Smart Systemic-Risk Scores[*]

Sylvain Benoit[†]

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Abstract

I propose a new systemic-risk score to identify and regulate systemically important financial institutions (SIFIs) by using an alternative weighting scheme based on volatility to aggregate all systemic-risk facets. Following a portfolio management approach, I equalize the risk contribution of each systemic-risk component to the cross-sectional volatility of my *smart* systemic-risk scores. To discriminate between several systemic-risk scores, I apply an axiomatic framework to express supervisor preferences among systemic-risk scores. Such preferences are based on the expected value of the cross-sectional dispersion of systemic-risk scores over the years.

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[†]Université Paris-Dauphine, Université PSL, France. E-mail: sylvain.benoit@dauphine.psl.eu.

1 Introduction

The systemic-risk scoring methodology currently implemented worldwide by the Basel Committee on Banking Supervision (BCBS) is both simple and intuitive (BCBS, 2011; BCBS, 2013; BCBS, 2014b; and BCBS, 2018). It aggregates information about five broad categories of systemic importance – size, interconnectedness, substitutability/financial institution infrastructure, complexity, and cross-jurisdictional activity – to calculate a systemic-risk score for each financial institution under scrutiny. Financial institutions are ranked based on this score, and those labeled as systemically important financial institutions (SIFIs) go to a risk bucket where they must face an additional capital requirement due to the systemic regulation imposed by Basel III.

For assessing systemic importance of SIFIs, the regulator cares about (1) the aggregation of these multiple sources of risk into an individual systemic-risk score and (2) the cross-sectional profile (distribution) of systemic-risk scores across banks. On the one hand, to compute the current systemic-risk score, the BCBS uses an equally weighted average of the five categories since the primary intention of the committee is to give all categories equal weights (BCBS, 2013). On the other hand, the ranking of these individual systemic-risk score matters since it is used to identify and regulate SIFIs.

Benoit, Hurlin, and Pérignon (2018) provide a complete overview of this systemic-risk scoring methodology and identify several shortcomings in it. One of them is related to the weighted average used to compute the systemic-risk score. The use of an equal weighting scheme provides an unintended consequence: this scoring method overweights the most volatile categories and conversely underweights the less volatile ones, as shown theoretically and empirically in Benoit et al. (2017). In practice, there are two standard and straightforward ways to correct for this statistical bias. One way is to standardize each category, whereas the other way is to trim outliers by capping some of the categories, as the BCBS does with the substitutability category. Currently, the substitutability category is capped at 500 basis points (bps), but this cap could be removed in the near future (BCBS, 2018), which would exacerbate the mechanical domination of the most volatile categories in the systemic-risk score.

In this paper, I propose an alternative solution to data transformation to fix this pitfall by modifying the equal weighting scheme to compute the systemic-risk score. I introduce a new systemic-risk score, which I call the "*smart* systemic-risk score", where the weighting scheme equalizes the risk contribution of the five systemic-risk categories to the volatility of the systemic-risk score across banks. Weights are so determined endogenously, satisfy the supervisory preference about an equal "weight" of each category in determining the systemic-risk score, and reduce banks' lobbying on capping the most volatile categories since the weighting of volatile categories will be lower than the weights attributed to less volatile categories. To the best of my knowledge, this is the first paper to propose a new weighting scheme for computing systemic-risk scores.

The equally weighted risk contribution (ERC) method is a passive investment strategy (Kolm, Tütüncü, and Fabozzi, 2014), intensively used in portfolio management with the bloom of smart beta portfolios. These smart beta approaches include alternative-weighted portfolios where the risk of the portfolio is more effectively managed than in the equally weighted portfolio. The main advantage of such a risk-parity method is to minimize the total distance between all the risk contributions of each asset. To achieve this goal, when the risk contribution of the ith asset to the risk (volatility) of the portfolio is high, then the weighting of this asset in the ERC portfolio is lower, all other things being equal. In contrast, if the risk contribution is low, then the weighting of this asset in the ERC portfolio increases.

I provide a theoretical foundation to discriminate between several systemic-risk scores and to argue that my *smart* systemic-risk scores offer a coherent alternative to the official methodology. The BCBS considers systemic-risk scores as a loss-given-default (LGD) concept rather than a probability of default (PD) concept (BCBS, 2011) since it aims to evaluate the potential impact of a global bank's failure on the financial system rather than the likelihood of such a default. The larger the systemic footprint of the bank on the system is, the higher its regulatory capital. Thus, a systemic-risk score is not a summary statistic (a single real number) quantifying the level of risk in the economy. However, I show that the expected value of the cross-sectional dispersion of systemic-risk scores over the years satisfies the axiomatic framework introduced by Chen, Iyengar, and Moallemi (2013) and can be used as a *global* systemic-risk measure, to reveal supervisors' preferences for the best weighting scheme.[1]

Using regulatory data for a sample of 80 global banks from 20 countries between 2014 and 2017, I compute two *smart* systemic-risk scores as an alternative to the BCBS Score, one based on systemic-risk categories and the other based on systemic-risk indicators. The two *smart* scores lead to similar (slightly higher) aggregate surcharges of regulatory capital relative to the one emerging from the current framework. This means that changing the weighting scheme slightly alters the composition of the risk buckets. I observe that banks scoring high in a particular category, such as the four largest custodian banks in the world – JP Morgan Chase, Citigroup, Bank of New York Mellon, and State Street – are not immune to my approach.

This paper contributes to the literature on systemic-risk measurement (Acharya et al.,

[1]In this framework, the *global* systemic-risk measure cannot be used as a systemic-risk thermometer and tracked over time (across scenarios).

2017; Acharya, Engle, and Richardson, 2012; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017; and Huang, Zhou, and Zhu (2009)) by proposing the *smart* systemic-risk score, where the ERC method is used to compute the weight of each systemic-risk category. While the debate on how useful are systemic-risk measures based on market data is at play (Idier, Lam, and Msonnier, 2009; Zhang et al., 2015, Brownlees et al., 2018; and Löffler and Raupach, 2018), only few papers focus on the scoring approach currently used by the regulator since 2011 (Benoit, Hurlin, and Pérignon, 2018). By analogy to portfolio management (Lehar, 2005), the systemic-risk score can be viewed as a portfolio of K risky categories (indicators), and its manager is the Basel Committee with a primary goal of not favoring any particular facet of systemic risk. Thus, my paper contributes to a branch that studies how to allocate systemic risk appropriately across contributors (Brunnermeier and Oehmke, 2013; Brunnermeier and Cheridito, 2014; Gouriéroux and Monfort, 2013). The use of the cross-sectional dispersion of systemic-risk scores as an aggregation function echoes the research of Menkveld (2017), where he proposes the standard deviation of aggregate loss as the input of the crowding index rather than the average of aggregate loss.

The remainder of this paper is structured as follows. I present the scoring methodology currently used by the BCBS in Section 2. In Section 3, I introduce the axiomatic framework proposed by Chen, Iyengar, and Moallemi (2013) and apply it to the systemic-risk score used by the regulator. This framework allows us to emphasize that the cross-sectional volatility of systemic-risk scores is of utmost importance for expressing supervisors' preferences. In Section 4, I describe (in Section 4.1) the ERC method used to construct my *smart* systemic-risk scores, where I equalize the risk contribution of each systemic-risk component to the cross-sectional volatility of these scores. I implement in Section 4.2 my *smart* systemic-risk scores using actual regulatory data for a sample of 80 large, international banks from 2014 to 2017. I conclude my paper in Section 5.

2 Global systemically important banks

The systemic-risk scoring 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 Table 1 and BCBS, 2014b). The aim of this section is to theoretically and empirically describe this scoring approach.

2.1 Assessment methodology

Perhaps 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 its securities financing transactions, its credit derivatives and its counterparty risk exposures as well as some off-balance-sheet commitments. The *interconnectedness* category comprises three indicators: the bank's intra-financial system assets, its intra-financial system liabilities, 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 in replacing the services provided by the bank if it failed. The three related indicators are the bank's payment activity, the assets under custody held by the bank, and its total underwriting transactions in both 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 is, the higher the costs and the time needed to resolve a failing bank. Finally, the *cross-jurisdictional* category combines two indicators of 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.

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 combining F_k indicators (X_{ikf}) associated with category k, normalized by their sums:[2]

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

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). The indicators X_{ikf} of non-Eurozone banks are converted into Euro using fiscal year-end exchange rates to permit aggregation across currency zones.[3] 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.

To give the same importance to each category, the BCBS considers an equally weighted

[2] If I 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.

[3] Using spot exchange rates may have unintended consequences on the systemic score, especially in a period of high volatility in exchange rates, as illustrated by Benoit, Hurlin, and Pérignon (2018).

index with $\omega_k = \bar{\omega}_k = 1/K = 20\%$. Under this assumption, an increase of 10% of a given category can be offset by a decrease of 10% in another category. In addition, the BCBS applies a 5% cap to the substitutability category and no cap to the other categories.[4] Accordingly, the systemic-risk score becomes

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

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 was published in 2012. With such a cut-off, any global bank that contributes to more than 1.3% of the risk in 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.[5] 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 ranges 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 to increase their scores any further.

[4]The BCBS acknowledges that the substitutability category has an abnormally high influence on the value of the systemic-risk scores. On page 6 (BCBS, 2013), 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.*"

[5]The score ranges are [130-229] for bucket 1, [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 was published.

2.2 Empirical illustration

In this replication exercise, I implement the BCBS methodology between 2014 and 2017 by collecting the values of the 12 indicators required to compute the five systemic-risk categories at the end of the fiscal year.[6] These regulatory data mainly come from bank websites. The main difference between my approach and the replication exercise provided by Benoit, Hurlin, and Pérignon (2018) is that I consider only the main sample of the G-SIB assessment methodology.[7] This sample includes the largest 75 banks in the world, as determined by the Basel III leverage ratio exposure measure, along with any banks that were designated as G-SIB in the previous year but are not otherwise part of the top 75 (see Appendix A for the complete list of banks considered each year).

I start by scaling each bank-level indicator by the sum of this indicator across the main-sample banks considered by the BCBS.[8] The current systemic-risk score can be computed by using indicators or categories. The two sets of data produce the same BCBS systemic-risk score $\bar{S}$ due to the equal weighting scheme. I label as the BCBS Score the output of Equation 3, and I label as the uncapped BCBS Score the results provided by Equation 2 with $\omega_k = \bar{\omega}_k$. For ease of presentation, I mainly discuss the results for 2016 and 2017 since there are no missing values in my SIFI assessment sample.[9]

Tables 1 and 2 report summary statistics, expressed in basis points (except for skewness), on systemic-risk indicators (Panel A), categories (Panel B) and scores (Panel C). The mean values are not informative since by construction, the sum of market shares across banks is

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

[7] For further details, see the G-SIB assessment samples available at https://www.bis.org/bcbs/gsib/gsib_assessment_samples.htm.

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

[9] Results for the year 2014 and 2015 are available upon request.

always equal to 10,000, leading to an average value of 131.58 basis points. This remark also holds for systemic-risk scores, and the cut-off value (130 basis points) used by the supervisor to separate the SIFI territory from the non-SIFI territory is close to this average value. Cross-sectional volatilities across indicators and categories are heterogeneous. The substitutability category appears to be the most volatile (standard deviation equal to 191 in 2017), which explains why the Basel Committee applies a cap on this specific category. After the 5% cap is applied, the standard deviation for this category decreases to 132. Such a winsorizing leads to outliers' disappearance in the BCBS Score; as a consequence, the maximum value for the current BCBS Score is equal to 467, whereas it is 588 for the uncapped BCBS Score, which could be removed in the next review of the assessment methodology (BCBS, 2018).

I report SIFI names with their respective BCBS Scores and risk buckets for 2016 and 2017 in Tables 3 and 4. First, I follow Section 2.1 and perfectly replicate the list of SIFIs published since 2014 by the Financial Stability Board (FSB). Second, this allows us to identify banks identified as SIFI based on supervisory judgement since their scores are below 130 basis points. These banks are Groupe BPCE (126) and Nordea (123) in 2016 and Royal Bank of Scotland (128) and Nordea (115) in 2017. Third, I confirm that the cap benefits only the largest custodian banks in the world: JP Morgan Chase, Citigroup, Bank of New York Mellon, and State Street. Fourth, the total extra capital requirement for systemic risk in 2017 is equal to EUR 304.15 billion, as reported in Table 5. Despite the constant number of SIFIs since 2014 (30), this total increased by 37.15%. The reduction in regulatory capital (due to bucket downgrade) produced by the cap on the substitutability category for the four custodian banks is substantial, EUR 19.74 billion in 2017, and ranges from 4.31% in 2016 to 10.36% in 2014 of the total extra capital requirements.

Bostandzic and Weiß (2018) find that European banks contribute more to global systemic risk than banks in the United States, even if they have the similar exposure to systemic crises, and that stringent capital regulations decrease the average exposure of banks to systemic risk. However, capital surcharges for G-SIBs are not always effective for managing systemic-risk especially when the financial network topology is not taking into account (Poledna, Bochmann, and Thurner, 2017). Re-shaping the topology of financial networks is also key for managing systemic risk. In addition, Battiston et al., 2012, show that a financial network can be most resilient for intermediate levels of risk diversification, and not when this is maximal.

While the scoring approach allocates systemic risk to individual financial institutions and allows management of such systemic risk by setting additional capital requirements, no discussion has emerged about the use of an equal weighting scheme to average systemic-risk categories. As shown empirically in Tables 1 and 2, the cross-sectional dispersion of systemic-risk categories (indicators) is not similar, and I argue that the supervisor should care about it when setting up its scoring approach. Indeed, these cross-sectional dispersions and the correlations between systemic-risk categories (indicators) are two key components for capturing the risk topography of the multiple facets of systemic risk.

3 Axioms for systemic-risk measures

To finalize its scoring approach, the BCBS has made several arbitrary choices. One of them is related to the weighted average used to combine the K systemic-risk categories into an individual systemic-risk score. As shown in Section 2, the supervisor uses an equally weighted average, and this decision is of the first order when the regulator ranks banks based on their scores. The aim of this section is to ground this weighted average choice in the axiomatic framework proposed by Chen, Iyengar, and Moallemi (2013) to reveal supervisors' preferences.

3.1 Decomposition of systemic-risk scores

The economy, composed of a finite set of banks $\mathscr{B}$ and a finite set of scenarios Θ, is defined by a matrix $X \in \mathbb{R}^{|\mathscr{B}|\times|K|\times|\Theta|}$ where the quantity x_{ik}^{θ} is the market share of bank i for the systemic-risk category k in scenario θ.[10] I consider $X^{\theta} \in \mathbb{R}^{|\mathscr{B}|\times|K|}$ the matrix of outcomes in scenario θ across all banks; then, $\underset{(N;1)}{S^{\theta}} = \underset{(N;K)}{X^{\theta}} \underset{(K;1)}{\omega}$ corresponds to a systemic-risk score where ω is a column vector of weights. I refer to $S^{\theta} \in \mathbb{R}^{|\mathscr{B}|}$ as the cross-sectional profile of a systemic-risk score across all banks of the economy in scenario θ. A realization of X in scenario θ is given by the yearly output of Equation 1:

$$X^{\theta} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1k} & \dots & x_{1K} \\ x_{21} & x_{22} & \dots & x_{2k} & \dots & x_{2K} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ik} & \dots & x_{iK} \\ \vdots & \vdots & \dots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \dots & x_{Nk} & \dots & x_{NK} \end{pmatrix}^{\theta}.$$

Alternatively, one may prefer the observations coming from the indicators (rather than the categories); in this case x_{ik}, is replaced by $\frac{X_{ikf}}{\sum_{i=1}^{N} X_{ikf}}$, and the dimension of the column vector of weights ω is now equal to the number of indicators (i.e., 12).

A particularity of this economy is that several systemic-risk scores can be computed by the supervisory entity to accurately capture the systemic footprint of all banks belonging to the system under scrutiny. Indeed, before focusing on the distribution (cross-sectional profile) of systemic-risk score across all banks of the economy, the allocation of all systemic-risk facets to the construction of a systemic-risk score matters. When alternative weights $\hat{\omega}$ are considered for multiplying the X matrix, I end up with a new systemic-risk score $\hat{S} \in \mathbb{R}^{|\mathscr{B}|\times|\Theta|}$. Now, the

[10] For ease of presentation, I use θ as exponent to refer to a given scenario even if I have a total of T scenarios labeled as θ_1, θ_2,$\cdots$, θ_t, $\cdots$, θ_T.

quantity $\hat{S}_i^\theta$ is the systemic-risk score of bank i in scenario θ when $\hat{\omega}$ is used for combining the multiple facets of systemic risk.

Let us define the following notation to describe the cross-sectional profile of systemic-risk scores: the column vector $\mathbf{1}_{\mathscr{B}} \in \mathbb{R}^{|\mathscr{B}|}$ denotes a cross-sectional score profile in a scenario where each bank has the same score. This occurs when all systemic-risk scores are equal to $\sum_{i=1}^{N} S_i^\theta / N$ and echoes the clone property of Brunnermeier and Cheridito (2014). Similarly, the vector $\mathbf{1}_\Theta \in \mathbb{R}^{|\Theta|}$ denotes a column vector of ones in all scenarios. The matrix $\mathbf{I}_{\mathscr{S}} \triangleq \mathbf{1}_{\mathscr{B}} \mathbf{1}_\Theta^\top \in \mathbb{R}^{|\mathscr{B}| \times |\Theta|}$ denotes a systemic-risk score that is identical for each bank in each scenario. Alternatively, the matrix $\mathbf{I}_{\mathscr{B}K} \in \mathbb{R}^{|\mathscr{B}| \times |K| \times |\Theta|}$ denotes an economy where the market shares X across all banks and categories are identical. Regardless of the column vector of weights ω used, when $\mathbf{I}_{\mathscr{B}K}$ is true then $\mathbf{1}_{\mathscr{B}}$ is satisfied, the reverse is not true.

My model, illustrated in Figure 1, describes the choice faced by the supervisor about the tuning of the column vector of weights. In this general example, the supervisor should be able to determine which vector of weights he prefers among ω, $\hat{\omega}$ and $\bar{\omega}$ to compute the systemic-risk score. To answer this question, I introduce the axiomatic framework of Chen, Iyengar, and Moallemi (2013), which defines a *global* systemic-risk measure as follows: A *global* systemic-risk measure is a function $\rho : \mathbb{R}^{|\mathscr{B}| \times |\Theta|} \to \mathbb{R}$ that satisfies the following conditions for all systemic-risk scores $S, \hat{S}, \bar{S} \in \mathbb{R}^{|\mathscr{B}| \times |\Theta|}$ of a given economy with N banks exposed to several scenarios:

(i) *Monotonicity*: If $S \geq \hat{S}$, then $\rho(S) \geq \rho\left(\hat{S}\right)$.

(ii) *Positive homogeneity (of degree one)*: For all nonnegative scalars $\alpha \geq 0, \rho(\alpha S) = \alpha \rho(S)$.

(iii) *Preference consistency*: Define a partial order $\succeq_\rho$ on cross-sectional score profiles as follows: $S^\theta \succeq_\rho \hat{S}^\theta$, i.e., $\hat{S}^\theta$ is preferred to S^θ, iff $\rho\left(S^\theta \mathbf{1}_\Theta^\top\right) \geq \rho\left(\hat{S}^\theta \mathbf{1}_\Theta^\top\right)$. Suppose that $\forall\ \theta \in \Theta$, $S^\theta \succeq_\rho \hat{S}^\theta$. Then, $\rho(S) \geq \rho\left(\hat{S}\right) \geq \rho(\mathbf{I}_\mathscr{S})$.

(iv) *Convexity*:

(a) *Outcome convexity*: Suppose $S = \alpha\hat{S} + (1-\alpha)\bar{S}$, for a given scalar $0 \leq \alpha \leq 1$. Then, $\rho(S) \leq \alpha\rho\left(\hat{S}\right) + (1-\alpha)\rho\left(\bar{S}\right)$

(b) *Risk convexity*: Suppose $\rho\left(S^\theta \mathbf{1}_\Theta^\top\right) = \alpha\rho\left(\hat{S}^\theta \mathbf{1}_\Theta^\top\right) + (1-\alpha)\rho\left(\bar{S}^\theta \mathbf{1}_\Theta^\top\right)$, $\forall\ \theta \in \Theta$ and for a given scalar $0 \leq \alpha \leq 1$. Then, $\rho(S) \leq \alpha\rho\left(\hat{S}\right) + (1-\alpha)\rho\left(\bar{S}\right)$.

(v) *Normalization*: $\rho(\mathbf{I}_\mathscr{S}) = 0$.

The conditions for a *global* systemic-risk measure can be motivated as follows: The monotonicity condition (1) reflects that if one score S has systematically larger values in every scenario than another score $\hat{S}$, the former score is less preferred. The positive homogeneity condition (2) requires that the *global* systemic-risk measure increase in proportion to the scale of the systemic-risk scores.[11] The preference consistency condition (iii) reveals the supervisor's preferences over cross-sectional profiles of systemic-risk scores across scenarios. The convexity conditions (iv) highlight the benefits of diversification, and the risk of a combination of two systemic-risk scores is always lower or equal to the two individual risks of the cross-sectional profiles. The normalization condition (v) requires the *global* systemic risk of identical systemic-risk scores for each bank in each scenario to be equal to zero. This convenient choice of scaling underlines a pitfall of the current methodology arising when banks are clones since no banks may survive to a large systematic shock (Acharya and Yorulmazer,

[11]These first two conditions mathematically hold but are not particularly relevant in the regulatory scoring approach since by construction, the sum of all market shares across banks is equal to 100% for each scenario $\theta \in \Theta$, regardless of the systemic-risk score used. Thus, multiplying a cross-sectional profile of systemic-risk score S^θ by α does not make sense due to the normalization process defined in Equation 1.

2007; Wagner, 2010). In this case, all systemic-risk scores are similar, making it impossible for the supervisor to designate SIFIs.

Chen, Iyengar, and Moallemi (2013) state in their Theorem 1 that any *global* systemic-risk measures $\rho : \mathbb{R}^{|\mathscr{B}|\times|\Theta|} \to \mathbb{R}$ admit a decomposition equivalent to the choice of a base (univariate) risk measure $\eta : \mathbb{R}^{|\Theta|} \to \mathbb{R}$, and of an aggregation function $\Lambda : \mathbb{R}^{|\mathscr{B}|} \to \mathbb{R}$. In my setting, this decomposition has the following form:

$$\rho(S) = (\eta \circ \Lambda)(S) \triangleq \eta\left[\Lambda\left(S^{\theta_1}\right), \Lambda\left(S^{\theta_2}\right), \ldots, \Lambda\left(S^{\theta_T}\right)\right], \quad \forall\, S \in \mathbb{R}^{|\mathscr{B}|\times|\Theta|}, \tag{4}$$

where Λ is the aggregation function over the cross-sectional profiles of systemic-risk scores S in each scenario. Once each cross-sectional profile in a single scenario is aggregated into a real number, then the univariate risk measure η is run on these aggregated outcomes across scenarios. The base risk measure η is a coherent risk measure since it satisfies all the axioms of Artzner et al. (1999).[12] In contrast, the aggregation function Λ satisfies the conditions of *monotonicity*, *positive homogeneity*, *convexity* and *normalization* but not the cash invariance condition.

3.2 Preferences based on cross-sectional dispersion

To apply a *global* systemic-risk measure to a given systemic-risk scores, a supervisor must deal with both the cross-sectional profile of scores across banks and the distribution of aggregated outcomes across scenarios.

The most natural way to aggregate individual systemic-risk scores into a real number is to use the sum operator. However, in the regulatory framework, $\sum_{i=1}^{N} S_i^\theta = \sum_{i=1}^{N} \hat{S}_i^\theta = \ldots = \sum_{i=1}^{N} \bar{S}_i^\theta = 10,000$ and does not allow discrimination between a given systemic-risk score. Since the total number of banks N is the same for each systemic-risk score, taking the first moment of this

[12] In Appendix B, I provide an illustration of such a coherent risk measure with the volatility.

cross-sectional distribution is also not informative. Looking at the second moment is thus the next logical candidate. The volatility of the systemic-risk score across banks satisfies all the axioms of the aggregation function and provides meaningful information about the dispersion of such a score. An overly high dispersion means that some financial institutions contribute in a large (and, conversely, small) measure to the risk of the system, whereas low dispersion leads to more similar financial institutions that are potentially more substitutable in case of systemic bankruptcy.

I propose the following function to aggregate cross-sectional profiles of systemic-risk scores in a given scenario into a scalar:

$$\Lambda_{Disp.}(S^{\theta}) = \sigma_{S^{\theta}}, \quad \forall\ S^{\theta} \in \mathbb{R}^{|\mathscr{B}|}. \tag{5}$$

This aggregation function considers the volatility of systemic-risk scores across banks as an additional source of information, capturing the heterogeneity of the financial system. I assume there is a given distribution $p \in \mathbb{R}_{+}^{|\Theta|}$ over the space of scenarios T, and I define the individual risk measure to be the expectation (the first moment):

$$\eta_{Exp.} = p^{\top} y, \tag{6}$$

$$\eta_{Exp.} = \mathrm{E}\Big[y\Big], \quad \forall\ y \in \mathbb{R}^{|\Theta|}. \tag{7}$$

Then, the *global* systemic-risk measure is given by

$$\rho_{Disp.}(S) = \eta_{Exp.}\left[\Lambda_{Disp.}\left(S^{\theta_1}\right), \Lambda_{Disp.}\left(S^{\theta_2}\right), \ldots, \Lambda_{Disp.}\left(S^{\theta_T}\right)\right], \tag{8}$$

$$\rho_{Disp.}(S) = \mathrm{E}\left[\sigma_{S^{\theta_1}}, \sigma_{S^{\theta_2}}, \ldots, \sigma_{S^{\theta_T}}\right], \quad \forall\ S \in \mathbb{R}^{|\mathscr{B}| \times |\Theta|}. \tag{9}$$

Supervisor preferences are based on the expectation of the cross-sectional volatility of systemic-risk scores across scenarios. In the regulatory framework, a scenario corresponds to a year, and I assume that each scenario has the same probability p of occurrence, leading to a simple average of the cross-sectional dispersion of systemic-risk scores over the years.

To determine the supervisor's preference between the universe of scores, $S, \hat{S}, \ldots, \bar{S}$, I must compute and compare $\rho_{Disp.}(S), \rho_{Disp.}(\hat{S}), \ldots, \rho_{Disp.}(\bar{S})$ in order to select the lowest value as established in the preference consistency axiom. These averages of dispersion are affected only by the choice of column vector ω to compute S since input matrix X is identical for all systemic-risk scores. The weighting scheme used to compute the systemic-risk score is thus the cornerstone of my setting.

The preference consistency condition also implies independence from irrelevant alternatives (see Kreps, 1988). One of the primary goals of the Basel Committee is not to favor any particular facet of systemic risk. This means that finding the weights that minimize the expected value of the cross-sectional volatility of systemic-risk scores over the years is not the best solution since it will load heavily on the lowest volatile categories (indicators). In the same vein, finding the weights that maximize the utility function of the supervisor is not viable since it implies knowing such a utility function and will not guarantee an equal contribution of each systemic-risk facet.

4 Alternative weighting scheme

In this section, I borrow from the portfolio management literature and propose an alternative to the naive equally weighted average of categories (indicators) to compute systemic-risk scores. Such a $1/K$ portfolio offers attractive features, such as the fact that this portfolio is not easily outperformed by optimal portfolios, as illustrated by DeMiguel, Garlappi, and Uppal (2009). However, the emergence of smart beta exchange-traded funds (ETFs), using alternative index construction rules, paves the road to new diversification strategies that are ideal for managers who want to minimize the risk of their portfolios.

4.1 The ERC method

Based on Equation 9 and supervisory statements, the BCBS plays the role of a manager who wants to select column vector of weights $\hat{\omega}$ satisfying both (1) low expectations of cross-sectional dispersion of systemic-risk scores over the years and (2) equal contribution of each systemic-risk categories (indicators).

The ERC method (Qian, 2005) displays such characteristics. First, it equalizes the risk contribution of each systemic-risk component to the cross-sectional volatility of the systemic-risk scores. Second, as shown theoretically by Maillard, Roncalli, and Teïletche (2010) with portfolios, the volatility of a systemic-risk score based on ERC weights is systematically lower than or equal to the current volatility of the BCBS systemic-risk score based on equal weights. My new systemic-risk score based on this ERC weighting scheme is dubbed as the *smart* systemic-risk score.

To describe the ERC method, I first define the marginal risk contribution and the total risk contribution. Let σ_k^2 be the variance of category k, σ_{kl} be the covariance between categories k and l, and Ω be the covariance matrix. The volatility of the systemic-risk score is given by $\sigma_S = \sqrt{\omega' \, \Omega \, \omega} = \sqrt{\sum_{k=1}^{K} \omega_k^2 \, \sigma_k^2 + \sum_{k=1}^{K} \sum_{l \neq k}^{K} \omega_k \, \omega_l \, \sigma_{kl}}$ where $\omega = (\omega_1, \omega_2, \; \ldots, \omega_K)$ is the column vector of weights. The marginal risk contribution for the k^{th} category, $\delta_{\omega_k} \sigma_S$, is defined as

$$\delta_{\omega_k} \sigma_S = \frac{\delta \sigma_S}{\delta \omega_k} = \frac{\omega_k \, \sigma_k^2 + \sum_{l \neq k}^{K} \omega_l \, \sigma_{kl}}{\sigma_S}. \tag{10}$$

The marginal risk contribution of category k gives the change in the volatility of the score induced by a small increase in the weight of this component. The risk of the systemic-risk score is then equal to the sum of the risk contributions of the K categories:

$$\sigma_S = \sum_{k=1}^{K} \left(\omega_k \times \delta_{\omega_k} \sigma_S\right). \tag{11}$$

In a risk-parity strategy-based portfolio, the risk contribution of the k^{th} category $(\omega_k \times \delta_{\omega_k}\sigma)$ is equal to a given target b_k where $\sum_{k=1}^{K} b_k = \sigma_S$, and $0 < b_k < \sigma_S$. The ERC strategy is a special case of the risk-parity method where $b_k = b_l = b$ for all k, l. Based on Equation 11, the risk of the *smart* systemic-risk score $\hat{S}$ is then equal to $\sigma_{\hat{S}} = K \times b$, and the optimal weights satisfying these constraints are defined as follows:

$$\hat{\omega} = \left\{ \omega \in [0,1]^K : \sum_{k=1}^{K} \omega_k = 1,\ \omega_k \times \delta_{\omega_k} \sigma_S = b = \frac{\sigma_S}{K} \ \ \forall\ k \in \Big[1, ..., K\Big] \right\} \tag{12}$$

To compute the *smart* systemic-risk score corresponding to the risk-balanced score, I must equalize the risk contribution of each systemic-risk category. I must verify that the weights of each category are between 0 and 1 and then sum to 1. Then, the *smart* systemic-risk score is simply given by

$$\hat{S}_i = \sum_{k=1}^{K} \hat{\omega}_k \times x_{ik}, \tag{13}$$

Due to the endogeneity of the optimization program, since the volatility of the score (σ_S) is a function of the weighting parameters (ω), there is no closed-form solution when $K > 2$. I use a numerical algorithm to find a solution to the program described in Equation 12.

To sum up, my *smart* systemic-risk score is located between the current BCBS Score $(1/K)$ and the minimum-variance score.[13] The *smart* score coincides with the BCBS Score only when all volatilities are the same for each category. This happens especially when market shares X are equal to the matrix $\mathbf{I}_{\mathscr{B}K}$ or when X is standardized, as proposed by Benoit, Hurlin, and Pérignon (2018). As a consequence, based on the axioms provided in Section 3,

[13] The minimum-variance score is not a relevant alternative, as explained in Section 3.2.

the *smart* score $\hat{S}$ given by Equation 13 is systematically preferred by the supervisor to the current (uncapped) BCBS Score, $\bar{S} = \sum_{k=1}^{K} \bar{\omega}_k \times x_{ik}$, since $\rho_{Disp.}(\bar{S}) \geq \rho_{Disp.}(\hat{S})$.

4.2 Empirical analysis

The *smart* systemic-risk score can be computed by using indicators or categories. While the two sets of data produce the same BCBS Score $\bar{S}$, two distinct *smart* systemic-risk scores $\hat{S}$ can be computed. They are labeled the ERC^{cat} Score and the ERC^{ind} Score and correspond to Equation 13. Their discrepancies are due to the use of 2 different covariance matrices in the optimization program described in Section 4.1. These two sets of ERC weighting parameters emphasize the importance of the relationship (covariance) between indicators, and between categories.

To verify empirically that $\rho_{Disp.}(\bar{S}) \geq \rho_{Disp.}(\hat{S})$, I reduce my sample of banks to the 61 banks belonging to the main sample over the study period for which I have no missing data.[14] As expected, the cross-sectional volatility of the ERC^{cat} Score and the ERC^{ind} Score is systematically lower than the volatility of the uncapped BCBS Score, as detailed in Table 5. *Smart* scores are systematically compared to the uncapped BCBS Score since the winsorizing of the substitutability category to compute the BCBS Score currently in use modifies the X matrix, leading to an unfair comparison. When averaging the cross-sectional volatilities, I end up with the following results: $\rho_{Disp.}(\bar{S}) = 123$ for the uncapped BCBS Score, $\rho_{Disp.}(\hat{S}) = 113$ for the ERC^{cat} Score, and $\rho_{Disp.}(\hat{S}) = 118$ for the ERC^{ind} Score. This empirically confirms that *smart* scores are indeed preferred by the supervisor ($\bar{S} \succeq_{\rho_{Disp.}} \hat{S}$). In other words, ERC weights should be used rather than equal weights for computing systemic-risk scores.

[14] I do so to provide a fair comparison. However, since cross-sectional profiles of systemic-risk scores are aggregated into a scalar (the volatility) for each year, a different number of banks over the years could be allowed.

The summary statistics on *smart* scores reported in Tables 1 and 2 confirm that *smart* scores exhibit similar moments to the uncapped BCBS Score. In 2017, the cross-sectional volatility of the ERC^{cat} Score (104 basis points) and the ERC^{ind} Score (107) is lower than the volatility of the uncapped BCBS Score (111) and quite close to the volatility of the BCBS Score (103). This shows that there is no need to put a cap on the substitutability category to reach a similar standard deviation and skewness since these two moments of the ERC^{cat} Score and of the BCBS Score are very close. In addition, the maximum values are less affected; in 2017, the highest values are 536 and 567 for the ERC^{cat} Score and the ERC^{ind} Score, respectively. These values are slightly lower than the maximum uncapped BCBS Score (588) compared to 467 for the BCBS Score.

Computing the risk contribution of each category to the cross-sectional volatility of the BCBS Score highlights the discrepancies between the marginal contribution of each category (as in Equation 10) since an equally weighted average is used. The top panel of Figure 2 shows that the marginal contribution of each category is proportional to its cross-sectional volatility, as reported in Panel B of Table 2. The higher the cross-sectional volatility of a category is, the larger its marginal contribution in the cross-sectional volatility of the BCBS Score. For instance, the risk contribution of the substitutability category is 32 basis points out of the 111 basis points of the volatility of the uncapped BCBS Score, corresponding to 28% of the total risk. When capping the substitutability category, the standard deviation of the BCBS Score is now equal to 103 basis points, and the substitutability category accounts for 22 basis points, corresponding to 22% of the total risk. In this case, the complexity category has the larger risk contribution, corresponding to 26% (26.32/103.17) of the standard deviation of the BCBS Score. The results are similar for the systemic-risk indicators, as displayed in the top panel of Figure 3.[15]

In contrast, the risk contribution of each category (indicator) to the risk of the *smart* score is equal by definition (see the top panel of Figure 2). To reduce the risk contribution of the most volatile categories, the weight applied to these categories for computing the *smart* systemic-risk score shrinks, whereas the weight of the less volatile categories increases their risk contribution, as illustrated in the bottom panel of Figures 2 and 3. The sum of all these risk contributions (i.e., the cross-sectional volatility of the systemic-risk score) for the *smart* score based on categories (103) or based on indicators (107) are lower than the one from the uncapped BCBS Score (111), which empirically illustrates the fact that the volatility of my *smart* score is systematically lower than the volatility of the BCBS Score.

By setting smaller weights for the most volatile categories, I create positive incentives for banks, especially non-SIFIs, to increase their risk taking in these categories without be heavily (and quickly) penalized by additional capital requirements. I argue that this pattern may increase financial stability since banks will become more substitutable by allowing some banks to increase their market shares in specialized activities, such as the custody services. In contrast, banks will tend to reduce their risk taking in an area where there is smaller cross-sectional dispersion because such a risk category (indicator) mechanically carries more weight in the final score.

I display the evolution of the risk contribution of each category between 2014 and 2017 with the BCBS weights in Figure 4 and with the ERC^{cat} weights in Figure 5. The cross-sectional volatility of the uncapped BCBS Score has decreased over time because the risk contributions of the interconnectedness, substitutability, complexity, and cross-jurisdictional

[15] The risk contribution of the total exposures indicator (size category) to the volatility of the BCBS Score appears abnormally high due to its weight of 20%, whereas the weights of the other indicators are at least half as large.

activity have dropped by 19.61%, 14.76%, 22.95%, and 10.57%, respectively, whereas the risk contribution of the size has increased by 1.27%. From 2014, the risk of the ERC^{cat} Score has also decreased since the risk contribution of each category decreases by 12.98%. The weighting parameters for each category used to compute these risk contributions are plotted in Figure 6. To ensure an equal risk contribution over the years across categories, the weight of the size becomes smaller, whereas the weight of the interconnectedness grows rather than remaining constant as with the other three categories. In other words, the volatility of the size category has increased whereas the volatility of the interconnectedness has decreased over the year.

I show in Figure 7 the yearly evolution of the risk contribution of each category with the ERC^{cat} weights when these parameters remain constant over time (parameters are set based on 2014 data). This out-of-sample analysis confirms a higher risk contribution for the size category at the end of the period compared to the beginning. I observe a severe drop in the risk contributions of interconnectedness and complexity between 2016 and 2017. This figure confirms that the current systemic-risk methodology does not address the "too-big-to-fail" issue at the system level. While the size of most American and European banks has decreased since 2014, this decrease has been compensated for by a boom in the size of Chinese bank, among others, leading to higher risk contributions from the size category. This observation illustrates perfectly the purpose of the current regulation, which only ranks financial institutions without monitoring the risk at the system level.

I display all systemic scores for 2016 and 2017 in descending order in Figures 8 and 9, and I complete Tables 3 and 4 with the SIFIs identified by the ERC^{cat} Score and the ERC^{ind} Score. In 2016, the ERC^{cat} Score identifies 29 SIFIs, whereas the ERC^{ind} Score identifies 30 SIFIs. In both cases, Groupe BPCE is directly identified as SIFI, but Nordea is in the non-SIFI territory. Few bucket changes are observed. With the ERC^{cat} Score, Bank of China is now in bucket 2 rather than bucket 1, whereas BNP Paribas goes down one bucket, saving 0.5% of regulatory capital. With the ERC^{ind} Score, BNP Paribas also goes to bucket 2 rather than bucket 3, Industrial Bank is now labeled as a SIFI, and the largest custodian bank (JP Morgan) no longer enjoys the cap on the substitutability category since its ERC^{ind} Score is equal to 564, corresponding to risk bucket 5. In 2017, neither of the two banks (Royal Bank of Scotland and Nordea) added by supervisory judgement are identified by my *smart* scores. However, three new banks go to the SIFI territory based on the ERC^{ind} Score: Industrial Bank, China Misheng Bank and Groupe BPCE (also identified as SIFI by the ERC^{cat} Score). With the ERC^{cat} Score, two banks must reduce their regulatory capital (Bank of China and Deutsche Bank), whereas one bank has to increase its regulatory capital (JP Morgan). With the ERC^{ind} Score, I observe 6 bucket changes. JP Morgan and Citigroup go up one bucket and do not benefit from the cap, and Credit Suisse also has to increase its regulatory capital, whereas I observe a reduction for Bank of America, Bank of China and Deutsche Bank. All these bucket changes generate an appreciation of the total surcharge of capital requirements compared to the current one, as reported in Table 5. For example, in 2017, the aggregated surcharge is EUR 309.61 billion for the ERC^{cat} Score and EUR 318.89 billion for the ERC^{ind} Score compared to EUR 304.15 billion for the BCBS Score.

As theoretically set in Section 3, when supervisor preferences are based on the expectation of cross-sectional dispersion of systemic-risk scores over the years, *smart* scores are preferred to the BCBS Score (uncapped). In Figures 10 and 11, I illustrate this point by displaying the cross-sectional mean and volatility of four systemic-risk scores and of the five (twelve) systemic-risk categories (indicators) for 2017.[16] As an alternative to *smart* scores and BCBS Scores, I compute both a score minimizing its cross-sectional variance (MinVar Score) and a score maximizing the usual utility function (Opt. Score).[17] As expected, *smart* scores have a lower volatility than the BCBS Score but a higher volatility than the MinVar Score. When constructing systemic-risk scores based on categories, I observe that the MinVar Score corresponds to the interconnectedness category, which illustrates perfectly the fact that this alternative is not relevant since only one category contributes to the construction of this score. An additional irrelevant score is disclosed with the Opt. Score corresponding to the intersection of the utility curve and the efficient frontier for a given aversion coefficient. Indeed, reaching the higher level of utility does not guarantee (1) that each category contributes with the same importance to the systemic-risk score and (2) that the volatility of the Opt. Score is lower than the volatility of the *smart* score, as shown in Figure 11. Finally, by assuming that the supervisor owns the same utility function as an investor, I provide another advantage with my *smart* score, which is that its utility is always larger than that of the (uncapped) BCBS Score.

5 Conclusion

This paper contributes to the literature on systemic-risk measurement by proposing a *smart* systemic-risk score where the ERC method is used to compute the vector of weights used for the computation of systemic-risk scores. While thousands of vectors of weights can be proposed, I argue that applying the axiomatic framework of Chen, Iyengar, and Moallemi (2013) to the scoring approach allows discrimination between these alternative weighting

[16]Figures for 2014, 2015, and 2016 are similar.

[17]The utility function is given by $\mathrm{E}\left(S\right) - \frac{\phi}{2}\sigma_S^2$ where the utility increases with the cross-sectional mean of the systemic-risk score and decreases with the cross-sectional volatility of the score weighted by half of the aversion coefficient ϕ.

schemes. Based on my framework, the best weighting scheme is the one (1) providing the lowest expectation of cross-sectional dispersion of systemic-risk scores over the years and (2) satisfying the primary goal of the BCBS of not favoring any particular facet of systemic risk.

The ERC method can be applied consistently to systemic-risk categories or indicators. Weights are endogenously determined and take into account the volatility of each component but also their correlation, as suggested by the Association of Supervisors of Banks of the Americas (ASBA) in 2017.[18] Such an approach is also perfectly designed for dealing with the inclusion of additional indicators, such as the forthcoming *trading volume* indicator in the substitutability category (BCBS, 2018), since weights do not have to be determined exogenously via supervisory judgement. Letting the data speak in computing systemic-risk scores does not imply systematically adjusting this vector of weights on a yearly basis. The vector of weights could be modified at each revision of the methodology similar to the bucket thresholds, which remain fixed for several years.

This methodology, which does not require data transformation, identifies the same SIFIs as the current systemic-risk score, but due to bucket changes, the capital surcharge required by my *smart* scores is slightly larger. The main advantage of these scores based on the ERC method is that an increase of 10% in a given category can no longer be offset by a 10% decrease in another category. Consequently, banks' incentives to manage their systemic footprint are now restored since my *smart* scores increase incentives for banks to reduce (increase) their risk contribution in categories (indicators) characterized by a smaller (larger) dispersion of banks (see Laffont and Tirole, 1993; Laffont and Martimort, 2001, for the theory of incentives).

The output provided by the ERC method is particularly interesting for the supervisor

[18] For a complete overview of the comments received by the BCBS on its consultative document (BCBS, 2017), please go to `https://www.bis.org/bcbs/publ/comments/d402/overview.htm`.

since it equalizes the risk contribution of each systemic-risk component to the cross-sectional volatility of the systemic-risk score as required by the regulator. In addition, banks scoring high on a highly volatile category are less penalized than with the uncapped BCBS Score since the weight on such a category or indicator is lower than the $1/K$ weight. Ad hoc adjustment like the cap of the substitutability is no longer required, and there is no need to find alternative methodologies for the substitutability category anymore (BCBS, 2018).

While the scoring approach allocates systemic risk to individual financial institutions to manage systemic risk by setting additional capital requirements for internalizing negative externalities, no systemic-risk measure at a system-wide level is provided by the supervisor. Every year, the sum of each systemic-risk score across banks is equal to 10,000. The larger the market share of a bank within the system is, the higher its regulatory capital. However, aggregate regulatory capital through time does not necessarily mean that a systemic event is more likely. It just means that the cost to the system will be larger. Regardless of these negative externalities on society that are now internalized by financial institutions, I would like to know whether the financial system – and, as a result, the global economy – is more stable now than it was a few years ago. I leave this question open for future research.

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Table 1: Summary statistics (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 four systemic-risk scores (BCBS Scores uncapped and capped and the two *smart* systemic-risk scores) in Panel C.

Panel A: Systemic-risk indicators						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Total exposures	131	94	103	1.5	32	463
2a. Intra-financial system assets	134	109	100	0.9	12	451
2b. Intra-financial system liabilities	133	104	102	0.8	2	415
2c. Securities outstanding	131	113	91	1.2	10	425
3a. Payments activity	130	60	210	3.5	0	1,160
3b. Assets under custody	130	39	313	3.9	0	1,686
3c. Underwriting activity	131	56	180	1.9	0	730
4a. OTC derivatives	131	37	206	1.8	0	798
4b. Trading and AFS securities	131	67	157	2.2	1	839
4c. Level 3 assets	132	43	177	1.6	0	680
5a. Cross-jurisdictional claims	130	71	150	1.8	0	766
5b. Cross-jurisdictional liabilities	131	84	145	1.6	0	705
Panel B: Systemic-risk categories						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Size	131	94	103	1.5	32	463
2. Interconnectedness	133	106	87	0.9	13	401
3. Substitutability	131	59	197	3.0	2	1,091
3. Substitutability (cap=5%)	113	59	131	1.7	2	500
4. Complexity	131	60	159	1.7	1	709
5. Cross-jurisdictional activity	131	81	146	1.7	0	735
Panel C: Systemic-risk scores						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
BCBS score (uncapped)	131	88	116	1.6	19	582
BCBS score	128	88	107	1.3	19	464
ERC^{cat} score	131	93	108	1.4	23	527
ERC^{ind} score	132	91	112	1.6	21	563

Table 2: Summary statistics (2017)

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 four systemic-risk scores (BCBS Scores uncapped and capped and the two *smart* systemic-risk scores) in Panel C.

Panel A: Systemic-risk indicators						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Total exposures	132	94	102	1.6	32	466
2a. Intra-financial system assets	134	105	99	0.8	15	393
2b. Intra-financial system liabilities	133	104	105	0.8	1	430
2c. Securities outstanding	131	111	88	1.3	11	426
3a. Payments activity	131	66	191	3.3	0	1,199
3b. Assets under custody	132	43	304	3.9	0	1,650
3c. Underwriting activity	132	58	174	2.0	0	774
4a. OTC derivatives	132	41	201	1.8	0	797
4b. Trading and AFS securities	143	69	165	2.2	2	859
4c. Level 3 assets	132	59	164	1.6	0	770
5a. Cross-jurisdictional claims	133	84	146	1.7	0	754
5b. Cross-jurisdictional liabilities	132	81	148	1.8	0	771
Panel B: Systemic-risk categories						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
1. Size	132	94	102	1.6	32	466
2. Interconnectedness	133	109	83	0.9	23	411
3. Substitutability	131	63	191	3.0	2	1,103
3. Substitutability (cap=5%)	115	63	132	1.8	2	500
4. Complexity	135	61	150	1.5	5	654
5. Cross-jurisdictional activity	133	86	146	1.8	0	763
Panel C: Systemic-risk scores						
	Mean	Median	Std Dev.	Skewness	Minimum	Maximum
BCBS score (uncapped)	133	99	111	1.6	19	588
BCBS score	130	99	103	1.3	19	467
ERC^{cat} score	133	103	104	1.4	21	536
ERC^{ind} score	133	104	107	1.5	18	567

Table 3: List of systemically important financial institutions (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 *smart* systemic-risk scores based on categories in descending order (Column 4), and based on indicators in descending order (Column 5) as of November 2016. The systemic-risk scores of all banks are reported in parentheses. 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 parentheses. A $\bullet$ indicates banks identified as SIFIs by supervisory judgement. The reported cut-off values are provided by the BCBS.

Bucket	Additional Capital	BCBS Score (30)	ERC^{cat} Score (29)	ERC^{ind} Score(30)
5 [530-629]	3.5%	Empty	Empty	JP Morgan Chase (564)
4 [430-529]	2.5%	JP Morgan Chase* (464/583)	JP Morgan Chase (527)	Citigroup (482)
		Citigroup* (430/495)	Citigroup (454)	
3 [330-429]	2.0%	HSBC (417)	HSBC (410)	HSBC (395)
		Deutsche Bank (358)	Deutsche Bank (332)	Deutsche Bank (350)
		Bank of America (346)	Bank of America (332)	Bank of America (339)
		BNP Paribas (330)		
2 [230-329]	1.5%	Barclays (308)	BNP Paribas (320); Barclays (292)	BNP Paribas (316); Barclays (307)
		Credit Suisse (285)	Credit Suisse (277); Mitsubishi UFJ FG (275)	Credit Suisse (302)
		Mitsubishi UFJ FG (270)	ICBC (271)	Wells Fargo (261)
		Goldman Sachs (253)	Wells Fargo (246)	Goldman Sachs (258)
		ICBC (252)	Bank of China (243)	Mitsubishi UFJ FG (256)
		Wells Fargo (250)	Goldman Sachs (240)	ICBC (250)
1 [130-229]	1.0%	Bank of China (224)	China Construction Bank (223)	Bank of China (217)
		Morgan Stanley (213)	Santander (213)	Bank of New York Mellon (215)
		China Construction Bank (210)	Agricultural Bank of China (208)	Morgan Stanley (214)
		Société Générale (210)	Société Générale (204)	Société Générale (208)
		Santander (202)	Morgan Stanley (199)	China Construction Bank (205)
		UBS (199)	UBS (194)	UBS (202)
		Agricultural Bank of China (191)	Bank of New York Mellon (187)	Santander (196)
		Groupe Crédit Agricole (168)	Groupe Crédit Agricole (175)	Agricultural Bank of China (191)
		Mizuho FG (168)	Mizuho FG (168)	Groupe Crédit Agricole (169)
		Bank of New York Mellon* (161/227)	Sumitomo Mitsui FG (166)	State Street (162)
		Royal Bank of Scotland (155)	Unicredit Group (157)	Sumitomo Mitsui FG (161)
		Sumitomo Mitsui FG (155)	Royal Bank of Scotland (154)	Mizuho FG (160)
		Unicredit Group (149)	ING Bank (151)	Unicredit Group (156)
		State Street* (149/172)	State Street (139)	Royal Bank of Scotland (154)
		ING Bank (141)	Standard Chartered (136)	ING Bank (141)
		Standard Chartered (134)	Groupe BPCE (131)	Standard Chartered (135)
		Groupe BPCE$^{\bullet}$ (126)		Groupe BPCE (132)
		Nordea$^{\bullet}$ (123)		Industrial Bank (132)

Table 4: List of systemically important financial institutions (2017)

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 *smart* systemic-risk scores based on categories in descending order (Column 4), and based on indicators in descending order (Column 5) as of November 2017. The systemic-risk scores of all banks are reported in parentheses. 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 parentheses. A $\bullet$ indicates banks identified as SIFIs by supervisory judgement. The reported cut-off values are provided by the BCBS.

Bucket	Additional Capital	BCBS Score (30)	ERC^{cat} Score (29)	ERC^{ind} Score(31)
5 [530-629]	3.5%	Empty	JP Morgan Chase (536)	JP Morgan Chase (567)
4 [430-529]	2.5%	JP Morgan Chase* (468/588)		Citigroup (435)
3 [330-429]	2.0%	HSBC (411) Citigroup* (410/452) Bank of America (340) Deutsche Bank (334)	Citigroup (418) HSBC (396)	HSBC (387)
2 [230-329]	1.5%	BNP Paribas (312) Barclays (292) Mitsubishi UFJ FG (287) ICBC (268) Goldman Sachs (255) China Construction Bank (252) Wells Fargo (243) Bank of China (232)	Bank of America (320); Deutsche Bank (311) BNP Paribas (302); Mitsubishi UFJ FG (290) ICBC (284) Barclays (279) China Construction Bank (261) Bank of China (247) Goldman Sachs (246) Wells Fargo (244)	Deutsche Bank (328); Bank of America (323) BNP Paribas (294); Barclays (290) Mitsubishi UFJ FG (275) ICBC (264) Goldman Sachs (264) Wells Fargo (254) China Construction Bank (253) Credit Suisse (236)
1 [130-229]	1.0%	Credit Suisse (229) Morgan Stanley (214) Société Générale (200) Santander (193) Mizuho FG (187) UBS (185) Sumitomo Mitsui FG (181) Agricultural Bank of China (176) Groupe Crédit Agricole (161) ING Bank (160) Bank of New York Mellon* (153/215) State Street* (149/171) Royal Bank of Canada (145) Unicredit Group (135) Standard Chartered (133) Royal Bank of Scotland$^{\bullet}$ (128) Nordea$^{\bullet}$ (115)	Credit Suisse (220) Morgan Stanley (201) Société Générale (201) Santander (201) Agricultural Bank of China (197) Sumitomo Mitsui FG (191) Mizuho FG (187) UBS (181) Bank of New York Mellon (174) Groupe Crédit Agricole (166) ING Bank (166) Unicredit Group (142) Royal Bank of Canada (141) State Street (138) Standard Chartered (135) Groupe BPCE (131)	Bank of China (225); Morgan Stanley (215) Société Générale (204) Bank of New York Mellon (200) UBS (186) Sumitomo Mitsui FG (185) Santander (184) Mizuho FG (182) Agricultural Bank of China (175) Groupe Crédit Agricole (160) State Street (160) ING Bank (154) Industrial Bank (144) Royal Bank of Canada (142) Unicredit Group (139) China Minsheng Bank (134) Standard Chartered (133) Groupe BPCE (131)

Table 5: Cross-sectional volatility and capital surcharge

This table reports the cross-sectional volatility (expressed in percentage points) of systemic-risk scores and the aggregate regulatory surcharge in capital (expressed in EUR billion) due to systemic risk in 2014, 2015, 2016, and 2017. For comparison, the reported cross-sectional volatilities are based on the 61 banks belonging to the main sample over the study period.

		Year 2014	Year 2015	Year 2016	Year 2017
	BCBS Score (uncapped)	132	125	119	114
Cross-sectional	BCBS Score	120	114	109	105
Volatility	ERC^{cat} Score	120	116	110	105
	ERC^{ind} Score	127	121	115	108
Aggregate	BCBS Score (uncapped)	247.39	279.13	313.33	323.39
Regulatory	BCBS Score	221.76	261.90	298.87	304.15
Capital	ERC^{cat} Score	241.57	285.65	301.83	309.61
Surcharge	ERC^{ind} Score	215.68	271.10	312.60	318.89

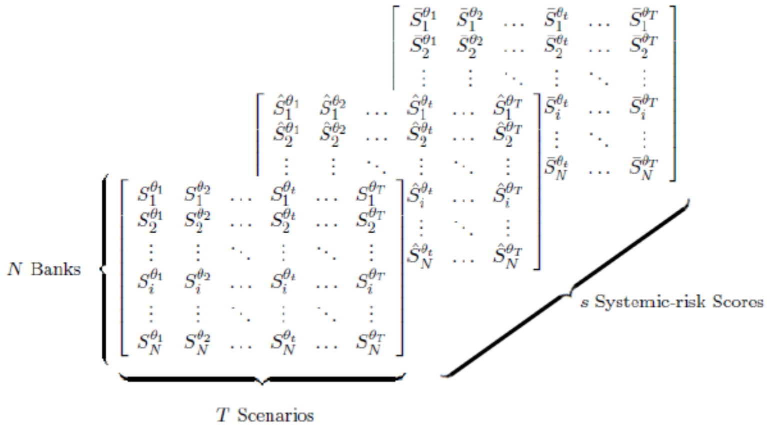

Figure 1: Model illustration

This figure describes the single economy of my framework composed of a finite set of banks $\mathscr{B}$, a finite set of future scenarios Θ, and a finite set of systemic-risk scores $\mathscr{W}$. The scalar $S_i^{\theta_t}$ is the systemic-risk score of bank i in scenario θ_t when the column vector of weights ω is used for multiplying the i^{th} row of matrix X^{θ_t} (which captures the multiple facets of systemic risk). Similarly, $\hat{S}_i^{\theta_t}$ is the systemic-risk score of bank i in scenario θ_t when the column vector of weights $\hat{\omega}$ is used.

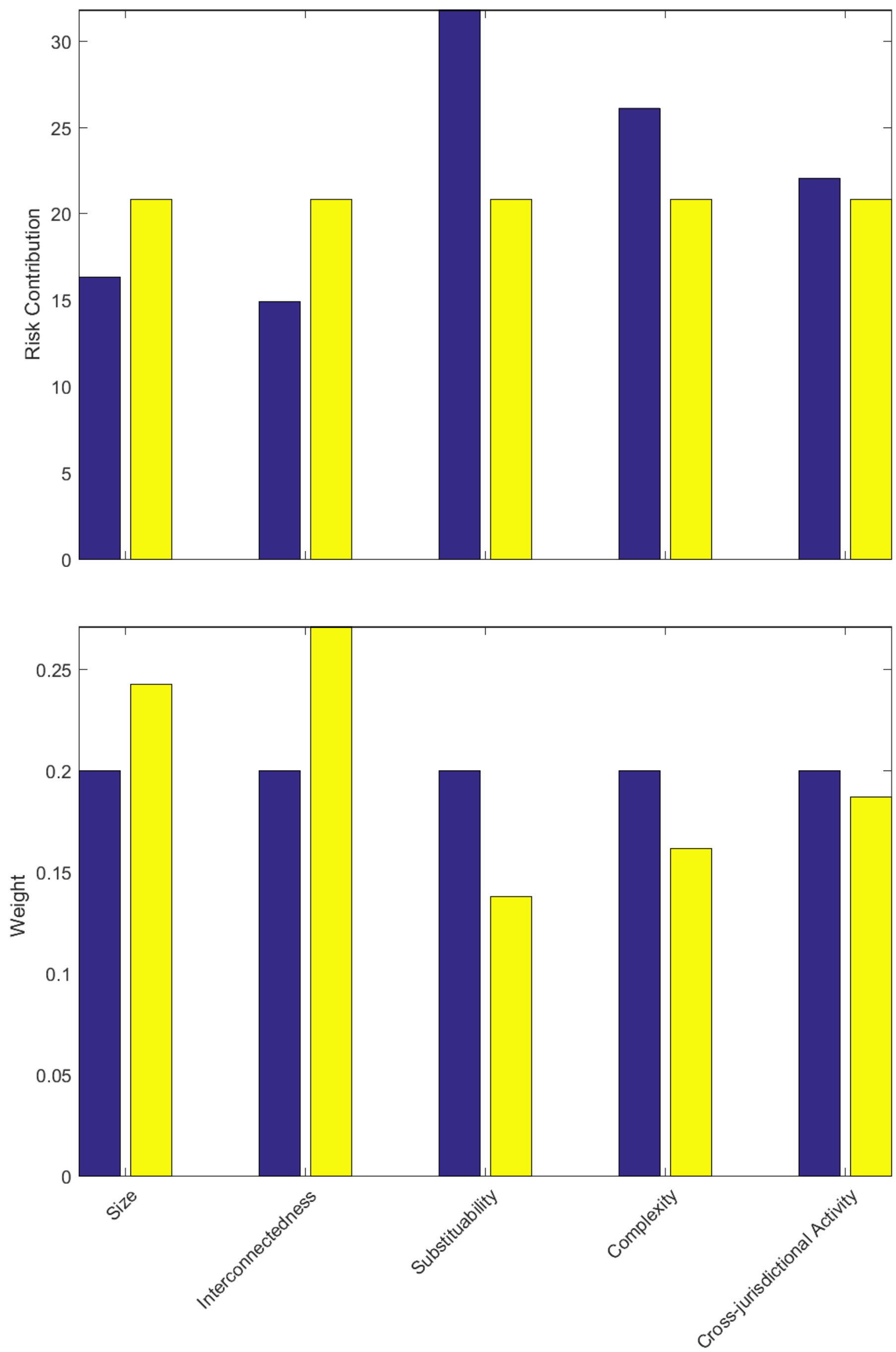

Figure 2: Risk contribution and weight for each systemic-risk category (2017)

This figure reports on top the risk contribution and on the bottom the weight of the five systemic-risk categories used in the uncapped BCBS Score (dark blue bars) and in the ERC^{cat} Score (yellow bars) for the year 2017.

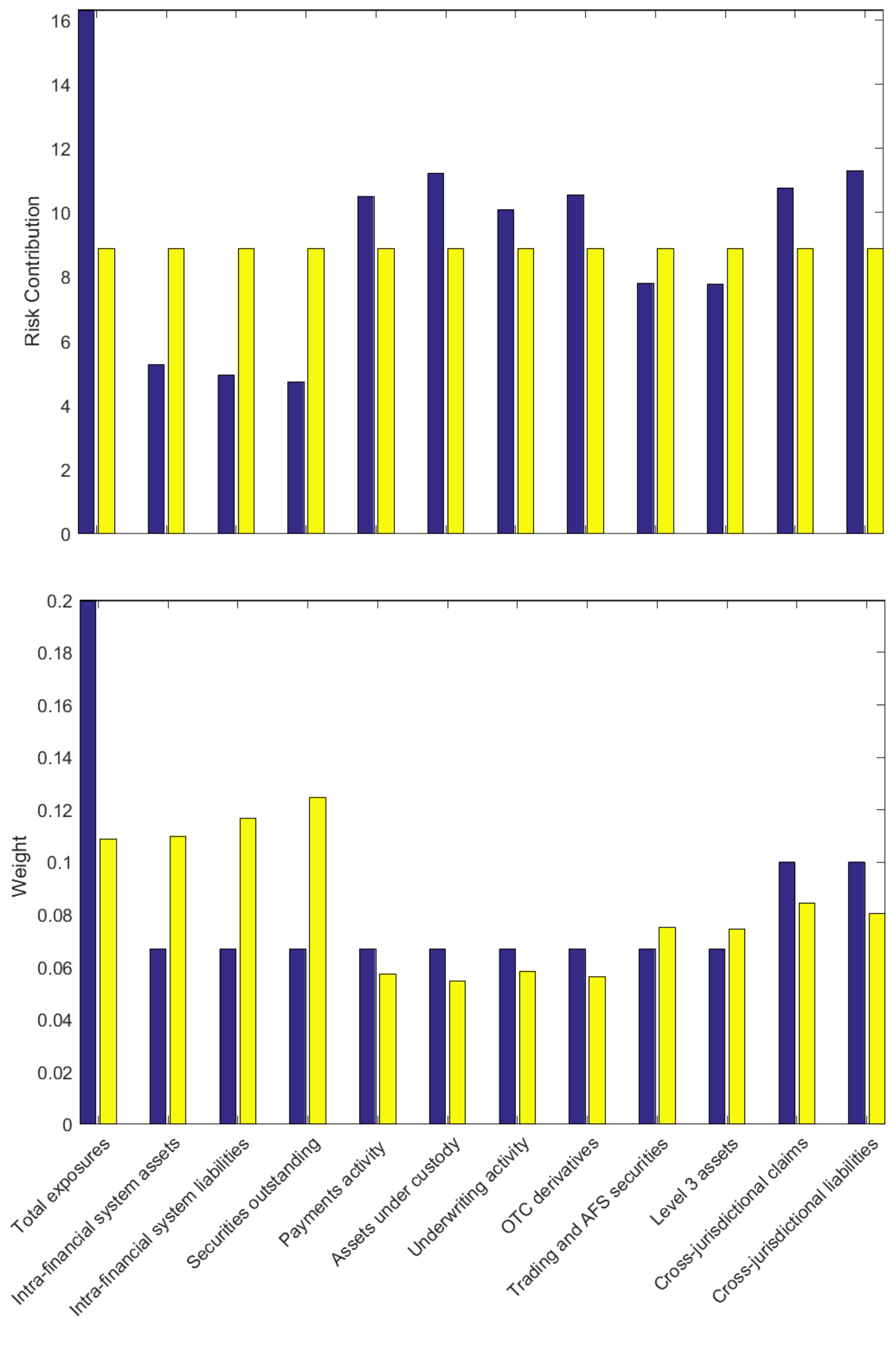

Figure 3: Risk contribution and weight for each systemic-risk indicator (2017)

This figure reports on top the risk contribution and on the bottom the weight of the twelve systemic-risk indicators used in the uncapped BCBS Score (dark blue bars) and in the ERC^{ind} Score (yellow bars) for the year 2017.

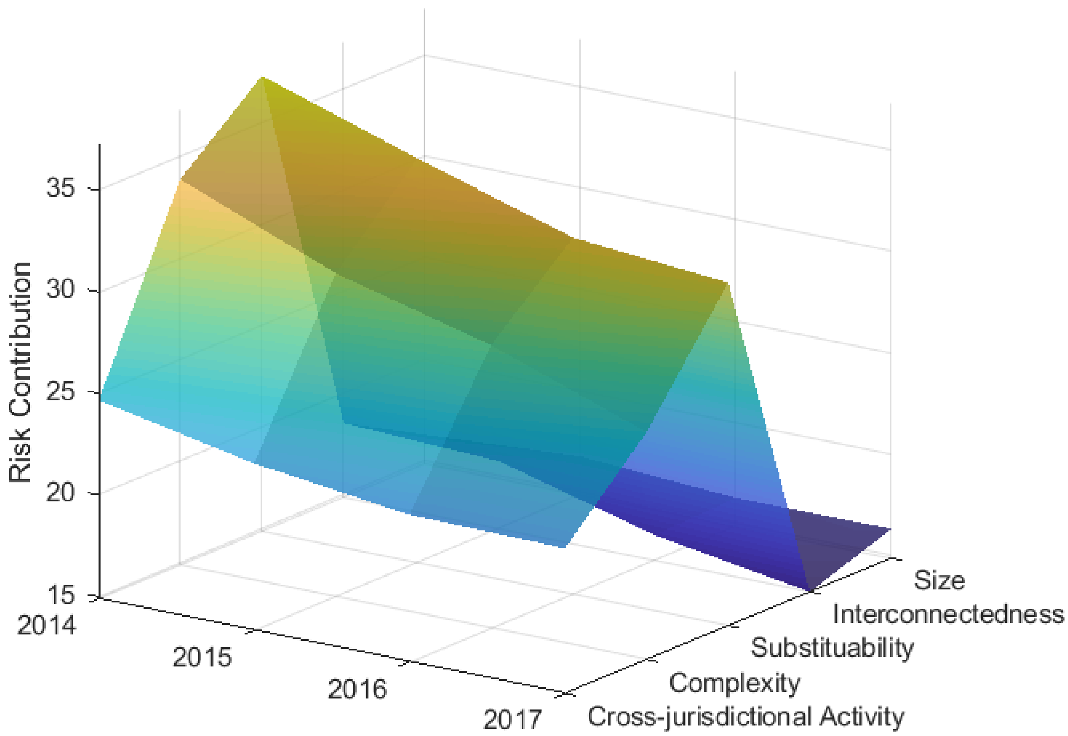

Figure 4: Evolution over time of the risk contribution for each systemic-risk category with BCBS weights

This figure reports the yearly evolution over time (from 2014 to 2017) of the risk contribution of the five systemic-risk categories with the current BCBS weights.

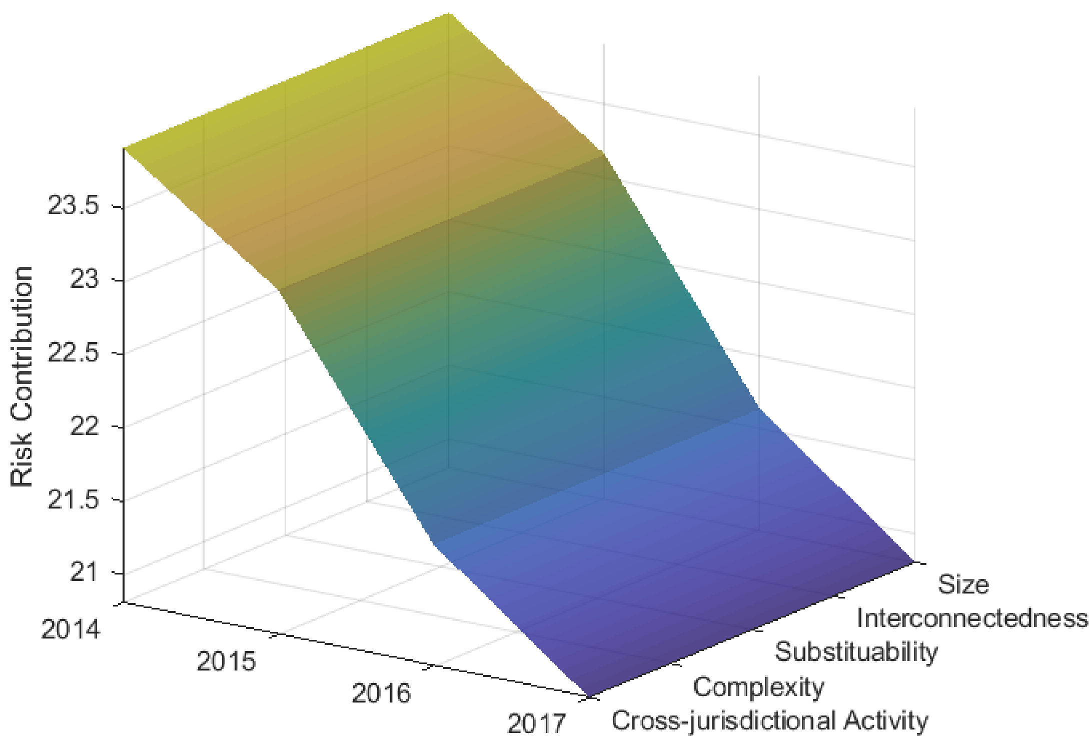

Figure 5: Evolution over time of the risk contribution for each systemic-risk category with ERC weights

This figure reports the yearly evolution over time (from 2014 to 2017) of the risk contribution of the five systemic-risk categories when the ERC weights based on categories.

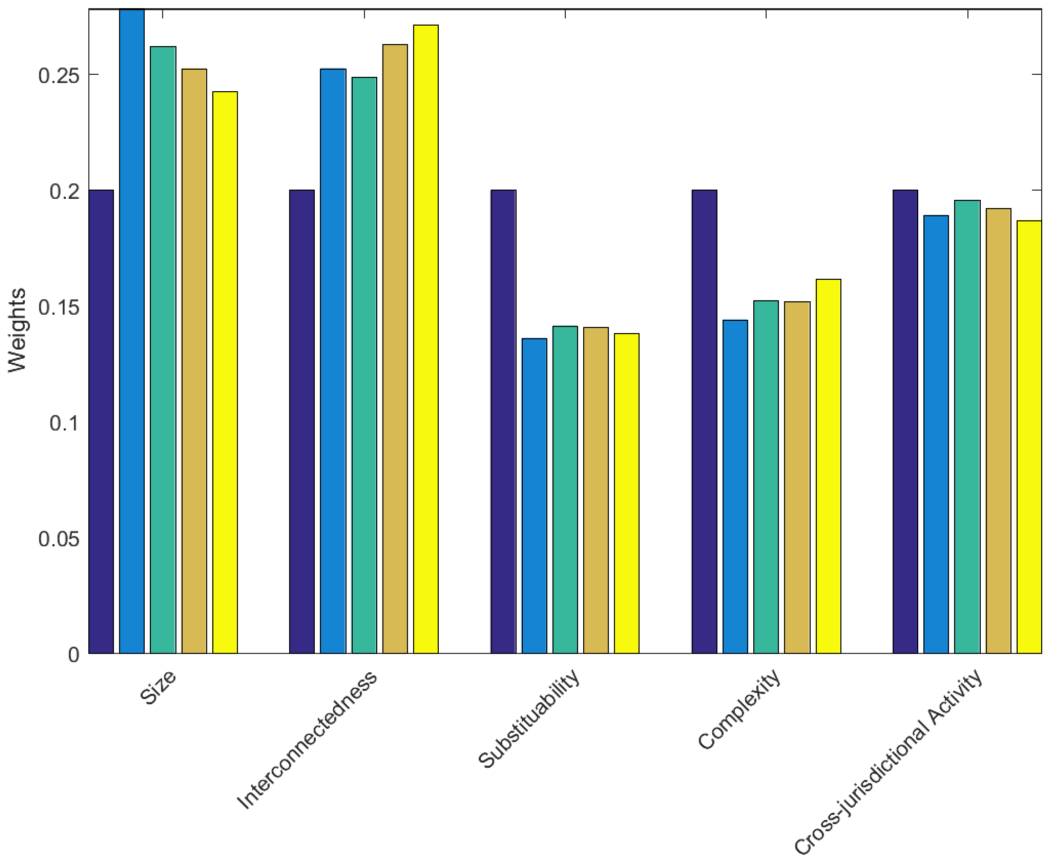

Figure 6: Equal weights vs. ERC weights (category)

This figure reports the weights of each category used by the BCBS methodology (dark blue bars) to construct the systemic-risk score, and the ERC weights for the year 2014 (light blue bars), 2015 (green bars), 2016 (orange bars), and 2017 (yellow bars).

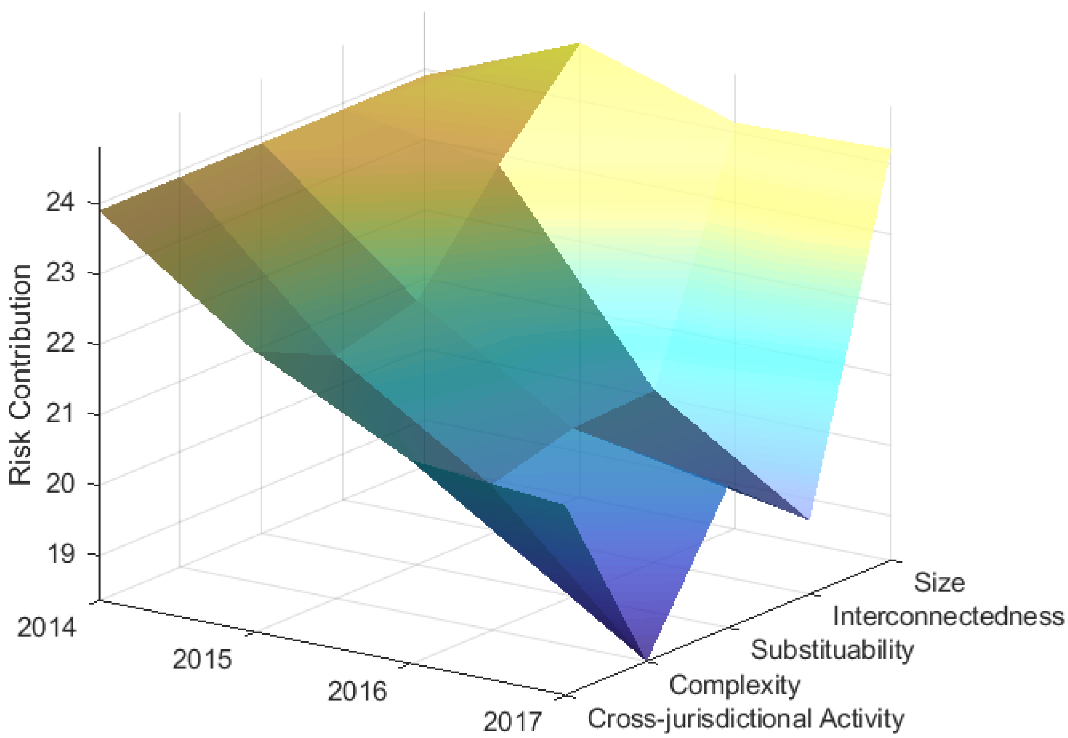

Figure 7: Evolution over time of the risk contribution for each systemic-risk category with constant ERC weights

This figure reports the yearly evolution over time (from 2014 to 2017) of the risk contribution of the five systemic-risk categories when the ERC weights based on categories remain constant over time. The ERC weights are set at the beginning of the period (2014).

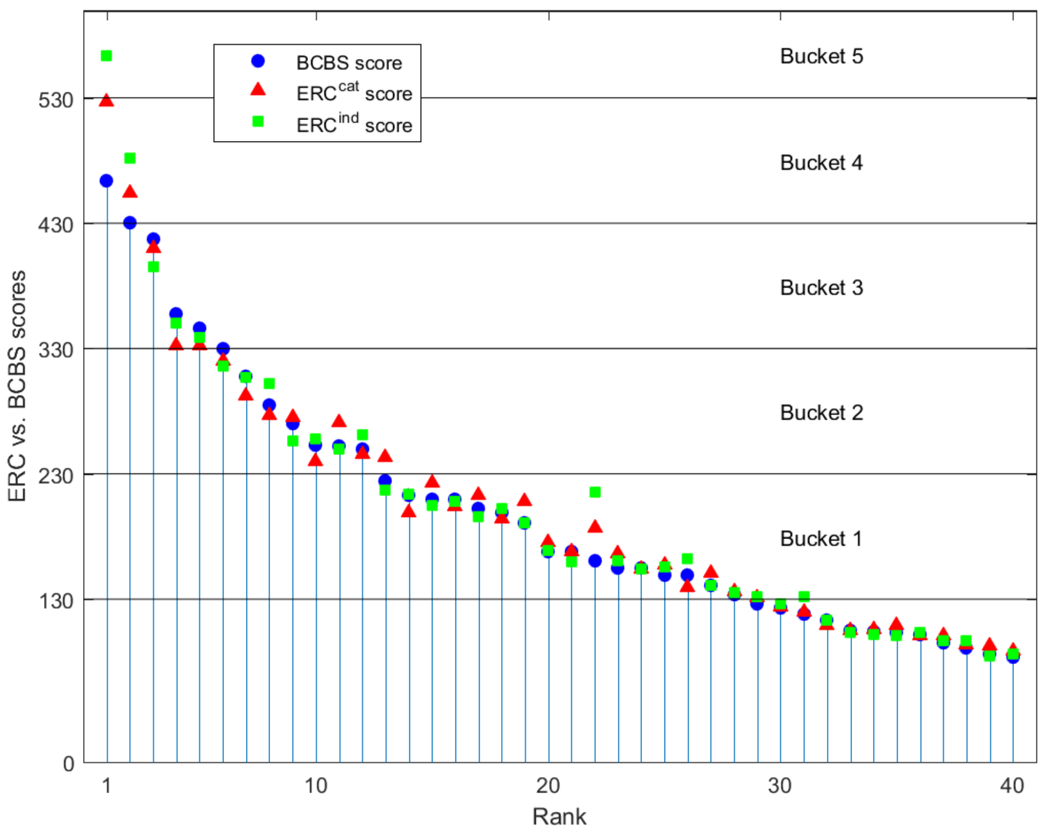

Figure 8: SIFI ranking based on smart systemic-risk (2016)

This figure displays the BCBS systemic-risk scores (blue circles) in descending order and the corresponding *smart* systemic-risk scores as of 2016 (red triangles for the equally-weighted risk contribution score based on categories and green square for the equally-weighted risk contribution score based on indicators). 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.

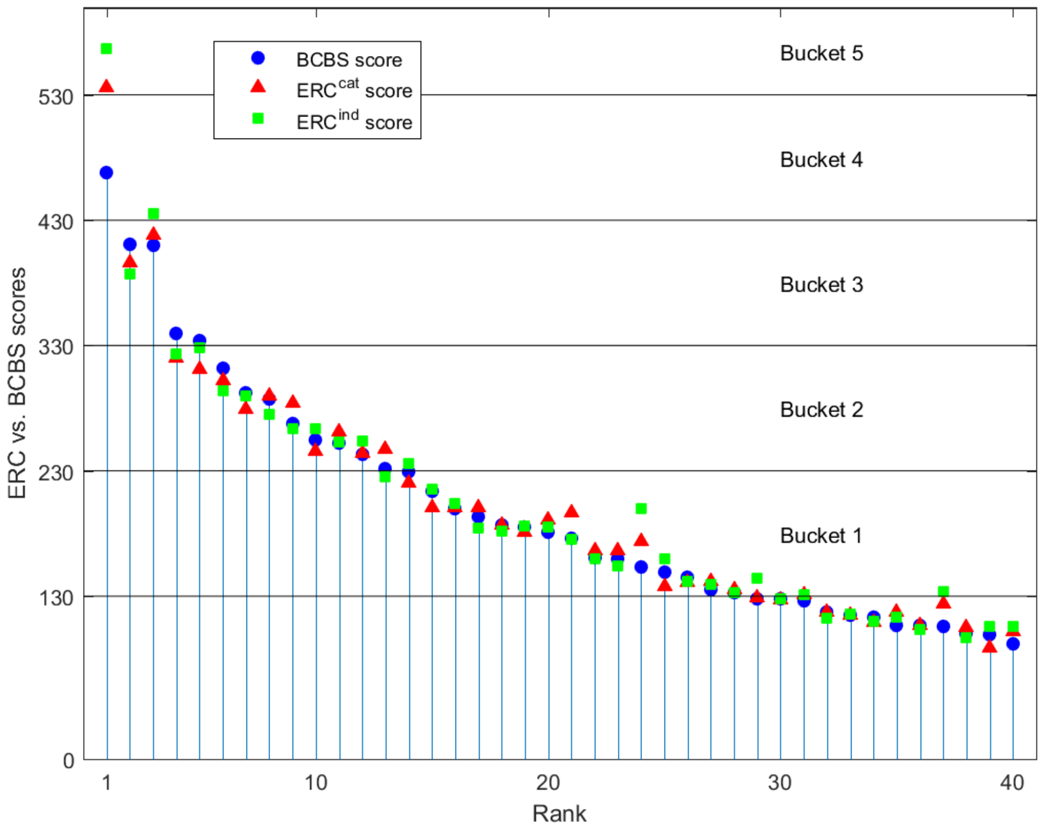

Figure 9: SIFI ranking based on smart systemic-risk (2017)

This figure displays the BCBS systemic-risk scores (blue circles) in descending order and the corresponding *smart* systemic-risk scores as of 2016 (red triangles for the equally-weighted risk contribution score based on categories and green square for the equally-weighted risk contribution score based on indicators). 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.

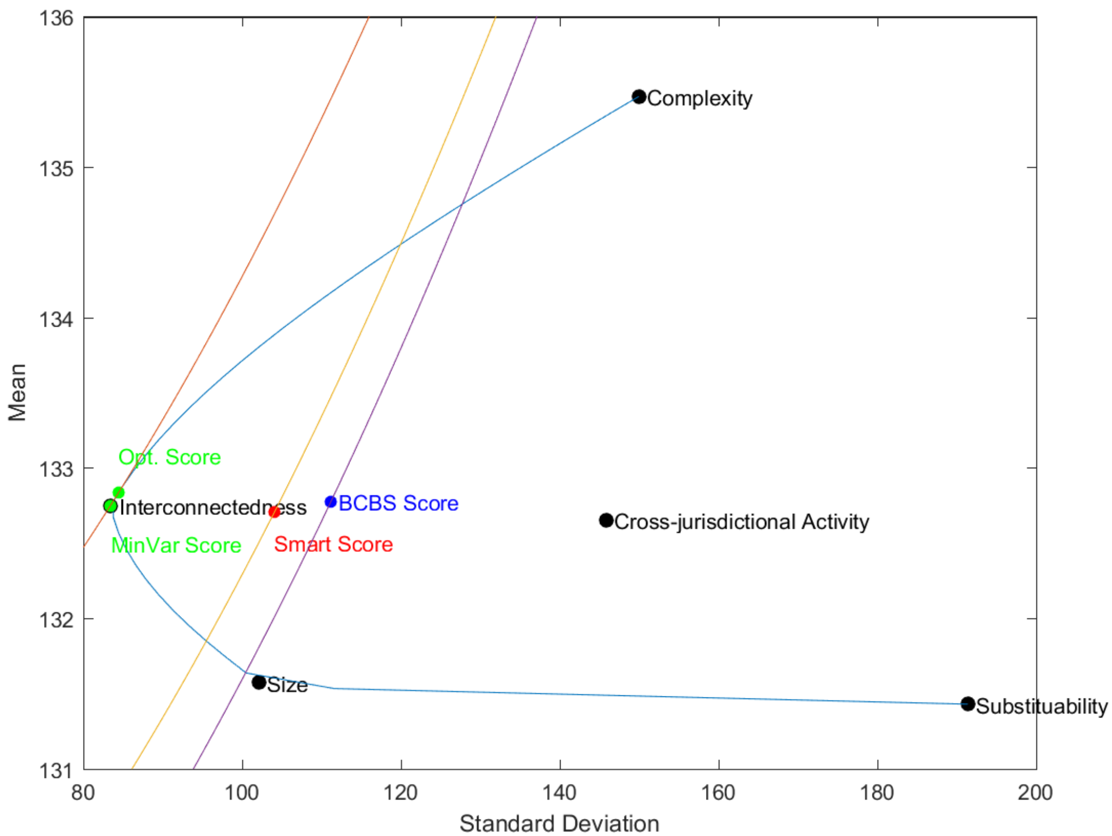

Figure 10: Mean-variance representation of systemic-risk scores based on categories (2017)

This figure displays the cross-sectional mean and standard deviation of the 4 systemic-risk scores (optimal, minimum-variance, uncapped BCBS, and smart based on categories) and of the 5 systemic-risk categories for the year 2017. Utility curves are also reported.

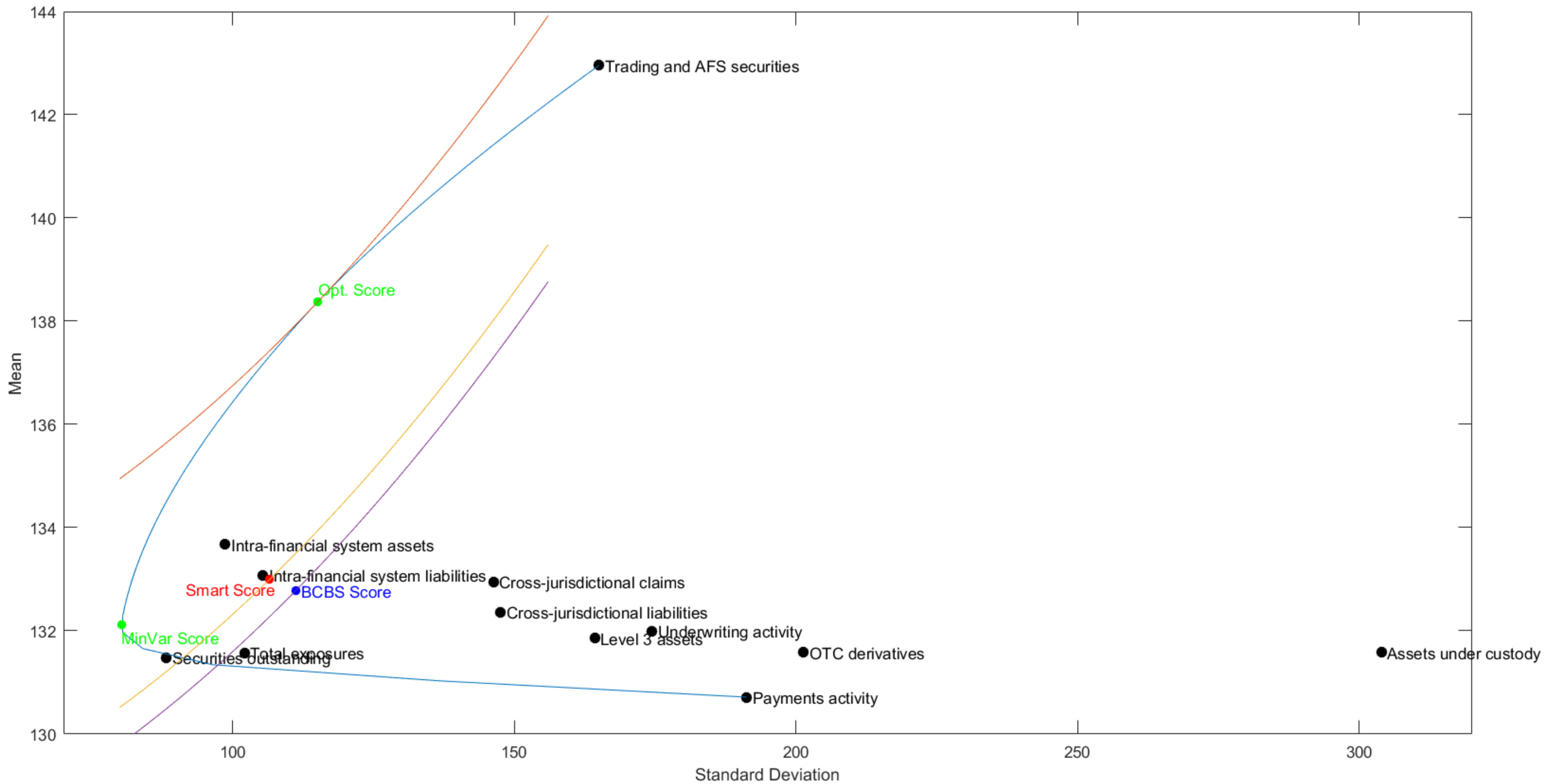

Figure 11: Mean-variance representation of systemic-risk scores based on indicators (2017)

This figure displays the cross-sectional mean and standard deviation of the 4 systemic-risk scores (optimal, minimum-variance, uncapped BCBS, and smart based on indicators) and of the 12 systemic-risk indicators for the year 2017. Utility curves are also reported.

Appendix A SIFI assessment sample

This table displays the 80 banks appearing at least once in the main sample of the regulatory framework between 2014 and 2017, along with their country of origin and the year in which I collect data. "Yes" or "No" indicates whether the bank belongs to the main sample for the mentioned year. "NA" means that the bank belongs to the main sample, but its data are not available.

	Bank name	Country	2014	2015	2016	2017
1.	ANZ	Australia	NA	NA	Yes	Yes
2.	Commonwealth	Australia	NA	NA	Yes	Yes
3.	National Australia Bank	Australia	NA	NA	Yes	Yes
4.	Westpac	Australia	NA	NA	Yes	Yes
5.	Banco Bradesco	Brazil	NA	NA	No	Yes
6.	Banco Do Brasil	Brazil	NA	NA	Yes	Yes
7.	Caixa Economica Federal	Brazil	NA	NA	Yes	Yes
8.	Itaú Unibanco	Brazil	NA	NA	Yes	Yes
9.	Bank of Montreal	Canada	Yes	Yes	Yes	Yes
10.	Bank of Nova Scotia	Canada	Yes	Yes	Yes	Yes
11.	Canadian Imperial Bank of Commerce (CIBC)	Canada	Yes	Yes	Yes	Yes
12.	Royal Bank of Canada	Canada	Yes	Yes	Yes	Yes
13.	Toronto Dominion Canada Trust	Canada	Yes	Yes	Yes	Yes
14.	Agricultural Bank of China	China	Yes	Yes	Yes	Yes
15.	Bank of Beijing	China	No	No	Yes	Yes
16.	Bank of China	China	Yes	Yes	Yes	Yes
17.	Bank of Communications	China	Yes	Yes	Yes	Yes
18.	China Construction Bank	China	Yes	Yes	Yes	Yes
19.	China Everbright Bank	China	Yes	Yes	Yes	Yes
20.	China Guangfa Bank	China	NA	Yes	Yes	Yes
21.	China Merchant Bank	China	Yes	Yes	Yes	Yes
22.	China Minsheng Bank	China	Yes	Yes	Yes	Yes
23.	Citic	China	Yes	Yes	Yes	Yes
24.	Hua Xia Bank	China	Yes	Yes	Yes	Yes
25.	Industrial and Commercial Bank of China (ICBC)	China	Yes	Yes	Yes	Yes
26.	Industrial Bank	China	Yes	Yes	Yes	Yes
27.	Ping an Bank	China	Yes	Yes	Yes	Yes
28.	Shanghai Pudong	China	NA	Yes	Yes	Yes
29.	Danske Bank	Denmark	Yes	Yes	Yes	Yes
30.	BNP Paribas	France	Yes	Yes	Yes	Yes
31.	Crédit Mutuel	France	Yes	Yes	Yes	Yes
32.	Groupe BPCE	France	Yes	Yes	Yes	Yes
33.	Groupe Crédit Agricole	France	Yes	Yes	Yes	Yes
34.	Société Générale	France	Yes	Yes	Yes	Yes
35.	Commerzbank	Germany	Yes	Yes	Yes	Yes
36.	Deutsche Bank	Germany	Yes	Yes	Yes	Yes
37.	DZ Bank	Germany	Yes	Yes	Yes	Yes
38.	State Bank of India	India	Yes	Yes	Yes	Yes
39.	Intesa San Paolo	Italy	Yes	Yes	Yes	Yes
40.	Unicredit	Italy	Yes	Yes	Yes	Yes
41.	Mitsubishi UFJ FG	Japan	Yes	Yes	Yes	Yes
42.	Mizuho FG	Japan	Yes	Yes	Yes	Yes
43.	Nomura Holdings	Japan	Yes	Yes	Yes	Yes
44.	Sumitomo Mitsui FG	Japan	Yes	Yes	Yes	Yes
45.	Sumitomo Mitsui Trust Holdings	Japan	Yes	Yes	Yes	Yes
46.	The Norinchukin Bank	Japan	Yes	Yes	Yes	Yes
47.	Hana Bank	Korea	NA	Yes	Yes	Yes
48.	Kookmin	Korea	No	No	Yes	Yes
49.	Shinhan	Korea	NA	Yes	Yes	Yes
50.	ABN AMRO	Netherlands	Yes	Yes	Yes	Yes
51.	ING Bank	Netherlands	Yes	Yes	Yes	Yes
52.	Rabobank	Netherlands	Yes	Yes	Yes	Yes
53.	DNB Bank	Norway	Yes	Yes	No	No
54.	Sberbank	Russia	Yes	Yes	Yes	Yes
55.	DBS Bank	Singapore	Yes	Yes	Yes	Yes

	Bank name	Country	2014	2015	2016	2017
56.	BBVA	Spain	Yes	Yes	Yes	Yes
57.	Criteria Caixa-Holding	Spain	Yes	Yes	Yes	Yes
58.	Santander	Spain	Yes	Yes	Yes	Yes
59.	Handelsbanken	Sweden	Yes	Yes	No	No
60.	Nordea	Sweden	Yes	Yes	Yes	Yes
61.	SEB	Sweden	Yes	Yes	Yes	No
62.	Credit Suisse	Switzerland	Yes	Yes	Yes	Yes
63.	UBS	Switzerland	Yes	Yes	Yes	Yes
64.	Barclays	United Kingdom	Yes	Yes	Yes	Yes
65.	HSBC	United Kingdom	Yes	Yes	Yes	Yes
66.	Lloyds	United Kingdom	Yes	Yes	Yes	Yes
68.	Royal Bank of Scotland	United Kingdom	Yes	Yes	Yes	Yes
69.	Standard Chartered	United Kingdom	Yes	Yes	Yes	Yes
70.	Bank of America	United States	Yes	Yes	Yes	Yes
71.	Bank of New York Mellon	United States	Yes	Yes	Yes	Yes
72.	Capital One	United States	No	No	Yes	Yes
73.	Citigroup	United States	Yes	Yes	Yes	Yes
74.	Goldman Sachs	United States	Yes	Yes	Yes	Yes
75.	JP Morgan Chase	United States	Yes	Yes	Yes	Yes
76.	Morgan Stanley	United States	Yes	Yes	Yes	Yes
77.	PNC	United States	Yes	Yes	Yes	Yes
78.	State Street	United States	Yes	Yes	Yes	Yes
79.	US Bancorp	United States	Yes	Yes	Yes	Yes
80.	Wells Fargo	United States	Yes	Yes	Yes	Yes

Appendix B The volatility as a coherent measure of risk

I use the axiomatic framework proposed by Artzner, Delbaen, Eber, and Heath (1999) to show that the volatility is a coherent risk measure at a single-firm level.

Let X and Y be two random variables. With $\mathrm{V}(X)$ I indicate the variance of X, and with $\sigma_X = \sqrt{\mathrm{V}(X)}$ its standard deviation (volatility).

- *Monotonicity*: If X is considered riskier than Y, then $\sigma_X \geq \sigma_Y$. In other words, X is more volatile than Y.
- *Positive homogeneity*: For all nonnegative scalars $\alpha \geq 0$, $\sqrt{\mathrm{V}(\alpha X)} = \alpha \sqrt{\mathrm{V}(X)}$.
- *Sub-additivity*: I know that $\mathrm{corr}(X, Y) \in [-1; 1]$

$$\begin{aligned}
\mathrm{V}(X+Y) &= \mathrm{V}(X) + \mathrm{V}(Y) + 2\ \mathrm{corr}(X,Y)\ \sigma_X\ \sigma_Y, \text{ but } \max\left(\mathrm{corr}(X,Y)\right) = 1, \text{ then} \\
\mathrm{V}(X+Y) &\leq \mathrm{V}(X) + \mathrm{V}(Y) + 2\ \sigma_X\ \sigma_Y \\
\Leftrightarrow \sigma_{X+Y}^2 &\leq \sigma_X^2 + \sigma_Y^2 + 2\ \sigma_X\ \sigma_Y \\
\Leftrightarrow \sigma_{X+Y}^2 &\leq (\sigma_X + \sigma_Y)^2 \\
\Leftrightarrow \sqrt{\sigma_{X+Y}^2} &\leq \sqrt{(\sigma_X + \sigma_Y)^2} \\
\Leftrightarrow \sigma_{X+Y} &\leq \sigma_X + \sigma_Y
\end{aligned}$$

- *Translation (Cash) Invariance*: For all scalars $c \in \mathbb{R}$, $\sqrt{\mathrm{V}(X+c)} = \sqrt{\mathrm{V}(X)}$.
- *Normalization*: $\sigma_0 = 0$.

When combining the notions of sub-additivity and positive homogeneity, I end up with the notion of *convexity*: for a given scalar $0 \leq \alpha \leq 1$, then $\sigma_{\alpha\ X+(1-\alpha)\ Y} \leq \alpha\ \sigma_X + (1-\alpha)\ \sigma_Y$.