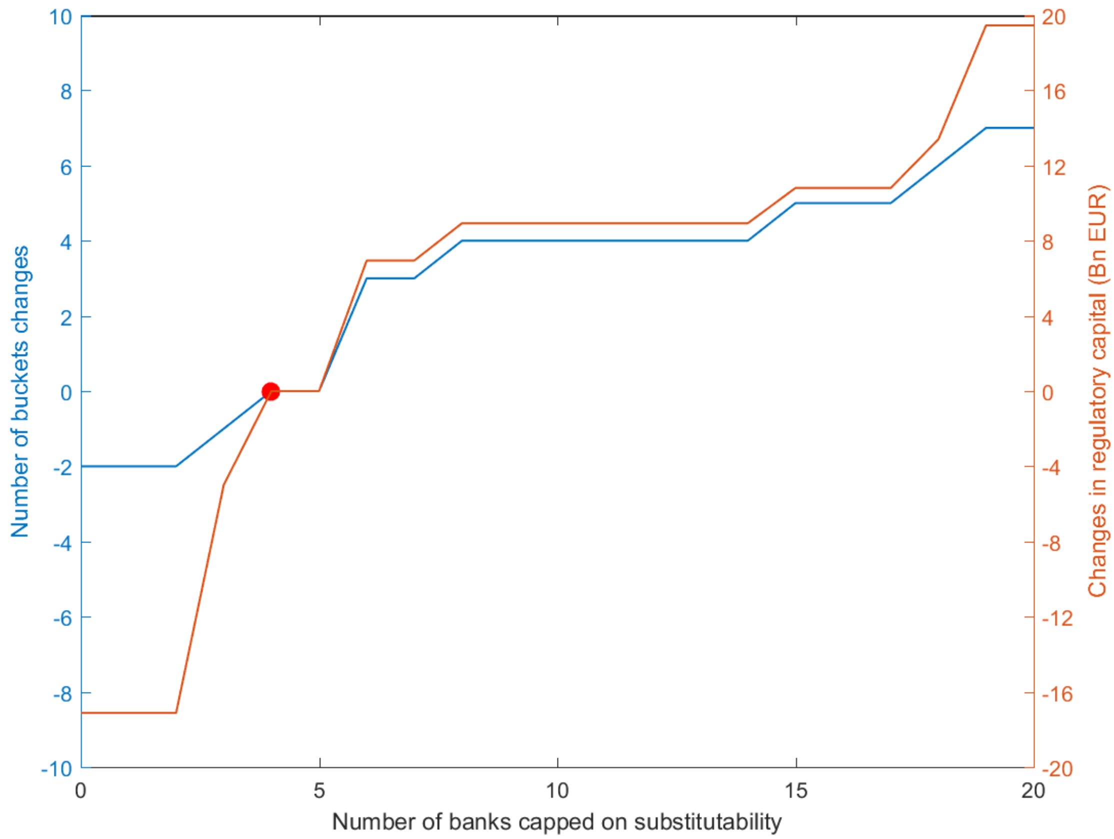


Figure 3: Bucket and capital changes with a cap on substitutability

This figure reports the number of bucket changes (blue line, left y-axis) and its equivalent amount in EUR billion of changes in aggregate regulatory capital (red line, right y-axis) when the number of banks affected by the cap on substitutability gradually changes from 0 to 20 compared to the current situation provided by the BCBC methodology. The red dot corresponds to a benchmark situation in which four banks are capped at 5% on the substitutability category.

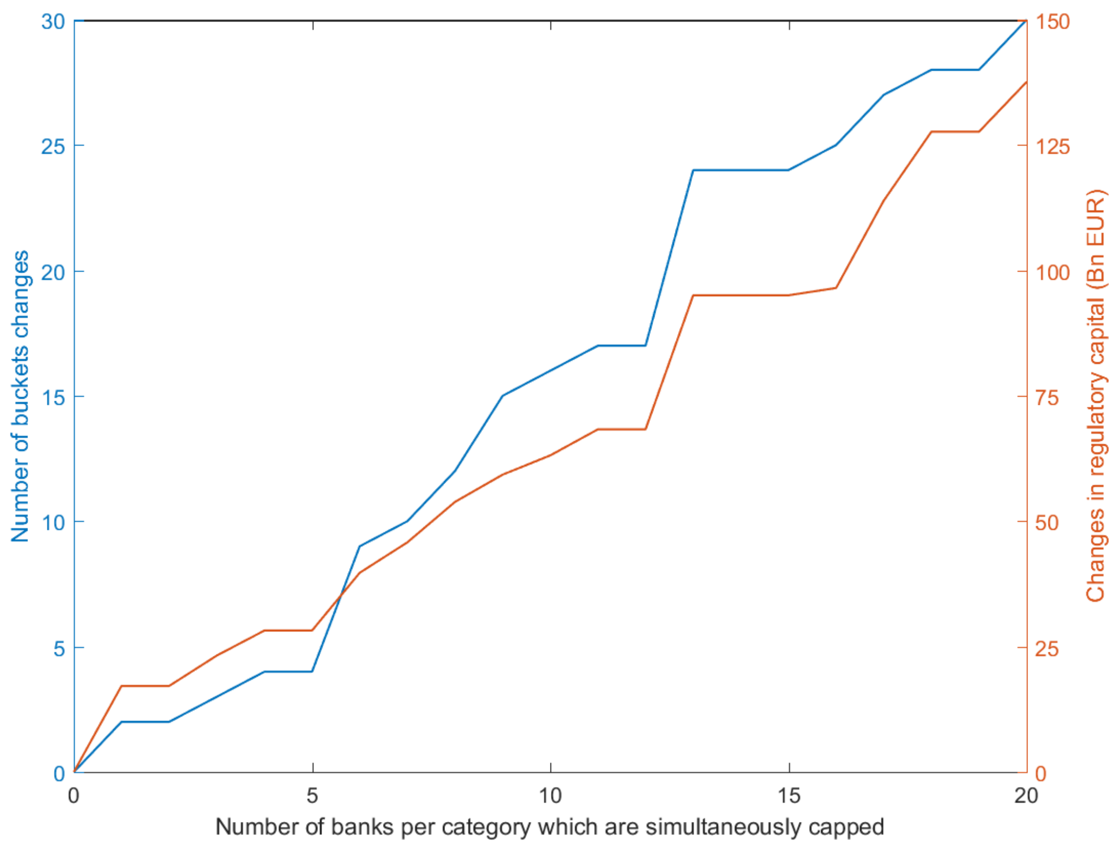


Figure 4: Bucket and capital changes with a cap on all categories

This figure reports the number of bucket changes (blue line, left y-axis) and its equivalent amount in EUR billion of changes in aggregate regulatory capital (red line, right y-axis) when the number of banks simultaneously affected by caps on size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity gradually changes from 0 to 20 compared to a benchmark situation in which no bank is capped.

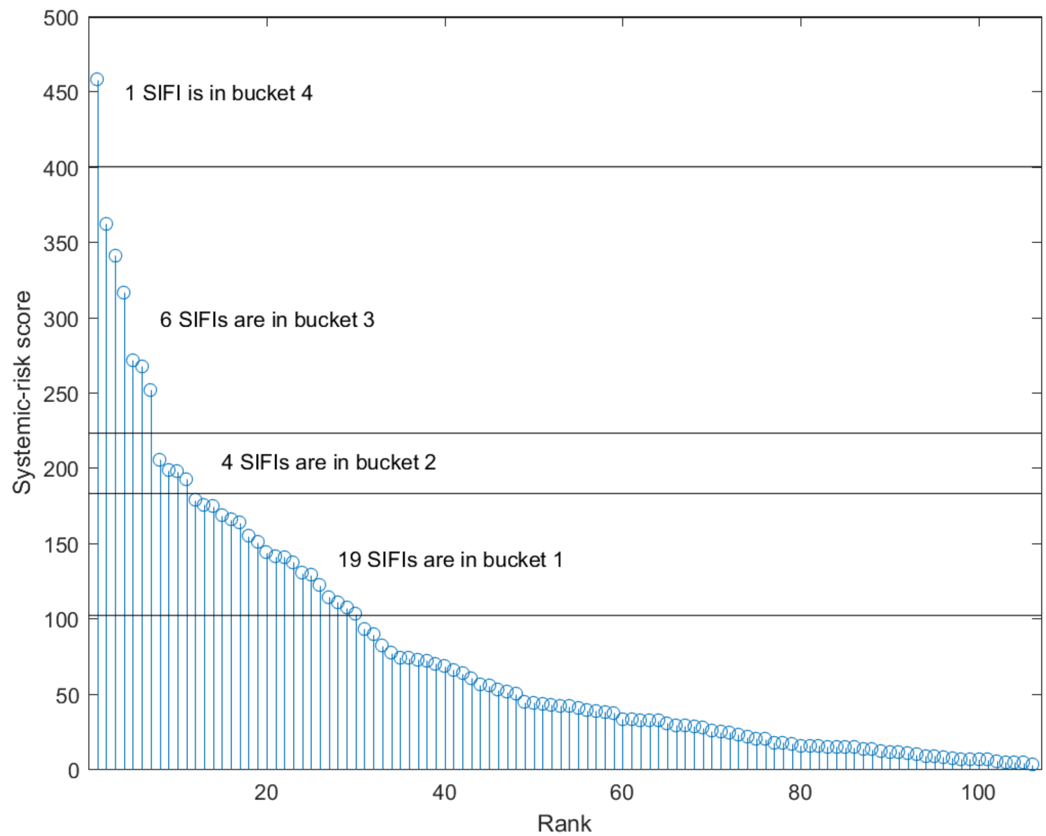


Figure 5: SIFI ranking based on standardized categories

This figure displays the systemic-risk score based on the standardized categories of the 106 sample banks in descending order. Each circle represents a bank and solid lines are the cut-off values used to allocate the top 30 banks into four systemic-risk buckets. Cut-off values are 102, 183, 223, and 400, which correspond to major discontinuities in the score values.

Table 1: Summary statistics

This table reports summary statistics expressed in basis points (except for skewness) on the 12 systemic-risk indicators in Panel A, on the five systemic-risk categories plus the substitutability category capped at 5% in Panel B, and on the two systemic-risk scores (BCBS scores and scores based on standardized categories) in Panel C.

	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
Panel A: Indicators						
1. Total exposures	97	51	100	1.6	6	421
2a. Intra-financial system assets	104	62	109	1.3	1	483
2b. Intra-financial system liabilities	98	60	108	1.6	0	530
2c. Securities outstanding	95	58	91	1.4	0	433
3a. Payments activity	97	34	193	4.0	0	1,248
3b. Assets under custody	99	14	283	4.5	0	1,746
3c. Underwriting activity	104	36	177	2.3	0	760
4a. OTC derivatives	95	7	195	2.4	0	844
4b. Trading and AFS securities	97	37	150	2.7	0	812
4c. Level 3 assets	95	27	154	2.2	0	632
5a. Cross-jurisdictional claims	95	36	137	2.2	0	742
5b. Cross-jurisdictional liabilities	94	40	136	2.3	0	800
Panel B: Categories	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Size	97	51	100	1.6	6	421
2. Interconnectedness	99	72	96	1.4	4	482
3. Substitutability	100	40	183	3.6	0	1,168
3. Substitutability (cap=5%)	86	40	124	2.1	0	500
4. Complexity	96	34	152	2.4	0	762
5. Cross-jurisdictional activity	95	36	135	2.2	0	771
Panel C: Systemic-risk scores	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
BCBS	95	50	107	1.7	3	495
Standardized	78	42	87	1.9	3	458

Table 2: Correlation among systemic-risk categories

This table reports the Pearson correlation coefficients among the five systemic-risk categories. The substitutability category is capped at 5%.

Pearson Corr. Coeff.	Size	Interconnectedness	Substitutability (cap=5%)	Complexity	Cross-jurisdictional activity
Size	100%	92%	56%	74%	69%
Interconnectedness	92%	100%	68%	85%	78%
Substitutability (cap=5%)	56%	68%	100%	68%	52%
Complexity	74%	85%	68%	100%	66%
Cross-jurisdictional activity	69%	78%	52%	66%	100%
Average	72%	81%	61%	73%	66%

Table 3: List of systemically important financial institutions (year 2015)

This table reports the rank (Column 1), the risk-bucket number with its respective Financial Stability Board (FSB) cut-off scores (Column 2), the additional capital requirement expressed as a percentage of risk-weighted assets (Column 3), the identity of the top 30 systemically important banks as identified by the FSB in alphabetical order (Column 4) and in descending order (Column 5), and the top 30 systemically important banks as identified by systemic-risk scores based on standardized categories in descending order (Column 6), as of November 2015. Systemic-risk scores of all banks are reported in parenthesis. A $*$ indicates that the substitutability category of the bank is capped at 5% and the systemic-risk score without this cap is also reported in parenthesis. Reported cut-off values do not apply to systemic-risk scores based on standardized categories.

Rank	Bucket	Additional Capital	FSB (Alphabetical)	FSB (Descending)	Standardized Categories (Descending)
	5 [530-629]	3.5%	Empty		
1	4	2.5%	HSBC (440)	JP Morgan Chase* (495/629)	JP Morgan Chase (458)
2	[430-529]		JP Morgan Chase* (495/629)	HSBC (440)	
3			Barclays (350)	Citigroup* (427/495)	Citigroup (363); HSBC (342)
4	3	2.0%	BNP Paribas (405)	BNP Paribas (405)	BNP Paribas (317); Barclays (272)
5	[330-429]		Citigroup* (427/495)	Deutsche Bank (360)	Deutsche Bank (268)
6			Deutsche Bank (360)	Barclays (350)	Bank of America (252)
7			Bank of America (325)	Bank of America (325)	Credit Suisse (206)
8	2	1.5%	Credit Suisse (270)	Credit Suisse (270)	Mitsubishi UFJ FG (199)
9	[230-329]		Goldman Sachs (261)	Goldman Sachs (261)	Goldman Sachs (198)
10			Mitsubishi UFJ FG (243)	Mitsubishi UFJ FG (243)	ICBC (193)
11			Morgan Stanley (236)	Morgan Stanley (236)	
12			Agricultural Bank of China (165)	ICBC (219)	Bank of China (179)
13			Bank of China (209)	Royal Bank of Scotland (213)	Morgan Stanley (176)
14			Bank of New York Mellon* (151/225)	Société Générale (211)	Santander (175)
15			China Construction Bank (168)	Bank of China (209)	Royal Bank of Scotland (169)
16			Groupe BPCE (152)	Santander (209)	Wells Fargo (166)
17			Groupe Crédit Agricole (187)	Wells Fargo (203)	Société Générale (164)
18			ICBC (219)	UBS (190)	Groupe Crédit Agricole (155)
19	1	1.0%	ING Bank (132)	Groupe Crédit Agricole (187)	China Construction Bank (151)
20	[130-229]		Mizuho FG (160)	China Construction Bank (168)	UBS (144)
21			Royal Bank of Scotland (213)	Unicredit Group (166)	Agricultural Bank of China (142)
22			Nordea (130)	Agricultural Bank of China (165)	Bank of New York Mellon (141)
23			Santander (208)	Mizuho FG (160)	Unicredit Group (138)
24			Société Générale (210)	Groupe BPCE (152)	Groupe BPCE (131)
25			Standard Chartered (142)	Bank of New York Mellon* (151/225)	Mizuho FG (129)
26			State Street* (147/168)	State Street* (148/168)	Sumitomo Mitsui FG (122)
27			Sumitomo Mitsui FG (142)	Sumitomo Mitsui FG (142)	Standard Chartered (115)
28			UBS (189)	Standard Chartered (142)	ING Bank (111)
29			Unicredit Group (165)	ING Bank (132)	State Street (108)
30			Wells Fargo (203)	Nordea (130)	Nordea (104)

Appendix 1 Indicators used in the systemic-risk score

Panel A reports all systemic-risk categories, along with their associated systemic-risk indicators, used in the BCBS methodology. Respective weights are reported in parenthesis. Panel B reports summary statistics expressed in EUR million, except for skewness, on the 12 systemic-risk indicators.

Panel A: Composition and weights

Category (and weighting)	Individual (and weighting)
1. Size (20%)	1. Total exposures as defined for use in the Basel III leverage ratio (20%)
2. Interconnectedness (20%)	2a. Intra-financial system assets (6.67%)
	2b. Intra-financial system liabilities (6.67%)
	2c. Securities outstanding (6.67%)
3. Substitutability/financial institution infrastructure (20%)	3a. Payments activity (6.67%)
	3b. Assets under custody (6.67%)
	3c. Underwritten transactions in debt and equity markets (6.67%)
4. Complexity (20%)	4a. Notional amount of over-the-counter (OTC) derivatives (6.67%)
	4b. Trading and available-for-sale securities (6.67%)
	4c. Level 3 assets (6.67%)
5. Cross-jurisdictional activity (20%)	5a. Cross-jurisdictional claims (10%)
	5b. Cross-jurisdictional liabilities (10%)

Panel B: Summary statistics

	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Total exposures	718,028	377,746	736,778	1.6	43,407	3,106,475
2a. Intra-financial system assets	81,825	48,458	85,818	1.3	1,067	380,055
2b. Intra-financial system liabilities	87,327	52,849	95,429	1.6	193	470,167
2c. Securities outstanding	116,619	70,719	111,695	1.4	131	528,463
3a. Payments activity	20,614,266	7,191,749	41,161,432	4.0	0	266,183,904
3b. Assets under custody	1,153,632	165,645	3,283,298	4.5	0	20,288,944
3c. Underwriting activity	55,394	18,942	94,231	2.3	0	404,166
4a. OTC derivatives	6,028,956	458,827	12,433,261	2.4	2,529	53,758,627
4b. Trading and AFS securities	31,824	12,241	49,170	2.7	1	266,275
4c. Level 3 assets	6,267	1,797	10,125	2.2	0	41,559
5a. Cross-jurisdictional claims	164,579	61,537	236,424	2.2	78	1,279,307
5b. Cross-jurisdictional liabilities	148,090	62,780	213,692	2.3	0	1,254,073

Appendix 2 Numerical Illustration

Using simulation, we illustrate the fact that any ranking based on raw (non-standardized) data is driven by the most volatile categories. To illustrate this point, let us assume that the K categories are independently distributed with a common mean but have different cross-sectional variances. We assume that the categories are generated by:

$$x_{ij} = \beta + a_j \; u_i, \tag{A1}$$

where $\beta > 0$, u_i is an *i.i.d.* uniform variable on $[-1, 1]$ and $a_j = 10 \times j$. Note that by definition, $(u_i) = 1/3$. In this simple example, the K categories have a mean equal to β but $(x_K) > ... > (x_1)$ since $(x_j) = (100/3) \times j^2$. By simulation, we generate a series of realizations for x_{ij}, and S_i, and then compare (1) the firms' ranking based on the equally weighted systemic-risk score to (2) the firms' ranking based on each of the K categories. In accordance with BCBS (2013), we use $K = 5$ categories and $N = 75$ banks.

Panel A of Figure A1 displays the average rank correlations (Spearman) measured between the ranking based on S_i (Equation 2) and the category j. The average rank correlations are based on 1,000 simulations. We can verify that the correlation increases with the variance of the category: the higher the volatility of the category, the more similar are the rankings based on the score and the category.[16] The fact that the systemic-risk scores are distorted by the most volatile categories comes in violation of the BCBS's intention to give all categories equal weights. The high sensitivity of the scores with respect to volatility seems to be an unintended consequence of the current methodology.

Panel B of Figure A1 displays the corresponding average rank correlations between the rankings based on the modified score $\widetilde{S}_i$ and the initial category j. As expected, the suggested correction guarantees that each category contributes equally to the systemic-risk score as desired by the BCBS.

[16] We obtain similar results when we allow the K categories to have different means (β_j).

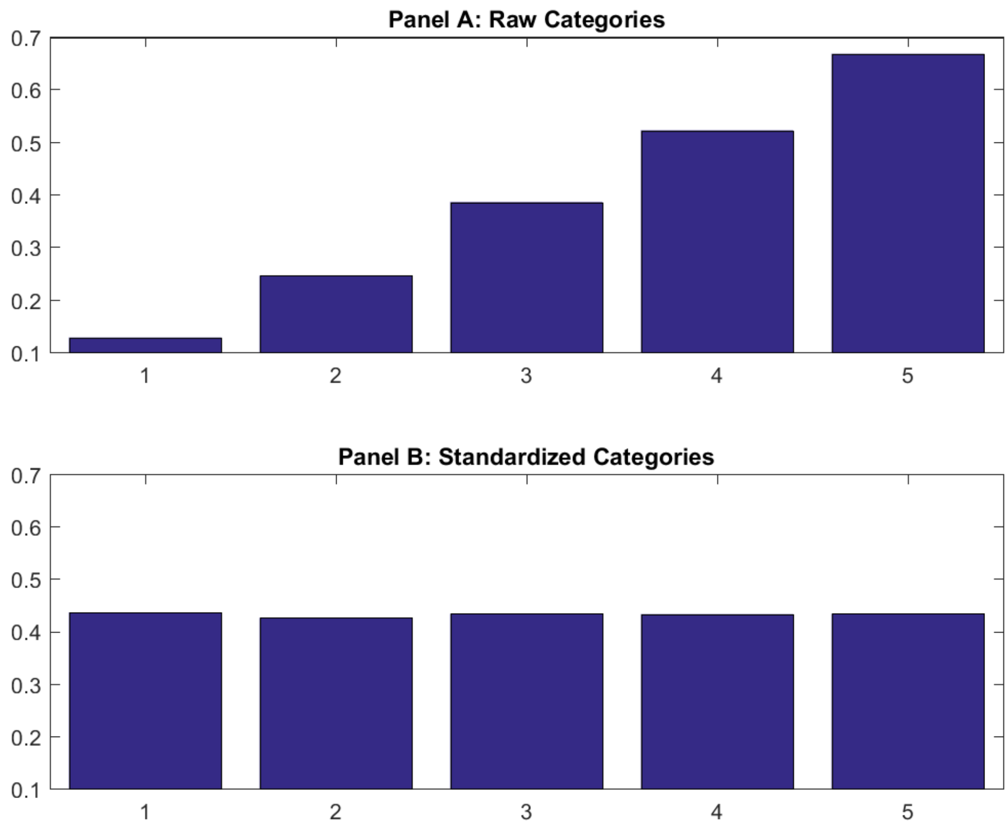


Figure A1: Correlation between score-based rankings and category-based rankings

Panel A (respectively Panel B) displays the Spearman average rank correlation coefficient measured between the ranking based on systemic-risk scores with raw (standardized) categories and category j, $j = 1, ..., 5$. Average rank correlations are based on 1,000 simulations.

Appendix 3 SIFIs assessment sample

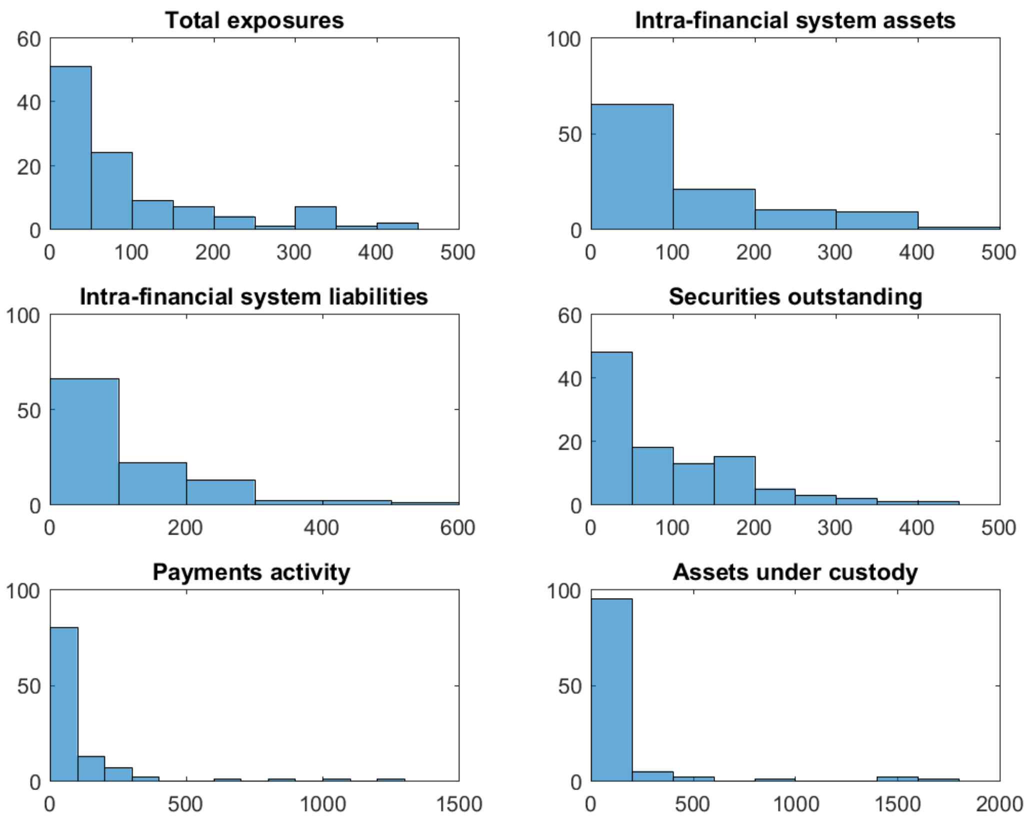
This table displays the 114 sample banks, along with their country of origin, the regulatory sample they belong to, and the specific source of the regulatory data. Inclusion in a regulatory sample is as of year-end 2014. Sources: European Banking Authority (interactive tool), Banking Organizations Systemic Risk Report (FR Y-15), and banks' individual websites (regulatory report).

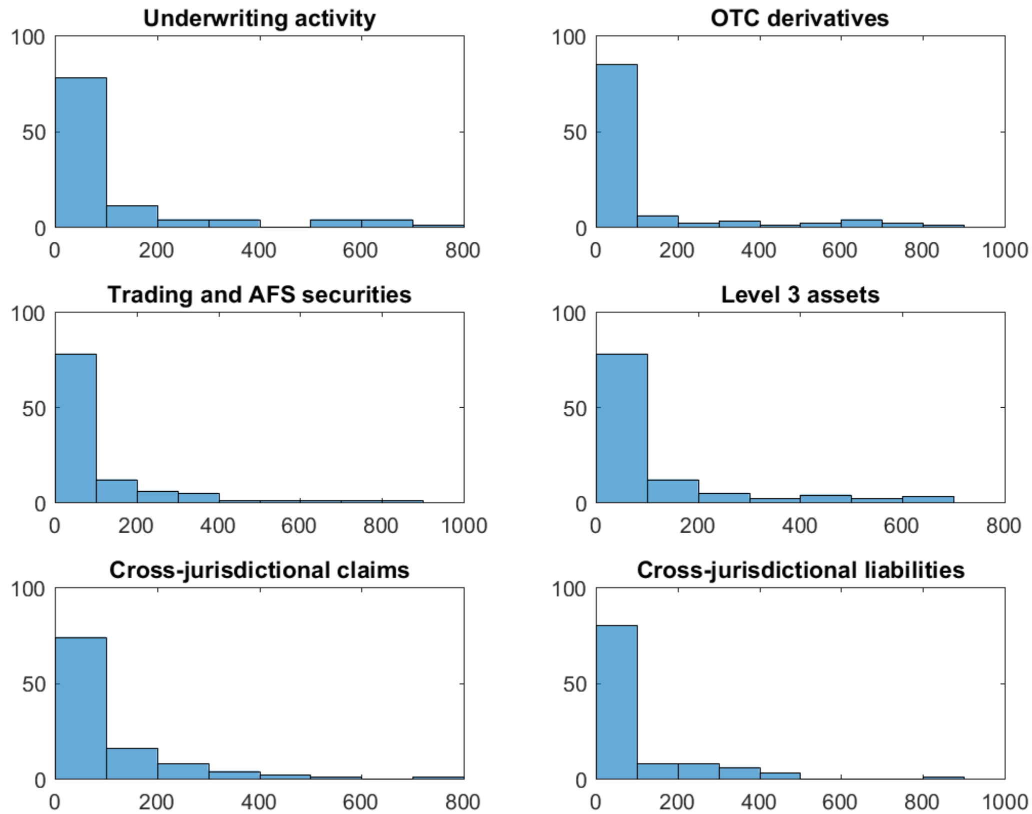
Country	Bank name	Sample	Source
Australia	ANZ	Main	Not Available
Australia	Commonwealth	Main	Not Available
Australia	National Australia Bank	Main	Not Available
Australia	Westpac	Main	Not Available
Austria	Erste Group	National	EBA - Interactive tool
Belgium	KBC	Additional	EBA - Interactive tool
Brazil	Banco Bradesco	Main	Not Available
Brazil	Banco do Brasil	Main	Not Available
Brazil	Caixa	Main	Not Available
Brazil	Itaú Unibanco	Main	Not Available
Canada	Bank of Montreal	Main	Regulatory Report
Canada	Bank of Nova Scotia	Main	Regulatory Report
Canada	Canadian Imperial Bank of Commerce	Main	Regulatory Report
Canada	Royal Bank of Canada	Main	Regulatory Report
Canada	Toronto Dominion Canada Trust	Main	Regulatory Report
China	Agricultural Bank of China	Main	Regulatory Report
China	Bank of China	Main	Regulatory Report
China	Bank of Communications	Main	Regulatory Report
China	China Construction Bank	Main	Regulatory Report
China	China Everbright Bank	Main	Regulatory Report
China	China Guangfa Bank	Main	Regulatory Report
China	China Merchant Bank	Main	Regulatory Report
China	China Minsheng Bank	Main	Regulatory Report
China	Citic	Main	Regulatory Report
China	Hua Xia Bank	Main	Regulatory Report
China	Industrial and Commercial Bank of China (ICBC)	Main	Regulatory Report
China	Industrial Bank	Main	Regulatory Report
China	Ping An Bank	Main	Regulatory Report
China	Shanghai Pudong	Main	Regulatory Report
Denmark	Danske Bank	Main	EBA - Interactive tool
France	BNP Paribas	Main	EBA - Interactive tool
France	Crédit Mutuel	Main	EBA - Interactive tool
France	Groupe BPCE	Main	EBA - Interactive tool
France	Groupe Crédit Agricole	Main	EBA - Interactive tool
France	La Banque Postale	Additional	EBA - Interactive tool
France	Sociéte Générale	Main	EBA - Interactive tool
Germany	Bayern LB	Additional	EBA - Interactive tool
Germany	Commerzbank	Main	EBA - Interactive tool
Germany	Deutsche Bank	Main	EBA - Interactive tool
Germany	DZ Bank	Main	EBA - Interactive tool
Germany	Helaba	Additional	EBA - Interactive tool
Germany	LBBW	Additional	EBA - Interactive tool
Germany	Nord/LB	Additional	EBA - Interactive tool
India	State Bank of India	Main	Regulatory Report
Italy	Intesa San Paolo	Main	EBA - Interactive tool
Italy	Monte dei Paschi di Siena	Additional	EBA - Interactive tool
Italy	Unicredit	Main	EBA - Interactive tool
Japan	Mitsubishi UFJ FG	Main	Regulatory Report
Japan	Mizuho FG	Main	Regulatory Report
Japan	Nomura Holdings	Main	Regulatory Report
Japan	Sumitomo Mitsui FG	Main	Regulatory Report
Japan	Sumitomo Mitsui Trust Holdings	Main	Regulatory Report
Japan	The Norinchukin Bank	Main	Regulatory Report

Country	Bank name	Sample	Source
Korea	Hana Bank	Main	Regulatory Report
Korea	Kookmin	Additional	Regulatory Report
Korea	Shinhan	Main	Regulatory Report
Korea	Woori Bank	Additional	Regulatory Report
Netherlands	ABN AMRO	Main	EBA - Interactive tool
Netherlands	ING Bank	Main	EBA - Interactive tool
Netherlands	Rabobank	Main	EBA - Interactive tool
Norway	DNB Bank	Main	EBA - Interactive tool
Russia	Sberbank	Main	Regulatory Report
Singapore	DBS Bank	Main	Regulatory Report
Singapore	OCBC	Additional	Regulatory Report
Singapore	UOB	Additional	Regulatory Report
Spain	BBVA	Main	EBA - Interactive tool
Spain	BFA	Additional	EBA - Interactive tool
Spain	Criteria Caixa-Holding	Main	EBA - Interactive tool
Spain	Santander	Main	EBA - Interactive tool
Sweden	Handelsbanken	Main	EBA - Interactive tool
Sweden	Nordea	Main	EBA - Interactive tool
Sweden	SEB	Main	EBA - Interactive tool
Sweden	Swedbank	Additional	EBA - Interactive tool
Switzerland	Credit Suisse	Main	Regulatory Report
Switzerland	UBS	Main	Regulatory Report
United Kingdom	Barclays	Main	EBA - Interactive tool
United Kingdom	HSBC	Main	EBA - Interactive tool
United Kingdom	Lloyds	Main	EBA - Interactive tool
United Kingdom	Nationwide	Additional	EBA - Interactive tool
United Kingdom	Royal Bank of Scotland	Main	EBA - Interactive tool
United Kingdom	Standard Chartered	Main	EBA - Interactive tool
United States	Ally Financial Inc.	National	FR Y-15
United States	American Express Company	National	FR Y-15
United States	Bancwest Corporation	National	FR Y-15
United States	Bank of America	Main	FR Y-15
United States	Bank of New York Mellon	Main	FR Y-15
United States	BB&T Corporation	National	FR Y-15
United States	BBVA Compass Bancshares, Inc.	National	FR Y-15
United States	BMO Financial Corp.	National	FR Y-15
United States	Capital One	Additional	FR Y-15
United States	Citigroup	Main	FR Y-15
United States	Citizens Financial Froup, Inc.	National	FR Y-15
United States	Comerica Incorporated	National	FR Y-15
United States	Deutsche Bank Trust Corporation	National	FR Y-15
United States	Discover Financial Services	National	FR Y-15
United States	Fifth Third Bancorp	National	FR Y-15
United States	Goldman Sachs	Main	FR Y-15
United States	HSBC North America Holdings Inc.	National	FR Y-15
United States	Huntington Bancshares Incorporated	National	FR Y-15
United States	JP Morgan Chase	Main	FR Y-15
United States	Keycorp	National	FR Y-15
United States	M&T Bank Corporation	National	FR Y-15
United States	Morgan Stanley	Main	FR Y-15
United States	MUFG Americas Holdings Corporation	National	FR Y-15
United States	Northern Trust Corporation	National	FR Y-15
United States	PNC	Main	FR Y-15
United States	Regions Financial Corporation	National	FR Y-15
United States	Santander Holdings USA, Inc.	National	FR Y-15
United States	State Street	Main	FR Y-15
United States	Suntrust Banks, Inc.	National	FR Y-15
United States	TD Bank US Holding Company	National	FR Y-15
United States	US Bancorp	Main	FR Y-15
United States	Wells Fargo	Main	FR Y-15
United States	Zions Bancorporation	National	FR Y-15

Appendix 4 Distributions of the 12 systemic-risk indicators

The 12 histograms show the distributions of the 106 sample banks' total exposures, intra-financial system assets, intra-financial system liabilities, securities outstanding, payment activity, assets under custody, underwritten activity, OTC derivatives, trading and AFS securities, level 3 assets, cross-jurisdictional claims, and cross-jurisdictional liabilities, respectively. Data are as of year-end 2014.




Underwriting activity
100
50
0
0
200
400
600
800
OTC derivatives
100
50
0
0
200
400
600
800
1000
Trading and AFS securities
100
50
0
0
200
400
600
800
1000
Level 3 assets
100
50
0
0
200
400
600
800
Cross-jurisdictional claims
100
50
0
0
200
400
600
800
Cross-jurisdictional liabilities
100
50
0
0
200
400
600
800
1000

Appendix 5 List of systemically important financial institutions (year 2014)

This table reports the rank (Column 1), the risk-bucket number with its respective Financial Stability Board (FSB) cut-off scores (Column 2), the additional capital requirement expressed as a percentage of risk-weighted assets (Column 3), the identity of the top 30 systemically important banks as identified by the FSB in alphabetical order (Column 4) and in descending order (Column 5), and the top 30 systemically important banks as identified by systemic-risk scores based on standardized categories in descending order (Column 6), as of November 2014. Systemic-risk scores of all banks are reported in parenthesis. A $*$ indicates that the substitutability category of the bank is capped at 5% and the systemic-risk score without this cap is also reported in parenthesis. A $\bullet$ indicates banks identified as SIFIs by supervisory judgement. Reported cut-off values do not apply to systemic-risk scores based on standardized categories.

Rank	Bucket	Additional Capital	FSB (Alphabetical)	FSB (Descending)	Standardized Categories (Descending)
	5 [530-629]	3.5%	Empty		
1	4	2.5%	HSBC (477)	JP Morgan Chase* (505/646)	JP Morgan Chase (443)
2	[430-529]		JP Morgan Chase* (505/646)	HSBC (477)	
3			Barclays (385)	Citigroup* (426/494)	HSBC (360); Citigroup (351)
4	3	2.0%	BNP Paribas (408)	Deutsche Bank* (417/445)	Deutsche Bank (313); BNP Paribas (304)
5	[330-429]		Citigroup* (426/494)	BNP Paribas (408)	Barclays (280)
6			Deutsche Bank* (417/445)	Barclays (385)	Bank of America (227)
7			Bank of America (305)	Bank of America (305)	Mitsubishi UFJ FG (194)
8	2	1,5%	Credit Suisse (264)	Credit Suisse (264)	Morgan Stanley (191)
9	[230-329]		Goldman Sachs (247)	Morgan Stanley (259)	Credit Suisse (190)
10			Mitsubishi UFJ FG (242)	Goldman Sachs (247)	
11			Morgan Stanley (259)	Mitsubishi UFJ FG (242)	
12			Royal Bank of Scotland (239)	Royal Bank of Scotland (239)	
13			Agricultural Bank of China (133)	Société Générale (226)	Royal Bank of Scotland (181); Goldman Sachs (179)
14			Bank of China (182)	Groupe Crédit Agricole (218)	Groupe Crédit Agricole (176)
15			Bank of New York Mellon* (150/209)	UBS (201)	Société Générale (170)
16			BBVA• (93)	Santander (196)	Santander (158)
17			Groupe BPCE (141)	Bank of China (182)	ICBC (158)
18			Groupe Crédit Agricole (218)	ICBC (181)	Bank of China (153)
19	1	1.0%	ICBC (181)	Wells Fargo (172)	UBS (147)
20	[130-229]		ING Bank (145)	Mizuho FG (152)	Wells Fargo (134)
21			Mizuho FG (152)	Bank of New York Mellon* (150/209)	Bank of New York Mellon (127)
22			Nordea• (121)	State Street* (148/162)	Unicredit Group (119)
23			Santander (196)	Unicredit Group (148)	Mizuho FG (117)
24			Société Générale (226)	ING Bank (145)	Sumitomo Mitsui FG (117)
25			Standard Chartered (134)	Sumitomo Mitsui FG (142)	Groupe BPCE (116)
26			State Street* (148/162)	Groupe BPCE (141)	ING Bank (115)
27			Sumitomo Mitsui FG (142)	Standard Chartered (134)	Agricultural Bank of China (111)
28			UBS (201)	Agricultural Bank of China (133)	China Construction Bank (111)
29			Unicredit Group (148)	China Construction Bank (124)	Nordea• (96)
30			Wells Fargo (172)	Royal Bank of Canada (123)	BBVA• (73)