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An empirical foundation for calibrating the G-SIB surcharge

Alexander Jiron, Wayne Passmore and Aurite Werman[1]

Abstract

As developed by the Basel Committee on Banking Supervision (BCBS), the expected impact framework is the theoretical foundation for calibrating the capital surcharge applied to global systemically important banks (G-SIB surcharge). This paper describes four improvements to the current implementation of the BCBS expected impact framework. We (i) introduce a theoretically sound and an empirically grounded approach to estimating a probability of default (PD) function; (ii) apply density-based cluster analysis to identify the reference bank for each G-SIB indicator; (iii) recalibrate the systemic loss-given-default (LGD) function that determines G-SIB scores, using both the current system based on supervisory judgment and using an alternative system based on CoVaR; and (iv) derive a continuous capital surcharge function to determine G-SIB capital surcharges. Our approach would strengthen the empirical and theoretical foundation of the G-SIB surcharge framework. Moreover, the continuous surcharge function would reduce banks' incentive to manage their balance sheets to reduce systemic capital surcharges, mitigate cliff effects, allow for the lifting of the cap on the substitutability score and penalise growth in the category for all G-SIBs. We conclude with some thoughts about the use of these two capital surcharge functions for monitoring G-SIBs' capital adequacy.

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Contents

An empirical foundation for calibrating the G-SIB surcharge ... 2

1. Introduction ... 1
   - 1.1 Background ... 1
   - 1.2 Current implementation of the BCBS expected impact framework ... 1
   - 1.3 Improvements to the expected impact framework ... 2
2. Data ... 4
   - PD function ... 4
   - G-SIB scores for reference bank score calculation and LGD parameter calibration ... 6
   - LGD calibration using CoVaR ... 6
3. Applying extreme value theory to the PD function ... 6
4. Selection of the reference bank ... 11
5. Social LGD ... 15
6. Continuous surcharge functions ... 18
7. Impact analysis using the supervisory surcharge function ... 21
8. Impact analysis using the CoVaR surcharge function ... 22
9. Conclusion and other considerations ... 24
   - 9.1 Strengthening empirical basis and transparency of current framework ... 24
   - 9.2 Lifting the substitutability cap ... 24
   - 9.3 Removing cliff effects from current framework and balancing incentives to shrink ... 24
   - 9.4 Comparing the supervisory and CoVaR-based surcharge frameworks ... 25
   - 9.5 Monitoring capital surcharges and systemic risk ... 25
   - References ... 26

Appendix A: Mathematical derivation of G-SIB capital surcharge function ... 27

Appendix B: GPD threshold selection ... 29

Appendix C: DBSCAN results for all indicators ... 30

Appendix D: Dollar delta-CoVaR calculation ... 33

1. Introduction

1.1 Background

The failure of large, interconnected and systemically important financial banks (G-SIBs) can endanger global financial stability and have severe impacts on the real economy. During the Great Financial Crisis (GFC) of 2007–09, policymakers intervened to prevent the failure of these institutions and to alleviate enormous stress in the financial system. Following this crisis, the BCBS and individual home country regulators introduced measures to reduce the likelihood and severity of a G-SIB failure in the future. Specifically, the BCBS established a higher loss absorbency (HLA) standard, with the aim of increasing the going-concern loss absorbency of a G-SIB by requiring these firms to hold additional capital in accordance with their systemic importance.[2] Requiring these firms to hold additional capital reduces risk to the financial system, and the standard aims to reduce the expected impact of a G-SIB's failure so that it is equal to the expected impact of a non-G-SIB's failure.[3] According to the BCBS methodology for calibrating this HLA standard, G-SIBs must hold Common Equity Tier 1 (CET1) capital commensurate with their "G-SIB score". This additional capital buffer is the G-SIB capital surcharge.

1.2 Current implementation of the BCBS expected impact framework

The expected impact framework focuses on the expected social loss (ESL) of a bank's failure. Expected social loss is equal to the systemic social losses that would occur if the bank failed (social LGD), discounted by its PD:

$$ESL = social\ LGD * PD \quad (1)$$

The goal of the expected impact framework is to increase the capital surcharge of a G-SIB in order to reduce the firm's PD so that the expected systemic social loss from the failure of the G-SIB equals that of a reference bank, r. The reference bank is defined as the most systemically important bank that is not a G-SIB. Effectively, the reference bank is a benchmark for acceptable social loss, and it may be thought of as the most systemically important bank that authorities would allow to fail without extraordinary government intervention. Mathematically, the expected impact framework is characterised by the following equation:

$$ESL_{G\text{-}SIB} = ESL_r \quad (2)$$

Since the components of expected social loss are PD and LGD, this is equivalent to:

$$PD_{G\text{-}SIB} * LGD_{G\text{-}SIB} = PD_r * LGD_r \implies \frac{LGD_{G\text{-}SIB}}{LGD_r} = \frac{PD_r}{PD_{G\text{-}SIB}} \quad (3)$$

The expected loss of a G-SIB is set equivalent to that of the reference bank through a reduction of PD. No capital surcharge to account for systemic risk is applied to the reference bank, but the selection of the reference bank matters for the G-SIB surcharge calculation. Under the current framework, supervisors have selected 130 bp as both the reference bank score and as the threshold for G-SIB

[2] See Financial Stability Institute, *The G-SIB framework – Executive Summary*, October 2018, www.bis.org/fsi/fsisummaries/g-sib_framework.pdf.

[3] See Berger et al (2019); Acharya et al (2012); and Laeven et al (2016).

designation. If a bank's G-SIB score exceeds 130 bp, it is classified as a G-SIB, and supervisors apply a capital surcharge to lower its PD.

For banks that are not systemically important, PD and LGD can be estimated directly using information on bank failures. Failures of these banks have limited negative consequences for society. For G-SIBs, however, neither PD nor social LGD is straightforward, in large part because data on defaulted G-SIBs do not exist. G-SIBs are not resolved easily and failures often involve mergers or substantial government support.

The BCBS's current implementation of the expected impact framework does not posit an explicit function for PD. Rather, the PD function can be considered implicit within the methodology. The current implementation uses regulatory judgment to implicitly specify PD and social LGD functions (their product must always yield ESL_r in the expected impact framework) and a method for calculating a proxy for social LGD (the G-SIB score).

Even though social losses are difficult to define or measure, a G-SIB by definition must have a higher social LGD than a non-G-SIB. The BCBS has developed a methodology for calculating a G-SIB score, intending for the score to reflect a G-SIB's social LGD. The G-SIB score is calculated based on 12 indicators, mapped to categories of bank size, interconnectedness, the lack of readily available substitutes or financial institution infrastructure for the services they provide ("substitutability"), cross-jurisdictional activity, and complexity, with each of the five categories receiving equal weight. For each bank, the score for a particular indicator is calculated by dividing the individual bank amount by the aggregate amount summed across all banks in the sample (a "global market share" concept). Each of the categories (and each of the individual indicator values) is assumed to map linearly to a bank's systemic importance score, with the exception of substitutability, which is composed of payments activity, underwritten transactions, and assets under management indicators.

The current implementation of the expected impact framework includes a cap on the substitutability category. The cap limits the maximum substitutability score to 500 bp. Since each category is weighted by 20% to arrive at a bank's overall G-SIB score, the substitutability category can account for no more than 100 bp of any bank's overall G-SIB score. Some observers have argued that the cap on substitutability introduces to the framework uneven incentives to shrink in systemic importance across categories, and that removing the cap would better balance incentives to shrink across categories and indicators. The BCBS established the cap because of concerns that the category had an outsized influence on the final G-SIB score.

Moreover, the current methodology allows firms to grow within score "buckets" of 100 bp, while maintaining the same capital surcharge. Moving to the next bucket results in a capital surcharge increase of 50 bp. This system creates cliff effects and features uneven disincentives for growth. Under this system, a bank at the lower end or midpoint of its score bucket could grow its score significantly with no change in its capital surcharge, while a bank at the higher end of its score bucket could see a 50 bp capital surcharge increase for a smaller score increase. While the framework is designed to incentivise banks to reduce their systemic importance, the strength of this incentive varies based on where in a bucket a G-SIB's score lies. The advantage of buckets is that smaller movements in G-SIB scores do not increase a bank's regulatory capital requirement, thus reducing volatility in capital requirements.

Finally, in the current implementation, the relationship between the social LGD and the G-SIB score is unknown. Furthermore, the G-SIB score is not calibrated to any measurable concept of social LGD.

1.3 Improvements to the expected impact framework

Under the current implementation of the expected impact framework, the G-SIB framework:

- Posits no explicit function for PD;

- Relies on a reference bank score that was selected using supervisory consensus and has not been updated since 2012;
- Introduces uneven incentives to shrink across categories by maintaining the cap on the substitutability category;
- Features cliff effects by relating G-SIB score to capital surcharge using a step function; and
- Has no link to a measurable concept of social LGD.

This paper describes an approach that seeks to improve upon these elements of the expected impact framework as currently implemented – a simple, continuous and empirically grounded surcharge function.

There are four significant advantages to our approach. First, we introduce an explicit PD function with a theoretical and empirical basis. In this alternative framework, PD is estimated using extreme value theory, which is an appropriate modelling technique for the extreme tails of return distributions and, in particular, for extreme tails that are thinly populated by actual events.

Second, we introduce the use of density-based cluster analysis (DBSCAN) to construct a reference bank score for each indicator. Unlike the current framework, where the reference bank score for each indicator is unidentified, our approach is explicit by indicator and varies across indicators. In our approach, cluster analysis would replace supervisory discretion in the selection of the reference bank. Here, a bank's systemic importance is based on its "uniqueness", which is measured by the availability of banks that are close substitutes. "Uniqueness" indicates a lack of substitute banks and therefore a higher social LGD. The reference bank, for a given indicator, is defined as the bank with the largest market share of an indicator that is not "unique", as determined by an analytically sound technique.

Third, we introduce a new explicit LGD function. We use two new supervisory parameters, while requiring LGD to increase exponentially as a bank's G-SIB score rises. Our approach is consistent with the view that there is an exponentially higher social cost of G-SIB failure when the bank is more systemically important. The LGD function, combined with the other components listed above, also allows for a lifting of the substitutability cap introduced in 2013. At the time of its introduction, the cap was set to allow the substitutability category to remain an important factor in the determination of systemic importance, while limiting its potential impact to 100 bp (one bucket) of a bank's G-SIB score.[4] Our framework preserves substitutability as a key determinant of a bank's score and increases the incentive to reduce concentration in the provision of payment, underwriting and asset custody services when banks have larger market shares. In addition, this approach maintains G-SIB capital surcharges within their current range.

The parameters of the LGD function can also be estimated using CoVaR as a measure of social LGD (Adrian and Brunnermeier (2016)). CoVaR is a measure of the social losses (the "spillover" effects) imposed on the financial system when a systemically important financial institution falters. This approach relates the G-SIB score to a well-grounded measure of LGD and also provides an estimate of the importance of non-linear effects as the G-SIB score for a bank increases.

The fourth advantage to our approach is its explicit and continuous nature. The estimated PD and LGD function parameters, revised reference bank score and a firm's G-SIB score are clearly understood inputs to a continuous G-SIB capital surcharge function. In contrast, the current G-SIB surcharge buckets, which are set at 50 bp increments and where each surcharge "bucket" corresponds to a 100 bp range in calculated G-SIB score, has no underlying analytical structure. Under the current framework, surcharge buckets create cliff effects in surcharge levels, and fail to capture increases in social cost as intra-bucket

[4] The BCBS stated that the substitutability category had "a greater impact on the assessment of systemic importance than the Committee initially intended for banks that are dominant in the provision of payment, underwriting, and asset custody services" because the category has a skewed distribution relative to other categories. See BCBS, *Global systemically important banks – revised assessment framework* , March 2017.

scores rise, strengthening incentives to manage scores by "window dressing". A continuous function for capital surcharges reduces incentives to manage scores.

Table 1 provides an overview of key features of the current G-SIB methodology and the alternative approach.

Comparison of current methodology and alternative approach — Table 1

	Current methodology	Alternative approach
Based on expected impact framework	Yes	Yes
PD function	No explicit PD function	Explicit PD function estimated using extreme value theory
Reference bank score	130, based on supervisory consensus	150, based on density-based clustering analysis
Calculation of G-SIB score	0.2 * calculated score for each of five categories; substitutability score may not exceed 100 bp $s_i = \Sigma_{k\neq5}^{K} 0.2 * x_{ik} + 0.2 * \min(x_{i5,\,500})$ where substitutability category is k=5	0.2 * calculated score for each of five categories; no cap on substitutability $s_i = \Sigma_{1}^{k} 0.2 * x_{ik}$
Social (LGD) function	Calculated G-SIB score reflects bank's social LGD	Explicit social LGD function with exponential form and two parameters. One version is empirically based.
Surcharge function	Step function; 100 bp score buckets correspond to 50 bp capital surcharge buckets	Continuous function

Our continuous G-SIB capital surcharge function is calculated by combining parameters from an explicit PD function, an updated reference bank score, a bank's uncapped G-SIB score, and calibrated parameters of an LGD function to result in the following simple and continuous functional form:

$$G\text{-}SIB\ capital\ surcharge = ce^{a+b(G\text{-}SIB\ score-r)} - c \quad (4)$$

where c is the output of an explicit PD function, r is an updated reference bank score calculated using density-based cluster analysis for each indicator, and a and b are calculated based on parameters of the PD function and parameters of the LGD function. When estimated and calibrated values are substituted into equation (4), the capital surcharge function that matches the conservative nature of the *current* G-SIB framework is (with rounding):

$$G\text{-}SIB\ capital\ surcharge = 8.5e^{0.1+0.0004(G\text{-}SIB-150)} - 8.5 \quad (5)$$

The following sections describe the derivation and justification of each of these values in further detail.

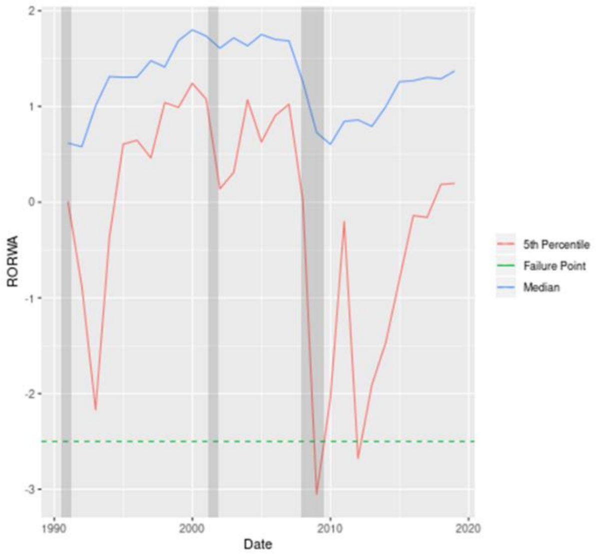
2. Data

PD function

For the purposes of estimating a PD function, our sample is constructed using annual balance sheet data on global banks with inflation-adjusted total consolidated assets of more than $50 billion from 1990 to 2018. We obtain data on net income, total consolidated assets, total risk-weighted assets (RWA), total net loans, and trading account assets from S&P Market Intelligence. We use the personal consumption expenditure (PCE) price index, excluding food and energy, available via Federal Reserve Economic Data (FRED) to calculate inflation-adjusted total consolidated assets with 2018 as the base year.[5] We calculate returns on risk-weighted assets (RORWA) as the ratio between net income and total RWA. If total RWA data are not available, we impute values based on a simple model,[6] regressing total RWA on total net loans, trading account assets, and other assets. Finally, we eliminate extreme outliers in terms of RORWA.[7]

Overall, this sample consists of an unbalanced panel of 2,404 bank-year observations with 351 distinct banks. Over the entire sample period, RORWA ranges from -20.7% to 18.2% with a median of 1.23%. The average RORWA is 1.17% with a standard deviation of 1.68%. The 5th percentile of the RORWA distribution is approximately -0.68%. In the estimation of the PD function below, we focus on the 7.5% tail of the RORWA distribution, which consists of 181 bank-year observations with 80 distinct banks. In this subsample, RORWA ranges from approximately 0% to -20.7% with a mean of -2.3% and a median of -1.26%.

Return on risk-weighted assets for banks with more than $50 billion in total consolidated assets: 1990-2018 — Graph 1



Sources: Federal Reserve Bank of St. Louis, FRED; S&P Global, Market Intelligence; and authors' calculations.

At the height of the GFC, the median RORWA in our global sample was still positive and the median firm did not breach the failure point (Graph 1). In contrast, the 5th percentile of RORWA was just below -3%, and therefore 5% of banks in our sample did breach the failure point during that period. The

[5] See Federal Reserve Bank of St. Louis, *Personal consumption expenditures excluding food and energy (chain-type price index) (PCEPILFE)*, https://fred.stlouisfed.org/series/PCEPILFE.

[6] If total net loans, trading account assets or other assets are also unavailable, a cruder fallback option is used, regressing total risk-weighted assets on only total consolidated assets.

[7] The exclusion of outliers can be important because the tail of distribution is thinly populated. We exclude all RORWA values lower than -40% or greater than 100% (0.02% trimming).

5th percentile of RORWA also breached the failure point in 2012, as the sovereign debt crisis in the euro zone worsened.

G-SIB scores for reference bank score calculation and LGD parameter calibration

Furthermore, we obtain public annual data on G-SIB indicator values for banks in the G-SIB assessment main sample as well as the corresponding global denominators from the BIS for 2013 to 2018. The main sample of the G-SIB assessment consists of the largest 75 global banks in a given year along with some occasional adjustments.[8] From these data, we calculate banks' G-SIB scores under the assumption that the cap on the substitutability category remains in place, and under the assumption that the cap is lifted. Over our entire sample, G-SIB scores under the current methodology ranged from 13 bp to 504 bp, with a median of 88 bp. The average G-SIB score is 128 bp with a standard deviation of 106 bp. Meanwhile, uncapped G-SIB scores range from 13 bp to 646 bp, with the same median but slightly higher mean of 132 bp and standard deviation of 115 bp. These G-SIB score data are used in calibrating the LGD functions below. In addition, banks' market shares in each G-SIB indicator are calculated from these data and used in constructing a reference bank score below.

LGD calibration using CoVaR

We obtain data on daily equity returns for the banks in the main sample of the G-SIB assessment between 2013 and 2018 via Bloomberg. Our sample consists of 73 banks. Eleven banks in the main sample did not have equity returns data available in Bloomberg.[9] We obtain returns data on the MSCI ACWI index from Bloomberg as well. Using these data, we calculate banks' year-end dollar delta-CoVaR from 2013 to 2018 based on simple implementation of Adrian and Brunnermeier (2016). We set the significance level at 2.15% to match the unconditional PD of the reference bank (estimated below). Therefore, our measure of dollar delta-CoVaR estimates the impact, roughly speaking, on the stock market of a decline in the equity return of a given bank from its median value to a value associated with the 2.15% quantile of the bank's historical return distribution (see Appendix D for more detail on the methodology). Finally, we merge these dollar delta-CoVaR data with G-SIB score data, resulting in an unbalanced panel with 405 firm-year observations.

3. Applying extreme value theory to the PD function

Our approach specifies an explicit, theoretically justified function that relates the level of capital held by a bank to its PD. Such a PD function is not explicit under the current implementation of the expected impact framework.

Given the large social costs of a potential G-SIB failure, governments have in the past intervened to prevent the failure of G-SIBs. As a result, there is an absence of historical data on the failure of G-SIBs with which to estimate a PD function. Our approach leverages historical RORWA data and uses low RORWA

8 See BCBS, *Global systemically important banks: revised assessment methodology and the higher loss absorbency requirement*, July 2018, for details on main sample criteria.

9 Caixa Economica, Credit Mutuel, BPCE, Norinchukin, BayernLB, China Guangfa, DZ Bank, NongHyup, Rabobank, Nationwide, and LBBW.

as a proxy for default.[10] Negative RORWA observations represent losses. In this framework, a bank is assumed to fail if it experiences a RORWA that reduces its capital level by more than the failure point f

$$RORWA \leq -f \tag{6}$$

$$k + RORWA \leq k - f \tag{7}$$

where k represents a given firm's starting capital level, $k - f$ represents the minimum viable capital level, and f is the failure point, which we set to 2.5% of RWA. Implicitly, the latter assumes that banks hold only their minimum CET1 capital requirement and their capital conservation buffer (CCB). If such a bank experienced a RORWA of less than -2.5%, it would completely deplete its CCB of 2.5% of RWA, breaching its minimum capital requirement and, therefore, it is assumed, requiring government support to avoid failure. This framework reflects Basel capital requirements, and does not take into account more stringent jurisdiction-specific capital requirements.

Overall, failure in the global population of banks with over $50 billion in inflation-adjusted total consolidated assets is rare. Extreme value theory (EVT) allows us to estimate the probability of events that almost never occur. Intuitively, this is accomplished by extrapolating from the sparsely populated tail of a distribution based on the distances among a limited number of data points. This key characteristic makes EVT appropriate for estimating the probability that a low RORWA will deplete a bank's capital buffer. EVT is also particularly useful for the modelling of financial returns that are not normally distributed and exhibit fat tails (see Carmona (2014), Rocco (2014), Nikzad and McDonald, (2017), Singh et al (2017)). Furthermore, EVT allows for the consistent estimation of tail distributions for a broad range of underlying distributions. This largely eliminates the need to identify the underlying distribution of rare events. Passmore and van Hafften (2019) first introduced the use of EVT for estimating a PD function for G-SIB capital surcharge purposes.[11]

Applying the Pickands–Balkema–de Haan theorem, for a sufficiently low threshold μ, the distribution of RORWA *conditional on being below the threshold* is asymptotically distributed according to a generalized Pareto distribution (GPD) for a broad range of underlying distributions of RORWA (including all Gaussian distributions). Assuming the underlying distribution of RORWA falls within this broad range, we do not need to actually identify this distribution. Combining this *conditional* distribution of RORWA with the *unconditional* probability of RORWA falling below the threshold μ yields the *unconditional* distribution of RORWA below the threshold:

$$\mathbb{P}(RORWA \leq x | RORWA \leq \mu) = F(x) = \left(1 + \frac{\xi(\mu - x)}{\sigma}\right)^{\frac{-1}{\xi}}, \qquad \xi > 0 \tag{8}$$

[10] Of note, no G-SIB failures exist in the sample due to robust government support for G-SIBs in times of economic stress, and G-SIB RORWA data from stress periods reflect extensive government intervention to prevent G-SIB failure. In the absence of a counterfactual, we use data that reflect observed historical experience for the largest global banks.

[11] The methodology of Passmore and van Hafften (2019) relies upon the generalized extreme value (GEV) distribution for calibrating capital surcharges. The GEV distribution is typically used to model the distribution of the maximum or minimum of large blocks of data from a sample, and is appropriate for modelling the minimum RORWA across banks at a given time or across time for a given bank. The PD function modifies Passmore and van Hafften (2019) by relying instead on the generalized Pareto distribution, which is used to model exceedances and is more efficient in its use of limited data.

$$\mathbb{P}(RORWA \leq \mu) = \omega \tag{9}$$

$$\mathbb{P}(RORWA \leq x) = \mathbb{P}(RORWA \leq \mu)\, \mathbb{P}(RORWA \leq x | RORWA \leq \mu)$$
$$= \omega\, F(x) = \omega \left(1 + \frac{\xi(\mu - x)}{\sigma}\right)^{\frac{-1}{\xi}},\ x \leq \mu \tag{10}$$

This peak-over-threshold (POT) approach can be used to model the tail distribution of RORWA below a sufficiently low threshold.[12] This approach involves "slicing the tail," or separating extreme RORWA below a threshold μ from the rest of the RORWA data, and modelling this subset of low RORWA data as being distributed according to a GPD with threshold μ, scale parameter σ, and shape parameter ξ. Threshold μ represents the largest RORWA below which the GPD well approximates the distribution of RORWA. The scale parameter is a measure of variance. The key parameter is ξ, which measures the fat-tailedness of the RORWA distribution and is determined by the prevalence of extreme loss events in the data. A ξ greater than zero indicates the distribution is fat tailed.

For our sample, we selected threshold μ equivalent to the 7.5th percentile of the distribution of RORWA by graphically determining the maximum threshold below which the estimated shape parameter is relatively stable (see Appendix B).[13, 14] This is a common graphical approach for selecting the threshold under the POT approach. Given this selected threshold, we estimated the scale and shape parameters using maximum likelihood (ML), resulting in point estimates of approximately 1.68% and 0.28%, respectively. The estimated shape parameter indicates moderate fat-tailedness in the distribution of RORWA with a similar order of magnitude as seen in other financial data. Finally, we used the empirical sample proportion (the ML estimator) as our estimate of the unconditional probability of experiencing a RORWA of less than the 7.5% threshold. Combining these estimates yields the following estimated unconditional probability for RORWA below the threshold:

$$\mathbb{P}(RORWA \leq x) = 0.075(1 - 0.167x)^{-3.57}, \qquad x \leq \mu \tag{11}$$

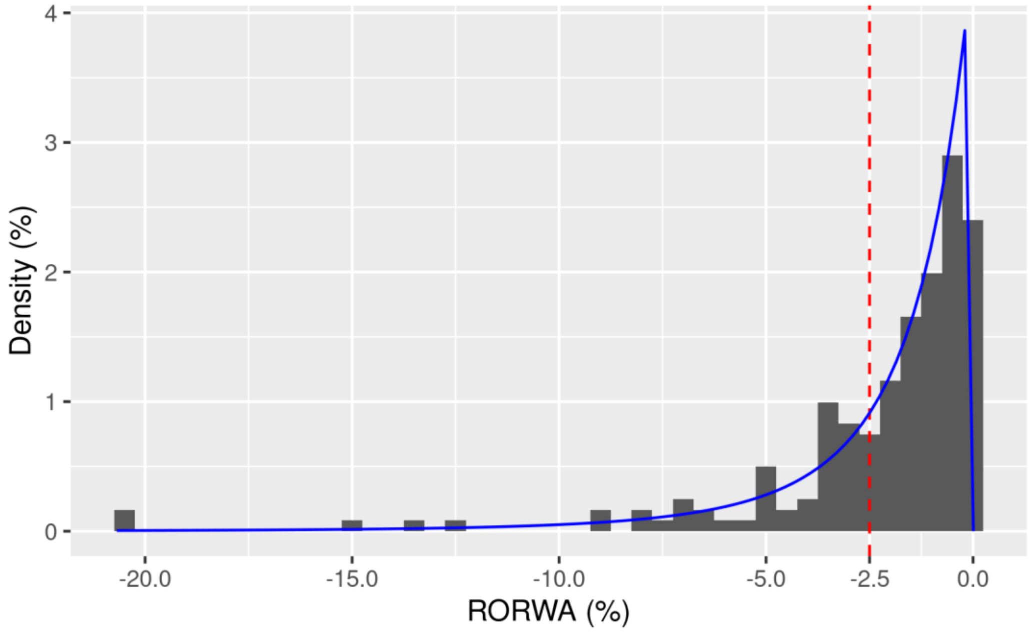
[12] We are concerned with the *lower* tail of the distribution of RORWA. EVT is usually formulated assuming the model applies to the upper tail; modelling the lower tail would require multiplying RORWA by -1.

[13] We iteratively fit a GPD to the data using maximum likelihood, restricting the number of the observations in the sample each time. After plotting the value of shape parameter ξ against the number of observations used for the estimation (the rank of the threshold), we identified the 7.5th percentile as the highest threshold below which the value of ξ remains relatively stable. See Appendix B.

[14] By the invariance property, if a random variable conditional on being below a given threshold is distributed according to a GPD, then the random variable conditional on being below an *even lower* threshold is also distributed according to a GPD with the *same* shape parameter.

Comparing the 7.5% tail of returns on risk-weighted assets and the estimated probability density function

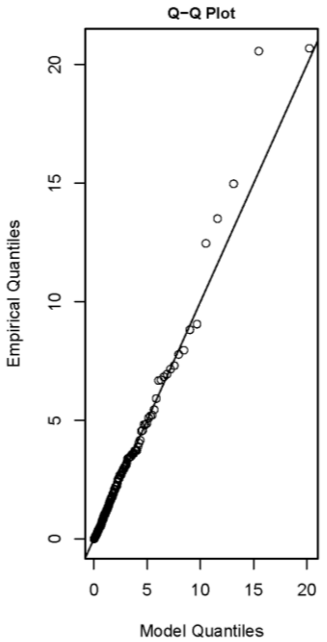
Graph 2



Sources: Federal Reserve Bank of St. Louis, FRED; S&P Global, Market Intelligence; authors' calculations.

Graph 2 compares the empirical distribution of the 7.5% tail of RORWA and the estimated probability density function (PDF) based on the POT approach. The model appears to fit reasonably well, except for a few particularly extreme observations. To further explore the appropriateness of the model, we compared the empirical and modelled quantiles. In Graph 3, quantiles from the tail of the RORWA distribution (y-axis) are plotted against quantiles of the GPD (x-axis). This Q-Q plot is a common tool for assessing whether a given distribution fits the data well – the closer the plotted points fall on the reference line, the better the fit. Once again, it appears that the fit is reasonably tight.

GPD fit on 7.5% tail for banks with over $50 billion in total consolidated assets	Graph 3



If a bank were required to hold capital surcharge s, then its failure point would increase from f to $f + s$. That is, it would fail if it experienced a RORWA of less than $-(f + s)$. Under our implementation, a bank required to hold a 1% capital surcharge would fail if it experienced a RORWA less than 3.5% (the sum of the capital surcharge and the 2.5% CCB). Therefore, requiring a capital surcharge would lower a bank's PD. More formally, the PD function would be as follows:

$$PD(s) = \mathbb{P}(RORWA \leq -(f + s)) = \omega\left(1 + \frac{\xi(\mu + f + s)}{\sigma}\right)^{\frac{-1}{\xi}}, -f \leq \mu \text{ and } s \geq 0 \quad (12)$$

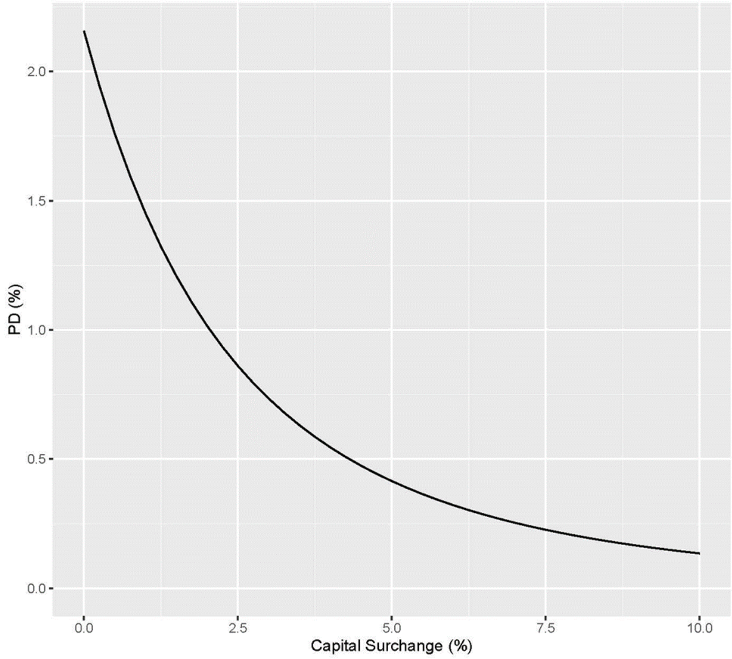
Based on our estimates above, the resulting PD function is:

$$PD(s) = 0.075(1.42 + 0.167\, s)^{-3.57}, \qquad s \geq 0 \quad (13)$$

Based on this PD function, a bank that is not required to hold any capital surcharge would have an annual PD of 2.15%, while a bank that is required to hold a capital surcharge of 1% would have a PD of 1.45% (Graph 4). Every incremental reduction in PD would require incremental increases in capital surcharges: while reducing PD from 1.5% to 1% would require a capital surcharge that is 1.1 percentage point higher, further reducing PD from 1% to 0.5% would require an increase in capital surcharge of 2.3 percentage points (Graph 4).

PD function estimated for banks with over $50 billion in total consolidated assets: 1990–2018

Graph 4



4. Selection of the reference bank

As noted above, a key component of the expected impact framework is the identification of the reference bank with which a G-SIB is compared. The reference bank is defined as the most systemically important bank that is not itself a G-SIB. For example, the G-SIB framework states that "one way to consider the relative systemic impact [of a G-SIB] is to assume that (…) the bank just below the cutoff point is the reference bank (…)".[15] In selecting the reference bank, we rely on a concept of "uniqueness" – that is, the absence of similar banks – in terms of banks' market shares in the various indicators.

Concretely, we leverage density-based cluster analysis with noise (DBSCAN) to select a reference bank (see Ester et al (1996)).[16] For each of the 12 G-SIB indicators, we calculate the mean global market share between 2013 and 2018 for each of the banks in the main sample and then apply the DBSCAN algorithm to identify clusters. We select the indicator-specific parameter for the maximum distance at which the algorithm considers two points as close to each other, based on graphical inspection of the "elbow" plots for each indicator. This is a common graphical approach to selecting this parameter, but it requires some modeller judgment.

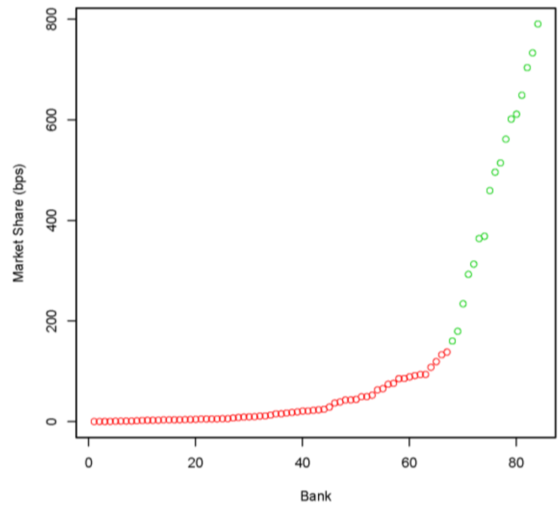
15 See BCBS, *Global systemically important banks: Assessment methodology and the additional loss absorbency requirement*, July 2018, p 16.

16 DBSCAN is a non-parametric clustering algorithm that identifies groups of observations with many nearby neighbours, referred to as clusters, and outliers that are relatively isolated from neighbours (Schubert et al (2017)). DBSCAN is one of the most common clustering algorithms. The DBSCAN algorithm requires two tuning parameters. One parameter, *eps*, specifies the maximum distance between two points for them to be considered close to each other. The second parameter, *minPoints*, specifies the minimum number of points necessary to form a cluster. The DBSCAN algorithm is sensitive to these specified parameters. All else equal, a small minpoints parameter will result in many small clusters, while a large minpoints parameter will result in most observations being classified as outliers. We set the *minPoints* parameter to four, and selected indicator-specific *eps* parameters ranging from 0.1 to 0.2.

To identify the reference bank for each indicator, we assume that the first (lowest) cluster represents the set of banks that are not "unique". Therefore, we define the reference bank as the bank with the largest market share in the first cluster. Of course, the reference bank score is sensitive to this assumption. If only one cluster is identified and the rest of the observations are outliers, then this definition is natural. However, where more than one cluster is identified, alternative definitions of the reference bank are possible. Nonetheless, we believe our approach is reasonable and conservative.

As an example, Graph 5 plots the rank of a bank against its market share for the notional amount of OTC derivatives indicator. For this indicator, DBSCAN identified only one cluster highlighted in red, while all the observations highlighted in green were identified as outliers. The rightmost observation in the single cluster is the reference bank – the "typical" bank with the highest market share. Meanwhile, the observations in green represent "unique" banks. Note that the reference bank demarcates a "jump" in the observations.

DBSCAN results for notional amount of OTC derivatives — Graph 5

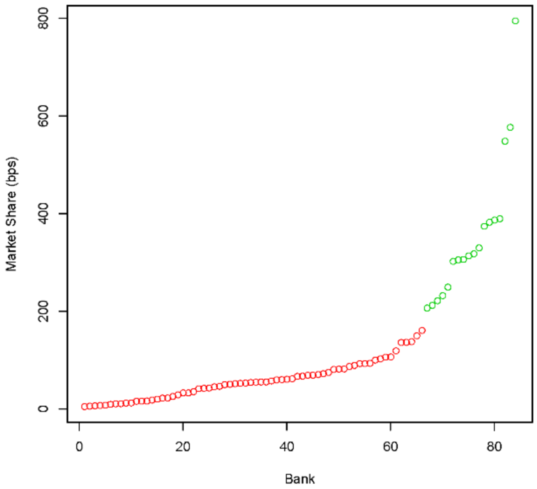


Sources: Bank for International Settlements, *High level indicator values and disclosures*; and authors' calculations.

In contrast, trading and AFS securities is an example of an indicator that is not easily broken into one main cluster and a series of outliers (Graph 6). In fact, DBSCAN identified one large cluster (the lowest cluster) and three smaller additional clusters (as well as outliers) for this indicator. Under our approach, the existence of several distinct clusters does not preclude us from determining a reference bank. We designate all banks with a market share of over 160 bp (the rightmost point of the first cluster) as systemically important. On the other hand, if DBSCAN groups a bank in a cluster with other banks that have very small market shares in the indicator, a case may exist not to designate that bank as "unique". Generally, the distribution of market shares differs among the various indicators (see Appendix C for the distributions of all indicators).

DBSCAN results for trading and AFS securities

Graph 6



Sources: Bank for International Settlements, *high level indicator values and disclosures*; and authors' calculations.

Importantly, the selected reference bank is different for each indicator. Therefore, the overall reference bank is a composite. This feature is an improvement upon the current methodology, which uses a reference bank G-SIB score of 130 bp; this choice is based on supervisory judgment and not mapped to specific indicator scores. By identifying a reference bank score (market share) for each indicator, applying the current indicator weights, and aggregating these scores according to the current methodology, we arrive at a revised reference bank score, r, of 152 bp, which we round to 150 bp (Tables 2 and 3). This reference bank score could be recalculated on a periodic basis or to account for material changes in the global sample, and would provide the public with greater transparency into the regulatory definition of systemic activity.

All else equal, a higher reference bank score will result in a lower G-SIB surcharge for all G-SIBs, while a lower reference bank score will result in a higher G-SIB surcharge. Our analysis suggests that the key impact of revising the reference bank score (using end-2018 data) would be the de-designation of three current G-SIBs.[17]

[17] The G-SIB scores of Unicredit, Standard Chartered, and Toronto Dominion would not exceed a score threshold of 150 (current and uncapped scores as of end-2018 are 142, 140, and 131, respectively).

Reference bank score by indicator

Table 2

Indicators	Global market share of DBSCAN-identified reference bank (A)	Weight (B)	Reference bank score by indicator (C = A*B)
Total Exposures Score	116	20.0%	23
Intra-Financial System Assets Score	112	6.7%	7
Intra-Financial System Liabilities Score	110	6.7%	7
Securities Outstanding Score	207	6.7%	14
Payment Activity Score	150	6.7%	10
Assets Under Custody Score	115	6.7%	8
Underwritten Transactions Score	181	6.7%	12
Notional Amount OTC Derivatives Score	138	6.7%	9
Trading and AFS Securities Score	160	6.7%	11
Level 3 Assets Score	159	6.7%	11
Cross-Jurisdictional Claims Score	215	10.0%	22
Cross-Jurisdictional Liabilities Score	185	10.0%	19

Reference bank score by category

Table 3

Categories	Global market share of DBSCAN-identified reference bank, aggregated to category (A)	Weight (B)	Reference bank score by category (C = A*B)
Size Score	116	20.0%	23
Interconnectedness Score	143	20.0%	29
Substitutability Score	148	20.0%	30
Complexity Score	152	20.0%	30
Cross-Jurisdictional Activity Score	200	20.0%	40
Reference bank score			***152***

Combining the expected impact equation, the PD function, and the above-mentioned revised reference bank score r yields the following G-SIB capital surcharge function, s (see Appendix A for the mathematical derivation):

$$s = \left(f + \mu + \frac{\sigma}{\xi}\right)\left[\left(\frac{LGD(g)}{LGD(r)}\right)^{\xi} - 1\right] \tag{14}$$

where g is the G-SIB score of a given bank and $LGD(.)$ is the social LGD function. Inserting the estimate parameters above, we arrive at the following equation:

$$s = 8.5\left[\left(\frac{LGD(g)}{LGD(150)}\right)^{0.28} - 1\right] \quad (15)$$

5. Social LGD

Our approach introduces an exponential function with two parameters relating a bank's G-SIB score to its normalised social LGD:

$$\frac{LGD(g)}{LGD(r)} = \begin{cases} e^{\alpha+\beta(g-r)}, & g > r \\ e^{\beta(g-r)}, & g \leq r \end{cases} \quad (16)$$

where the alpha parameter, α, represents the "jump" in social LGD between non-G-SIBs and G-SIBs and the beta parameter captures the continuous relationship between G-SIB score and social LGD. The exponential functional form incorporates the intuition that incremental increases in systemic importance lead to ever larger increases in social LGD: a 10 bp increase in market share should not translate to the same absolute increase in social LGD for all firms.

Combining this normalised social LGD function into the surcharge function above yields:

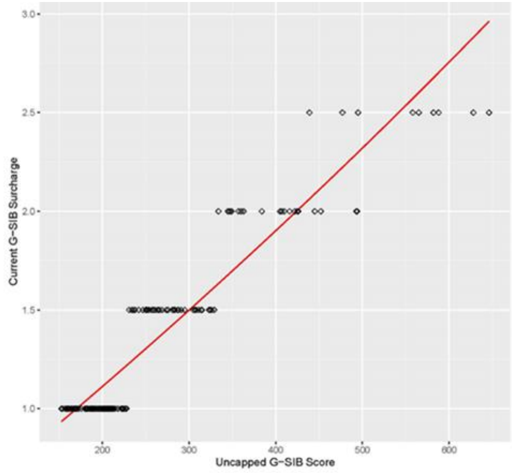
$$s = \left(f + \mu + \frac{\sigma}{\xi}\right)\left[e^{\alpha\xi+\beta\xi(g-r)} - 1\right] \quad (17)$$

Plugging in the estimated parameters above results in the following:

$$s = 8.5\left[e^{0.28\alpha+0.28\beta(g-150)} - 1\right] \quad (18)$$

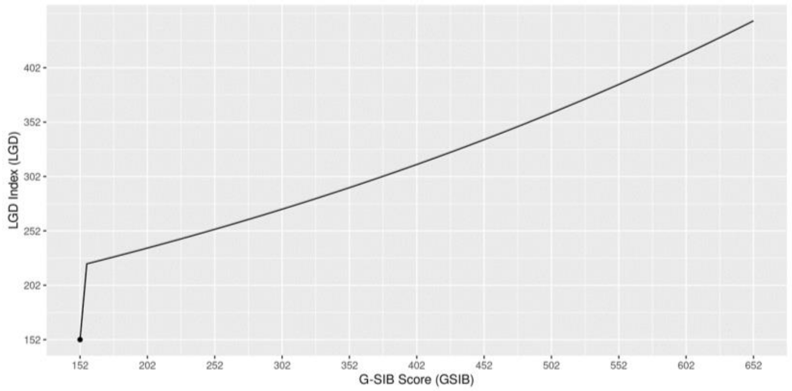
In our first approach to incorporating LGD, we calibrate the alpha and beta parameters to 1) allow for the removal of the cap on the substitutability category and 2) maintain the general level of capital surcharges based on the current supervisory consensus. We operationalise this task by finding the values of these parameters that minimise the sum of squared residuals between banks' G-SIB surcharges under the current framework and the G-SIB surcharges calculated under our approach, using *uncapped* G-SIB scores (Graph 7). Using G-SIB indicator data from 2013 to 2018 for the main sample, the calibrated values of α and β are 0.36 and 0.0014, respectively. It is worth noting that this calibrated alpha parameter captures the "jump" in surcharge from 0 to 1% at the reference bank score under the current framework. Graph 8 plots our calibrated social LGD function (indexed to start at the reference bank score).

Fit of surcharges based on explicit social LGD function and uncapped scores to current surcharges	Graph 7



Sources: Bank for International Settlements, *High level indicator values and disclosures*; and authors' calculations.

Social LGD Function	Graph 8



If the supervisory consensus were to change, this could be reflected by recalibrating the α and β parameters. Alternative approaches to calibrating the social LGD function that do not require maintaining the current level of conservatism are also possible. Here, we present an alternative that uses CoVaR.

CoVaR for bank i at time t is:

$$\Delta CoVaR_{it} = \beta_{it} \left(VaR_{2.15\%}^{it} - VaR_{50\%}^{it} \right) \tag{19}$$

We estimate β_{it} for each firm i on date t based on quantile regression of the overall market's return on a bank's individual market returns using a three-year rolling window. $VaR_{q\%}^{it}$ is the estimated $q\%$ quantile of firm i on date t using a three-year rolling window (see Appendix D for more detail on the methodology). We are particularly interested in the 2.15% quantile because it is associated with the PD of the reference bank.

Since we are interested in LGD, we focus on dollar CoVaR:

$$\Delta^{\$}\boldsymbol{CoVaR_{it}} = \boldsymbol{MV_{it}}\, \boldsymbol{\beta_{it}} \left(\boldsymbol{VaR_{2.15\%}^{it}} - \boldsymbol{VaR_{50\%}^{it}} \right) \tag{20}$$

where $\boldsymbol{MV_{it}}$ is the market value of equity of firm $\boldsymbol{i}$ on date $\boldsymbol{t}$.

For the purposes of estimating an alternative CoVaR-based LGD function, we assume that the unobservable LGD of a given bank is proportional to its dollar delta-CoVaR on a given date:

$$LGD(g_{i,t}) \propto \Delta^{\$}CoVaR_{i,t} \tag{21}$$

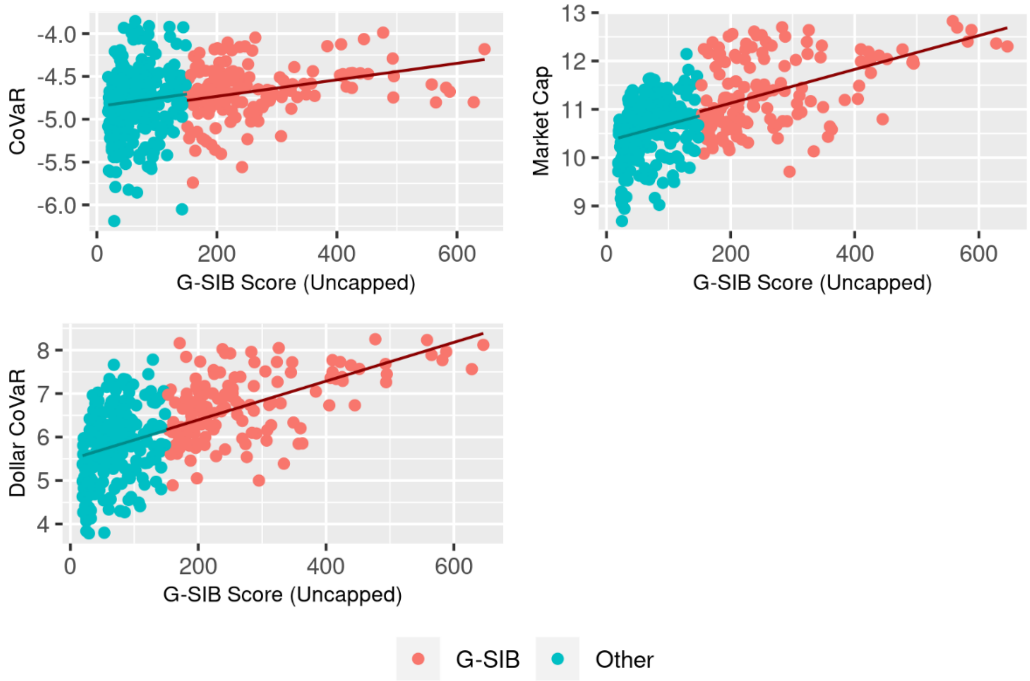
where $g_{i,t}$ is the uncapped G-SIB score and $\Delta^{\$}CoVaR_{i,t}$ is dollar delta-CoVaR for bank i on date t. Furthermore, we assume that the relationship between dollar delta-CoVaR and G-SIB score is log-linear with a potential discontinuity at the reference bank score:

$$\log(\Delta^{\$}CoVaR_{i,t}) = \gamma + \theta\ G\text{-}SIB_{i,t} + \delta\ Uncapped\ G\text{-}SIB\ Score_{i,t} + \varepsilon_{i,t} \tag{22}$$

where $Uncapped\ G\text{-}SIB\ Score_{i,t}$ is the uncapped G-SIB score of bank i on date t, while $GSIB_{i,t}$ is an indicator variable for whether a given bank would have been designated as a G-SIB based on its uncapped G-SIB scores, using a revised reference bank score of 150 bp.

Using our sample, we ran an ordinary least squares (OLS) regression based on equation (22), which yields an estimated value of 0.015 for θ (although insignificant) and an estimated value of 0.004 for δ (significant at 1% level). Graph 9 graphically depicts the results of our OLS model. There is a significant positive relationship between dollar delta-CoVaR and uncapped G-SIB scores visible in Graph 9, but no clear discontinuity at the reference bank score.

Relationship between dollar delta-CoVaR and uncapped G-SIB score — Graph 9



Source: Bank for International Settlements, *High level indicator values and disclosures;* author's calculations based on daily equity data from Bloomberg Finance LP.

Combining equations (16), (21), and (22) results in the following:

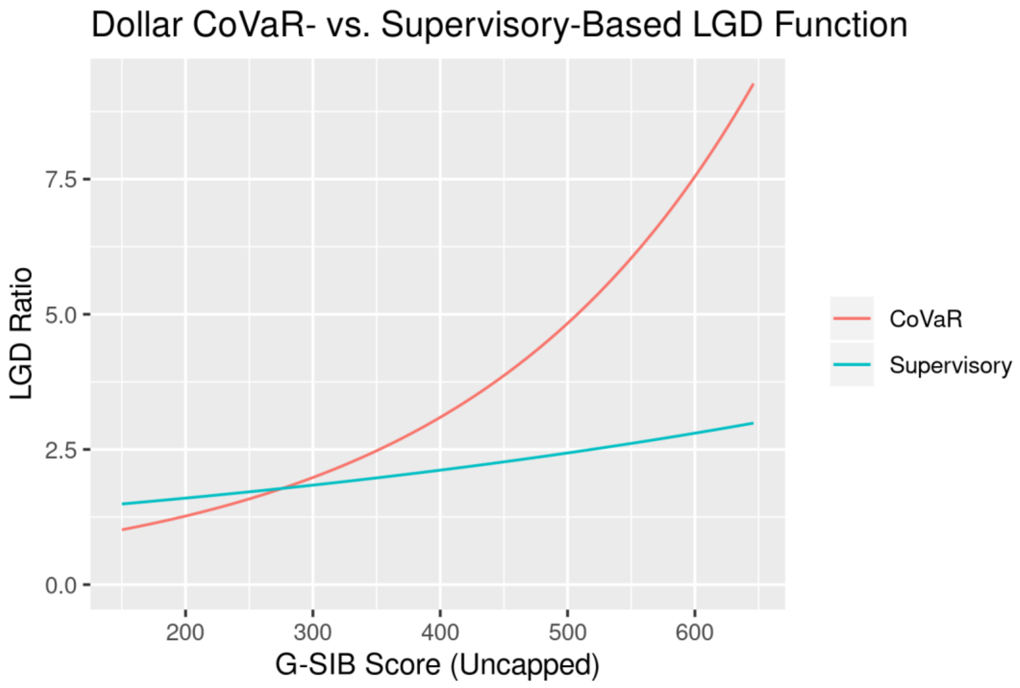
$$\frac{LGD(g)}{LGD(r)} = e^{\theta + \delta\,(g-r)} \tag{23}$$

Finally, substituting the values of θ and δ estimated above yields:

$$\frac{LGD(g)}{LGD(r)} = e^{0.015 + 0.004\,(g-150)} \quad (24)$$

The slope parameter in the CoVaR-based LGD function is an order of magnitude larger than in the LGD function calibrated to current supervisory judgment. However, the "jump" at the reference bank score has been eliminated in the former. This is borne out in the graphical comparison of the two LGD functions in Graph 10. Initially, the latter exceeds the former because of the "jump," but eventually the former substantially outstrips the latter.

LGD function: CoVaR-based vs. supervisory judgment-based — Graph 10



6. Continuous surcharge functions

Our two continuous G-SIB surcharge functions take as inputs the estimated parameters of the PD function, the revised reference bank score, and the calibrated parameters of the social LGD functions above (with rounding):

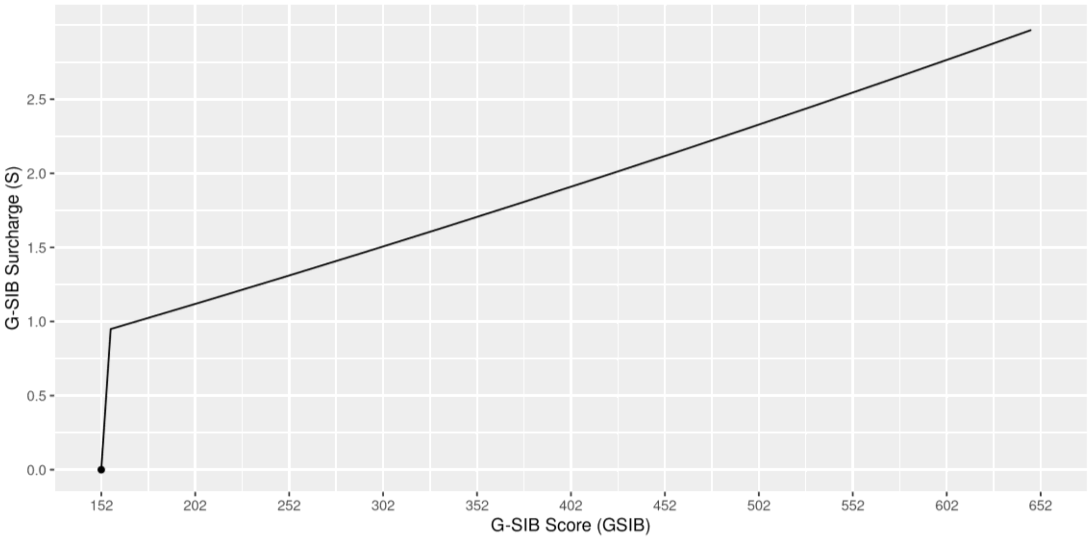
$$Supervisory\ G\text{-}SIB\ Capital\ Surcharge = 8.5\ e^{0.1+0.0004(GSIB\ Score-150)} - 8.5 \quad (25)$$

$$CoVaR\ G\text{-}SIB\ Capital\ Surcharge = 8.5\ e^{0.0042+0.0013\,(g-150)} - 8.5 \quad (26)$$

The two functions are charted below.

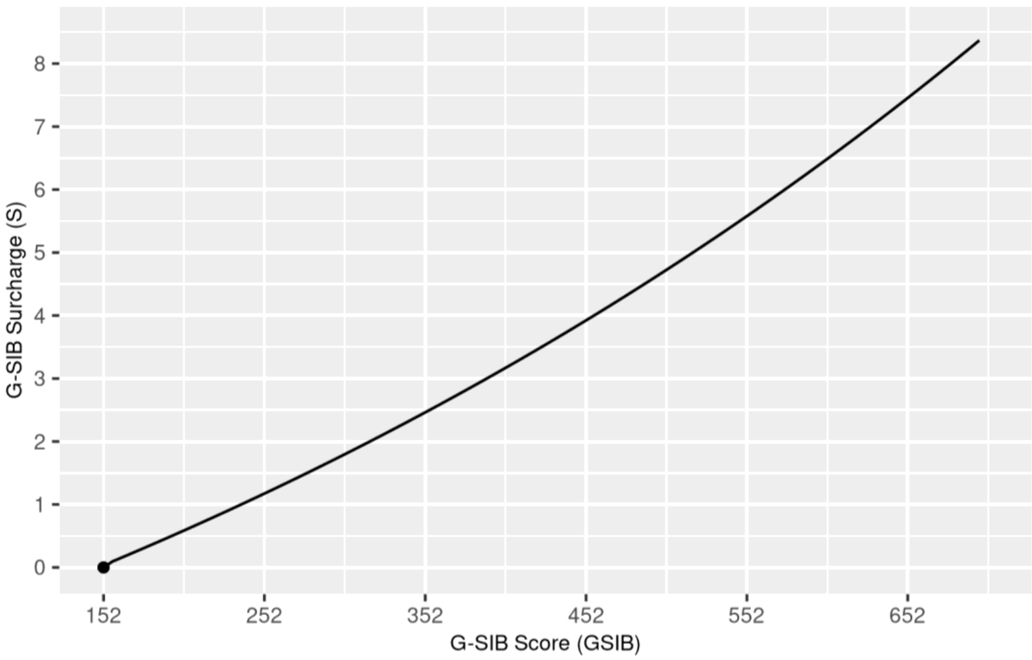
Continuous surcharge function based on supervisory judgment

Graph 11



CoVaR-based continuous surcharge function

Graph 12



Key to our alternative framework is the idea that an increase in systemic importance for the most systemically important banks should require a higher increase in capital surcharges, relative to an increase in systemic importance for less systemically important banks. By stepping through the PD function, the constant expected loss (CEL) curve, and the social LGD function, we demonstrate that within our framework, the same absolute increase in G-SIB score leads to larger increases in G-SIB surcharge for more systemically important G-SIBs. As the cap on the substitutability score is removed in our framework, this principle holds for an increase in indicator score regardless of category.

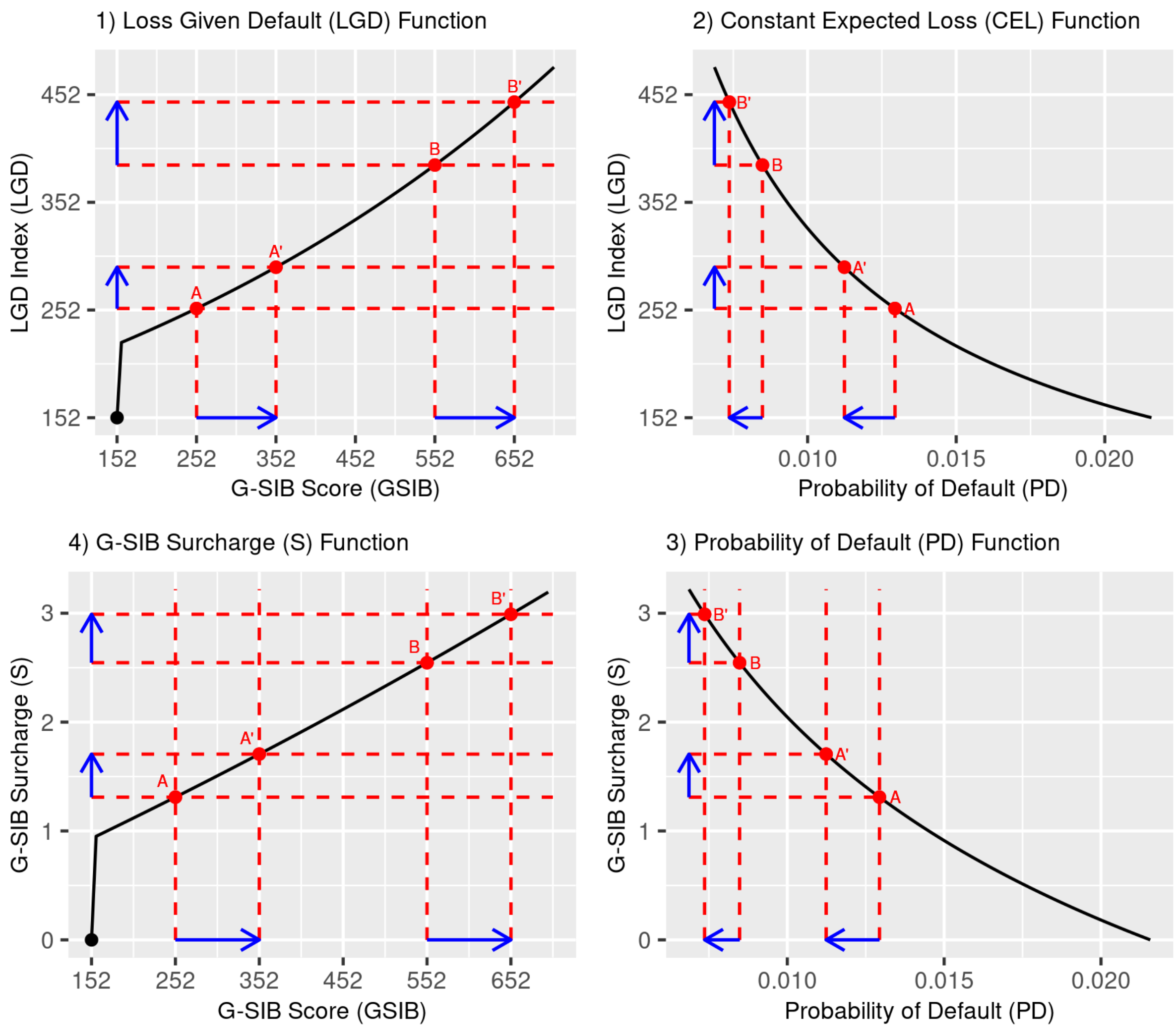
The example in the four plots in Graph 13 uses the supervisory social LGD function described in Section 5; the CEL function implicit in the expected impact framework itself; the PD function described in Section 3; and the continuous G-SIB capital surcharge function described above. The CEL function reflects the concave relationship between PD and social LGD required by the expected impact framework:

$$PD_{G\text{-}SIB} * LGD_{G\text{-}SIB} = PD_r * LGD_r \implies PD_{G\text{-}SIB} = PD_r \frac{LGD_r}{LGD_{G\text{-}SIB}} .$$

For a given G-SIB with a given social LGD, the required PD results in an expected loss equal to that of the reference bank, which is a constant.

We contrast the cases of Banks A and B – G-SIBs with initial scores of 252 and 552, respectively. The social LGD function reflects an exponential relationship between G-SIB score and social LGD, so that a 100 bp increase in Bank B's score (moving from B to B') results in a higher increase in social LGD than does a 100 bp increase in the score for Bank A (moving from A to A'). The increase in social LGD for both banks requires a reduction in PD to set the expected loss for each G-SIB equivalent to that of the reference bank. In the PD function, this reduction in PD, in turn, requires a greater increase in the G-SIB capital surcharge for Bank B than for Bank A. The surcharge function, which relates a bank's (uncapped) G-SIB score to its G-SIB capital surcharge, brings the social LGD, constant expected loss condition, and PD functions together, requiring a higher increase in surcharge for more systemically important G-SIBs. Graph 12 reflects the updated framework with a social LGD function calibrated to current surcharges with uncapped G-SIB scores, but the continuous surcharge function based on a social LGD function calibrated using dollar delta-CoVaR would similarly show an exponential relationship between G-SIB score and social LGD.

Impact of changes in social LGD for G-SIBs A and B — Graph 13



7. Impact analysis using the supervisory surcharge function

On average, implementing the continuous G-SIB capital surcharge function fit to current capital surcharges would reduce banks' surcharges by approximately 10 bp. The most material impacts of adopting the alternative framework would be the removal of Unicredit, Standard Chartered and Toronto Dominion from the list of banks subject to the G-SIB capital surcharge. These banks all have G-SIB scores that fall below the revised reference bank score of 150 bp.

China Construction, Morgan Stanley and Bank of New York Mellon would experience the largest increases in G-SIB surcharges (18 bp, 11 bp and 11 bp, respectively), while Wells Fargo, Goldman Sachs and Barclays would see the largest declines in their surcharges (–28 bp, –27 bp and –12 bp, respectively). It is worth noting that the two largest decreases and the largest increase are for banks near the "cliff" (230 bp) between buckets 1 and 2 under the current framework. All other banks' capital surcharges would change by 10 bp or less.

Impact of implementing continuous surcharge function

Table 4

(Using end-2018 data)

Firm	Country	G-SIB Score Current	G-SIB Score Uncapped	G-SIB Bucket Current	G-SIB Capital Surcharge (%) Current	G-SIB Capital Surcharge (%) Alternative[18]	G-SIB Capital Surcharge (%) Impact (bp)
JP Morgan	US	437	565	4	2.5	2.58	8
HSBC	GB	425	425	3	2	1.98	-2
Citigroup	US	382	426	3	2	1.99	-1
Bank of America	US	323	323	2	1.5	1.57	7
BNP Paribas	FR	314	314	2	1.5	1.53	3
MUFG	JP	307	307	2	1.5	1.51	1
Deutsche Bank	DE	295	295	2	1.5	1.46	-4
ICBC	CN	288	288	2	1.5	1.43	-7
Bank of China	CN	287	287	2	1.5	1.43	-7
Barclays	GB	276	276	2	1.5	1.38	-12
Goldman Sachs	US	236	236	2	1.5	1.23	-27
Wells Fargo	US	234	234	2	1.5	1.22	-28
China Construction	CN	224	224	1	1	1.18	18
Morgan Stanley	US	206	206	1	1	1.11	11
Santander	ES	201	201	1	1	1.1	10
Société Générale	FR	198	198	1	1	1.08	8
Credit Suisse	CH	196	196	1	1	1.08	8
Mizuho	JP	194	194	1	1	1.07	7
Crédit Agricole	FR	188	188	1	1	1.05	5
SMFG	JP	186	186	1	1	1.04	4
UBS	CH	182	182	1	1	1.02	2
Agricultural Bank	CN	180	180	1	1	1.02	2
ING Bank	NL	169	169	1	1	0.97	-3
RBC	CA	153	153	1	1	0.91	-9
BNY Mellon	US	152	205	1	1	1.11	11
Unicredit	IT	142	142	1	1	0	-100
Standard Chartered	GB	140	140	1	1	0	-100
State Street	US	140	157	1	1	0.93	-7
Toronto Dominion	CA	131	131	1	1	0	-100
Average							-10.41

8. Impact analysis using the CoVaR surcharge function

Using CoVaR as a measure of LGD provides an independent and market-based assessment of the size of the G-SIB capital surcharge. On average, implementing the continuous capital surcharge function with the CoVaR-based LGD function would reduce banks' surcharges by 13 bp. Similar to the continuous surcharge function discussed in Section 6, the use of this function would result in the removal of Unicredit, Standard Chartered and Toronto Dominion from the list of banks subject to the G-SIB capital surcharge.

[18] The alternative G-SIB capital surcharges were calculated using the *exact* value of all the estimated parameters. Therefore, there might be slight differences to those calculated using equation (25) due to parameter rounding.

The impact of implementing the CoVaR surcharge function would be material for those banks that experience the largest surcharge increases. JP Morgan, HSBC and Citigroup would each see their surcharges increase by more than 150 bp (331 bp, 151 bp and 153 bp, respectively). Adopting this function would also result in material declines for RBC, State Street and ING Bank (–95 bp, –91 bp and –78 bp, respectively). Seven other banks would experience surcharge declines of at least 50 bp under the CoVaR surcharge approach. The average change of –13 bp under this approach masks significant variation in the impact across individual banks.

Impact of implementing continuous surcharge function with CoVaR as measure of LGD

(Using end-2018 data) Table 5

		G-SIB Score		G-SIB Bucket	G-SIB Capital Surcharge (%)		
Firm	Country	Current	Uncapped	Current	Current	Alternative[19]	Impact (bp)
JP Morgan	US	437	565	4	2.5	5.81	331
HSBC	GB	425	425	3	2	3.51	151
Citigroup	US	382	426	3	2	3.53	153
Bank of America	US	323	323	2	1.5	2.07	57
BNP Paribas	FR	314	314	2	1.5	1.95	45
MUFG	JP	307	307	2	1.5	1.86	36
Deutsche Bank	DE	295	295	2	1.5	1.71	21
ICBC	CN	288	288	2	1.5	1.62	12
Bank of China	CN	287	287	2	1.5	1.61	11
Barclays	GB	276	276	2	1.5	1.47	-3
Goldman Sachs	US	236	236	2	1.5	0.98	-52
Wells Fargo	US	234	234	2	1.5	0.96	-54
China Construction	CN	224	224	1	1	0.84	-16
Morgan Stanley	US	206	206	1	1	0.63	-37
Santander	ES	201	201	1	1	0.58	-42
Société Générale	FR	198	198	1	1	0.54	-46
Credit Suisse	CH	196	196	1	1	0.52	-48
Mizuho	JP	194	194	1	1	0.5	-50
Crédit Agricole	FR	188	188	1	1	0.43	-57
SMFG	JP	186	186	1	1	0.41	-59
UBS	CH	182	182	1	1	0.36	-64
Agricultural Bank	CN	180	180	1	1	0.34	-66
ING Bank	NL	169	169	1	1	0.22	-78
RBC	CA	153	153	1	1	0.05	-95

[19] The alternative G-SIB capital surcharges were calculated using the exact value of all the estimated parameters. Therefore, there might be slight differences to those calculated using equation (26) due to parameter rounding.

BNY Mellon	US	152	205	1	1	0.62	-38
Unicredit	IT	142	142	1	1	0	-100
Standard Chartered	GB	140	140	1	1	0	-100
State Street	US	140	157	1	1	0.09	-91
Toronto Dominion	CA	131	131	1	1	0	-100
Average							-13.07

9. Conclusion and other considerations

Our continuous G-SIB capital surcharge function improves upon key aspects of the current G-SIB methodology, while maintaining aspects (such as the expected impact framework and G-SIB score calculation) that are widely accepted by and familiar to banks and supervisors. Here, we provide two versions of a continuous surcharge function: the first approach is designed to provide a function that is in line with the G-SIB surcharges currently used by supervisors, while the second approach anchors the G-SIB scores of banks to an independent measure of social LGD.

9.1 Strengthening empirical basis and transparency of current framework

By stipulating explicit PD and social LGD functions, the alternative framework strengthens the empirical basis of the framework and improves the transparency of key inputs to the surcharge function. Furthermore, the updated reference bank score is calculated based on indicator-specific data and using a more refined technique for cluster analysis than the analysis that produced the current reference bank score of 130.

9.2 Lifting the substitutability cap

The implementation of the cap on the substitutability category eliminates the incentive to reduce systemic importance in this category once a bank has exceeded the cap. Capping removes the link between any increase or decrease in a bank's capital surcharge and its financial infrastructure activities (substitutability) in excess of the cap. By lifting the cap on the substitutability category and basing surcharges on uncapped G-SIB scores, the alternative framework re-establishes the link between changes in financial infrastructure activities (substitutability) and changes in capital surcharges for the most systemic firms in that category.

9.3 Removing cliff effects from current framework and balancing incentives to shrink

The current G-SIB methodology allows firms to grow within score "buckets" of 100 bp, while maintaining the same capital surcharge. Moving to the next bucket results in a capital surcharge increase of 50 bp (and 100 bp after bucket 4). This system creates cliff effects, and features uneven disincentives for growth. Under this system, a bank at the lower end or midpoint of its score bucket could grow its score significantly with no change in its capital surcharge, while a bank at the higher end of its score bucket could see a 50 bp capital surcharge increase for a smaller score increase. While the framework is designed to incentivise banks to reduce their systemic importance, the strength of this incentive varies based on the segment of the bucket in which a G-SIB's score lies.

Essentially, the continuous and exponential nature of these G-SIB capital surcharge functions maintains increasing incentives for banks to reduce their systemic importance. The continuous function requires an increase in surcharge for any bank that increases its systemic importance. Those increases will be highest for those banks with the highest G-SIB scores, reflecting the assumption that the social cost of a bank failure increases exponentially as systemic importance rises.

9.4 Comparing the supervisory and CoVaR-based surcharge frameworks

The CoVaR-based G-SIB surcharges provide an independent benchmark of the capital surcharge that lowers the expected loss of a G-SIB to that of the reference bank based on market information. Since the true nature of the LGD function is unknown, neither a market-based nor a supervisory framework is necessarily correct.

Generally, the CoVaR-based surcharges would result in declines in G-SIB surcharges, but the most systemically important firms would experience material increases in their G-SIB surcharges under the CoVaR-based approach. The difference implies that market participants see the largest and most systemic G-SIBs as a greater concern than other G-SIBs, which suggests focusing bank supervision resources depending on the weight given to market concerns.

9.5 Monitoring capital surcharges and systemic risk

Our system of empirically determined capital surcharges can be used to monitor the current G-SIBs in two ways. First, our supervisory framework can be used to highlight where the biggest gains are for banks from the cliffs and the substitutability cap. Second, the CoVar-based system provides an independent read from market participants on the nature of systemic risks across banks.

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Appendix A: Mathematical derivation of G-SIB capital surcharge function

$\boldsymbol{Definitions}$:

$f: failure\ point$

$s: capital\ surcharge$

$r: reference\ bank\ score$

$g: G\text{-}SIB\ score$

$RORWA: return\ on\ risk - weighted\ assets$

$LGD(\cdot): loss - given - default\ function$

$\mu: threshold$

$GPD(\mu, \sigma, \xi): generalized\ Pareto\ distribution\ with\ location\ \mu, scale\ \sigma, and\ shape\ \xi$

$\boldsymbol{Assumptions}$:

$A.1: \ -f \leq \mu$

$A.2: LGD(r) > 0$

$A.3: LDG(y) \geq LGD(x), \qquad \forall y \geq x$

$A.4: g \ \geq r$

$A.5: RORWA \mid RORWA \leq \ \mu \sim GPD(\mu, \sigma, \xi)$

$A.6: \xi > 0$

$A.6: \mathbb{P}(RORWA \leq \ \mu) > 0$

$\boldsymbol{Expected\ impact\ approach}$:

$$\mathbb{P}(RORWA \leq -f)\, LGD(r) = \ \mathbb{P}(RORWA \leq -f - s)\, LGD(g)$$

$$\mathbb{P}(RORWA \leq -f \mid RORWA \leq \ \mu)\, \mathbb{P}(RORWA \leq \ \mu)\, LGD(r)$$
$$= \ \mathbb{P}(RORWA \leq -f - s \ \mid RORWA \leq \ \mu)\, \mathbb{P}(RORWA \leq \ \mu)\, LGD(g)$$

$$\mathbb{P}(RORWA \leq -f \mid RORWA \leq \ \mu)\, LGD(r)$$
$$= \ \mathbb{P}(RORWA \leq -f - s \ \mid RORWA \leq \ \mu)\, LGD(g)$$

$$E.1: \frac{\mathbb{P}(RORWA \leq -f - s \ \mid RORWA \leq \ \mu)}{\mathbb{P}(RORWA \leq -f \mid RORWA \leq \ \mu)} = \frac{LGD(r)}{LGD(g)}$$

$\boldsymbol{Peak - over - threshold\ approach}$:

$$E.2: \mathbb{P}(RORWA \leq x \mid RORWA \leq \mu) = \left(1 + \frac{\xi(\mu - x)}{\sigma}\right)^{\frac{-1}{\xi}}, \qquad \forall x \leq \mu$$

$$\frac{\left(1 + \frac{\xi(\mu + f + s)}{\sigma}\right)^{\frac{-1}{\xi}}}{\left(1 + \frac{\xi(\mu + f)}{\sigma}\right)^{\frac{-1}{\xi}}} = \frac{LGD(r)}{LGD(g)}, \qquad substituting\ E.2\ into\ E.1$$

$$\left(\frac{1 + \frac{\xi(\mu + f + s)}{\sigma}}{1 + \frac{\xi(\mu + f)}{\sigma}}\right)^{\frac{-1}{\xi}} = \frac{LGD(r)}{LGD(g)}$$

$$\frac{1 + \frac{\xi(\mu + f + s)}{\sigma}}{1 + \frac{\xi(\mu + f)}{\sigma}} = \left(\frac{LGD(r)}{LGD(g)}\right)^{-\xi}$$

$$\frac{1 + \frac{\xi(\mu + f + s)}{\sigma}}{1 + \frac{\xi(\mu + f)}{\sigma}} = \left(\frac{LGD(g)}{LGD(r)}\right)^{\xi}$$

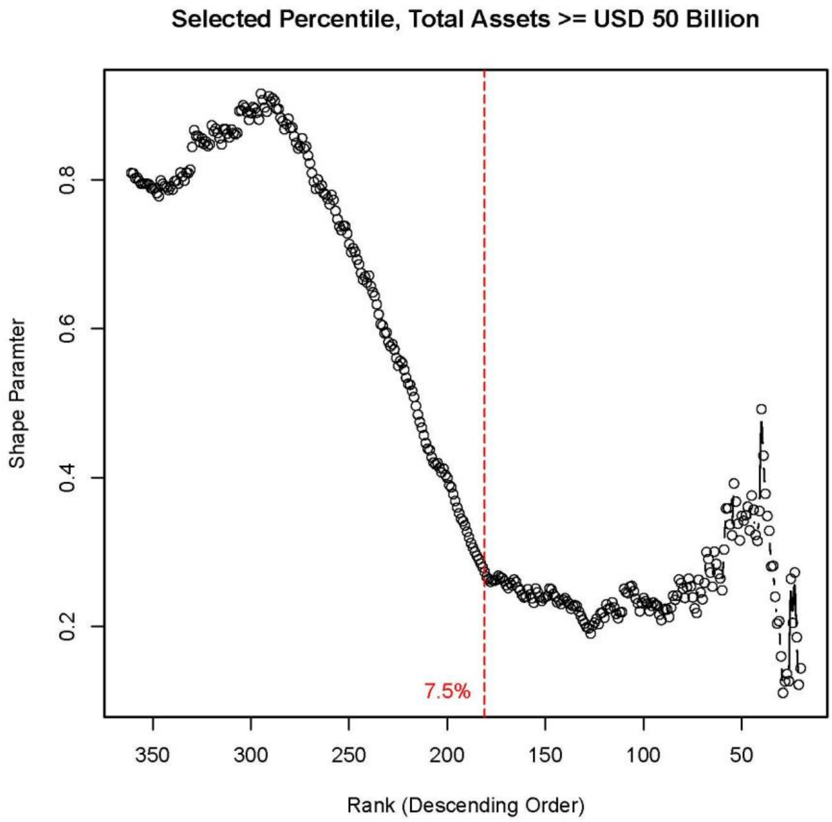
$$\frac{f + \mu + \frac{\sigma}{\xi} + s}{f + \mu + \frac{\sigma}{\xi}} = \left(\frac{LGD(g)}{LGD(r)}\right)^{\xi}$$

$$f + \mu + \frac{\sigma}{\xi} + s = \left(f + \mu + \frac{\sigma}{\xi}\right)\left(\frac{LGD(g)}{LGD(r)}\right)^{\xi}$$

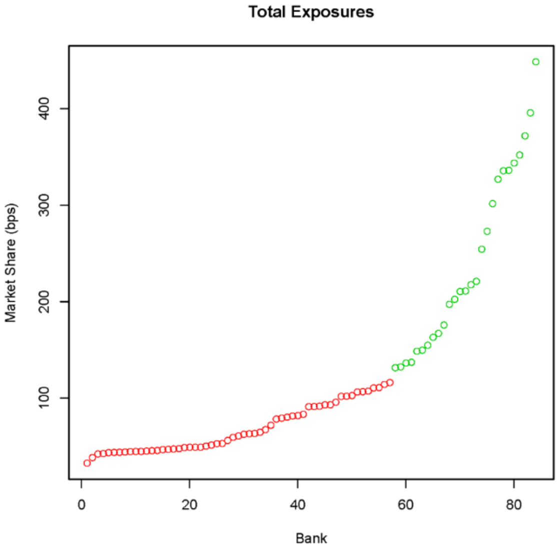
$$s = \left(f + \mu + \frac{\sigma}{\xi}\right)\left(\frac{LGD(g)}{LGD(r)}\right)^{\xi} - \left(f + \mu + \frac{\sigma}{\xi}\right)$$

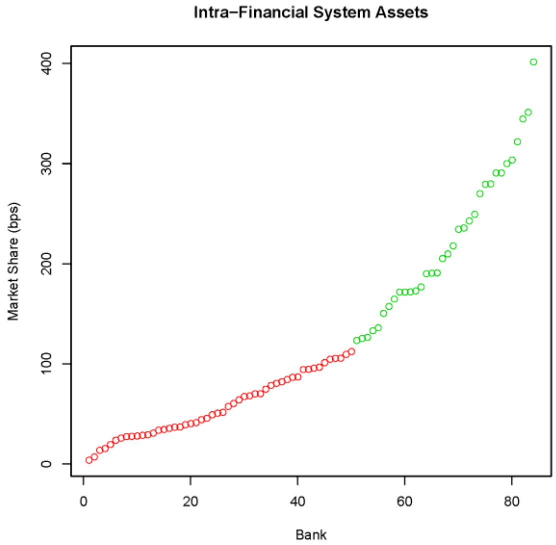
$$E.3: s = \left(f + \mu + \frac{\sigma}{\xi}\right)\left[\left(\frac{LGD(g)}{LGD(r)}\right)^{\xi} - 1\right]$$

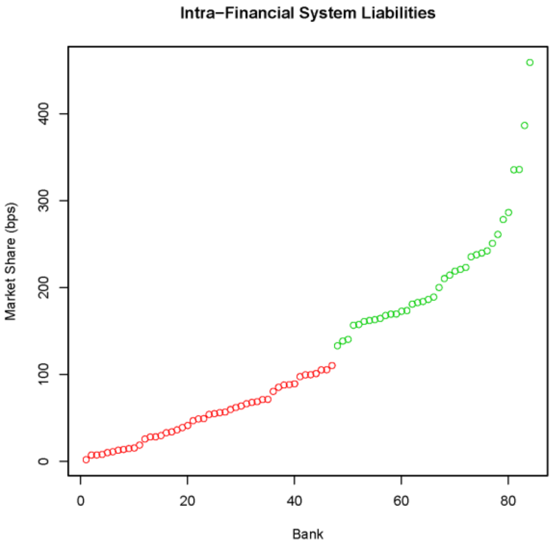
Appendix B: GPD threshold selection

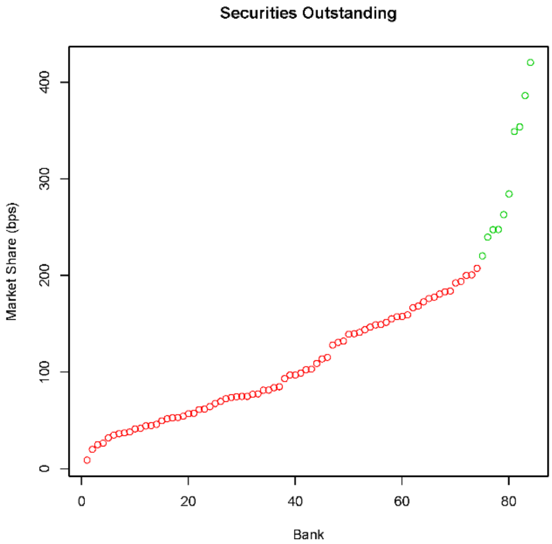


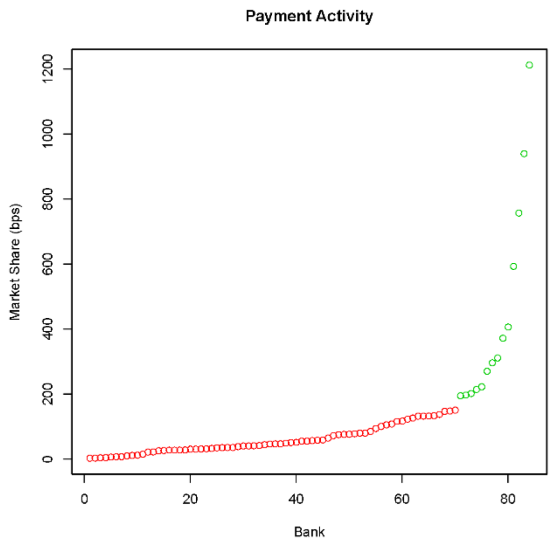
Appendix C: DBSCAN results for all indicators

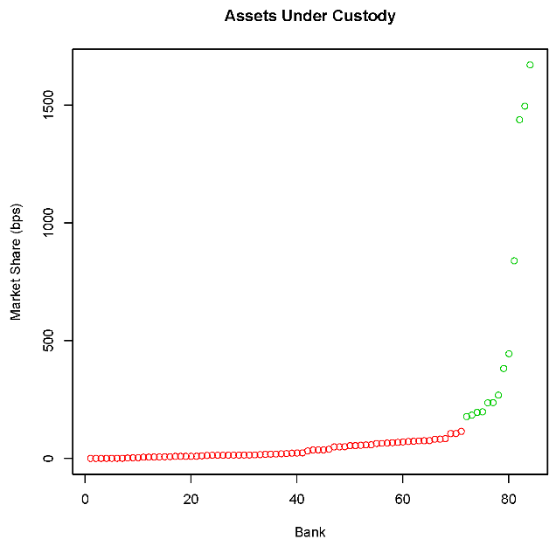


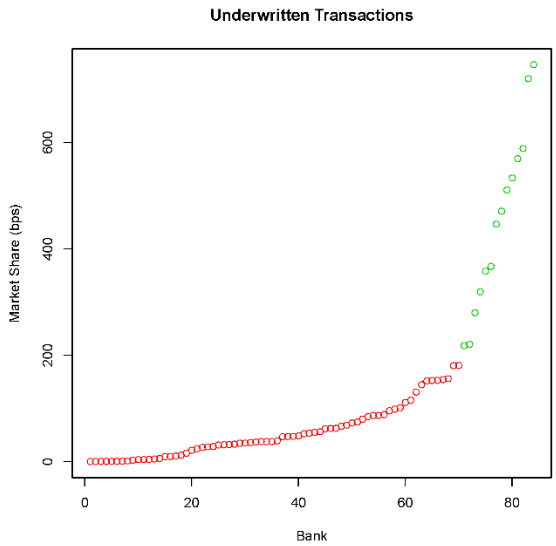


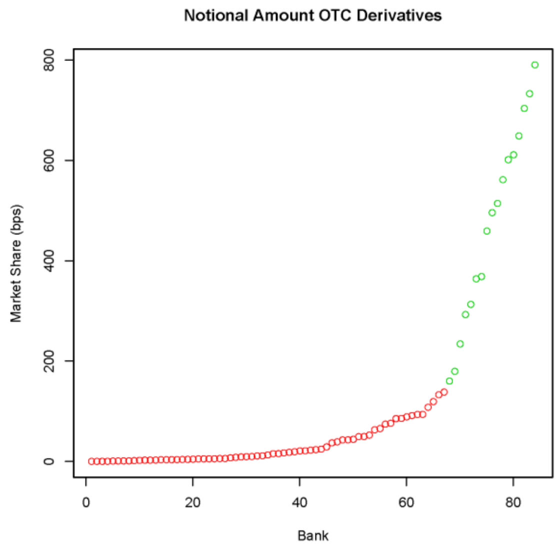


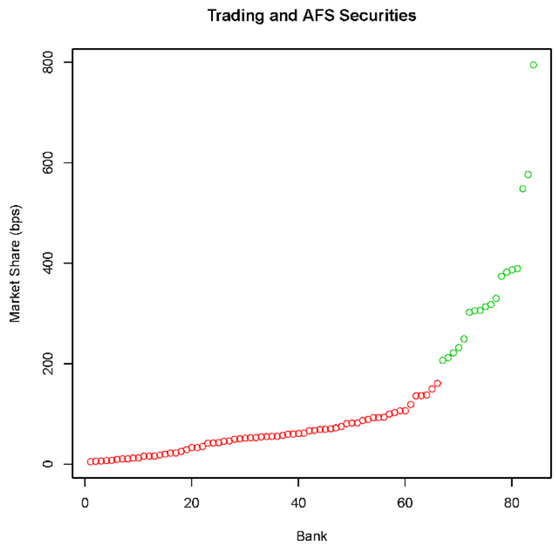


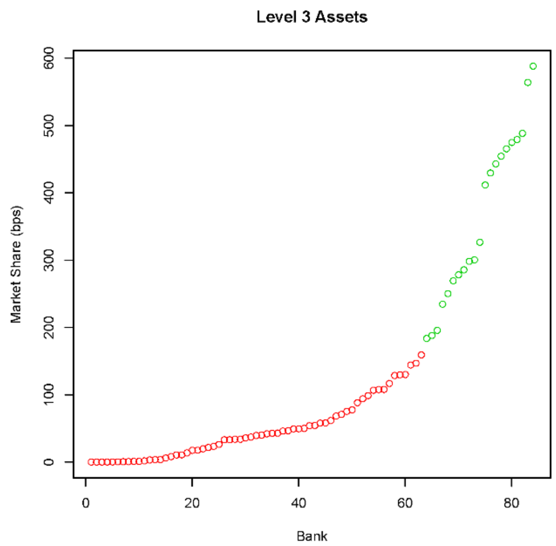

Payment Activity
Market Share (bps)
0
200
400
600
800
1000
1200
0
20
40
60
80
Bank

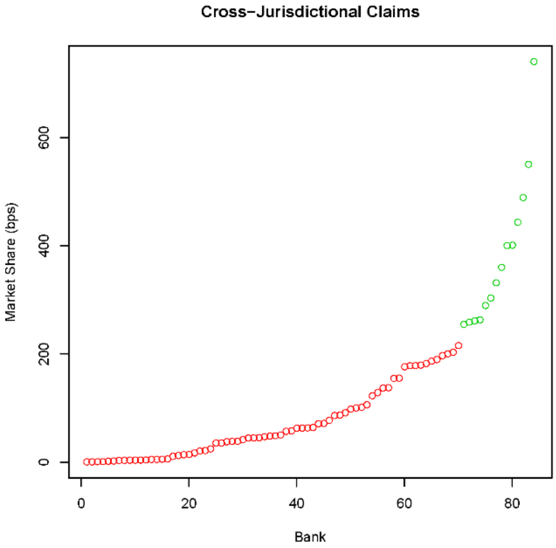

Assets Under Custody
Market Share (bps)
0
500
1000
1500
0
20
40
60
80
Bank

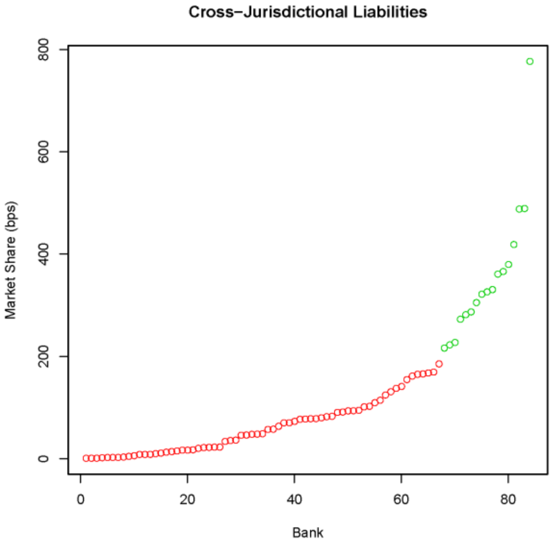

Underwritten Transactions
Market Share (bps)
0
200
400
600
0
20
40
60
80
Bank


Notional Amount OTC Derivatives
Market Share (bps)
0
200
400
600
800
0
20
40
60
80
Bank


Trading and AFS Securities
Market Share (bps)
0
200
400
600
800
0
20
40
60
80
Bank


Level 3 Assets
Market Share (bps)
0
100
200
300
400
500
600
0
20
40
60
80
Bank


Cross–Jurisdictional Claims
Market Share (bps)
0
200
400
600
0
20
40
60
80
Bank


Cross–Jurisdictional Liabilities
Market Share (bps)
0
200
400
600
800
0
20
40
60
80
Bank

Appendix D: Dollar delta-CoVaR calculation

The following quantile regression is run for each bank on each date using a three-year rolling window:

$$\mathbb{Q}_{2.15\%}\left(R_{MSCI,t} \,\middle|\, R_{i,t}\right) = \alpha_{i,t} + \beta_{i,t}\, R_{i,t} \; (D.1)$$

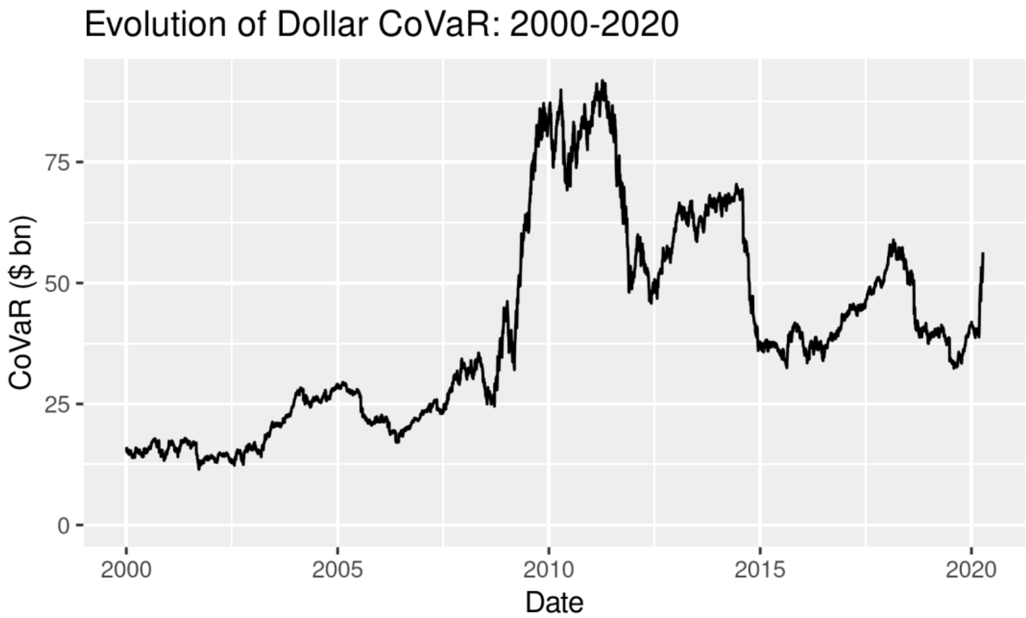
where $R_{MSCI,t}$ is the return on the MSCI ACWI index on date t and $R_{i,t}$ is the equity return of bank i on date t.

The dollar delta-CoVaR for each bank and date is then calculated as follows:

$$\Delta^{\$}CoVaR_{i,t} = MV_{i,t}\, \beta_{i,t} \left(VaR_{2.15\%}^{i,t} - VaR_{50\%}^{i,t}\right) (D.2)$$

where β_{it} is the estimated coefficient for each firm i on date t from $(D.1)$, $VaR_{q\%}^{i,t}$ is the estimated $q\%$ quantile of firm i on date t using a three-year rolling window, and $MV_{i,t}$ is the market value of equity of firm i on date t. Graph D.1. depicts the evolution of aggregated dollar delta-CoVaR from 2000 to 2020 for the G-SIB assessment main sample.

Aggregate dollar delta-CoVaR for G-SIB assessment main sample banks, 2000–20	Graph D.1



Source: Authors' calculations based on daily equity data from Bloomberg Finance LP over the period 1997–2020.

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