Pitfalls in Systemic-Risk Scoring*

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Abstract

We identify several shortcomings in the systemic-risk scoring methodology currently used to identify and regulate Systemically Important Financial Institutions (SIFIs). Using newly-disclosed regulatory data for 119 US and international banks, we show that the current scoring methodology severely distorts the allocation of regulatory capital among banks. We then propose and implement a methodology that corrects for these shortcomings and increases incentives for banks to reduce their risk contributions. Unlike current scores, our adjusted scores are mainly driven by risk indicators directly under the control of the regulated bank and not by factors that are exogenous to the bank, such as exchange rates or other banks' actions.

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1 Introduction

SIFIs, the acronym for Systemically Important Financial Institutions, is a palindrome. 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, complexity, and cross-jurisdictional activity. For non-Eurozone banks, categories are converted in Euros to be summed up across banks. In order not to favor any particular facet of systemic risk, the BCBS computes an equally-weighted average score of all categories.[1]

In this paper, we identify and correct two major shortcomings in the current systemic-risk scoring methodology. A first unintended consequence of the scoring method is to bias scores towards the categories that are most volatile in the cross section. Indeed, when variables are aggregated in absence of any form of standardization, they are effectively weighted by their

[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)).

standard deviation. In practice, there are two ways to correct for this statistical bias: (1) trimming outliers by capping some of the categories or (2) standardizing each category by its cross-sectional volatility. When computing extra capital charges for systemic risk, the BCBS implements the former strategy and applies a 5% cap to the substitutability category of each sample bank and no cap to the other categories. We show that this ad hoc choice materially affects the composition of the SIFI list and distorts the incentives of banks to reduce risk. Standardizing each category by its own volatility is shown to be an easy and efficient way to fix this problem.

The second shortcoming is related to the reference currency used to aggregate bank data across currency zones. We show that any depreciation of a currency with respect to the Euro mechanically *lowers* the score of the banks headquartered in this particular currency zone and increases the score of Eurozone banks. Similarly, any depreciation of the Euro favors Eurozone banks and penalizes non-Eurozone banks. In a period of strong swings in the FX markets, such as after the decision of the UK to leave the European Union (Brexit), such foreign-exchange effects have major distorting effects on the regulatory capital of global banks. These distortions can be removed by using a reference exchange rate which is kept constant from one year to the next. We show that such an alternative conversion scheme strengthens the incentives for banks to reduce their systemic-risk contribution.

Using regulatory data for a sample of 119 global banks from 22 countries between 2014 and 2016, we demonstrate that the number of categories actually capped, the level of the cap, as well as the selection of the reference currency have first-order effects on the list of SIFIs, and in turn on their regulatory capital. We show that slightly changing the capping scheme significantly alters the composition of the risk buckets. For instance in 2015, capping the substitutability category leads several banks to switch risk buckets and to an aggregate change in regulatory capital of more than EUR 17 billion. 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. We also show that annual exchange-rate changes have a non-trivial impact on the list of the SIFIs, which is an unfortunate feature of the current scoring method.

This paper contributes to the literature on systemic-risk measurement. As shown by Benoit *et al.* (2017), there are two main families of systemic-risk measures: those that aggregate low-frequency regulatory data (like the BCBS score; see Passmore and von Hafften (2017)) 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* (MES) and the *Systemic Expected Shortfall* (SES) of Acharya *et al.* (2017), the *Systemic Risk Measure* (SRISK) of Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2017), and the *Delta Conditional Value-at-Risk* (ΔCoVaR) of Adrian and Brunnermeier (2016). The key advantage of 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 2009. As a result, until very recently, academics were not in a position to conduct any empirical evaluation of this key policy tool. To the best of our knowledge, this is the first academic paper to analyze these regulatory data for all banks taking part of the worldwide SIFI assessment.

The main contribution of this paper is to show, both theoretically and empirically, that the official methodology to set capital charges for global banks is biased. As a consequence, the current systemic-risk scoring methodology sometimes creates incentives for the most risky banks to *increase* risk-taking. We also suggest a modification of the methodology to correct the biases and to uniquely identify SIFIs. By strengthening the link between banks' regulatory capital and the value of its systemic-risk categories, our adjusted scoring technique increases incentives for banks to limit risk-taking. Our approach can readily be used to compute regulatory capital or a systemic-risk tax on the banks that contribute the most to the risk of the financial system.[2] 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 here remains valid for any set of risk indicators.

We believe that recognizing the ad-hoc and non-incentive-compatible 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 the capital misallocation reported in this paper may also distort the distribution of credit and risk-taking of large banks (Behn, Haselmann, and Wachtel (2016)). 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

[2]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.

because such a 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 results in the same final score. Finally, a depreciation of a given currency with respect to the Euro will allow banks from this particular currency zone to increase risk-taking without altering their systemic-risk score.

Our approach is grounded in the theory of incentives (Laffont and Tirole (1993) and Laffont and Martimort (2001)). A fundamental result in this theory is that adding noise in a principal-agent model lowers the incentives for the agent to exert effort. We show that under the current scoring methodology, the regulatory surcharge of each SIFI is driven to a large extent by exogenous factors (i.e., noise), such as exchange rates or other banks' actions. Differently, our adjusted scoring technique either removes, or at least reduces, these extraneous influences and, as such, significantly increases the incentives for the bank to reduce its systemic-risk contribution. Empirically, we find that the correlation between changes in scores and changes in bank-specific risk indicators is 0.833 with the current methodology and 0.966 with our adjusted methodology.

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 used by banking regulators and implement it using actual regulatory data for a sample of global banks. In Section 4, we describe the main pitfalls of the current systemic-risk methodology and quantify their relative importance in the data. In Section 5, we explain how to correct for the biases and show that our modified approach can lead to drastically different conclusions. We compare the performance of the current scores with our modified scores in Section 6. We summarize and conclude our paper in Section 7.

2 The Economics of Systemic-Risk Regulation

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.[3] However, with little capital, even a small drop in asset value can make the bank insolvent, i.e., can lead to negative 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 premium paid by the banks is not risk-based or fairly priced, banks are tempted to take too much risk. Furthermore, an aggravating factor is moral hazard as banks shift their risk exposures when the probability of being bailed out by the Government is high. 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.

To protect taxpayers' money and ensure banks' equity holders have enough "skin in the game", 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, international banking 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 costs they inflict on the system and to create incentives for them to reduce such externalities.

[3] 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)).

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 Adrian and Brunnermeier (2016), Acharya *et al.* (2017), and Brownlees and Engle (2017)). These bank-level measures are by nature global as they do not specifically target any particular risk channel. Furthermore, they can be computed at a daily frequency and as such are more reactive than risk measures computed from 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 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.* (2017) for more details and references). Once the categories are identified, regulators are free to put more weight on those for which they have the lowest risk tolerance. When regulators have no economic reasons to favor any particular source of systemic risk, they 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 (Jiménez *et al.* (2015) and Behn, Haselmann, and Wachtel (2016)) and risk-taking (Becker and Opp (2014)). As a result, the choices of the categories used to compute the systemic score and of the aggregation process can have real effects. In the eventuality when the scoring methodology is biased towards a subset of categories or by swings in the FX market, both the distributions of credit and risk-taking in the economy can be distorted.

3 Measuring Systemic Risk

3.1 BCBS Methodology

The systemic-score methodology proposed by the BCBS has been implemented to identify SIFIs every year since 2012. It is based on 12 systemic-risk *indicators* which are combined into five main systemic-risk *categories*: size, interconnectedness, substitutability, complexity, and the cross-jurisdictional activity of the bank (see Appendix A and BCBS (2014b)).

Maybe the most natural dimension of systemic risk, the *size* of the financial institution, 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 *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 global financial system.[4]

Formally, each bank i, for $i = 1, ..., N$, is characterized by $K = 5$ systemic-risk categories denoted $x_{i1}, ..., x_{iK}$. Each category x_{ik} is obtained by aggregating F_k indicators (X_{ikf}) associated with category k, normalized by their sums:[5]

$$x_{ik} = \frac{1}{F_k} \sum_{f=1}^{F_k} \frac{X_{ikf}}{\sum\limits_{i=1}^{N} X_{ikf}} \times 10,000. \tag{1}$$

As the categories x_{ik} are expressed in basis points, they can be interpreted as the *market shares* of bank i for the various systemic-risk categories k (e.g., size, interconnectedness, etc.). The indicators X_{ikf} of non-Eurozone banks are converted in Euro using fiscal year-end exchange rates to permit aggregation across currency zones. To allow banks to compute their own scores, the regulator discloses, for each indicator, the sum across all banks, $\sum_{i=1}^{N} X_{ikf}$.

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

$$S_i = \sum_{k=1}^{K} \omega_k \times x_{ik}, \tag{2}$$

where ω_k corresponds to the weight (common to all banks) of category k in the systemic-risk score. Note that, by definition, all x_{ik}, for $k = 1, ..., K$, have an equal mean.

In order to give the same importance to each category, the BCBS considers an equally weighted index with $\omega_k = 1/K = 20\%$. Under this assumption, an increase of 10% of a given

[4] Passmore and von Hafften (2017) claim that the share of short-term funding should also be included in the list of systemic-risk categories.

[5] If we keep the same ordering for the categories as the BCBS, then $F_1 = 1$ for the size category, $F_2 = 3$ for interconnectedness, $F_3 = 3$ for substitutability, $F_4 = 3$ for complexity, and $F_5 = 2$ for cross-jurisdictional activity.

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.[6] Accordingly, the systemic-risk score becomes:

$$\bar{S}_i = \sum_{k=1}^{K} \omega_k \times \min(x_{ik}, cap_k), \tag{3}$$

with $cap_k = 5\%$ for the substitutability category and $cap_k = 100\%$ 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. This cut-off score has been set to 130 since the SIFI list of 2012. [7] With such a cut-off, any global bank that contributes to more than 1.3% of the risk of the system is deemed to be SIFI. 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.[8] All banks included in a given bucket face an extra capital charge that is added over and above existing capital requirements. The magnitude of the extra capital charge goes from 1% in bucket 1 to 3.5% in bucket 5.

The current scoring methodology exhibits several appealing features. For instance, fixing the cut-offs through time allows banks to forecast the bucket they will be in next year and forces them to reduce their risk indicators if they want to reduce their systemic-risk score. Furthermore, adding an extra empty 3.5%-bucket creates strong incentives for the highest-scoring banks for not increasing their scores any further.

[6] The BCBS (2013) acknowledges that the substitutability category 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.*"

[7] Passmore and von Hafften (2017) argue that the cut-off should be lower as to include more SIFIs.

[8] 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 the list of 2012.

3.2 Implementing the BCBS Methodology

The aim of this section is to implement the BCBS methodology between 2014 and 2016.[9] Following the BCBS, we consider two samples. 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 was designated as SIFI in the previous year. The additional sample is made of all banks with a leverage ratio exposure in excess of EUR 200 billion that are not included in the main sample. The additional sample also includes large banks that are under the supervision of national authorities (see Appendix C for the list of the 119 sample banks).

We collect the value of the 12 indicators required to compute the five systemic-risk categories at the end of the fiscal year from three different sources.[10] 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.[11] Third, for sample banks outside the EU and the US, we collect regulatory data directly from their individual websites. In total, we have complete data for 98 banks in 2014, 106 in 2015, and 117 in 2016.[12]

We start by scaling each bank-level indicator by the sum of this indicator across the main-sample banks considered by the BCBS.[13] For ease of presentation, we mainly discuss in the core of the paper the results for the year 2015. However, for completeness, we report all results for the years 2014 and 2016 in the Appendix A, as well as in Tables 2 and 4. We see in Panel A

[9] Our analysis only covers these three years because the bank-level regulatory data needed to compute the scores have been gradually disclosed since 2014.

[10] Most sample banks have their fiscal year-end on December 31 but some sample banks have their fiscal year-end in September 30 (Australia), October 31 (Canada), and in March 31 (Japan and India).

[11] 36 banks are currently monitored by the European Banking Authority and their data can be obtained at www.eba.europa.eu. 34 bank holding companies are monitored by the Federal Reserve since their total assets is greater than $50 billion, and their FR Y-15 reports are available at www.ffiec.gov.

[12] Unlike for 2014 and 2015, we have no missing data for the year 2016.

[13] Denominators are publicly available at http://www.bis.org/bcbs/gsib/denominators.htm.

of Table 1 that the various indicators exhibit strong heterogeneity in terms of cross-sectional volatility. For instance, the volatility for assets under custody (283) is three times larger than for securities outstanding (91). Furthermore, we observe that the cross-sectional distributions of all indicators 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 than 15% for assets under custody (with a skewness coefficient of 4.5).

We then combine the 12 indicators into five systemic-risk categories as described in Equation 1. We display the empirical distribution of each category in Figure 1, along with some summary statistics in Panel B of Table 1. By construction, the distributions of the systemic-risk categories remain skewed (for instance, the skewness coefficient of the substitutability category is 3.6) with strong differences in the volatility of the categories. The substitutability category is the most volatile (standard deviation equal to 183), which explains why the BCBS applies a cap on this specific category. As this category includes assets under custody, the cap only benefits to the largest custodian banks in the world: JP Morgan Chase, Citigroup, Bank of New York Mellon, and State Street. After applying the 5% cap, the standard deviation for this category decreases to 124. On average, the interconnectedness (respectively substitutability) category is the most (least) correlated with the other categories as reported in Appendix A.

To replicate the list of SIFIs published in 2015 by the FSB, we implement the methodology described in Section 3.1. We display all systemic scores in descending order in Figure 2, and we report the names and the scores of the top 30 banks in Table 3.[14] We see that we obtain

[14] As a cross-validation exercise, we systematically compare our scores with the ones disclosed for a subset of banks by the Office of Financial Research (Loudis and Allahrakha (2016)) and the Federal Financial Institutions Examination Council's web site (www.ffiec.gov).

exactly the same list of SIFIs as the FSB. Using the current cut-off scores, we allocate the 30 banks into five risk buckets and we get exactly the same bucket composition as the FSB. Finally, we compute the total extra capital requirement for systemic risk, which is equal to EUR 259.13 billion.

Interestingly, in 2016, the score of Groupe BPCE and Nordea is below the 130 cut-off (126 for BPCE and 123 for Nordea, see Table 4). Yet, these banks are qualified as SIFIs by the regulators. Indeed, these two banks have been added to the first bucket by a regulatory judgement of the FSB. Similarly in 2014, BBVA and Nordea were added to the SIFI list, although their score was below 130 (see Table 2).

Notice that this replication exercise provides additional information compared to the list of SIFIs disclosed by the FSB. Within each risk bucket, we are able to rank the financial institutions according to their systemic-risk score (Figure 2) whereas they are ranked by alphabetical order in the FSB's list. Furthermore, we observe that within each risk bucket, banks are usually equally-spread and show no sign of bunching below the cut-off values. Systematic bunching would indicate that some SIFIs strategically manage the value 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 SIFIs threshold, 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 and score = 108).

4 The Pitfalls of the Current Methodology

The scoring methodology proposed by the BCBS is simple and intuitive, and the resulting scores can easily be reproduced. However, the lack of theoretical foundation raises some issues concerning the arbitrary choices made about (1) the list of considered indicators, (2) the aggregation methodology, and (3) the cut-offs used to identify SIFIs and populate risk buckets. Beyond these arbitrary choices, the current methodology has also some unintended consequences induced by two specific assumptions, namely the use of a cap for some indicators and the use of year-end exchange rates to convert all indicators in Euro.

The aim of this section is to provide both a theoretical and an empirical analysis to highlight some of the pitfalls of the BCBS methodology. We first 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. We then illustrate the unintended consequences of potential fluctuation in the foreign-exchange rates on the identification of SIFIs.

4.1 Why Capping Inputs Leads to an Unstable SIFI List

Cross-sectional volatility effect. Computing a systemic-risk score by means of an equally-weighted average (as in Equation 3) 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 B for a simulation exercise). This effect will increase with the cross-sectional variation of any systemic-risk indicator. For 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 SIFI regulatory capital surcharges.

To address this effect and lower the weight of outliers, the BCBS applies a 5% cap on the substitutability category. As shown in Figure 1 and in 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.

However, this choice may have some important consequences. Indeed, capping reduces the relative importance of the three components of the substitutability category, 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 they were a major source of concern during the Lehman Brothers crisis (Adrian *et al.* (2014)).

More generally, an important feature of any 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 high on a capped category have no incentive whatsoever to reduce risk. Formally, given Equation 3, we have:

$$\frac{\partial \bar{S}_i}{\partial x_{ik}} = 0 \quad \text{if } x_{ik} > cap_k \tag{4}$$

As an example, consider a bank with a score of 12% on a given category that is capped at 5%. Reducing this category anywhere between 12% 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, another potential pernicious effect of allowing some categories to be capped is making lobbying more likely (Lambert (2015)). Indeed, when capping is an option, 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; again destroying the incentives for banks to curb excessive risk-taking.

Empirical illustration. To illustrate the effects of the cap, we compare the lists of SIFIs with and without a cap on the substitutability category in Table 4. Under the BCBS methodology, winsorizing categories mechanically 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 583, and similarly to 495 for Citigroup, to 227 for Bank of New York Mellon, and to 172 for State Street.

These new scores call for several changes in the bucket composition. We see in Table 3 that two out of the 30 SIFIs switch buckets because of the cap. JP Morgan Chase switches from bucket 5 to bucket 4, whereas Citigroup drops from bucket 4 to bucket 3 (saving half a percentage point in regulatory capital). 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, 8.94% of its Tier 1 capital, or 29% of its systemic-risk charge.[15] Similarly, the reduction in capital for Citigroup is $0.5\% \times 998 =$ EUR 4.99 billion, 3.63% of its Tier 1 capital, or 20% of its systemic-risk charge. 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).

In 2014, the impact of the cap is even larger. JP Morgan Chase switches from bucket 6 to bucket 4 (saving two percentage points in regulatory capital), whereas Citigroup and Deutsche Bank drops from bucket 4 to bucket 3. Thanks to the cap, JP Morgan Chase is able to reduce its regulatory capital by EUR 20.13 billion or 16.76% of its Tier 1 capital.

More generally, the volatility adjustment proposed by the BCBS is based on two arbitrary choices, namely the choice of the indicators that have to be capped and the values of the caps. It is important to recognize that capping the substitutability category of four banks is 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 dashed line, right axis) of changing the number of banks affected by the cap on substitutability from $\bar{N} = 0$ to $\bar{N} = 20$. 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 affects radically 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 $\bar{N}$ highest values of all five categories and reconstruct the buckets. Results

[15]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.

in Figure 4 indicate that capping 20 banks triggers 30 bucket changes and a reduction in regulatory capital of EUR 137 billion. This corresponds to more than 50% of the total extra regulatory capital due to the systemic-risk regulation (EUR 259.13 billion). This quantitative assessment clearly illustrates the limits of the volatility adjustment method proposed by the BCBS.

4.2 Why Using Year-End Exchange Rates Leads to an Unstable SIFI List

Exchange rate effect. Computing a systemic-risk score from risk market shares implies that the indicators of all banks have to be converted into a common, reference currency. Indeed, the systemic-risk scores are based on a set of indicators reported at the end of the fiscal year by the banks, in their local currency. Then, the BCBS converts the indicators of the non-Eurozone banks in Euro using the (daily spot) exchange rates applicable at their respective financial year-end, typically December 31 (BCBS (2015)). However, using spot exchange rates may have unintended consequences on the systemic score, especially in a period of high volatility for the exchange rates.[16]

To illustrate the effect of the exchange rate on the systemic-risk score, we consider a simple case in which there is only one exchange rate. Let us assume that there is N_e Eurozone banks indexed by $i = 1, ..., N_e$ and $N - N_e$ non-Eurozone banks. Denote by $\widetilde{X}_{ikf}$ the indicators for the non-Eurozone banks, expressed in a foreign currency unit and by e the spot exchange rate used by the BCBS.[17] For any Eurozone bank, the market share in the category k is then defined as:

$$x_{ik} = \frac{1}{F_k} \sum_{f=1}^{F_k} \frac{X_{ikf}}{X_{kf}} \times 10,000 \qquad \forall i \in \{1, ..., N_e\}. \tag{5}$$

[16] The potentially problematic effect of currency fluctuations on the systemic scores of global banks is also mentioned in a note from the Office of Financial Research by Glasserman and Loudis (2015).

[17] Most of these indicators are some stock variables but two of them are flow based (payments activity and underwritten activity). The BCBS uses the year-end exchange rate for both types of indicators.

Similarly, for a non-Eurozone bank, the market share is:

$$x_{ik} = \frac{1}{F_k} \sum_{f=1}^{F_k} \frac{e\widetilde{X}_{ikf}}{X_{kf}} \times 10,000 \qquad \forall i \in \{N_e + 1, ..., N\}, \tag{6}$$

where the total sum (over the N banks) of the indicator f is expressed in Euro as follows:

$$X_{kf} = \sum_{i=1}^{N_e} X_{ikf} + e \sum_{i=N_e+1}^{N} \widetilde{X}_{ikf}. \tag{7}$$

In this context, the impact of an appreciation of the foreign currency (e increases) is always negative for the market share of the Eurozone-banks:

$$\frac{\partial x_{ik}}{\partial e} = -\frac{10,000}{F_k} \sum_{f=1}^{F_k} \frac{X_{ikf} \ \sum_{i=N_e+1}^{N} \widetilde{X}_{ikf}}{X_{kf}^2} < 0 \quad \forall i \in \{1, ..., N_e\}, \tag{8}$$

since both the indicators X_{ikf} and $\widetilde{X}_{ikf}$ are positive. On the contrary, the impact of an appreciation of the foreign currency for the non-Eurozone banks is always positive:

$$\begin{aligned} \frac{\partial x_{ik}}{\partial e} &= \frac{10,000}{F_k} \sum_{f=1}^{F_k} \frac{\widetilde{X}_{ikf} X_{kf} - e\widetilde{X}_{ikf} \sum_{i=N_e+1}^{N} \widetilde{X}_{ikf}}{X_{kf}^2} \\ &= \frac{10,000}{F_k} \sum_{f=1}^{F_k} \frac{\widetilde{X}_{ikf} \left(X_{kf} - e \sum_{i=N_e+1}^{N} \widetilde{X}_{ikf} \right)}{X_{kf}^2} \\ &= \frac{10,000}{F_k} \sum_{f=1}^{F_k} \frac{\widetilde{X}_{ikf} \sum_{i=1}^{N_e} X_{ikf}}{X_{kf}^2} > 0 \qquad \forall i \in \{N_e + 1, ..., N\}. \end{aligned} \tag{9}$$

The systemic-risk score for each bank is still given by Equation 2. As a consequence, the impact of an appreciation of the foreign currency on the systemic score of a Eurozone bank is always negative, whereas it is always positive for a non-Eurozone bank (and inversely when we observe a depreciation of the foreign currency):

$$\frac{\partial S_i}{\partial e} = \sum_{k=1}^{K} \omega_k \times \frac{\partial x_{ik}}{\partial e} < 0 \quad \forall i \in \{1, ..., N_e\}, \tag{10}$$

$$\frac{\partial S_i}{\partial e} = \sum_{k=1}^{K} \omega_k \times \frac{\partial x_{ik}}{\partial e} > 0 \qquad \forall i \in \{N_e + 1, ..., N\}. \tag{11}$$

The message provided by the latter two equations is worrisome. Indeed, an appreciation of the Euro leads to higher systemic-risk scores for Eurozone banks, everything else being constant. Similarly, such an appreciation also implies a mechanical reduction in systemic risk scores for non-Eurozone banks. In contrast, a depreciation of the Euro leads to a reduction in the score of Eurozone banks and an increase in the score of non-Eurozone banks.

This result is in sharp contradiction with standard results in the macroeconomic literature on the relationship between exchange rates and fundamentals. Indeed, currency depreciations are typically associated with negative changes in future economic conditions (Engel and West (2005)) and increase the likelihood of banking crises (see the Twin Crises literature initiated by Kaminsky and Reinhart (1999)).

Empirical illustration. To assess the quantitative effect of the exchange rate on systemic scores, we report in Figure 5 the number of bucket changes (blue line, left y-axis) and the changes in regulatory capital (red dashed line, right y-axis), due to a depreciation or appreciation of the Euro relatively to the other currencies. All risk indicators, measured in local currencies, are assumed to be constant for all banks. The benchmark situation (represented by a red dot) corresponds to the BCBS results, based on the exchange rates used in 2015. The main takeaway from this figure is that even small variations in exchange rates can significantly distort the allocation of regulatory capital across banks even if the indicators reported by the bank are constant from one year to the next. When the Euro appreciates by 25%, 10 bucket changes are observed whereas seven bucket changes occur when the Euro depreciates by 25%. While the first bucket change due to a Euro strengthening begins after a rise of 8%, the impact is immediate when the Euro weakens since Nordea and ING Bank are not SIFIs anymore if the Euro depreciates by 4%. These bucket changes are associated with substantial capital reallocation across banks, the most severe depreciation of the Euro considered in the figure leads to an aggregate capital variation of more than EUR 33.5 billion. In contrast, the highest level of appreciation triggers a EUR 23 billion capital reallocation.

Figures 6 and 7 disentangle the exchange rate effects between Eurozone (blue bars) and non-Eurozone banks (red bars). An appreciation of the Euro systematically increases the systemic-risk score of Eurozone banks as shown in Equation 10. The sign switches for non-Eurozone banks in line with Equation 11. When the Euro appreciates by 25%, the 10 bucket changes can be broken down into six positive bucket changes for Eurozone banks (additional capital requirement of EUR 13 billion) and four negative bucket changes for non-Eurozone banks (reduction in capital requirement of EUR 10 billion).

5 How to Correct the Pitfalls

We propose a simple correction to alleviate the pernicious effects on systemic-risk scores of the volatility of the categories and of changes in exchange rates. The resulting adjusted systemic-risk scores lead to a unique set of SIFIs. By strengthening the connection between scores and bank categories, our modified scoring methodology increases the incentives for banks to reduce their risk contribution.

5.1 Adjusted Systemic-Risk Scores

We neutralize the impact of the exchange rate movements on the systemic-risk scores by setting reference exchange rates and not changing them from one year to the next. Category $\widetilde{x}_{ik}$ is given by:

$$\widetilde{x}_{ik} = \frac{1}{F_k} \sum_{f=1}^{F_k} \frac{\bar{e}_i \ \widetilde{X}_{ikf}}{\sum\limits_{i=1}^{N} \bar{e}_i \ \widetilde{X}_{ikf}} \times 10,000 \tag{12}$$

where $\bar{e}_i$ is set to one for Eurozone banks and $\bar{e}_i$ is the daily spot exchange rate as of December 2011.[18] On the other hand, to mitigate the volatility effect, all categories entering into the definition of the score are standardized by their own volatility (see Benoit *et al.* (2017)). Note that there is no need to subtract the mean of the $\widetilde{x}_{ik}$ as it is equal to $10,000/N$ for each category.[19] In that case, the systemic-risk score becomes:

$$\widetilde{S}_i = \sum_{k=1}^{K} \omega_k \times \frac{\widetilde{x}_{ik}}{\widetilde{\sigma}_k} \times R^{-1}, \tag{13}$$

where $\widetilde{\sigma}_k^2 = \mathrm{V}(\widetilde{x}_{ik})$ corresponds to the cross-sectional variance of category k. The purpose of the scaling factor $R = \sum_{k=1}^{K} \omega_k / \widetilde{\sigma}_k$ is to guarantee that the sum of all scores is 10,000 basis points. As a result, it allows us to use the same cut-off values as the BCBS. Note that the weight of each category is still equal to $\omega_k = 1/K$. To allow banks to compute their adjusted scores, the regulator needs to disclose the cross-sectional variance of each category.

An alternative volatility adjustment would consist in standardizing the indicators rather than the categories as in Equation 13. In practice, both types of adjustment lead to similar empirical results.

5.2 Empirical Illustrations

We now turn to the computation of the adjusted systemic-risk scores in Tables 2-4. We proceed in two steps: first, we only adjust for the effect of the cross-sectional volatility (column 4) and then we adjust for both the volatility and for foreign exchange rate effects (column 5). Table 3 shows that in 2015, when only adjusting for volatility, we obtain the exact same top 30 banks as the FSB but five banks switch buckets. Jointly adjusting for volatility and FX effects lead to the identification of more SIFIs. Indeed, Royal Bank of Canada, The Norinchukin Bank,

[18] We use 2011 as it is also the reference year for the cut-off values used to construct the risk buckets.

[19] Replacing $\widetilde{x}_{ik}$ by $\widetilde{x}_{ik} - \mathrm{E}(\widetilde{x}_k)$ would mechanically lead to the same final ranking.

and Nomura Holdings are now SIFI whereas State Street (rank = 33, and adjusted score = 127) is not SIFI anymore. In addition, JP Morgan Chase switches to bucket 5, leaving bucket 4 empty, and there is a total of 11 banks switching buckets. Based on this new bucket scheme, the total extra capital requirement is higher (EUR 276.21 billion) than the current level (EUR 259.13 billion).[20] On the one hand, seven banks have to increase their regulatory capital.[21] Collectively, this increase in regulatory capital accounts for 53% of their systemic-risk capital charge for the year 2015. On the other hand, four banks have to reduce their regulatory capital.[22] This reduction in regulatory capital accounts for 25% of their systemic-risk capital charge for the year 2015.

Interestingly in 2016, using adjusted systemic-risk scores allows us to identify 29 SIFIs out of 30 banks on the current FSB list, including Groupe BPCE (adjusted score = 147) which was added by supervisory judgement (current score = 126). Differently, for the year 2014, the total extra capital requirement is significantly higher (EUR 246.21 billion) than the level required by the FSB (EUR 214.39 billion). This finding suggests that collectively the two shortcomings discussed in this paper allowed global banks to save almost 15% of their regulatory capital in 2014.

6 Performance Analysis

In this section, we compare the performance of the systemic score currently implemented by the BCBS (see Section 3) and our adjusted systemic score (see Section 5). We use the

[20] Our results are consistent with the conclusion of Passmore and von Hafften (2017) according to which the current Basel's systemic-risk capital surcharges are too low.

[21] JP Morgan Chase increases its regulatory capital by EUR 12.13 billion (8.94% of Tier 1 capital), Mitsubishi UFG FG by EUR 3.84 billion (4.49%), Santander by EUR 2.93 billion (4.09%), Mizuho FG by EUR 2.24 billion (5.30%), Royal Bank of Canada by EUR 2.72 billion (10.22%), The Norinchukin Bank by EUR 2.31 billion (5.82%), and Nomura Holdings by EUR 1.30 billion (7.70%).

[22] HSBC decreases its regulatory capital by EUR 5.02 billion (4.58% of Tier 1 capital), Barclays by EUR 2.58 billion (4.92%), Morgan Stanley by EUR 1.88 billion (3.98%), and State Street by EUR 0.89 billion (8.09%).

theory of incentives to inform our performance analysis (Laffont and Tirole (1993); Laffont and Martimort (2001)). The key idea is that, in a principal-agent model, the addition of noise is reducing the incentives of the agent to exert effort. In the context of systemic-risk regulation, this means that the value of a systemic score of a given bank should mainly reflect the actions of this bank, and less so the actions of other banks or other effects not under the control of the bank.

Formally, a systemic score S_i of a bank i depends on a vector X_t of three elements: (1) its own K indicators expressed in national currency, X_{ikf} or $\widetilde{X}_{ikf}$, (2) the $(N-1)\,K$ indicators of the other banks $j \neq i$, X_{jkf} or $\widetilde{X}_{jkf}$, and (3) the spot exchange rates used to convert the indicators of the non-Eurozone banks in euro. The performance analysis we propose consists in determining the relative contributions of these three elements to the changes in the systemic-risk scores (given by Equation 3) between two consecutive years, denoted ΔS_i. The increment theorem implies that there exists an interior point X_0 such that:

$$
\begin{aligned}
\Delta S_i &= \Delta_{i,i} + \Delta_{i,j} + \Delta_{i,e} \\
&\equiv \underbrace{\sum_{k=1}^{K}\sum_{f=1}^{F_k}\frac{\partial S_i\left(X_0\right)}{\partial X_{ikf}}\Delta X_{ikf}}_{\text{effects of bank } i} + \underbrace{\sum_{j\neq i}^{N}\sum_{k=1}^{K}\sum_{f=1}^{F_k}\frac{\partial S_i\left(X_0\right)}{\partial X_{jkf}}\Delta X_{jkf}}_{\text{effects of the other banks}} \\
&+ \underbrace{\sum_{j=1}^{N}\frac{\partial S_i\left(X_0\right)}{\partial e_j}\Delta e_j}_{\text{effects of the exchange rates}} \qquad (14)
\end{aligned}
$$

where ΔX_{ikf} denotes the changes in indicator f (included in category k) observed for bank i, and Δe_j is the variation observed in the exchange rate used for bank j to convert all its indicators in euros. By definition, $\Delta e_j = 0$ for $j = 1, ..., N_e$.

Equation 14 allows us to break down into three components the score variation (expressed in basis points) for a given bank between two consecutive years. The first component $\Delta_{i,i}$

represents the change in score which would occur due to the changes observed in the bank's own indicators, all other things remaining equal. This contribution reflects the effects of the bank's risk-taking on its own systemic score, regardless of the decisions taken by the other banks and the evolution of the exchange rates. The $\Delta_{i,j}$ component corresponds to the score variation for bank i due to changes in the indicators of all other banks, assuming the risk indicators of bank i and the exchange rates both remain constant. Finally, the $\Delta_{i,e}$ component corresponds to the score variation due to the changes in the exchange rates.

Given this decomposition, a simple performance criterion is given by the correlation between the changes in systemic-risk scores $\{\Delta S_i\}_{i=1}^{N}$ and the change in the bank's own risk categories $\{\Delta_{i,i}\}_{i=1}^{N}$ computed for all sample banks. The more the score variations are driven by its own indicators contributions, the stronger the incentives of the bank to reduce its risk contribution are. Conversely, the least the score variations are driven by other banks' contributions or other exogenous factors, the weaker the incentives for the bank to reduce its risk contribution are.

For the adjusted systemic-risk score, the decomposition is:

$$\Delta\widetilde{S}_i = \widetilde{\Delta}_{i,i} + \widetilde{\Delta}_{i,j} = \underbrace{\sum_{k=1}^{K}\sum_{f=1}^{F_k}\frac{\partial\widetilde{S}_i\left(X_0\right)}{\partial X_{ikf}}\Delta X_{ikf}}_{\text{effects of bank } i} + \underbrace{\sum_{j\neq i}^{N}\sum_{k=1}^{K}\sum_{f=1}^{F_k}\frac{\partial\widetilde{S}_i\left(X_0\right)}{\partial X_{jkf}}\Delta X_{jkf}}_{\text{effects of the other banks}} \tag{15}$$

since by definition $\Delta\bar{e}_i = 0$ for all banks.[23]

We implement the score decompositions displayed in Equations 14 and 15 for all sample banks present in the main sample in 2014-2015 (Table 5) and in 2015-2016 (Table A5). Several results in Table 5 are worthwhile mentioning. The ΔS_i ranges from -60 and +45 basis points and the average of the absolute ΔS_i is 12.87 basis points. Given the fact that the average score

[23]Notice that the derivatives $\partial\widetilde{S}_i/\partial X_{ikf}$ and $\partial\widetilde{S}_i/\partial X_{jkf}$ are different from those in Equation 14. Indeed, they include the effects of the indicators on the cross-sectional variance of category k ($\widetilde{\sigma}_k^2$).

is 151.38 basis points, the economic magnitude of these annual changes appears important. In the case of BNP Paribas, the negative cumulative effect from the other banks' actions ($\Delta_{i,j} = -13.89$) and from FX rates ($\Delta_{i,e} = -24.63$) dominates the positive effects from the bank's own risk indicators ($\Delta_{i,i} = 33.30$). As a result, the net effect is a drop in the BCBS systemic-risk score of BNP Paribas ($\Delta S_i = -5.22$). In contrast, the adjusted score for this bank does increase since the FX effect is completely shut down. In the case of JP Morgan Chase, the beneficial effect of the reduction in risk indicators is almost totally compensated by the FX effect. Another useful exercise is to identify the reasons why a given bank becomes SIFI for the first time. Taking the example of China Construction Bank, which first became SIFI in 2015, we see that this was due to a significant increase in its risk indicators, and not because of other banks' actions or FX effects.

To give a more global view to the interaction between changes in scores (ΔS_i or $\Delta \widetilde{S}_i$) and changes in risk contributions ($\Delta_{i,i}$ or $\widetilde{\Delta}_{i,i}$), we display in Figure 9 a scatter plots between the change in scores and change in risk indicators for all sample banks. We conduct the analysis sequentially for the BCBS scores (left panels) and the adjusted scores (right panels), as well as for two sample periods (2014-2015 vs. 2015-2016). The pictures obtained for the two types of scores are strikingly different. Indeed, adjusted scores are more strongly related to the changes in risk contribution of each bank, compared to the BCBS scores. The analysis of the correlation coefficients further confirms this visual impression: $\text{corr}(\Delta\widetilde{S}_i, \widetilde{\Delta}_{i,i}) = 0.966 > \text{corr}(\Delta S_i, \Delta_{i,i}) = 0.833$ between 2014 and 2015 and $\text{corr}(\Delta\widetilde{S}_i, \widetilde{\Delta}_{i,i}) = 0.974 > \text{corr}(\Delta S_i, \Delta_{i,i}) = 0.844$ in 2015-2016. Overall, our findings indicate that our adjusted scores are mainly driven by risk indicators directly under the control of the regulated bank and not by factors that are exogenous to the bank, which is in line with the theory of incentives of Laffont and Tirole (1993).

7 Conclusion

Within less than ten years, the systemic-risk area has evolved 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.

Using novel data on various facets of systemic risk, we show that the official methodology currently used to identify SIFIs and compute their regulatory capital is biased. The current scoring methodology is shown to distort incentives for regulated banks to lower systemic risk and to fully internalize the negative externalities created by the SIFIs. For instance, banks have stronger incentives to reduce risk-taking in an area where there is greater cross-sectional variability because such risk indicator mechanically carries more weight in the final score. Alternatively, a bank has no incentives to reduce risk once the cap is exceeded. The current scoring methodology also allows non-Eurozone banks to increase systemic-risk taking when the Euro appreciates, without altering their regulatory capital. We show that the documented biases lead to severe misallocations of capital among banks and is easy to fix.

Overall, our study points toward the importance of having regulatory tools that 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, and potentially to improve, regulatory tools. We strongly believe that making systemic-risk regulation more transparent would enrich the regulatory debate and ultimately foster financial stability.

While the focus in this paper is on banking regulation, our findings also resonate with the current debate on the regulation of systemic risk in the insurance industry and the asset management industry (Wall Street Journal (2016)). Indeed, the current process for identifying systemically-important insurance companies or asset managers is very much inspired by the one developed for banks and, as such, shares some of its shortcomings.

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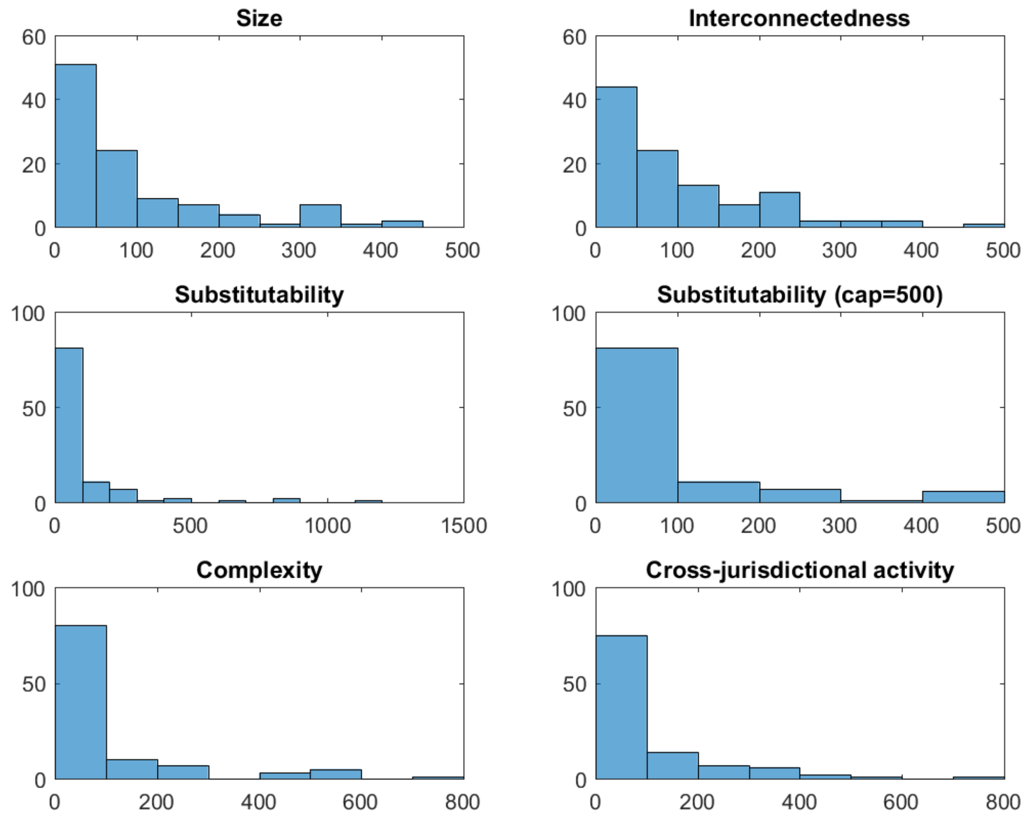

Figure 1: Distributions of the systemic-risk categories (year 2015)

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

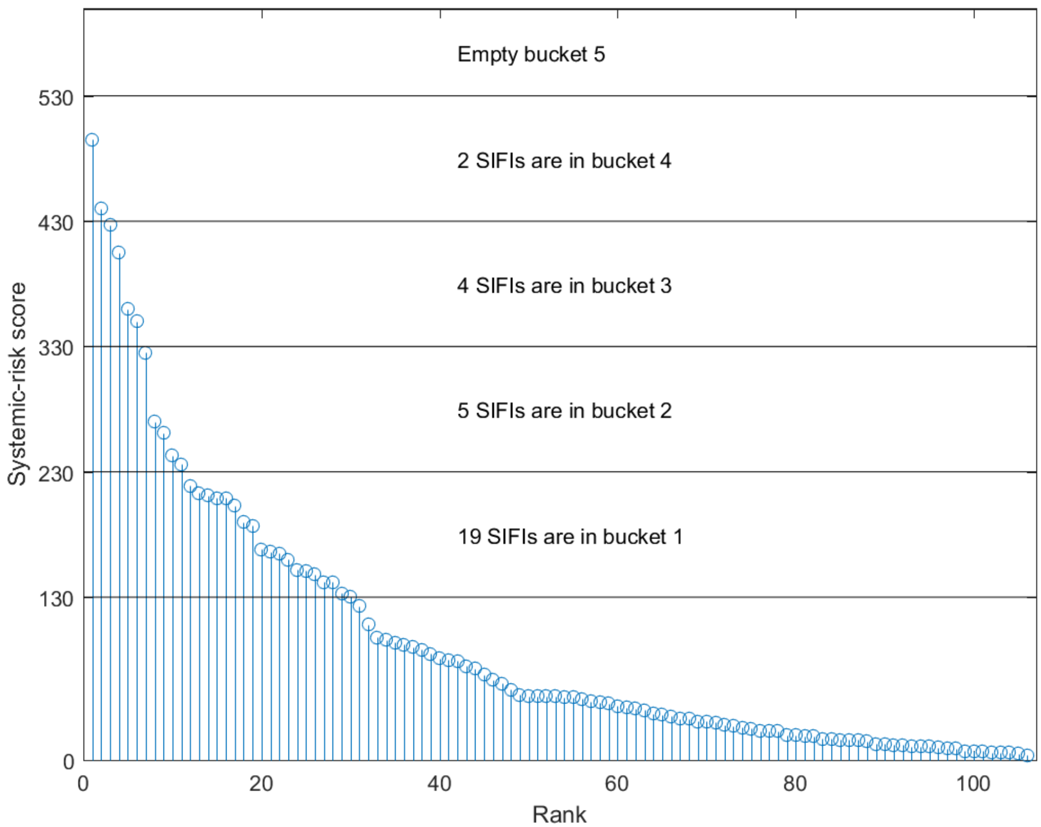

Figure 2: SIFI ranking based on the BCBS methodology (year 2015)

This figure displays the systemic-risk scores based on the BCBS methodology for the 106 sample banks as of 2015 in descending order. Each circle represents a bank and the horizontal lines denote the cut-off values used by the BCBS to allocate banks into systemic-risk buckets. Cut-off values are 130, 230, 330, 430, and 530.

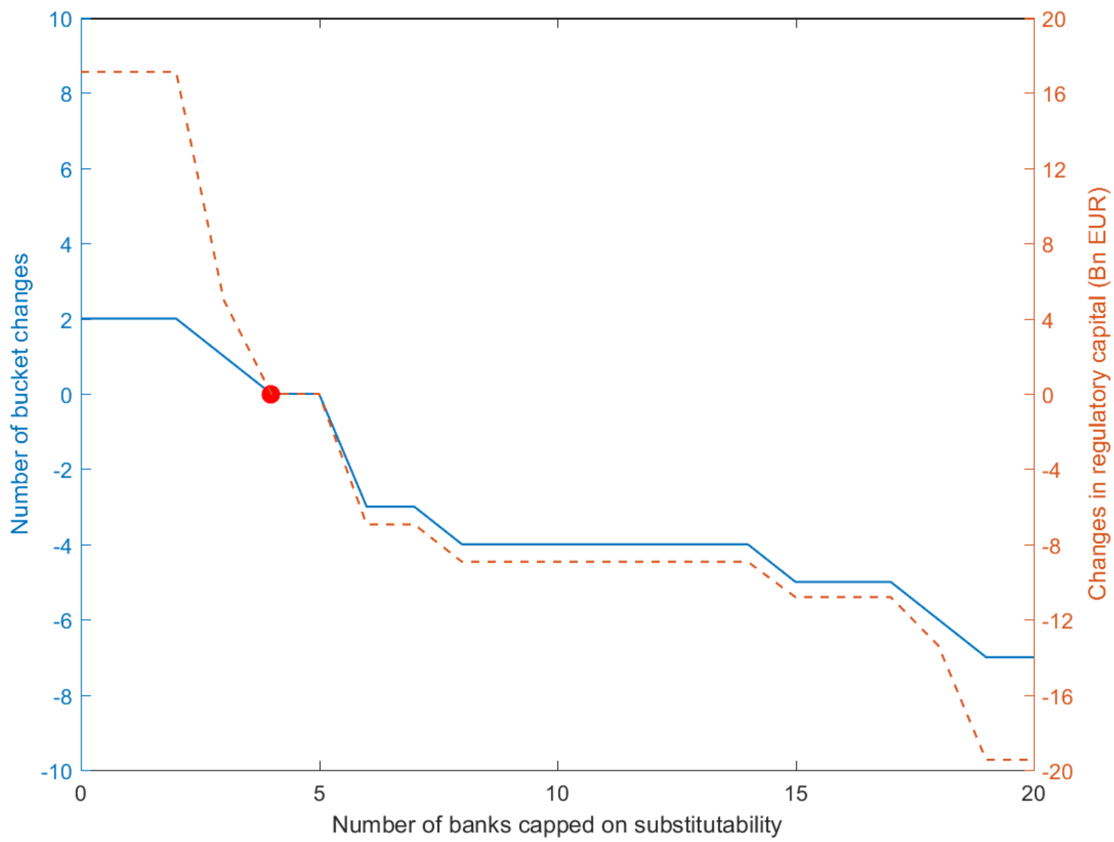

Figure 3: Bucket and capital changes with a cap on substitutability (year 2015)

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 dashed line, right y-axis) when the number of banks affected by the cap on substitutability gradually changes from 0 to 20. The reference point (red dot) is the situation as of 2015 in which four banks are capped at 5% on the substitutability category.

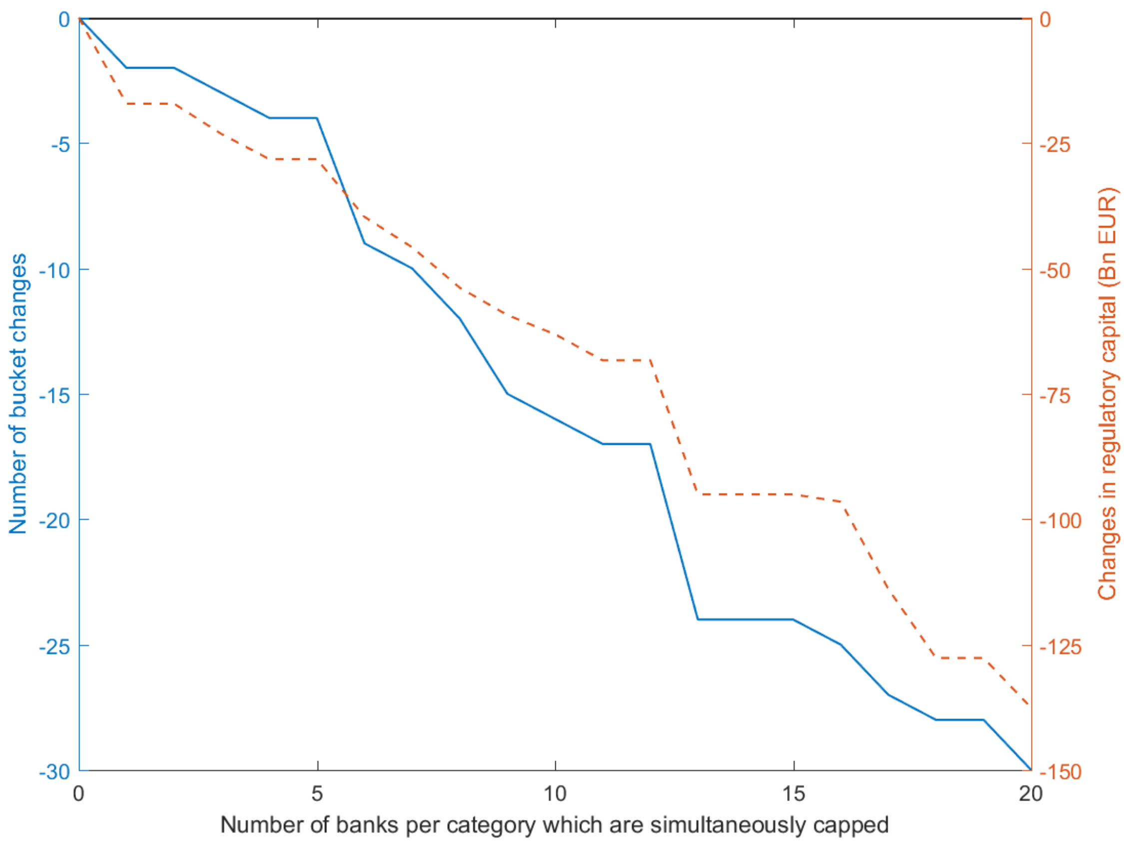

Figure 4: Bucket and capital changes with a cap on all categories (year 2015)

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 dashed 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.

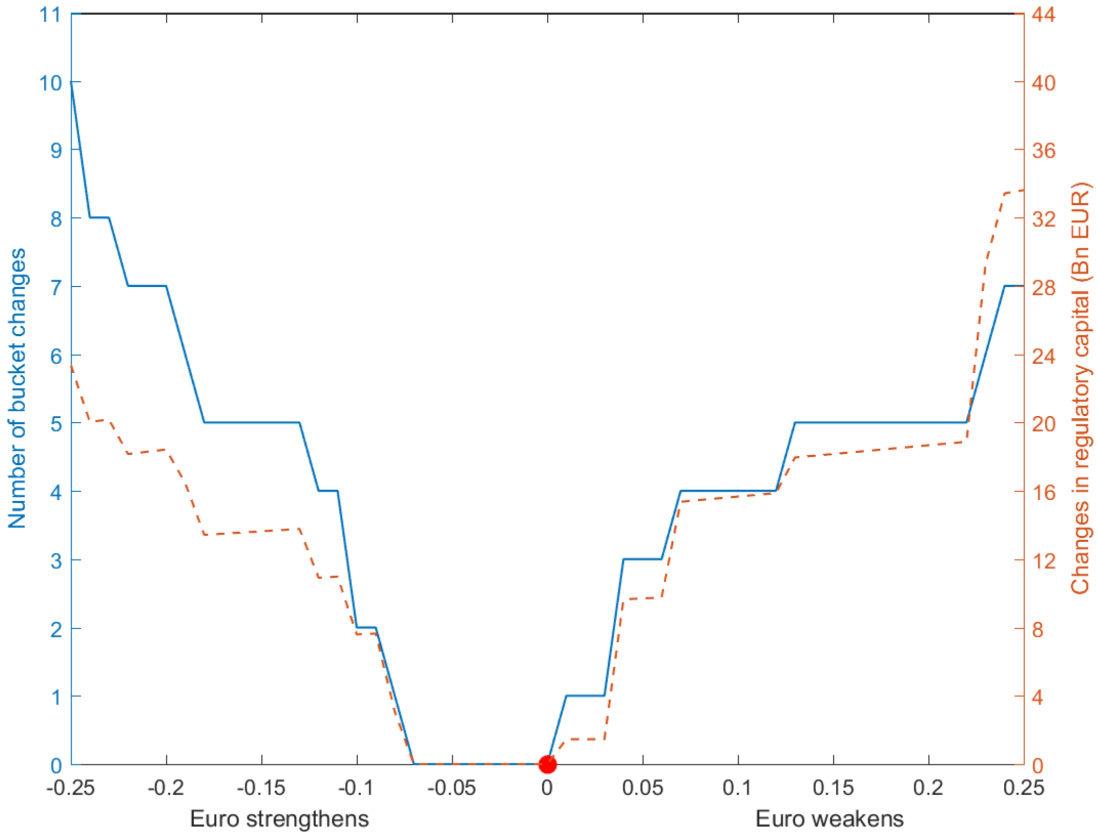

Figure 5: Bucket and capital changes when exchange rates vary (year 2015)

This figure reports the absolute number of bucket changes (blue line, left y-axis) and its equivalent amount in EUR billion of absolute changes in aggregate regulatory capital (red dashed line, right y-axis) when all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2015.

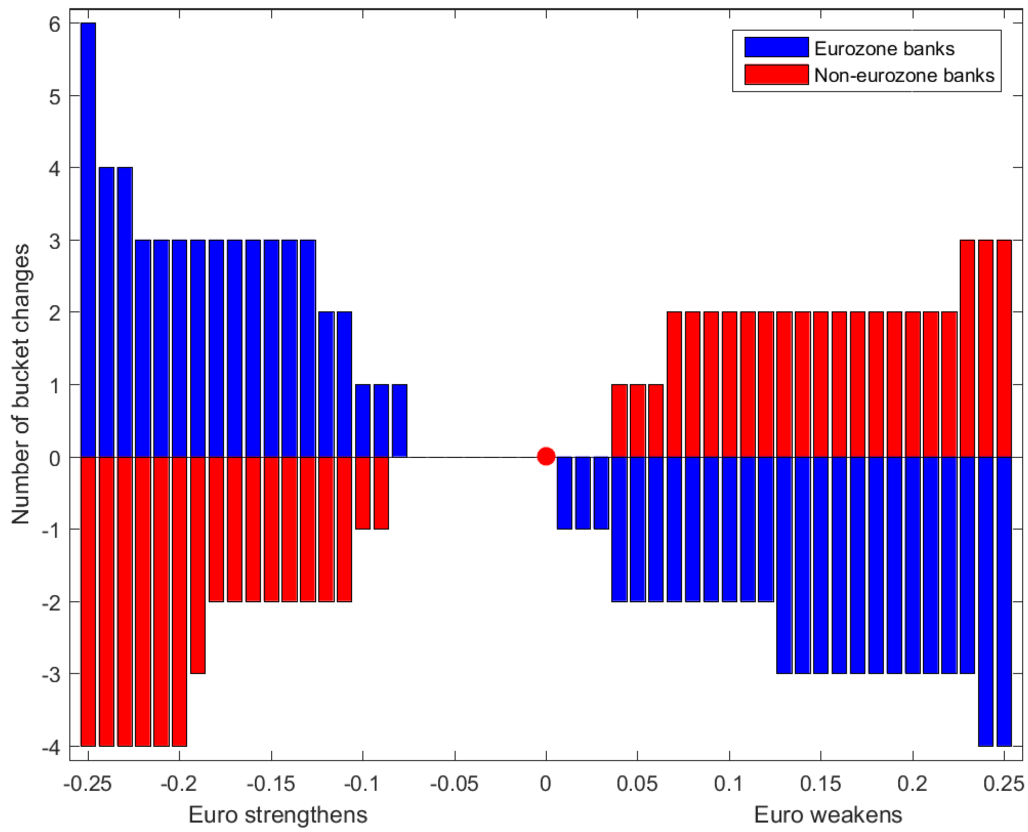

Figure 6: Bucket changes decomposition when exchange rates vary (year 2015)

This figure reports the number of bucket downgrade (blue bars) and the number of bucket upgrade (red bars) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2015.

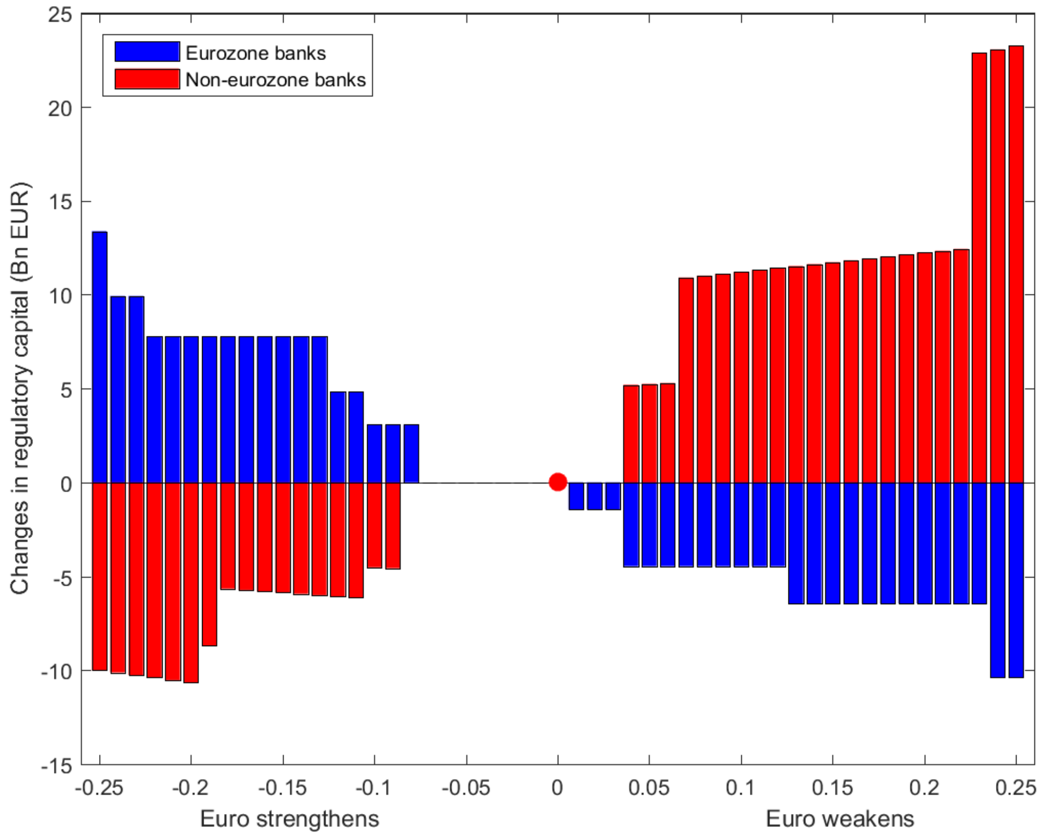

Figure 7: Capital changes decomposition when exchange rates vary (year 2015)

This figure reports the aggregate decrease in regulatory capital (blue bars) and the aggregate increase in regulatory capital (red bars) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2015.

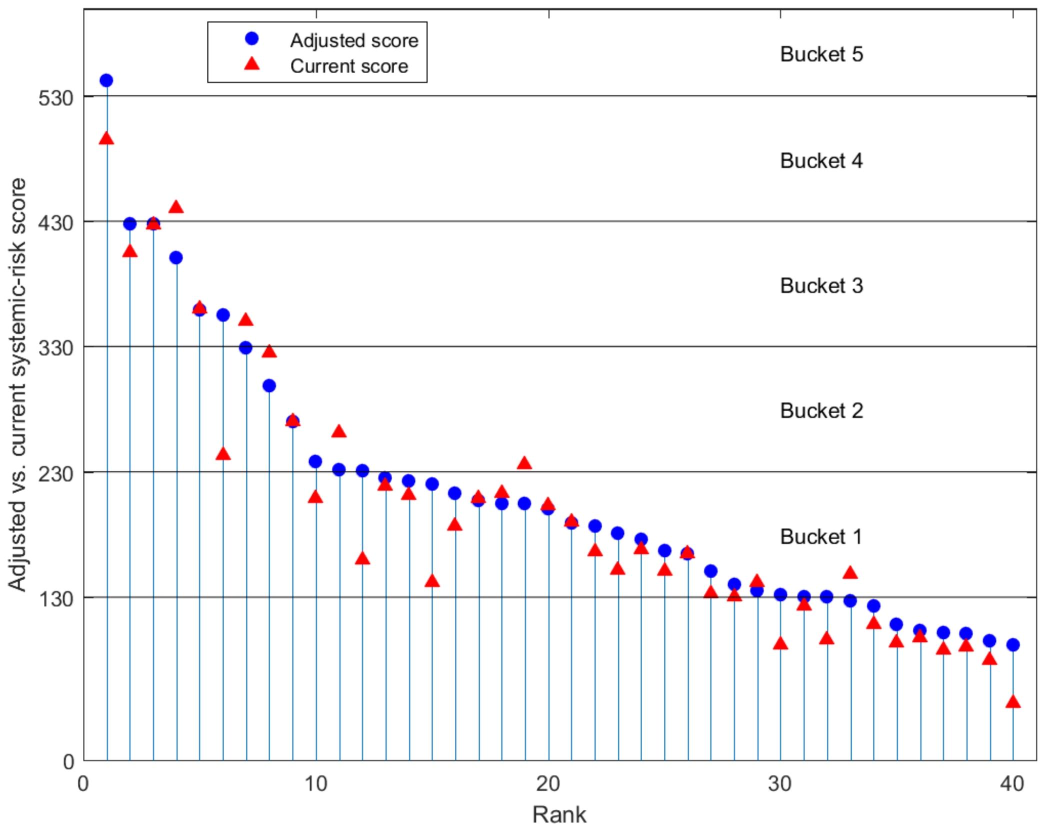

Figure 8: SIFI ranking based on adjusted scores (year 2015)

This figure displays the volatility and FX-adjusted systemic-risk scores (blue circles) in descending order and the corresponding BCBS systemic-risk scores as of 2015 (red triangles). The horizontal lines denote the cut-off values used to allocate banks into systemic-risk buckets. Cut-off values are 130, 230, 330, 430, and 530.

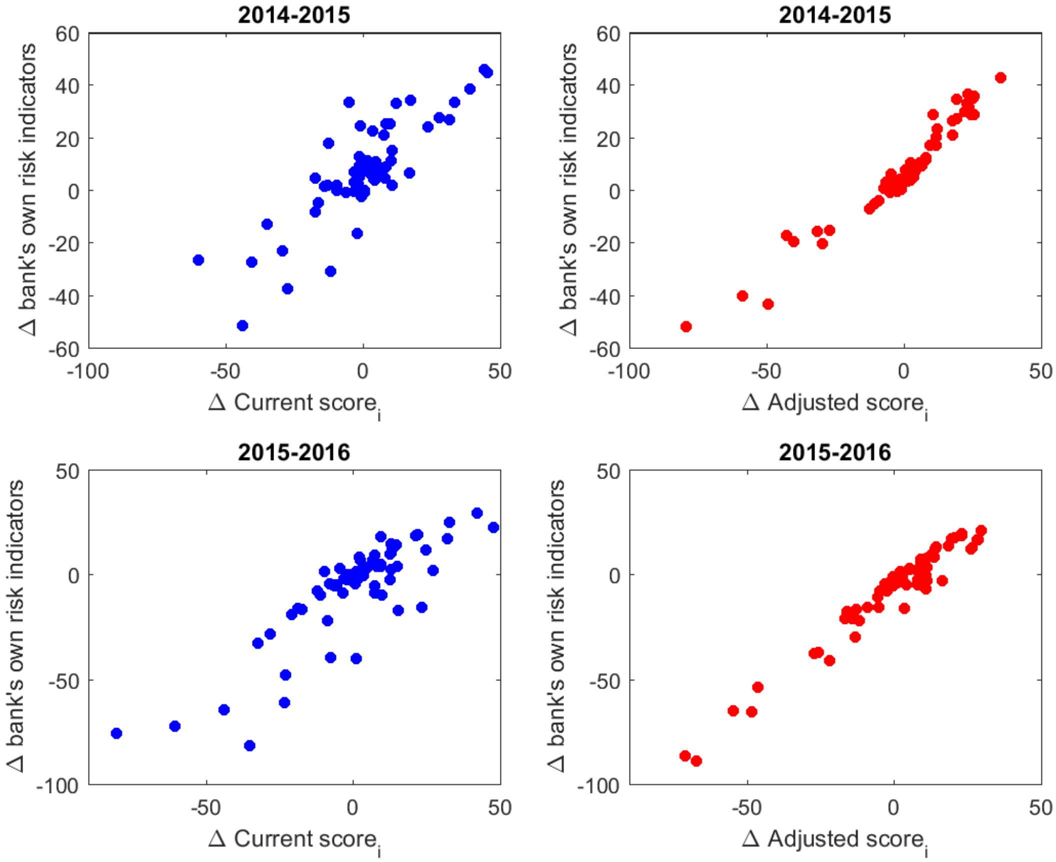

Figure 9: Effects of bank's own risk indicators on its systemic-risk score

The scatter plots display the changes in bank's own risk indicators ($\Delta_{i,i}$ for the two left panels and $\widetilde{\Delta}_{i,i}$ for the right two panels) and the changes in systemic-risk scores (current score ΔS_i for the left two panels and adjusted score $\Delta \widetilde{S}_i$ for the right two panels). Each dot represents a separate bank. The upper (respectively, lower) two panels report changes from 2014 to 2015 (from 2015 to 2016) for 64 (66) banks.

Table 1: Summary statistics (year 2015)

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 volatility and foreign exchange-adjusted systemic-risk scores) 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	99	40	151	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	2.3	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
Current score	95	50	107	1.7	3	495
Adjusted score	102	57	110	1.7	4	541

Table 2: List of systemically important financial institutions (year 2014)

This table reports the risk-bucket number with its respective Financial Stability Board (FSB) cut-off scores (Column 1), the additional capital requirement expressed as a percentage of risk-weighted assets (Column 2), the identity of the systemically important banks as identified by the FSB in descending order (Column 3), by the systemic-risk scores based on standardized categories in descending order (Column 4), and by the adjusted score in descending order (Column 5), 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 are provided by the BCBS.

Bucket	Additional Capital	Current Score (30)	Volatility-Adjusted Score (29)	Volatility and FX-Adjusted Score (31)
5 [530-629]	3.5%	Empty	JP Morgan Chase (564)	JP Morgan Chase (589)
4 [430-529]	2.5%	JP Morgan Chase* (505/646)	HSBC (467)	HSBC (484)
		HSBC (477)	Citigroup (452)	Citigroup (471)
3 [330-429]	2.0%	Citigroup* (426/494)	Deutsche Bank (401)	Deutsche Bank (421)
		Deutsche Bank* (417/445)	BNP Paribas (394)	BNP Paribas (414)
		BNP Paribas (408)	Barclays (361)	Barclays (364)
		Barclays (385)		Mitsubishi UFJ FG (348)
2 [230-329]	1.5%	Bank of America (305)	Bank of America (294); Mitsubishi UFJ FG (255)	Bank of America (306); Morgan Stanley (256)
		Credit Suisse (264)	Morgan Stanley (247)	Credit Suisse (254)
		Morgan Stanley (259)	Credit Suisse (243)	Groupe Crédit Agricole (243)
		Goldman Sachs (247)	Royal Bank of Scotland (235)	Goldman Sachs (239)
		Mitsubishi UFJ FG (242)	Groupe Crédit Agricole (232)	Royal Bank of Scotland (237)
		Royal Bank of Scotland (239)	Goldman Sachs (230)	Société Générale (231)
1 [130-229]	1.0%	Société Générale (226)	Société Générale (220)	Santander (218)
		Groupe Crédit Agricole (218)	ICBC (212)	Sumitomo Mitsui FG (212)
		UBS (201)	Santander (208)	Mizuho FG (208)
		Santander (196)	Bank of China (203)	ICBC (205)
		Bank of China (182)	UBS (190)	UBS (198)
		ICBC (181)	Wells Fargo (176)	Bank of China (197)
		Wells Fargo (172)	Bank of New York Mellon (157)	Wells Fargo (184)
		Mizuho FG (152)	Unicredit Group (157)	Unicredit Group (165)
		Bank of New York Mellon* (150/209)	Sumitomo Mitsui FG (155)	Bank of New York Mellon (164)
		Unicredit Group (148)	Groupe BPCE (154)	Groupe BPCE (162)
		State Street* (148/162)	Mizuho FG (152)	ING Bank (158)
		ING Bank (145)	ING Bank (151)	China Construction Bank (144)
		Sumitomo Mitsui FG (142)	China Construction Bank (149)	Agricultural Bank of China (143)
		Groupe BPCE (141)	Agricultural Bank of China (147)	Commerzbank(137)
		Standard Chartered (134)	Commerzbank(131)	Standard Chartered (136)
		Agricultural Bank of China (133)	Standard Chartered (131)	Nomura Holdings (136)
		Nordea$^{\bullet}$ (121)		Nordea (132)
		BBVA$^{\bullet}$ (93)		

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

This table reports the risk-bucket number with its respective Financial Stability Board (FSB) cut-off scores (Column 1), the additional capital requirement expressed as a percentage of risk-weighted assets (Column 2), the identity of the systemically important banks as identified by the FSB in descending order (Column 3), by the systemic-risk scores based on standardized categories in descending order (Column 4), and by the adjusted score in descending order (Column 5), 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 are provided by the BCBS.

Bucket	Additional Capital	Current Score (30)	Volatility-Adjusted Score (30)	Volatility and FX-Adjusted Score (32)
5 [530-629]	3.5%	Empty	JP Morgan Chase (565)	JP Morgan Chase (542)
4 [430-529]	2.5%	JP Morgan Chase* (495/629)	Citigroup (447)	
		HSBC (440)		
3 [330-429]	2.0%	Citigroup* (427/495)	HSBC (426)	Citigroup (428); BNP Paribas (428)
		BNP Paribas (405)	BNP Paribas (395)	HSBC (401)
		Deutsche Bank (360)	Barclays (339)	Deutsche Bank (359)
		Barclays (350)	Deutsche Bank (331)	Mitsubishi UFJ FG (355)
2 [230-329]	1.5%	Bank of America (325)	Bank of America (315)	Barclays (329); Bank of America (299)
		Credit Suisse (270)	Credit Suisse (255)	Credit Suisse (270)
		Goldman Sachs (261)	Mitsubishi UFJ FG (250)	Santander (238)
		Mitsubishi UFJ FG (243)	ICBC (247)	Goldman Sachs (232)
		Morgan Stanley (236)	Goldman Sachs (245)	Mizuho FG (231)
1 [130-229]	1.0%	ICBC (219)	Bank of China (228)	ICBC (225); Société Générale (223)
		Royal Bank of Scotland (213)	Santander (221)	Sumitomo Mitsui FG (220)
		Société Générale (211)	Morgan Stanley (217)	Groupe Crédit Agricole (213)
		Bank of China (209)	Royal Bank of Scotland (211)	Bank of China (207)
		Santander (209)	Wells Fargo (209)	Royal Bank of Scotland (205)
		Wells Fargo (203)	Société Générale (205)	Morgan Stanley (205)
		UBS (190)	Groupe Crédit Agricole (196)	Wells Fargo (201)
		Groupe Crédit Agricole (187)	China Construction Bank (194)	UBS (189)
		China Construction Bank (168)	Agricultural Bank of China (180)	Unicredit Group (187)
		Unicredit Group (166)	UBS (179)	Groupe BPCE (181)
		Agricultural Bank of China (165)	Unicredit Group (174)	China Construction Bank (176)
		Mizuho FG (160)	Bank of New York Mellon (170)	Bank of New York Mellon (167)
		Groupe BPCE (152)	Groupe BPCE (167)	Agricultural Bank of China (165)
		Bank of New York Mellon* (151/225)	Mizuho FG (162)	ING Bank (151)
		State Street* (148/168)	Sumitomo Mitsui FG (156)	Nordea (140)
		Sumitomo Mitsui FG (142)	Standard Chartered (144)	Standard Chartered (135)
		Standard Chartered (142)	ING Bank (140)	The Norinchukin Bank (132)
		ING Bank (133)	Nordea (130)	Royal Bank of Canada (130)
		Nordea (130)	State Street (130)	Nomura Holdings (130)

Table 4: List of systemically important financial institutions (year 2016)

This table reports the risk-bucket number with its respective Financial Stability Board (FSB) cut-off scores (Column 1), the additional capital requirement expressed as a percentage of risk-weighted assets (Column 2), the identity of the systemically important banks as identified by the FSB in descending order (Column 3), by the systemic-risk scores based on standardized categories in descending order (Column 4), and by the adjusted score in descending order (Column 5), as of November 2016. Systemic-risk scores of all banks are reported in parenthesis. A $\ast$ 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 are provided by the BCBS.

Bucket	Additional Capital	Current Score (30)	Volatility-Adjusted Score (29)	Volatility and FX-Adjusted Score (31)
5 [530-629]	3.5%	Empty	Empty	Empty
4 [430-529]	2.5%	JP Morgan Chase* (464/583) Citigroup* (430/495)	JP Morgan Chase (523) Citigroup (450)	JP Morgan Chase (451)
3 [330-429]	2.0%	HSBC (417) Deutsche Bank (358) Bank of America (346) BNP Paribas (330)	HSBC (401) Bank of America (334)	Citigroup (386); Deutsche Bank (357) Mitsubishi UFJ FG (347) BNP Paribas (340) HSBC (337)
2 [230-329]	1.5%	Barclays (308) Credit Suisse (285) Mitsubishi UFJ FG (270) Goldman Sachs (253) ICBC (252) Wells Fargo (250)	Deutsche Bank (329); BNP Paribas (315) Barclays (292); Credit Suisse (280) ICBC (275); Mitsubishi UFJ FG (272) Wells Fargo (249) Goldman Sachs (244) Bank of China (242)	Bank of America (286) Barclays (268) Credit Suisse (267) ICBC (239)
1 [130-229]	1.0%	Bank of China (224) Morgan Stanley (213) China Construction Bank (210) Société Générale (210) Santander (202) UBS (199) Agricultural Bank of China (191) Groupe Crédit Agricole (168) Mizuho FG (168) Bank of New York Mellon* (161/227) Royal Bank of Scotland (155) Sumitomo Mitsui FG (155) Unicredit Group (149) State Street* (149/172) ING Bank (141) Standard Chartered (134) Groupe BPCE$^{\bullet}$ (126) Nordea$^{\bullet}$ (123)	China Construction Bank (225) Agricultural Bank of China (213) Santander (207) Société Générale (203) Morgan Stanley (200) UBS (193) Bank of New York Mellon (180) Groupe Crédit Agricole (176) Sumitomo Mitsui FG (169) Mizuho FG (167) Unicredit Group (157) Royal Bank of Scotland (156) ING Bank (150) Groupe BPCE (134) Standard Chartered (134) State Street (134)	Société Générale (221); Santander (220) Sumitomo Mitsui FG (216); Wells Fargo (215) Mizuho FG (214); Goldman Sachs (208) Bank of China (206) China Construction Bank (195) Groupe Crédit Agricole (192) Agricultural Bank of China (185) UBS (184) Morgan Stanley (170) Unicredit Group (169) Bank of New York Mellon (160) ING Bank (160) Groupe BPCE (147) Royal Bank of Scotland (143) The Norinchukin Bank (133) Nomura Holdings (132) Nordea (131) Royal Bank of Canada (130)

Table 5: Decomposition of the changes in systemic-risk scores between 2014 and 2015

This table reports the decomposition of the changes in the two systemic-risk scores between 2014 and 2015 (ΔS_i in Column 3 and $\Delta \widetilde{S}_i$ in Column 7) due to changes in their own risk indicators ($\Delta_{i,i}$ in Column 4 and $\widetilde{\Delta}_{i,i}$ in Column 8), the changes in risk indicators of all other banks ($\Delta_{i,j}$ in Column 5 and $\widetilde{\Delta}_{i,j}$ in Column 9), and the changes in the exchange rates ($\Delta_{i,e}$ in Column 6). Values are expressed in basis points.

		BCBS				Adjusted		
Bank name	Country	ΔScore	Firm	Other	FX	ΔScore	Firm	Other
Bank of Montreal	CAN	2.52	6.57	-3.16	-0.88	2.93	6.72	-3.79
Bank of Nova Scotia	CAN	-6.33	-0.89	-4.36	-1.08	-10.58	-5.43	-5.15
CIBC	CAN	-1.59	1.13	-1.90	-0.82	-0.91	1.20	-2.11
Royal Bank of Canada	CAN	-1.45	9.03	-8.00	-2.48	2.56	10.44	-7.88
Toronto Dominion Canada Trust	CAN	10.59	15.11	-3.46	-1.06	11.91	17.03	-5.12
Agricultural Bank of China	CHI	33.49	33.38	-6.76	6.88	23.86	31.23	-7.37
Bank of China	CHI	27.77	27.44	-9.23	9.56	12.22	23.30	-11.08
Bank of Communications	CHI	10.28	11.24	-4.39	3.43	5.66	10.48	-4.81
China Construction Bank	CHI	45.40	44.71	-6.26	6.95	35.17	42.84	-7.68
China Everbright Bank	CHI	44.27	45.94	-3.66	1.98	25.65	28.81	-3.16
China Merchant Bank	CHI	8.38	8.91	-2.90	2.37	5.50	8.71	-3.21
China Minsheng Bank	CHI	6.69	7.13	-2.36	1.92	3.63	6.19	-2.55
Citic	CHI	5.89	6.82	-2.95	2.03	2.95	5.96	-3.01
Hua Xia Bank	CHI	3.76	4.12	-1.15	0.80	2.39	3.67	-1.28
ICBC	CHI	39.17	38.54	-8.87	9.50	22.78	32.87	-10.09
Industrial Bank	CHI	23.73	23.94	-3.48	3.26	17.89	20.73	-2.84
Ping an Bank	CHI	5.92	6.14	-1.47	1.24	3.44	4.92	-1.48
Danske Bank	DEN	-17.24	-8.26	-4.71	-4.27	-9.26	-3.98	-5.28
BNP Paribas	FRA	-5.22	33.30	-13.89	-24.63	19.20	34.64	-15.44
Crédit Mutuel	FRA	4.71	10.86	-2.50	-3.66	8.17	11.41	-3.24
Groupe BPCE	FRA	9.78	25.31	-6.76	-8.77	22.24	29.83	-7.59
Groupe Crédit Agricole	FRA	-35.03	-13.09	-9.79	-12.16	-27.04	-15.37	-11.66
Sociéte Générale	FRA	-17.42	4.33	-8.28	-13.47	-6.41	2.99	-9.40
Commerzbank	GER	-16.23	-4.79	-4.61	-6.83	-12.53	-7.34	-5.19
Deutsche Bank	GER	-60.03	-26.61	-10.76	-22.65	-58.82	-40.23	-18.59
DZ Bank	GER	-1.48	4.86	-2.62	-3.72	2.05	4.61	-2.56
State Bank of India	IND	4.16	3.93	-0.96	1.19	2.85	4.96	-2.10
Intesa San Paolo	ITA	-1.14	7.44	-3.78	-4.79	3.12	7.62	-4.50
Unicredit	ITA	17.33	34.04	-8.00	-8.72	25.27	34.83	-9.56
Mitsubishi UFG FG	JAP	-0.99	24.44	-10.28	-15.15	10.82	28.74	-17.92
Mizuho FG	JAP	8.46	24.96	-6.41	-10.09	25.54	35.84	-10.30
Nomura Holdings	JAP	-9.57	-0.32	-2.96	-6.29	-4.95	-1.07	-3.88
Sumitomo Mitsui FG	JAP	-1.28	12.68	-5.11	-8.85	11.78	19.90	-8.13
Sumitomo Mitsui Trust Holdings	JAP	-3.12	2.96	-2.38	-3.70	0.08	3.13	-3.05
The Norinchukin Bank	JAP	0.49	8.36	-2.32	-5.55	8.04	12.41	-4.37
ABN AMRO	NET	3.29	8.37	-2.44	-2.64	5.85	8.98	-3.13
ING Bank	NET	-13.06	1.59	-7.07	-7.57	-5.52	3.72	-9.24
Rabobank	NET	1.53	11.15	-5.02	-4.60	0.97	6.70	-5.73
DNB Bank	NOR	-9.49	1.73	-3.26	-7.96	0.68	4.12	-3.44
Sberbank	RUS	-12.67	17.70	-2.30	-28.07	24.45	28.52	-4.06
DBS Bank	SIN	7.41	8.47	-2.25	1.18	6.67	9.30	-2.64
BBVA	SPA	-3.16	6.74	-4.84	-5.07	1.36	7.64	-6.28
Criteria Caixa-Holding	SPA	-3.17	-0.39	-1.32	-1.45	-2.29	-0.48	-1.81
Santander	SPA	12.02	33.04	-10.13	-10.90	23.42	36.45	-13.03

		BCBS				Adjusted		
Bank name	Country	ΔScore	Firm	Other	FX	ΔScore	Firm	Other
Handelsbanken	SWE	-2.07	5.65	-2.47	-5.26	3.73	6.83	-3.10
Nordea	SWE	7.74	21.03	-6.21	-7.08	9.65	16.85	-7.20
SEB	SWE	-9.43	-0.02	-2.84	-6.57	-2.53	0.51	-3.03
Credit Suisse	SWI	3.50	22.58	-9.13	-9.95	17.59	26.26	-8.67
UBS	SWI	-13.85	1.33	-7.64	-7.53	-7.45	0.51	-7.96
Barclays	UK	-40.31	-27.47	-16.97	4.12	-31.52	-15.84	-15.68
HSBC	UK	-44.00	-51.75	-26.41	34.17	-79.16	-51.99	-27.18
Lloyds	UK	-1.66	2.10	-4.97	1.21	-3.11	2.48	-5.59
Royal Bank of Scotland	UK	-29.14	-23.00	-8.73	2.59	-29.59	-20.40	-9.19
Standard Chartered	US	8.20	4.30	-6.68	10.58	0.67	7.62	-6.95
Bank of America	US	17.08	6.39	-11.75	22.44	-4.53	6.13	-10.66
Bank of New York Mellon	US	0.58	-1.02	-2.40	4.00	3.16	9.36	-6.20
Citigroup	US	-2.02	-16.63	-10.81	25.42	-40.07	-19.74	-20.33
Goldman Sachs	US	10.78	1.83	-9.10	18.05	-5.41	1.05	-6.46
JP Morgan Chase	US	-11.74	-31.03	-11.32	30.61	-42.76	-17.21	-25.55
Morgan Stanley	US	-27.46	-37.42	-7.87	17.82	-49.48	-43.45	-6.03
PNC	US	0.69	-0.21	-1.29	2.19	-0.98	0.33	-1.31
State Street	US	-0.74	-2.40	-2.04	3.70	-1.31	4.10	-5.41
US Bancorp	US	4.15	3.69	-2.15	2.61	1.21	3.49	-2.28
Wells Fargo	US	31.62	26.61	-8.40	13.41	19.13	27.09	-7.95

Appendix A

Table A1: Summary statistics (year 2016)

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 volatility and foreign exchange-adjusted systemic-risk scores) in Panel C.

	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
Panel A: Indicators						
1. Total exposures	94	53	97	1.9	7	463
2a. Intra-financial system assets	96	63	98	1.3	1	451
2b. Intra-financial system liabilities	94	55	99	1.2	0	415
2c. Securities outstanding	98	72	88	1.4	0	425
3a. Payments activity	92	33	179	4.1	0	1,160
3b. Assets under custody	92	13	261	4.8	0	1,686
3c. Underwriting activity	88	27	156	2,6	0	730
4a. OTC derivatives	88	8	177	2.5	0	798
4b. Trading and AFS securities	92	43	138	2.7	0	839
4c. Level 3 assets	93	32	153	2.2	0	680
5a. Cross-jurisdictional claims	90	38	133	2.4	0	766
5b. Cross-jurisdictional liabilities	90	32	130	2.1	0	705
Panel B: Categories						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Size	94	53	97	1.9	7	463
2. Interconnectedness	96	65	87	1.3	4	401
3. Substitutability	91	32	168	3.7	0	1,091
3. Substitutability (cap=5%)	79	32	117	2.3	0	500
4. Complexity	91	32	140	2.3	0	709
5. Cross-jurisdictional activity	90	38	130	2.3	0	735
Panel C: Systemic-risk scores						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
Current score	90	48	101	1.7	3	464
Adjusted score	93	59	95	1.5	3	451

Table A2: Summary statistics (year 2014)

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 volatility and foreign exchange-adjusted systemic-risk scores) in Panel C.

Panel A: Indicators						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Total exposures	103	58	101	1.3	7	390
2a. Intra-financial system assets	105	64	116	1.6	1	513
2b. Intra-financial system liabilities	102	61	115	1.9	0	556
2c. Securities outstanding	100	72	92	1.2	1	401
3a. Payments activity	104	34	207	4.0	0	1,259
3b. Assets under custody	107	18	289	4.3	0	1,710
3c. Underwriting activity	105	30	179	2.4	0	820
4a. OTC derivatives	102	11	205	2.3	0	775
4b. Trading and AFS securities	105	34	165	2.8	0	978
4c. Level 3 assets	102	35	161	2.4	0	844
5a. Cross-jurisdictional claims	102	43	140	1.9	0	702
5b. Cross-jurisdictional liabilities	101	42	144	2.4	0	879
Panel B: Categories						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Size	103	58	101	1.3	7	390
2. Interconnectedness	102	74	99	1.5	3	434
3. Substitutability	105	41	191	3.5	0	1,209
3. Substitutability (cap=5%)	89	41	127	2.1	0	500
4. Complexity	103	42	164	2.4	0	864
5. Cross-jurisdictional activity	101	43	141	2.1	0	790
Panel C: Systemic-risk scores						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
Current score	100	57	113	1.8	4	504
Adjusted score	109	67	120	1.8	4	588

Table A3: 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, C, and D reports summary statistics expressed in EUR million, except for skewness, on the 12 systemic-risk indicators for the year 2016, 2015, and 2014, respectively.

Panel A: Composition and weights

Category (and weighting)	Indicator (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 (year 2016)

	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Total exposures	686,520	388,208	707,632	1.9	52,052	3,372,705
2a. Intra-financial system assets	77,352	50,907	79,114	1.3	563	365,308
2b. Intra-financial system liabilities	83,377	48,753	88,373	1.2	0	369,581
2c. Securities outstanding	122,872	90,224	109,697	1.4	0	531,149
3a. Payments activity	20,778,555	7,503,931	40,546,212	4.1	0	262,475,959
3b. Assets under custody	1,179,163	163,892	3,346,443	4.8	0	21,638,368
3c. Underwriting activity	52,643	15,947	93,090	2.6	0	434,236
4a. OTC derivatives	4,880,640	438,477	9,834,728	2.5	0	44,424,146
4b. Trading and AFS securities	30,049	13,944	44,874	2.7	3	272,933
4c. Level 3 assets	5,448	1,901	8,962	2.2	0	39,858
5a. Cross-jurisdictional claims	159,032	66,892	236,468	2.4	0	1,361,007
5b. Cross-jurisdictional liabilities	142,556	51,387	206,927	2.1	0	1,119,133

Panel C: Summary statistics (year 2015)						
	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	30,603	13,266	49,479	2.7	1	266,275
4c. Level 3 assets	6,267	1,797	10,125	2.2	0	41,559
5a. Cross-jurisdictional claims	164,759	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

Panel D: Summary statistics (year 2014)						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Total exposures	680,849	381,697	672,171	1.3	46,124	2,588,320
2a. Intra-financial system assets	80,859	49,145	89,193	1.6	645	396,151
2b. Intra-financial system liabilities	80,224	47,450	90,438	1.9	215	435,011
2c. Securities outstanding	108,634	77,939	99,466	1.2	979	434,339
3a. Payments activity	19,198,387	6,283,745	38,251,843	4.0	0	233,092,909
3b. Assets under custody	1,071,885	180,240	2,891,939	4.3	0	17,105,657
3c. Underwriting activity	47,019	13,615	80,319	2.4	0	368,163
4a. OTC derivatives	6,525,218	686,550	13,118,049	2.3	2,211	49,579,006
4b. Trading and AFS securities	34,630	11,265	54,547	2.8	38	323,634
4c. Level 3 assets	6,090	2,093	9,582	2.4	0	50,257
5a. Cross-jurisdictional claims	160,651	68,104	221,438	1.9	62	1,109,380
5b. Cross-jurisdictional liabilities	141,867	59,343	203,261	2.4	0	1,238,647

Table A4: Correlation among systemic-risk categories

This table reports in Panel A, B and C the Pearson correlation coefficients among the five systemic-risk categories for the year 2016, 2015, and 2014, respectively. The substitutability category is capped at 5%.

Panel A: Year 2016	Size	Interconnectedness	Substitutability (cap=5%)	Complexity	Cross-jurisdictional activity
Size	100%	89%	57%	73%	63%
Interconnectedness	89%	100%	69%	86%	74%
Substitutability (cap=5%)	57%	69%	100%	72%	51%
Complexity	73%	86%	72%	100%	67%
Cross-jurisdictional activity	63%	74%	51%	67%	100%
Average	71%	80%	62%	74%	64%
Panel B: Year 2015	**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%
Panel C: Year 2014	**Size**	**Interconnectedness**	**Substitutability (cap=5%)**	**Complexity**	**Cross-jurisdictional activity**
Size	100%	88%	57%	72%	72%
Interconnectedness	88%	100%	71%	84%	82%
Substitutability (cap=5%)	57%	71%	100%	75%	56%
Complexity	72%	84%	75%	100%	71%
Cross-jurisdictional activity	72%	82%	56%	71%	100%
Average	72%	81%	65%	75%	70%

Table A5: Decomposition of the changes in systemic-risk scores between 2015 and 2016

This table reports the decomposition of the changes in the two systemic-risk scores between 2015 and 2016 (ΔS_i in Column 3 and $\Delta \widetilde{S}_i$ in Column 7) due to changes in their own risk indicators ($\Delta_{i,i}$ in Column 4 and $\widetilde{\Delta}_{i,i}$ in Column 8), the changes in risk indicators of all other banks ($\Delta_{i,j}$ in Column 5 and $\widetilde{\Delta}_{i,j}$ in Column 9), and the changes in the exchange rates ($\Delta_{i,e}$ in Column 6). Values are expressed in basis points.

		BCBS				Adjusted		
Bank name	Country	ΔScore	Firm	Other	FX	ΔScore	Firm	Other
Bank of Nova Scotia	CAN	-4.44	3.03	4.16	-11.62	9.17	4.64	4.52
CIBC	CAN	2.59	6.60	1.99	-6.00	9.56	7.38	2.18
Royal Bank of Canada	CAN	-9.81	1.34	5.17	-16.32	7.61	1.72	5.89
Toronto Dominion Canada Trust	CAN	9.53	17.98	4.94	-13.40	23.09	18.61	4.48
Agricultural Bank of China	CHI	24.77	11.83	12.05	0.89	28.28	16.40	11.88
Bank of China	CHI	14.85	3.82	9.30	1.74	11.05	3.19	7.86
Bank of Communications	CHI	7.98	3.97	3.52	0.50	2.73	-1.24	3.97
China Construction Bank	CHI	42.14	29.01	12.07	1.06	28.41	16.42	11.99
China Everbright Bank	CHI	-32.24	-32.79	0.44	0.11	-16.10	-17.54	1.44
China Guangfa Bank	CHI	7.14	5.94	1.08	0.13	9.02	7.35	1.67
China Merchant Bank	CHI	12.72	9.75	2.63	0.33	11.21	7.74	3.46
China Minsheng Bank	CHI	12.86	10.28	2.30	0.27	12.44	9.06	3.38
Citic	CHI	21.98	18.95	2.76	0.27	20.69	17.30	3.39
Hua Xia Bank	CHI	2.15	1.18	0.87	0.10	2.08	0.97	1.10
ICBS	CHI	32.08	16.89	13.89	1.30	26.19	12.21	13.98
Industrial Bank	CHI	32.84	25.04	7.47	0.33	29.60	20.89	8.71
Ping an Bank	CHI	4.80	3.21	1.41	0.18	5.20	3.04	2.16
Shanghai Pudong	CHI	21.42	18.25	2.83	0.34	23.11	19.54	3.57
Danske Bank	DEN	-6.24	-5.63	3.53	-4.15	-3.02	-6.04	3.02
BNP Paribas	FRA	-80.37	-75.89	18.29	-22.77	-71.05	-86.72	15.67
Crédit Mutuel	FRA	6.67	6.88	3.95	-4.16	13.60	8.14	5.46
Groupe BPCE	FRA	-28.26	-28.27	8.56	-8.54	-26.99	-37.76	10.77
Groupe Crédit Agricole	FRA	-20.74	-19.12	9.37	-11.00	-11.65	-22.05	10.40
Sociéte Générale	FRA	-1.84	-0.06	11.58	-13.36	10.91	-0.59	11.50
Commerzbank	GER	-17.40	-16.48	5.16	-6.08	-14.30	-21.13	6.83
Deutsche Bank	GER	-3.12	-2.24	21.90	-22.78	16.34	-3.12	19.46
DZ Bank	GER	-6.39	-5.58	2.74	-3.56	-0.22	-5.53	5.31
State Bank of India	IND	2.54	0.99	1.37	0.18	2.22	1.20	1.01
Intesa San Paolo	ITA	-5.55	-4.76	3.97	-4.76	1.13	-4.18	5.31
Unicredit	ITA	-18.79	-16.00	6.41	-9.20	-9.00	-15.48	6.48
Mitsubishi UFG FG	JAP	27.17	2.04	13.28	11.85	11.00	-2.79	13.79
Mizuho FG	JAP	7.17	-9.05	8.85	7.37	-5.33	-15.63	10.30
Nomura Holdings	JAP	7.26	-5.21	8.19	4.28	8.00	-2.34	10.34
Sumitomo Mitsui FG	JAP	12.59	-2.47	8.09	6.98	7.90	-4.73	12.63
Sumitomo Mitsui Trust Holdings	JAP	9.52	4.98	2.29	2.25	10.36	7.10	3.27
The Norinchukin Bank	JAP	12.84	2.31	5.89	4.65	8.64	2.22	6.42
Hana Bank	KOR	14.62	14.06	1.05	-0.49	14.20	13.14	1.07
Shinhan	KOR	13.09	12.28	1.39	-0.59	13.88	12.30	1.58
ABN AMRO	NET	0.94	1.47	2.36	-2.89	5.29	2.21	3.09
ING Bank	NET	7.47	9.34	6.01	-7.88	18.57	13.83	4.75
Rabobank	NET	-10.98	-9.74	3.20	-4.45	-4.83	-8.00	3.17
Sberbank	RUS	-12.25	-7.74	2.19	-6.70	-12.83	-16.68	3.85
DBS Bank	SIN	0.93	-0.16	1.88	-0.79	1.36	-0.32	1.68

Bank name	Country	BCBS				Adjusted		
		ΔScore	Firm	Other	FX	ΔScore	Firm	Other
BBVA	SPA	12.97	14.59	3.97	-5.59	19.65	16.93	2.72
Criteria Caixa-Holding	SPA	-1.37	-1.16	1.16	-1.38	-0.05	-1.67	1.62
Santander	SPA	-8.04	-4.50	8.24	-11.77	-5.39	-11.03	5.64
Nordea	SWE	-6.96	-4.93	5.53	-7.55	-1.41	-6.16	4.75
SEB	SWE	-2.11	-2.35	2.12	-1.88	-0.62	-2.97	2.35
Credit Suisse	SWI	15.34	-17.11	19.53	12.92	10.83	-6.99	17.82
UBS	SWI	9.63	-9.96	10.62	8.96	4.30	-4.78	9.08
Barclays	UK	-43.93	-64.81	20.99	-0.11	-48.26	-65.44	17.19
HSBC	UK	-23.28	-61.23	15.15	22.80	-46.31	-53.90	7.59
Lloyds	UK	-3.33	-9.06	5.67	0.06	-2.38	-7.99	5.61
Royal Bank of Scotland	UK	-60.56	-72.46	11.83	0.07	-54.71	-65.22	10.51
Standard Chartered	US	-8.79	-22.18	5.85	7.54	-16.62	-20.86	4.25
Bank of America	US	23.49	-15.69	22.54	16.64	3.63	-16.17	19.80
Bank of New York Mellon	US	9.44	3.74	2.61	3.10	-0.27	-1.07	0.80
Citigroup	US	1.24	-40.18	23.72	17.70	-21.78	-41.15	19.37
Goldman Sachs	US	-7.73	-39.74	19.26	12.75	-13.21	-29.83	16.62
JP Morgan Chase	US	-35.02	-81.46	26.42	20.02	-67.20	-89.13	21.93
Morgan Stanley	US	-22.80	-47.91	14.07	11.05	-25.65	-37.44	11.79
PNC	US	3.51	-0.54	2.42	1.63	1.79	-0.48	2.27
State Street	US	0.80	-4.39	2.57	2.62	-2.96	-4.72	1.76
US Bancorp	US	1.74	-2.00	1.71	2.02	-0.65	-2.56	1.91
Wells Fargo	US	47.60	22.57	13.71	11.31	26.64	12.72	13.92

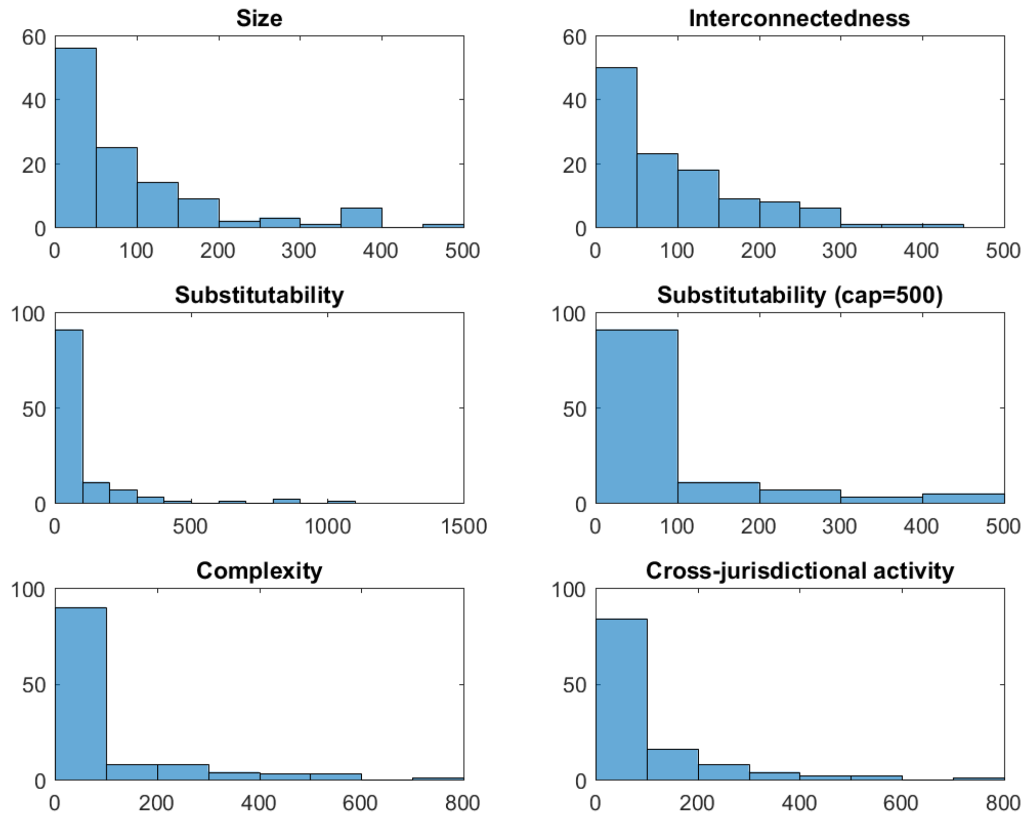

Figure A1: Distributions of the systemic-risk categories (year 2016)

The six histograms show the category score distributions of the 117 sample banks' size, interconnectedness, substitutability, substitutability capped at 5%, complexity, and cross-jurisdictional activity, respectively.

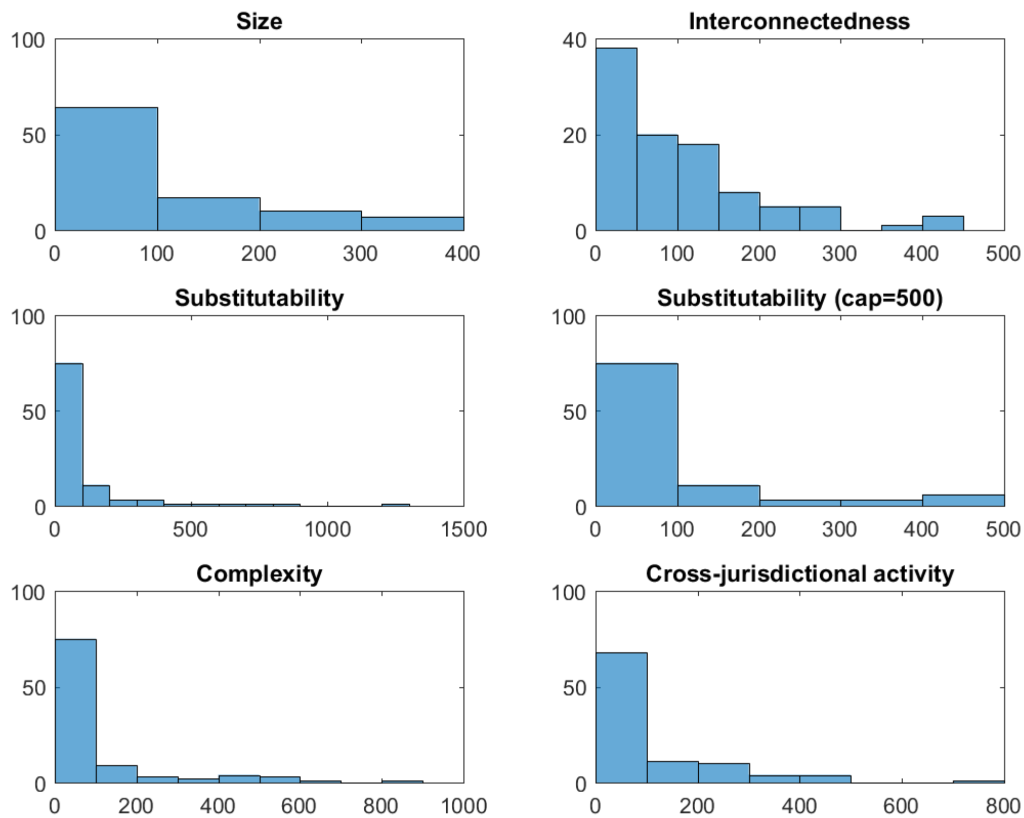

Figure A2: Distributions of the systemic-risk categories (year 2014)

The six histograms show the category score distributions of the 98 sample banks' size, interconnectedness, substitutability, substitutability capped at 5%, complexity, and cross-jurisdictional activity, respectively.

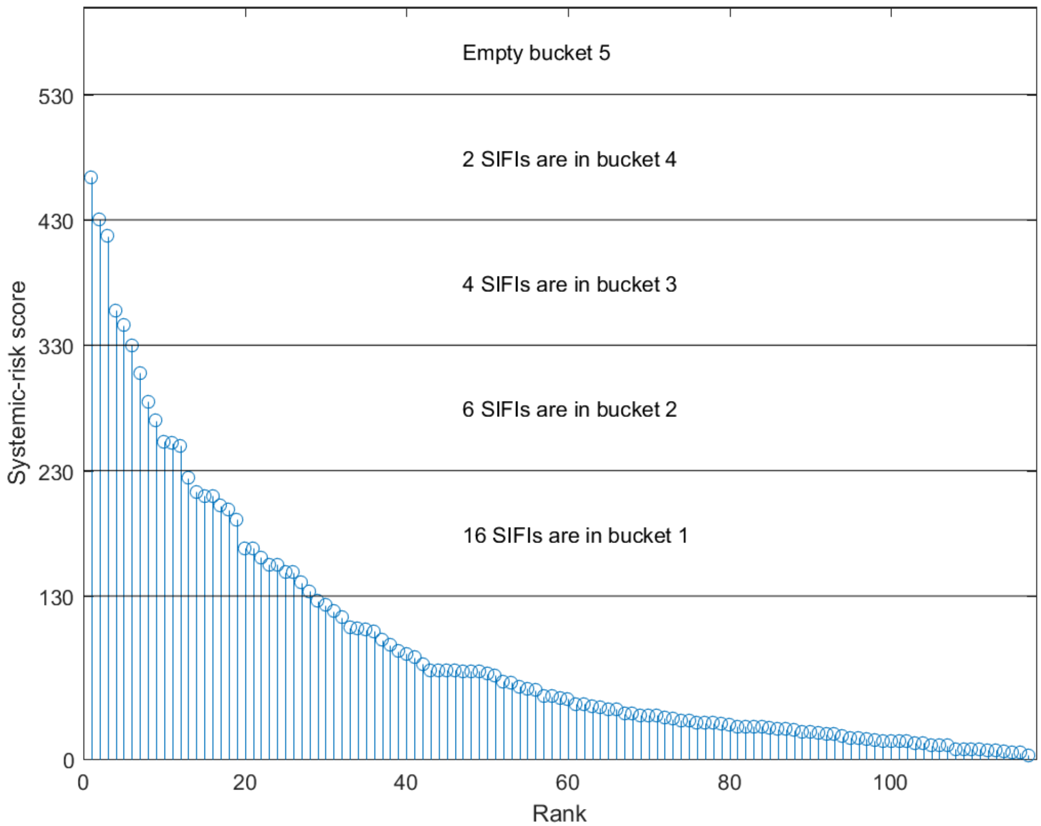

Figure A3: SIFI ranking based on the BCBS methodology (year 2016)

This figure displays the systemic-risk scores based on the BCBS methodology for the 117 sample banks as of 2016 in descending order. Each circle represents a bank and the horizontal lines denote the cut-off values used by the BCBS to allocate banks into systemic-risk buckets. Cut-off values are 130, 230, 330, 430, and 530.

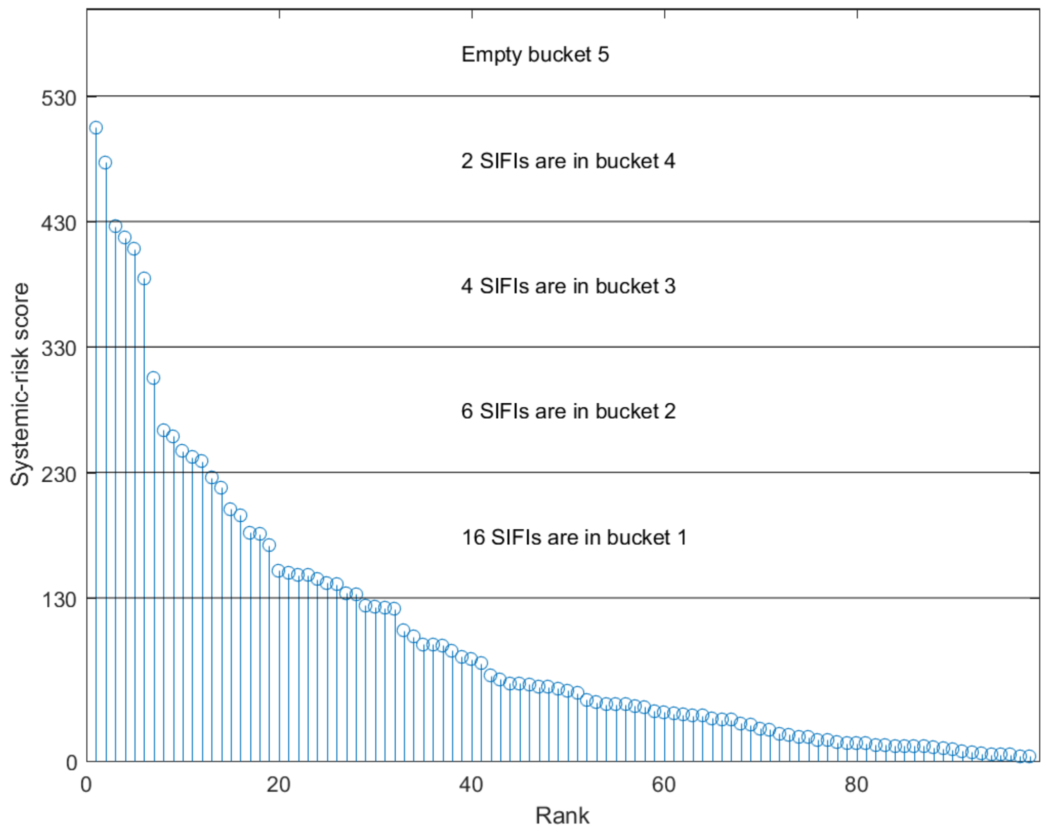

Figure A4: SIFI ranking based on the BCBS methodology (year 2014)

This figure displays the systemic-risk scores based on the BCBS methodology for the 98 sample banks as of 2014 in descending order. Each circle represents a bank and the horizontal lines denote the cut-off values used by the BCBS to allocate banks into systemic-risk buckets. Cut-off values are 130, 230, 330, 430, and 530.

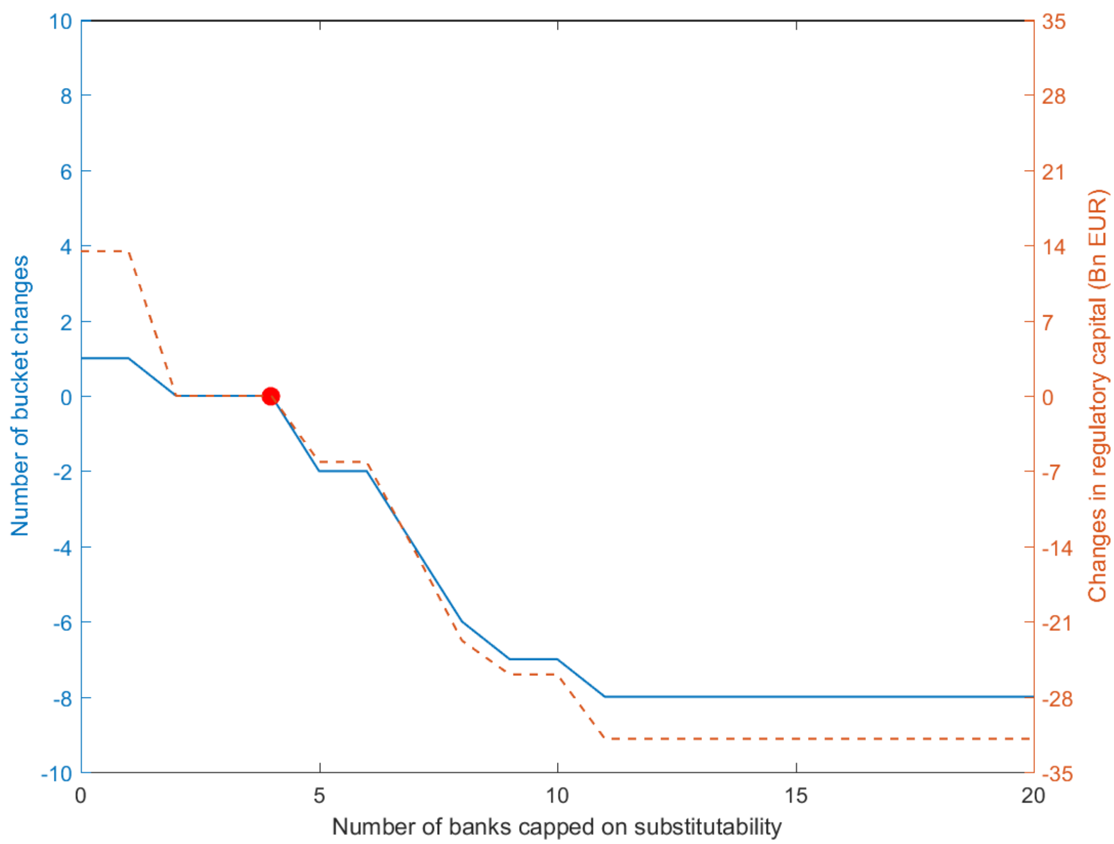

Figure A5: Bucket and capital changes with a cap on substitutability (year 2016)

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 dashed line, right y-axis) when the number of banks affected by the cap on substitutability gradually changes from 0 to 20. The reference point (red dot) is the situation as of 2015 in which four banks are capped at 5% on the substitutability category.

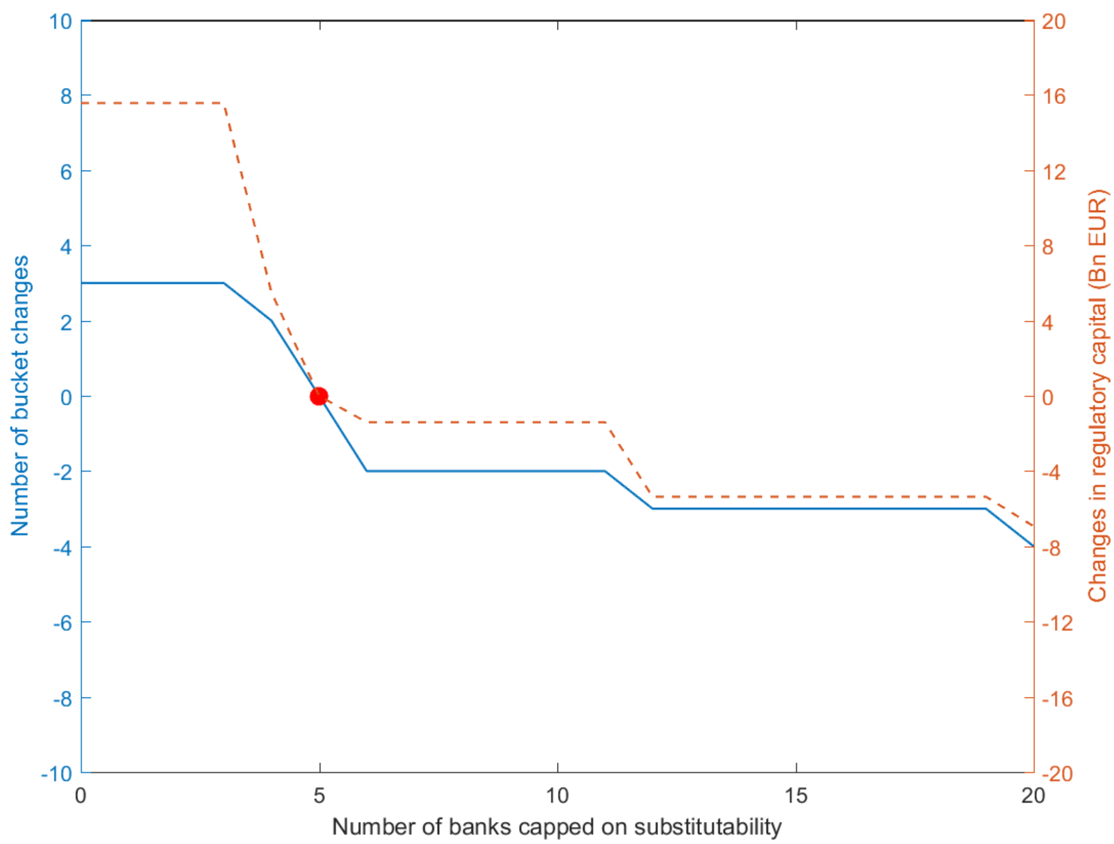

Figure A6: Bucket and capital changes with a cap on substitutability (year 2014)

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 dashed line, right y-axis) when the number of banks affected by the cap on substitutability gradually changes from 0 to 20. The reference point (red dot) is the situation as of 2015 in which five banks are capped at 5% on the substitutability category.

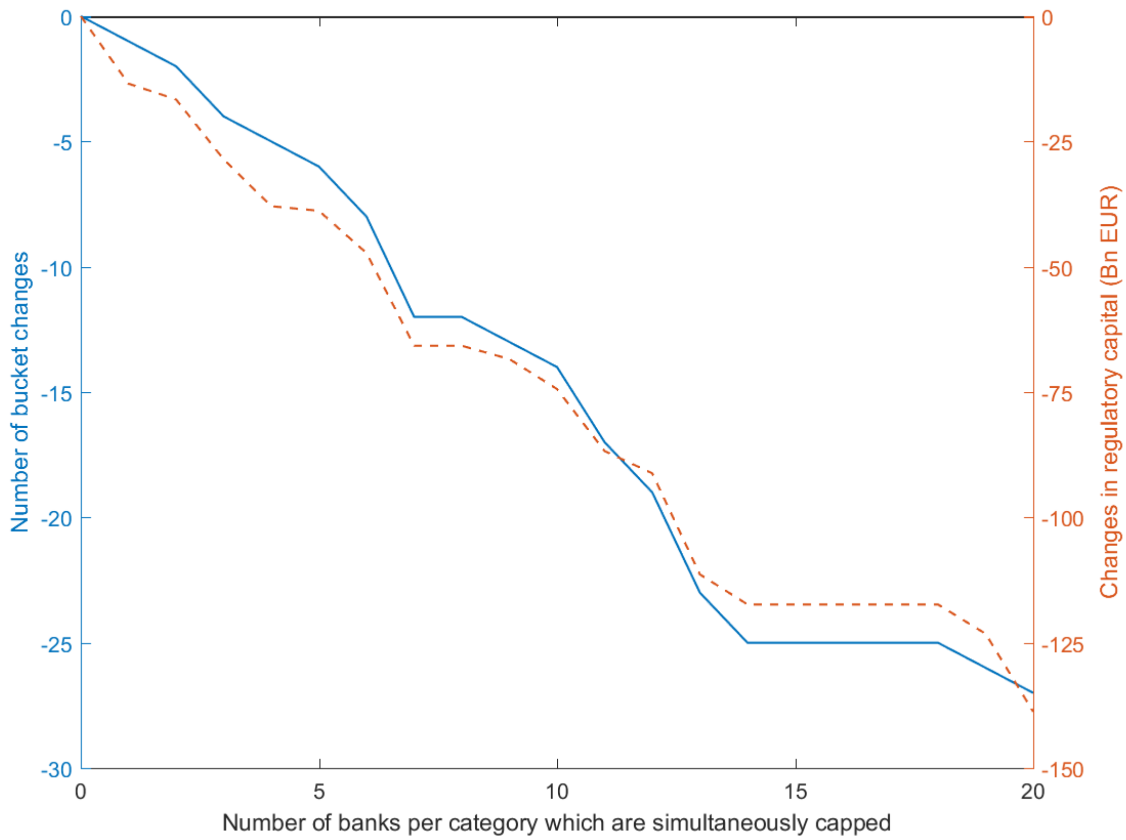

Figure A7: Bucket and capital changes with a cap on all categories (year 2016)

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 dashed 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.

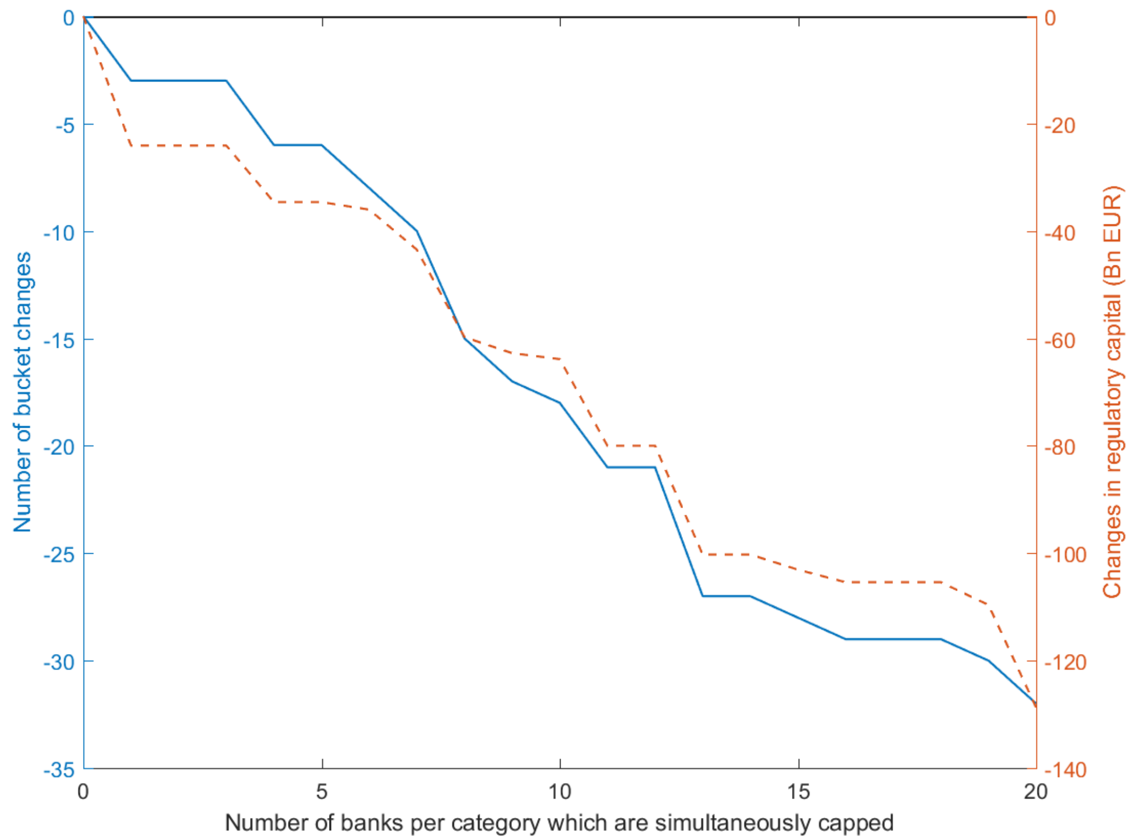

Figure A8: Bucket and capital changes with a cap on all categories (year 2014)

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 dashed 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.

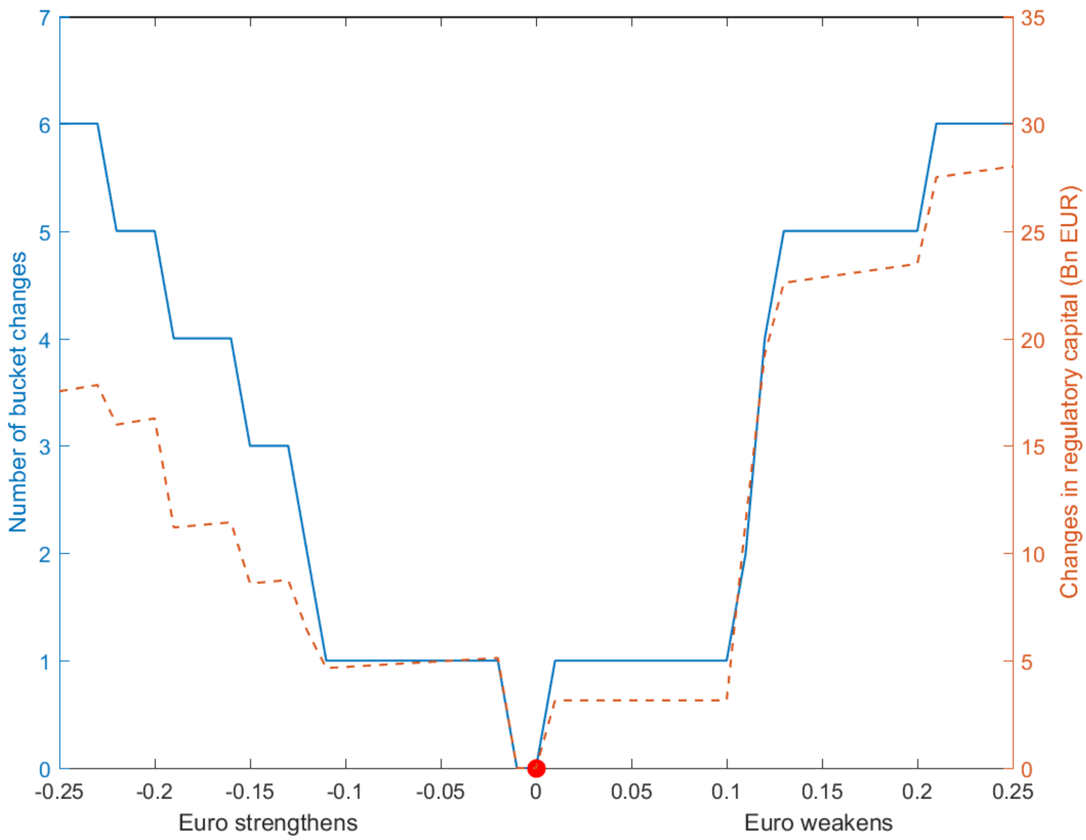

Figure A9: Bucket and capital changes when exchange rates vary (year 2016)

This figure reports the absolute number of bucket changes (blue line, left y-axis) and its equivalent amount in EUR billion of absolute changes in aggregate regulatory capital (red dashed line, right y-axis) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2016.

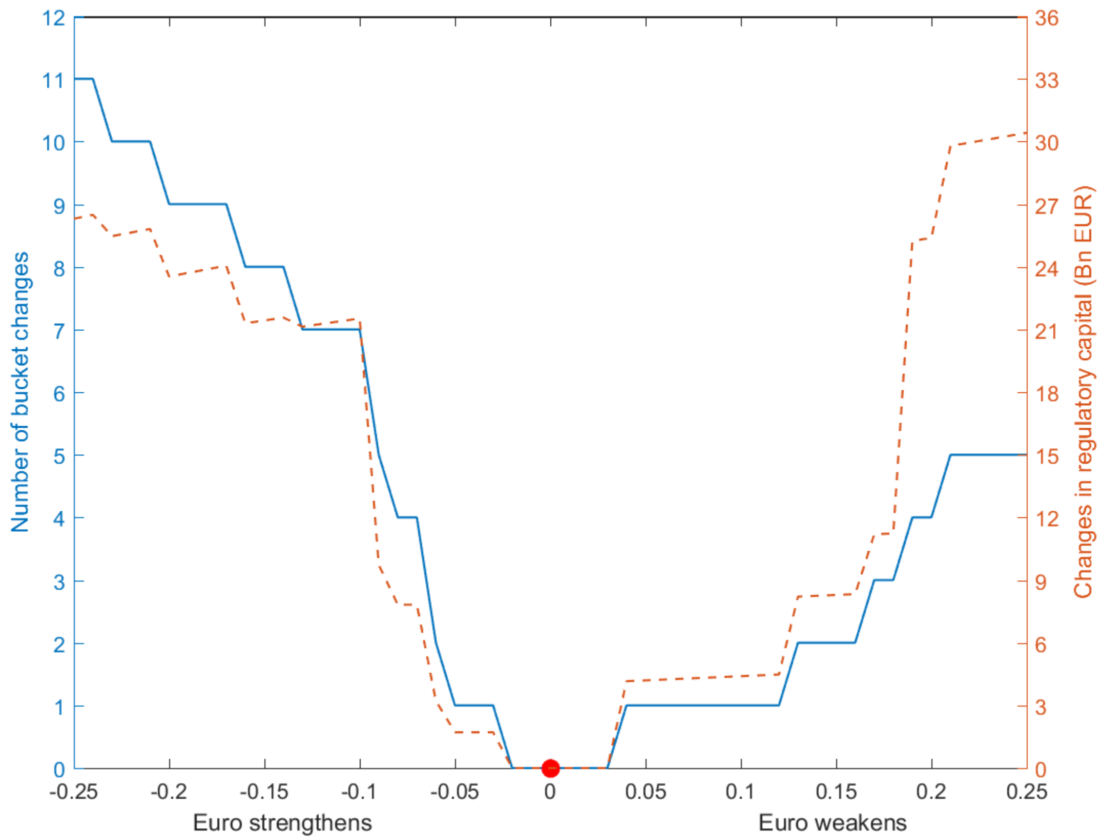

Figure A10: Bucket and capital changes when exchange rates vary (year 2014)

This figure reports the absolute number of bucket changes (blue line, left y-axis) and its equivalent amount in EUR billion of absolute changes in aggregate regulatory capital (red dashed line, right y-axis) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2014.

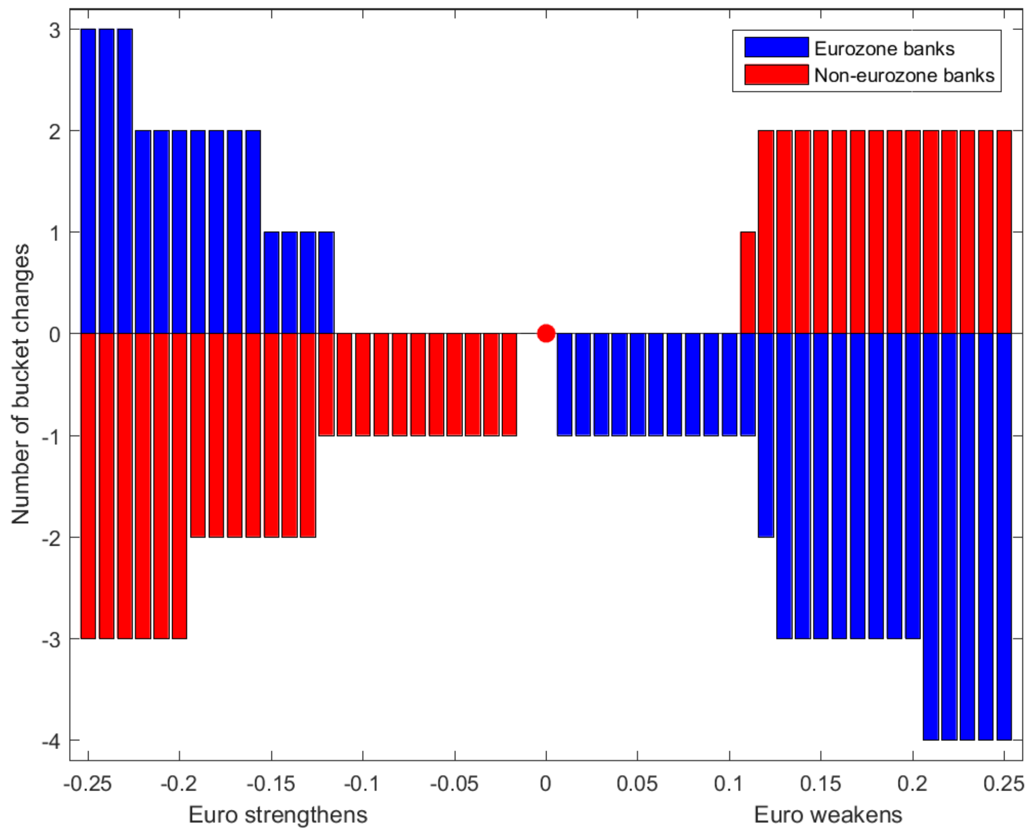

Figure A11: Bucket changes decomposition when exchange rates vary (year 2016)

This figure reports the number of bucket downgrade (blue bars) and the number of bucket upgrade (red bars) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2016.

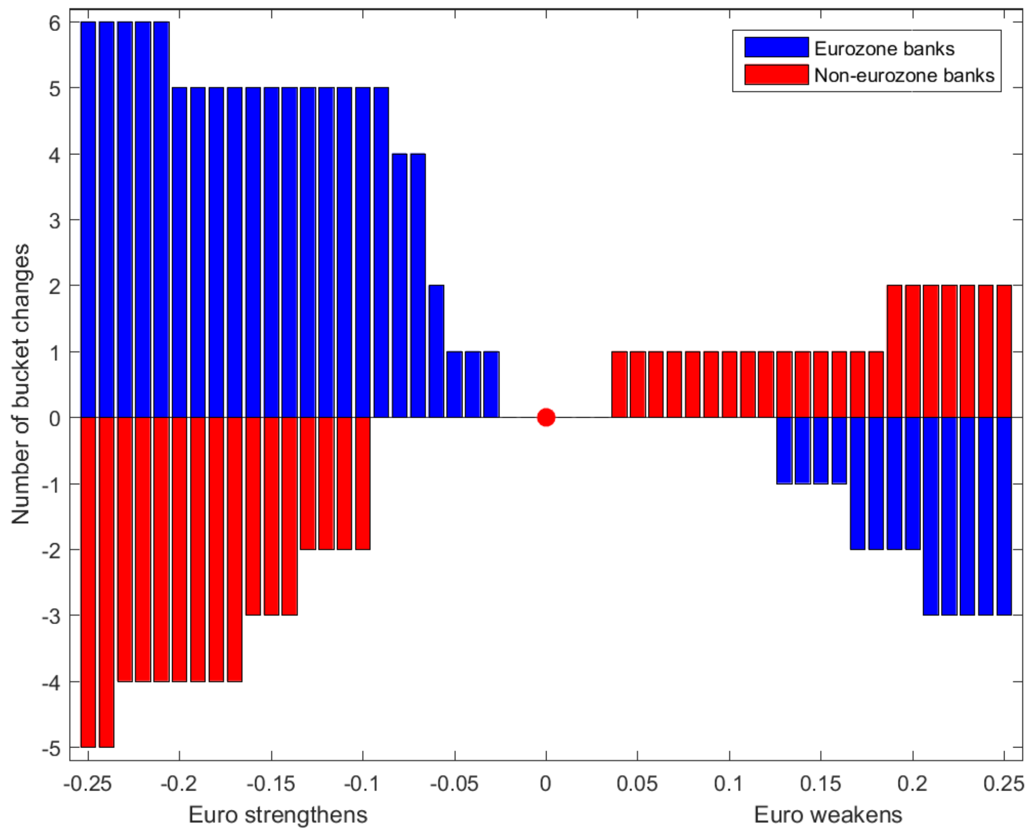

Figure A12: Bucket changes decomposition when exchange rates vary (year 2014)

This figure reports the number of bucket downgrade (blue bars) and the number of bucket upgrade (red bars) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2014.

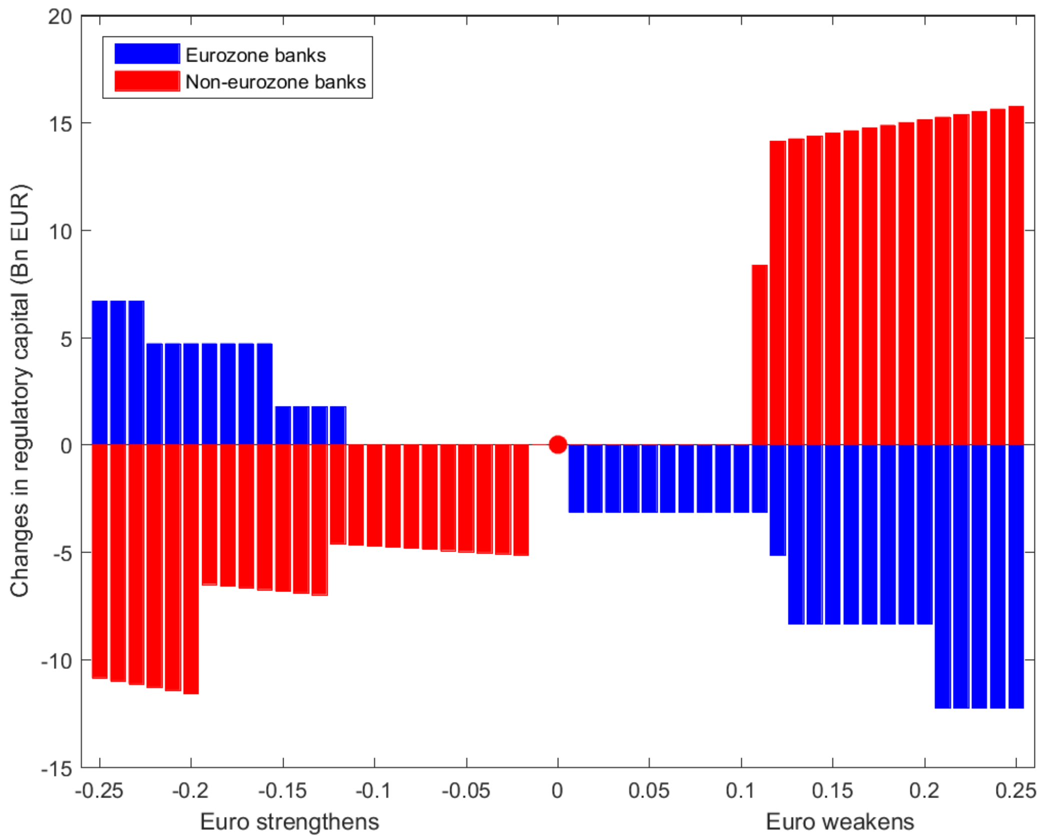

Figure A13: Capital changes decomposition when exchange rates vary (year 2016)

This figure reports the aggregate decrease in regulatory capital (blue bars) and the aggregate increase in regulatory capital (red bars) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2016.

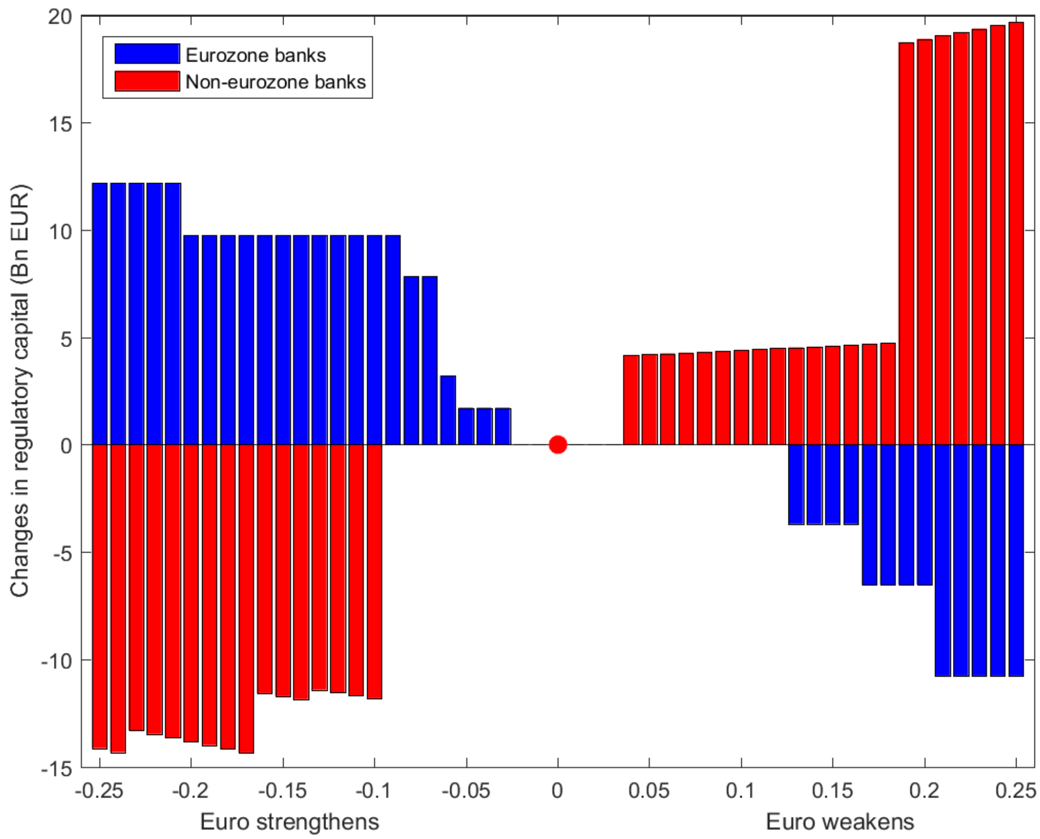

Figure A14: Capital changes decomposition when exchange rates vary (year 2014)

This figure reports the aggregate decrease in regulatory capital (blue bars) and the aggregate increase in regulatory capital (red bars) when the values of all currencies vary with respect to the Euro gradually from -25% to 25%. The reference point (red dot) is the situation as of 2014.

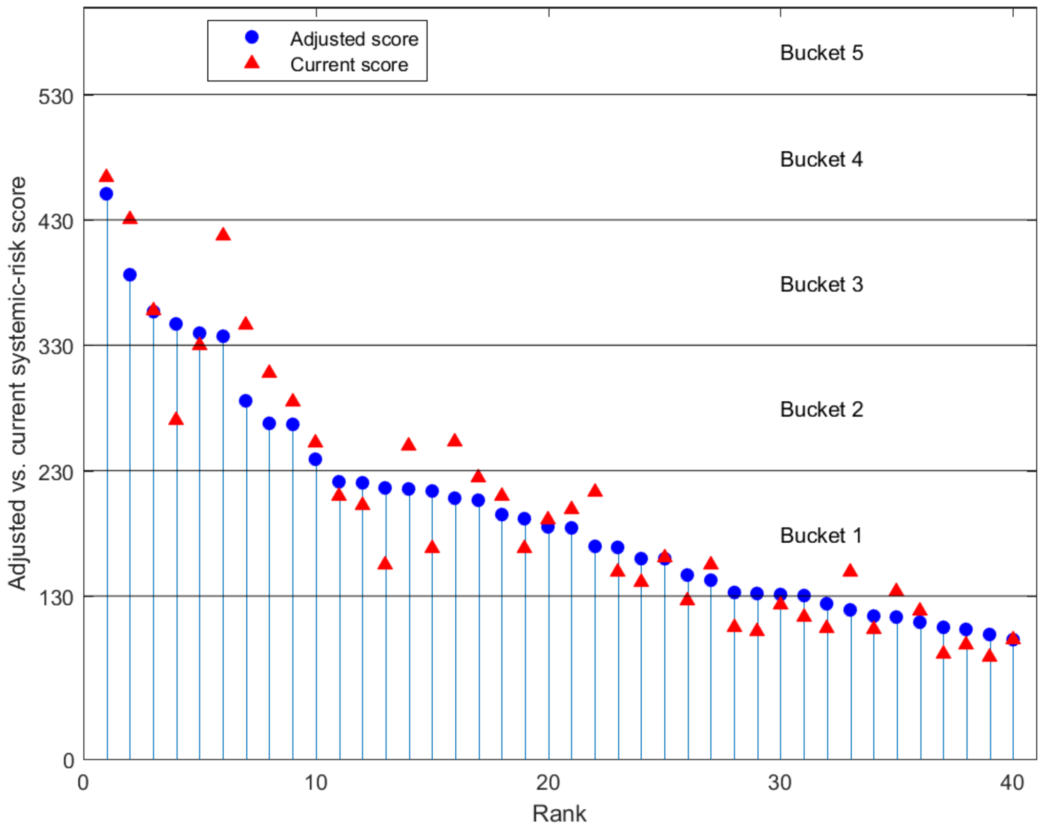

Figure A15: SIFI ranking based on adjusted scores (year 2016)

This figure displays the volatility and foreign exchange-adjusted systemic-risk scores (blue circles) in descending order and the corresponding BCBS systemic-risk scores as of 2016 (red triangles). The horizontal lines denote the cut-off values used to allocate banks into systemic-risk buckets. Cut-off values are 130, 230, 330, 430, and 530.

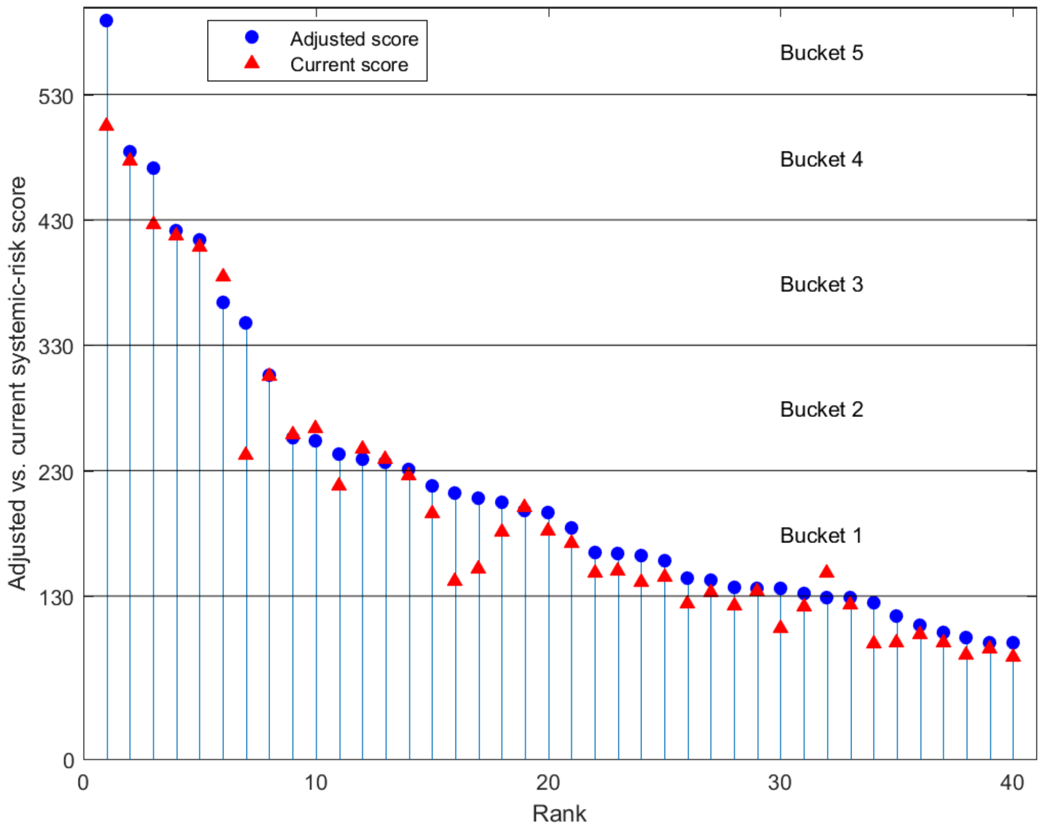

Figure A16: SIFI ranking based on adjusted scores (year 2014)

This figure displays the volatility and foreign exchange-adjusted systemic-risk scores (blue circles) in descending order and the corresponding BCBS systemic-risk scores as of 2014 (red triangles). The horizontal lines denote the cut-off values used to allocate banks into systemic-risk buckets. Cut-off values are 130, 230, 330, 430, and 530.

Appendix B Numerical Illustration

We illustrate the fact that any ranking based on raw (non-standardized) data is driven by the most volatile categories. 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:

$$x_{ik} = \beta + a_k \, u_i, \tag{B1}$$

where $\beta > 0$, u_i is an *i.i.d.* uniform variable on $[-1, 1]$ and $a_k = 10 \times k$. Note that by definition, $\mathrm{V}(u_i) = 1/3$. In this simple example, the K categories have a mean equal to β but $\mathrm{V}(x_{iK}) > ... > \mathrm{V}(x_{i1})$ since $\mathrm{V}(x_{ik}) = (100/3) \times k^2$. By simulation, we generate a series of realizations for x_{ik}, 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 B1 displays the average rank correlations (Spearman) measured between the ranking based on S_i (Equation 2) and category k. 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 the rankings based on the score and the category are.[24] 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 B1 displays the corresponding average rank correlations between the rankings based on the modified score $\widetilde{S}_i$ and category k. As expected, the suggested correction

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

guarantees that each category contributes equally to the systemic-risk score as desired by the BCBS.

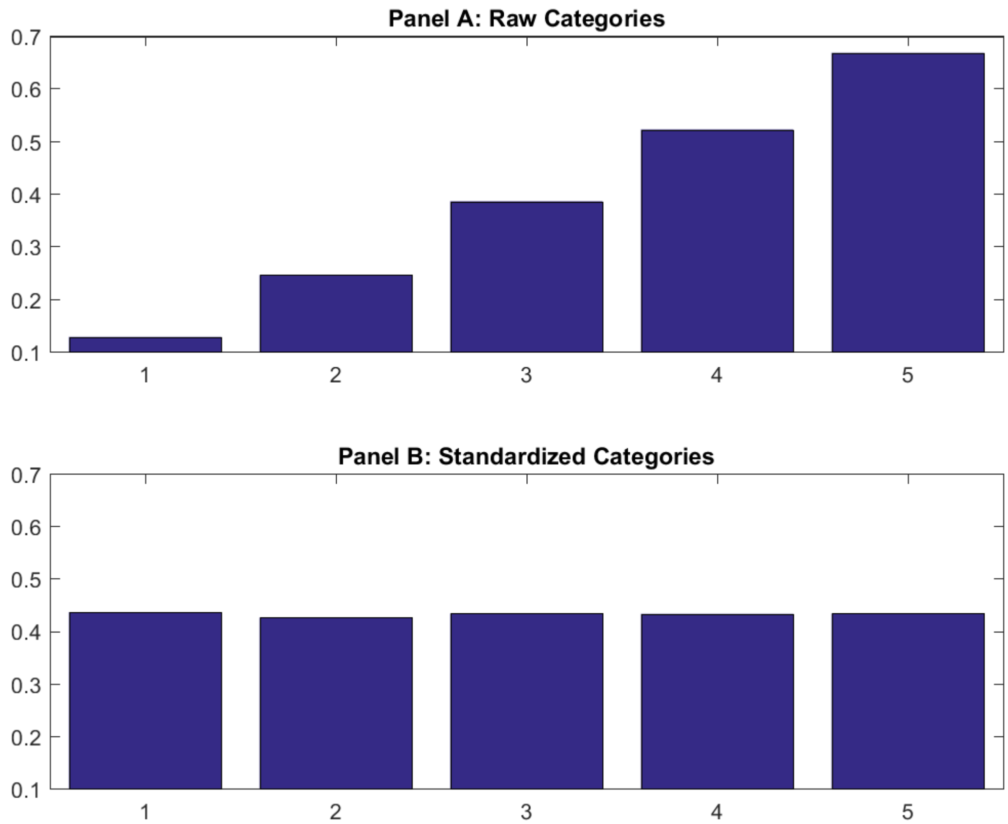

Figure B1: Correlation between score-based rankings and category-based rankings

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 k, $k = 1, ..., 5$. Average rank correlations are based on 1,000 simulations.

Appendix C SIFIs assessment sample

This table displays the 119 sample banks (appearing at least once in the analysis), 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 2015. 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
1.	Australia	ANZ	Main	Regulatory Report
2.	Australia	Commonwealth	Main	Regulatory Report
3.	Australia	National Australia Bank	Main	Regulatory Report
4.	Australia	Westpac	Main	Regulatory Report
5.	Austria	Erste Group	National	EBA - Interactive tool
6.	Belgium	KBC	Additional	EBA - Interactive tool
7.	Brazil	Banco Bradesco	Additional	Regulatory Report
8.	Brazil	Banco do Brasil	Main	Regulatory Report
9.	Brazil	Caixa	Main	Regulatory Report
10.	Brazil	Itaú Unibanco	Main	Regulatory Report
11.	Canada	Bank of Montreal	Main	Regulatory Report
12.	Canada	Bank of Nova Scotia	Main	Regulatory Report
13.	Canada	Canadian Imperial Bank of Commerce (CIBC)	Main	Regulatory Report
14.	Canada	Royal Bank of Canada	Main	Regulatory Report
15.	Canada	Toronto Dominion Canada Trust	Main	Regulatory Report
16.	China	Agricultural Bank of China	Main	Regulatory Report
17.	China	Bank of Beijing	Main	Regulatory Report
18.	China	Bank of China	Main	Regulatory Report
19.	China	Bank of Communications	Main	Regulatory Report
20.	China	China Construction Bank	Main	Regulatory Report
21.	China	China Everbright Bank	Main	Regulatory Report
22.	China	China Guangfa Bank	Main	Regulatory Report
23.	China	China Merchant Bank	Main	Regulatory Report
24.	China	China Minsheng Bank	Main	Regulatory Report
25.	China	Citic	Main	Regulatory Report
26.	China	Hua Xia Bank	Main	Regulatory Report
27.	China	Industrial and Commercial Bank of China (ICBC)	Main	Regulatory Report
28.	China	Industrial Bank	Main	Regulatory Report
29.	China	Ping an Bank	Main	Regulatory Report
30.	China	Shanghai Pudong	Main	Regulatory Report
31.	Denmark	Danske Bank	Main	EBA - Interactive tool
32.	Denmark	Nykredit	Additional	EBA - Interactive tool
33.	France	BNP Paribas	Main	EBA - Interactive tool
34.	France	Crédit Mutuel	Main	EBA - Interactive tool
35.	France	Groupe BPCE	Main	EBA - Interactive tool
36.	France	Groupe Crédit Agricole	Main	EBA - Interactive tool
37.	France	La Banque Postale	Additional	EBA - Interactive tool
38.	France	Sociéte Générale	Main	EBA - Interactive tool
39.	Germany	Bayern LB	Additional	EBA - Interactive tool
40.	Germany	Commerzbank	Main	EBA - Interactive tool
41.	Germany	Deutsche Bank	Main	EBA - Interactive tool
42.	Germany	DZ Bank	Main	EBA - Interactive tool
43.	Germany	Helaba		EBA - Interactive tool
44.	Germany	LBBW	Additional	EBA - Interactive tool
45.	Germany	Nord/LB	Additional	EBA - Interactive tool
46.	India	State Bank of India	Main	Regulatory Report
47.	Italy	Intesa San Paolo	Main	EBA - Interactive tool
48.	Italy	Monte dei Paschi di Siena		EBA - Interactive tool
49.	Italy	Unicredit	Main	EBA - Interactive tool
50.	Japan	Mitsubishi UFJ FG	Main	Regulatory Report
51.	Japan	Mizuho FG	Main	Regulatory Report
52.	Japan	Nomura Holdings	Main	Regulatory Report
53.	Japan	Sumitomo Mitsui FG	Main	Regulatory Report
54.	Japan	Sumitomo Mitsui Trust Holdings	Main	Regulatory Report
55.	Japan	The Norinchukin Bank	Main	Regulatory Report

	Country	Bank name	Sample	Source
56.	Korea	Hana Bank	Main	Regulatory Report
57.	Korea	KDC	Additional	Regulatory Report
58.	Korea	Kookmin	Main	Regulatory Report
59.	Korea	Nonghyup	Additional	Regulatory Report
60.	Korea	Shinhan	Main	Regulatory Report
61.	Korea	Wooribank	Additional	Regulatory Report
62.	Netherlands	ABN AMRO	Main	EBA - Interactive tool
63.	Netherlands	ING Bank	Main	EBA - Interactive tool
64.	Netherlands	Rabobank	Main	EBA - Interactive tool
65.	Norway	DNB Bank	Additional	EBA - Interactive tool
66.	Russia	Sberbank	Main	Regulatory Report
67.	Singapore	DBS Bank	Main	Regulatory Report
68.	Singapore	OCBC	Additional	Regulatory Report
69.	Singapore	UOB	Additional	Regulatory Report
70.	Spain	BBVA	Main	EBA - Interactive tool
71.	Spain	BFA	Additional	EBA - Interactive tool
72.	Spain	Criteria Caixa-Holding	Main	EBA - Interactive tool
73.	Spain	Santander	Main	EBA - Interactive tool
74.	Sweden	Handelsbanken	Additional	EBA - Interactive tool
75.	Sweden	Nordea	Main	EBA - Interactive tool
76.	Sweden	SEB	Main	EBA - Interactive tool
77.	Sweden	Swedbank	Additional	EBA - Interactive tool
78.	Switzerland	Credit Suisse	Main	Regulatory Report
79.	Switzerland	UBS	Main	Regulatory Report
80.	United Kingdom	Barclays	Main	EBA - Interactive tool
81.	United Kingdom	HSBC	Main	EBA - Interactive tool
82.	United Kingdom	Lloyds	Main	EBA - Interactive tool
83.	United Kingdom	Nationwide	Additional	EBA - Interactive tool
84.	United Kingdom	Royal Bank of Scotland	Main	EBA - Interactive tool
85.	United Kingdom	Standard Chartered	Main	EBA - Interactive tool
86.	United States	Ally Financial Inc.	National	FR Y-15
87.	United States	American Express Company	National	FR Y-15
88.	United States	Bancwest Corporation	National	FR Y-15
89.	United States	Bank of America	Main	FR Y-15
90.	United States	Bank of New York Mellon	Main	FR Y-15
91.	United States	BB&T Corporation	National	FR Y-15
92.	United States	BBVA Compass Bancshares, Inc.	National	FR Y-15
93.	United States	BMO Financial Corp.	National	FR Y-15
94.	United States	Capital One	Main	FR Y-15
95.	United States	Charles Schwab Corporation	National	FR Y-15
96.	United States	Citigroup	Main	FR Y-15
97.	United States	Citizens Financial Froup, Inc.	National	FR Y-15
98.	United States	Comerica Incorporated	National	FR Y-15
99.	United States	Deutsche Bank Trust Corporation	National	FR Y-15
100.	United States	Discover Financial Services	National	FR Y-15
101.	United States	Fifth Third Bancorp	National	FR Y-15
102.	United States	Goldman Sachs	Main	FR Y-15
103.	United States	HSBC North America Holdings Inc.	National	FR Y-15
104.	United States	Huntington Bancshares Incorporated	National	FR Y-15
105.	United States	JP Morgan Chase	Main	FR Y-15
106.	United States	Keycorp	National	FR Y-15
107.	United States	M&T Bank Corporation	National	FR Y-15
108.	United States	Morgan Stanley	Main	FR Y-15
109.	United States	MUFG Americas Holdings Corporation	National	FR Y-15
110.	United States	Northern Trust Corporation	National	FR Y-15
111.	United States	PNC	Main	FR Y-15
112.	United States	Regions Financial Corporation	National	FR Y-15
113.	United States	Santander Holdings USA, Inc.	National	FR Y-15
114.	United States	State Street	Main	FR Y-15
115.	United States	Suntrust Banks, Inc.	National	FR Y-15
116.	United States	TD Bank US Holding Company	National	FR Y-15
117.	United States	US Bancorp	Main	FR Y-15
118.	United States	Wells Fargo	Main	FR Y-15
119.	United States	Zions Bancorporation	National	FR Y-15