EUROPEAN CENTRAL BANK

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## How useful is market information for the identification of G-SIBs?

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# Contents

# Abstract

The Basel Committee on Banking Supervision (BCBS) framework used to identify global systemically important banks (G-SIBs) is based on banks' balance sheet information, leaving information derived from market data untapped. Among the most widely used market-based systemic risk measures, Adrian and Brunnermeier's (2016) Delta-Conditional Value at Risk (ΔCoVaR) best captures the system-wide loss-given-default (sLGD) and conditional impact concepts underlying the BCBS G-SIB methodology. In this paper we investigate, using a global sample of the largest banks, whether a score based on ΔCoVaR could be useful for ranking G-SIBs or for calibrating an alternative G-SIB indicator weighting scheme. In our first analysis we find that the ΔCoVaR score is positively correlated with all five of the systemic importance categories of the BCBS framework. However, considerable information/noise with regard to the ΔCoVaR score remains unexplained. Before more is known about this residual, a score based on ΔCoVaR is difficult to interpret and is inappropriate for identifying G-SIBs in a policy context. Besides, we find that a ranking based on ΔCoVaR is subject to substantial variability over time and across empirical specifications. In our second analysis we use ΔCoVaR to place the current static weighting scheme for G-SIB indicators on an empirical footing. To do this we regress ΔCoVaR on factors derived from the G-SIB indicators. This approach allows us to focus on the part of ΔCoVaR which can be explained by balance sheet information which alleviates the identified issues of interpretability and variability. The derived weights are highest for the cross-jurisdictional activity (43%) and size (27%) categories. We conclude that ΔCoVaR is not suitable for use as an alternative G-SIB score but could be useful for policymakers to pursue an empirically grounded weighting scheme for the existing G-SIB indicators.

**Keywords:** systemic risk measures, global systemically important banks, bank regulation.

**JEL codes:** G20, G21, G28.

# Non-technical summary

In this paper we analyse how ΔCoVaR – a frequently used measure of systemic importance relying on stock price information – relates to the balance sheet indicators used by policymakers in the context of the G-SIB assessment. The extensive literature on market-based systemic risk measures is worth studying, as it offers a complementary perspective on banks' systemic importance. We analyse the suitability of ΔCoVaR both for ranking G-SIBs and for calibrating an alternative G-SIB indicator weighting scheme.

Market data generally provide information which might correlate with or complement balance sheet information such as that used in the BCBS's methodology for assessing G-SIBs. The potential advantages of market-based measures over balance sheet indicators with regard to evaluating the systemic footprint of banks are (i) their forward-looking nature, (ii) their availability in real-time at high frequency and over a long time horizon, (iii) the low cost of gathering these data and the ease with which they may be compared, and (iv) the fact that they are able to capture non-linear dependencies. The challenges associated with using market-based indicators relate to (i) the unavailability of data for non-listed banks, as well as (ii) volatility reflecting factors not strictly related to the systemic footprint of a bank. For these reasons market-based measures may also be more difficult to interpret and use in policymaking.

Among the most commonly used market-based measures of systemic importance, ΔCoVaR, proposed by Adrian and Brunnermeier (2016), appears to have the greatest potential to proxy the impact a bank's distress would have on the wider economy. By contrast, other measures focus mostly on banks' probability of default (PD) or on the impact of system stress on a bank – e.g. SRISK, a measure proposed by Brownlees and Engle (2017). The first aspect is the relevant one when identifying G-SIBs in the spirit of the BCBS methodology.

For our empirical analysis we use a global sample of 73 publicly traded banks considered in the main sample in the BCBS G-SIB identification exercise. First, we construct a ΔCoVaR score and find that it is positively correlated with all five of the BCBS methodology's contagion channel categories, i.e. cross-jurisdictional activity, interconnectedness, complexity, substitutability and size. However, a correlation of 0.3 between the ΔCoVaR score and the overall G-SIB score suggests that ΔCoVaR contains a substantial amount of information other than that captured by the G-SIB indicators. Moreover, a bank which is identified as a G-SIB using the ΔCoVaR score is also identified as a G-SIB using the BCBS methodology only half of the time. Further work is still needed to evaluate whether and how the additional information contained in ΔCoVaR is linked to systemic importance. Lastly, there is considerable variation in banks' ΔCoVaR-based rankings depending on how and for what period of time we compute ΔCoVaR. We conclude that rankings based on ΔCoVaR alone are unsuitable for policy purposes as the unexplained part of ΔCoVaR is difficult to interpret and varies excessively.

Nevertheless, we find that the part of ΔCoVaR which can be attributed to the G-SIB indicators can still be useful for policy purposes, in particular to inform the weighting of the G-SIB indicators used to compute the overall G-SIB score. Currently, the weights of the indicators in the BCBS G-SIB methodology are not calibrated based on empirical evidence. Instead, standard setters have opted for simplicity, weighting the indicators equally within the five categories and in turn weighting the five categories equally to compute the final score. Following Passmore and von Hafften (2017), we use a factor analysis to determine the relative importance of each BCBS G-SIB indicator in explaining ΔCoVaR. The alternative weighting scheme allocates most weight to the cross-jurisdictional activity (43%) and size (27%) categories, as opposed to the current 20% weight for each. As the alternative weights are based on the part of ΔCoVaR which is explained by the established systemic importance proxies, neither the interpretability nor the variability of the new scores is an issue.

We conclude that while ΔCoVaR on its own is not suitable for identifying G-SIBs in a policy context, it could be useful in providing an empirically grounded weighting scheme for the BCBS G-SIB indicators.

# 1 Introduction

During the 2007-09 financial crisis, spillovers among financial institutions induced by the solvency and liquidity problems faced by some banks gave rise to system-wide financial distress which impaired the stability of the entire financial system. Since then, the largest, most interconnected and most complex banks have been subject to enhanced regulation, given the potential losses their failure might impose on the global banking system and economy. These institutions have been identified as global systemically important banks (G-SIBs) and are subject to additional loss absorbency requirements as set out in the BCBS G-SIB framework.

The approach used by BCBS (2011) to identify G-SIBs has both advantages and disadvantages. The G-SIB score is intuitive, easy to communicate and generally stable over time, making it suitable for policy purposes. At the same time, there are some drawbacks: (i) it is backward looking in nature, (ii) it may be less capable than market-based measures in identifying more recent trends or vulnerabilities which are not captured by end-of-year balance-sheet data (e.g. information contagion), and (iii) it may encourage and reflect window dressing towards the end of the reporting period[1].

Market data provide an alternative source of information which might be used to complement the balance sheet information used in the BCBS (2011) approach. The potential advantages of market-based measures include (i) their forward-looking nature, (ii) their availability in real-time at high frequency and over a long time horizon, (iii) the low cost of gathering these data and the ease with which they may be compared, and (iv) the fact that they are able to capture non-linear dependencies.[2] The challenges associated with using market-based indicators relate to (i) data availability (only publicly traded banks) as well as (ii) noisy and thus potentially misleading signals, such as the impact of volatile liquidity premiums amid periods of low market liquidity, particularly during times of financial distress or when accompanied by government intervention.[3] Market-based indicators can therefore be more difficult to interpret.[4]

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1 For example, Behn et al. (2019) show that G-SIBs are likely to reduce their activities around year-end, which in turn affects the buffer requirements they receive under the G-SIB framework.

2 For example, Adrian and Brunnermeier (2016) argue that as a result of different contagion channels the measured co-movement of institutions' assets and liabilities tends to rise above and beyond levels justified purely by fundamentals.

3 Löffler and Raupach (2018) demonstrate that a change in a bank's systematic risk, idiosyncratic risk, size or contagiousness may increase the risk of the financial system but lower the measured systemic risk contribution of the bank. This may indicate that measures of systemic risk, when applied through regulation, may incentivise banks to minimise their systemic risk contribution, which may create adverse outcomes for the financial system as a whole. In this regard, risk metrics used for policymaking should be kept simple, transparent and conceptually well defined.

4 Market-based measures typically do not distinguish between different contagion channels – instead they estimate the overall impact of all contagion channels on market prices. A change in a market-based measure cannot, therefore, be attributed to a specific contagion channel. While this is a drawback, the same feature renders market-based measures immune to the critique of the Basel methodology, according to which the methodology does not account for the potential magnification or double-counting of different contagion channels and assumes a linear increase of sLGD along with the indicator values.

Of the most widely used systemic importance measures based on market information, the ΔCoVaR measure proposed by Adrian and Brunnermeier (2016) is, in our view, conceptually closest to the loss-given-default (LGD) concept used by the BCBS in their assessment of G-SIBs. The BCBS (2018) states that "global systemic importance should be measured in terms of the impact that a bank's failure can have on the global financial system and wider economy, rather than the risk that a failure could occur". In Chapter 2, we provide a discussion and a categorisation of different measures which all rely on market data to measure systemic importance.

We then analyse what drives systemic importance as measured by ΔCoVaR. To do this we collect stock returns for all the publicly traded banks considered in the main sample of the BCBS G-SIB exercise from 2011 to 2018. Generally, we estimate ΔCoVaR using a parsimonious specification, whereby a bank's systemic importance rests on two determinants: (i) the sensitivity of market returns to changes in the bank's returns, and (ii) the magnitude of a bank's loss event relative to its median state. During the financial crisis high levels of average ΔCoVaR were driven mainly by large losses, while in later years the sensitivity of market returns played a more pronounced role. The cross-sectional variation in ΔCoVaR also depends mainly on the sensitivity of market returns to a bank's stock returns, while the magnitude of individual loss events is less relevant.

We also analyse which contagion channels drive systemic importance as measured by ΔCoVaR. To do this we compare the different indicators of systemic importance used in the BCBS G-SIB framework (i.e. cross-jurisdictional activity, size, interconnectedness, substitutability and complexity) with ΔCoVaR. We find that cross-jurisdictional claims and liabilities, complexity and substitutability capture some of the information provided by ΔCoVaR. Notably, the relationship between ΔCoVaR and a bank's size is ambiguous. The correlation with the size indicator is the lowest of all the indicators and the direction depends on a few outlier banks. The correlation with the overall G-SIB score is 0.3 and we conclude that ΔCoVaR contains a substantial amount of information in addition to that captured by the G-SIB indicators. Whether this residual information can be attributed to systemic importance or not is, however, a matter for future research.

Chapter 3 explores how for individual banks systemic importance differs when proxied by ΔCoVaR instead of the balance-sheet-based approach of the G-SIB framework. To do this we compare the relative ranking of banks under both approaches. In particular, we look at rank correlations as well as the share of G-SIBs identified. We find that while, on average, G-SIB scores and corresponding ΔCoVaR scores perform similarly across different specifications for ΔCoVaR, the respective ranking for individual banks can differ substantially from their ranking based on G-SIB scores and across specifications. Furthermore, we observe that rankings based on ΔCoVaR vary significantly over time. Meanwhile, the use of balance sheet data results in stable rankings.

In the last chapter of the paper we use ΔCoVaR to calibrate a weighting scheme for the balance-sheet-based indicators in the G-SIB framework. In the BCBS G-SIB methodology indicators are weighted equally within five categories and the five categories are in turn weighted equally to compute the final score. Although the weighting scheme is simple to apply and communicate, it has little empirical underpinning and relies on expert judgement. Assuming that ΔCoVaR is an observable proxy for the true unobservable systemic importance, as advocated by Adrian and Brunnermeier (2016) and others, it can be used to complement expert judgement and to determine the relative importance of the different transmission channels with regard to systemic importance. In line with Passmore and von Hafften (2017), we use market information to derive an alternative weighting scheme.[5] As a further refinement the marked-based information could be filtered in order to reduce the noise component that could arise from volatile market fluctuations.[6] As a first step we employ a factor analysis to construct a set of orthogonal factors which account for the maximum variation of information content of the G-SIB indicators. Next, as second step, these factors are used to explain ΔCoVaR. The coefficients derived from that second step regression are subsequently used to compute the weights of the individual indicators. The resulting weights suggest that – of the existing indicators – cross-jurisdictional activities in particular play a major role in determining a bank's systemic importance, with a combined weight of 43%. Other important determinants are size (27% weight) and, to a lesser extent, underwriting and OTC derivative activities (close to 10% weight each) as well as payment activities and assets under custody (close to 5% weight each). The remaining indicators from the G-SIB framework are dropped because the factor analysis suggests that they offer only limited additional explanatory power beyond what is already captured by the other indicators. While the resulting weights differ significantly from the weights in the BCBS methodology, given the high correlation between the single indicators we find the implied scores to be comparable with the BCBS G-SIB scores.

[5] Passmore and von Hafften (2017) use SRISK – proposed by Brownlees and Engle (2017) – rather than ΔCoVaR in their analysis. We argue that ΔCoVaR better captures the spirit of the BCBS methodology which focuses on the impact of a bank's default on the system. Instead, SRISK focuses on the impact of system stress on a certain bank.

[6] For example, one could consider taking moving averages on different time horizons or Hodrick-Prescott filters commonly used for macroeconomic variables.

# 2 Market-based measures of systemic importance

The BCBS identifies G-SIBs based on the impact their failure would have on the global economy. Conceptually, this identification is based on a bank's global sLGD rather than on its PD.[7] To capture banks' sLGD, the BCBS's approach uses five categories of indicators to compute the G-SIB score, i.e. size, substitutability, interconnectedness, cross-jurisdictional activity and complexity. The higher a bank's G-SIB score, the larger the effects that the failure of the bank are expected to have on the financial system and real economy.

In addition to the regulatory balance-sheet-based approach developed by the BCBS (2010) in order to identify G-SIBs, the academic and central banking literature contains a host of market-based systemic risk measures, albeit with quite different application scopes. A seminal contribution by Benoit et al. (2017) reviews the extensive literature on systemic risk measures from the perspective of their application in regulation. Importantly, the authors establish the differences between (mostly confidential) balance-sheet-based indicators and the market data used to derive global risk indicators which are available in real time. How to benefit from both aspects of risk measurement in regulation is considered by the authors to remain a challenge for academics and policymakers.

## 2.1 Categorisation of market-based systemic risk measures

Policymakers consider different systemic risk measures for different policy purposes and may even pool their information content – as is the case in Nucera et al. (2016). In our paper we focus on comparing ΔCoVaR with the BCBS G-SIB indicators as these follow the same systemic importance concept – the sLGD concept.

A first group of systemic importance measures is based on the LGD concept and captures the impact on the financial system conditional on an institution being in distress. A prominent example is the conditional value at risk (CoVaR) and ΔCoVaR established by Adrian and Brunnermeier (2016). ΔCoVaR captures the tail-dependency between an institution's stress event and the value at risk in the overall financial system. More precisely, it is defined as the difference between the unlikely but plausible losses incurred by the financial system if a specific institution is distressed and the possible losses incurred if the institution is in a normal state.

A second group computes the impact on an institution conditional on the financial system being in distress, which is also an LGD concept, but this time the other way around. Acharya et al. (2017) define the systemic risk contribution of a financial

7 See BCBS (2018) for more details. More precisely, the BCBS is of the view that "global systemic importance should be measured in terms of the impact that a bank's failure can have on the global financial system and wider economy, rather than the risk that a failure could occur".

institution as its propensity to be undercapitalised when the system as a whole is undercapitalised and propose their systemic expected shortfall index (SES) as a general measure. Building on Acharya et al. (2017), Brownlees and Engle (2017) introduce the SRISK index, which is defined as the expected capital shortage the firm would suffer if a systemic event were to occur. Both the SES and the SRISK are based on the concept of marginal expected shortfall (MES), which is the expected loss that shareholders of a financial firm would suffer conditional on the market experiencing a substantial decline.

A third group captures the PD approach, and comprises various measures aiming to compute a joint probability of distress, such as the distressed insurance premium proposed by Huang et al. (2009). Tarashev et al. (2010) present a methodology which takes measures of system-wide risk as inputs and allocates these to individual institutions using the Shapley value. Drehmann and Tarashev (2013) propose a measure used to evaluate the contribution of interconnected banks to systemic risk which depends materially on a bank's role in the interbank network. The authors further distinguish between participation and contribution-based systemic risk measures with the former aligned with the concept of PD and the latter more with that of LGD. As the two measures take different (conceptual) perspectives on systemic risk they can vary significantly with regard to the systemic importance of individual banks. Dungey et al. (2013) propose a network-based methodology to rank the systemic risk contributions made by individual institutions.

Similar to Benoit et al. (2017), we aim to enhance regulation by studying the potential information content of market-based measures for assessing banks' systemic risk contribution. Importantly, we argue that when comparing balance-sheet-based indicators and market-based measures, both should follow the same conceptual definition. The BCBS identifies and ranks G-SIBs based on the impact a bank's failure would have on the global financial system. It therefore relies on the same concept of systemic importance as the first group of market-based measures mentioned above. Also, some commonly used indicators of the second group, such as MES, can be constructed "the other way around" in the spirit of the BCBS G-SIB methodology. However, this is not how indicators such as MES are most commonly used.

In the rest of the paper we therefore focus on the most prominent representative of the first group, ΔCoVaR.

## 2.2 What does ΔCoVaR measure?

Following Adrian and Brunnermeier (2016), ΔCoVaR is defined as "the change in the value at risk of the financial system conditional on an institution being under distress relative to its median state". Taking the 99% value at risk as an example, $VaR_{0.99}$ of a stock index is the maximum amount which the stock index is likely to lose over the next day (or any other time unit), with a 99% probability. ΔCoVaR is computed as the difference between the value at risk of the financial system/global economy conditional on an institution being under distress (i.e. being in the1$^{st}$ percentile of its return distribution) and the value at risk of the financial system/global economy conditional on the institution being in its median state (i.e. 50th percentile). Formally, ΔCoVaR for bank i is:

$$\Delta CoVaR_i = System's\ VaR_{0.99} | institution\ i's\ VaR_{0.99} - System's\ VaR_{0.99} | institution\ i's\ VaR_{0.50} \quad (1)$$

As pointed out by Adrian and Brunnermeier (2016), ΔCoVaR is proportional to the covariance of the financial system and the individual institution for many distributional (e.g. Gaussian) assumptions. More generally, $\Delta \mathrm{CoVaR}_{0.99}$ is a function of two ingredients: the sensitivity of market returns to changes in the bank's returns (obtained using quantile regression at the 1st percentile)[8] as well as the difference between the institutions' value at risk at the 99th and 50th percentiles. In other words, a bank's systemic importance, as measured by ΔCoVaR, is greater (i) the more the returns of the market and the institution co-move in their lower tails, and (ii) the greater the difference is between the institution's return in normal times ($VaR_{0.5}$) and its return in times of stress ($VaR_{0.99}$).

ΔCoVaR captures the tail-dependency between the financial system and a particular institution, which has a number of virtues and caveats. On the one hand, ΔCoVaR is able to capture non-linear and complex spillover effects from a bank's distress onto the financial system via (i) direct exposures, i.e. via contractual links (counterparty credit risk), (ii) indirect exposures, i.e. via price effects and liquidity spirals, or (iii) common exposures, i.e. via similar portfolio allocation or exogenous aggregate macroeconomic shocks.[9] On the other hand, ΔCoVaR is a reduced-form measure and cannot identify the source and the transmission channels of systemic risk. In addition, the conditional tail-dependency measures correlation rather than causation. Therefore, a high tail-dependency could capture distress in the financial system which is unrelated to distress in the bank, and which simply happens to occur at the same time as the distress in the bank. Moreover, ΔCoVaR is estimated based on historical distributions, which may not fully capture the interdependence across banks during a period of crisis. In sum, while ΔCoVaR is able to capture complex transmission channels in a simple manner, it allows neither the degree of systemic importance to be directly attributed to a specific transmission channel nor unrelated confounding events to be filtered out.[10]

While transmission channels cannot be deduced directly from ΔCoVaR, some studies have empirically sought to establish what drives ΔCoVaR. Adrian and Brunnermeier (2016) find that higher leverage, greater maturity mismatch, larger size

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8 See the next section for details on how the sensitivity/coefficient is obtained empirically. In a nutshell, it is obtained by regressing market returns on the bank's returns using quantile regression techniques.

9 In their seminal paper, Adrian and Brunnermeier (2016) argue that indirect exposures are quantitatively more important, as market participants do not typically internalise the effects of a sell-off in financial assets.

10 See Adrian and Brunnermeier (2016), pp. 1712: "ΔCoVaR is a statistical tail-dependency measure and does not necessarily correctly capture externalities or spillover effects, for several reasons. First, the externalities are typically not fully observable in equilibrium, since other institutions might reposition themselves in order to reduce the impact of the externalities. Second, ΔCoVaR also captures common exposure to exogenous aggregate macroeconomic risk factors."

and higher asset valuations predict higher ΔCoVaRs across financial institutions. Analysing 54 large banks from 18 countries in the period 2009-11, Lopez-Espinosa et al. (2012) find that wholesale funding seems to be a robust determinant of ΔCoVaR, while relative size, leverage and marketable assets are not found to be statistically significant determinants. Furthermore, they argue that wholesale funding is a proxy for interconnectedness.

In this paper we contribute to this strand of literature and we seek to identify the transmission channels which drive systemic importance as measured by ΔCoVaR. In doing this we use the different systemic importance indicators used in the BCBS G-SIB framework, proxying for cross-jurisdictional activity, size, interconnectedness, substitutability and complexity. This also enables us to assess how much information the market-based measure holds in addition to the indicators based on balance sheet information. Whether this residual information can be attributed to systemic importance or whether it captures something else is, however, a matter for future research.

Löffler and Raupach (2018) show the possible pitfalls of systemic risk measures (including ΔCoVaR) and identify cases in which a change in a bank's "systematic risk, idiosyncratic risk, size or contagiousness increases the risk of the system but lowers the measured systemic risk contributions" of banks. To be precise, they find cases in which (i) an increase in a bank's stock return volatility (referred to as idiosyncratic risk), (ii) an increase in the market beta (referred to as systematic risk), as well as (iii) an increase in the bank's weight within the stock index reduces the bank's ΔCoVaR, although it increases the volatility of the weighted average of the stock return over all banks in the sample (referred to as systemic risk). While this result seems unintuitive, we do not believe it invalidates the use of ΔCoVaR in the context of G-SIBs. The BCBS methodology is based on an LGD concept rather than the volatility of a single bank or the volatility of the system, which are PD concepts. This result, although theoretically relevant, might not be valid, especially for major global banks[11], so it does not seem to be directly applicable to our analysis and we do not believe it invalidates the use of ΔCoVaR in our context. However, Löffler and Raupach (2018) argue that if structural buffers were calibrated using ΔCoVaR these properties might provide banks with an incentive to increase their idiosyncratic risk or their size in order to obtain lower buffers. We do not share this view. First, ΔCoVaR would not be the only determinant of systemic importance – for example, an increase in size would be captured and penalised by the traditional BCBS G-SIB indicator size. Second, microprudential buffers would be increased when idiosyncratic risks were increased. Third, it is quite difficult to believe that banks would actively manage their stock return volatility.

[11] Taking the share and the ratio between the idiosyncratic and the systemic volatility for the G-SIBs it is not clear whether the counter-results of Löffler and Raupach (2018) would apply (see Chart 1).

## 2.3 Computing ΔCoVaR

We follow the quantile estimation method outlined by Adrian and Brunnermeier (2016) to compute ΔCoVaR.[12] For our baseline specification we opt for an implementation which is parsimonious (no control variables) and relatively stable over time (we use a three-year rolling window estimation). We use the MSCI world index as a proxy for the entire financial/global economic system. Data for equity prices, market index and market capitalisation are available at a daily frequency and have been downloaded from Bloomberg for the period January 2005 to November 2018. We also collect data on the BCBS score and its 12 indicators from the BCBS G-SIB website as of 2013. Each year national supervisors report information on all banks with a leverage ratio exposure measure exceeding €200 billion as of the preceding financial year-end. For the calculation of the BCBS's scores and its indicators, each year the BCBS forms the G-SIB assessment sample, which comprises the 75 largest global banks (in terms of leverage exposure measure), any banks that were designated as G-SIBs in the previous year, and any banks that have been added to the sample by supervisory judgement. Our final sample consists of the 85 banks considered in the G-SIB exercises performed by the BCBS[13], with a regional breakdown of 31 Asian or Australian banks, 34 European banks and 20 American banks. We exclude 12 banks covered in the initial G-SIB assessment sample due to a lack of market data.[14]

We compute ΔCoVaR by estimating the components of the following equation:

$$\Delta CoVaR_i = \hat{\beta}^i_{0.99} * (VaR^i_{0.99} - VaR^i_{0.50}) \qquad (2)$$

where $\hat{\beta}^i_{0.99}$ is the estimated coefficient from a quantile regression for the 1st quantile of the MSCI world index, as our proxy for the global economy, on bank i's equity returns. $VaR^i_{0.50}$ and $VaR^i_{0.99}$ are computed as the median and 1st percentile of bank i's equity returns respectively. All three components are estimated over a three-year rolling window sample.

In our baseline specification we follow the most parsimonious specification in Adrian and Brunnermeier (2016). We found this specification to be best suited to our analyses and, from a policymaker's perspective, easy to implement and to communicate. There are, of course, a number of trade-offs compared with more elaborate specifications. First, we focus on estimates for ΔCoVaR at year-end. While our data allow us to look at daily estimates of ΔCoVaR, data on the G-SIB score and its sub-indicators are only available at an annual frequency. For this reason, we take banks' ΔCoVaR at year-end and compare it with the G-SIB score which relies on indicators measured at the same point in time. Second, we do not include additional control variables in our baseline specification. When using additional variables in

12 For details of the computation using quantile regression, we refer to Adrian and Brunnermeier (2016), Chapter III.B, page 1716.

13 Public data for the considered sample starting from 2015 are available here.

14 The following banks have been left out of the sample due to a lack of market data: BayernLB , Credit Mutuel, DZ Bank, LBBW, NORD/LB, Nationwide, Norinchukin, Rabobank, Wooribank, Caixa, China Guangfa and Kookmin.

estimating ΔCoVaR, these variables introduce an additional time series variation in the different estimates which is difficult to interpret. Meanwhile, in the more parsimonious baseline specification the estimates for $\hat{\beta}^{i}_{0.99}$, $VaR^{i}_{0.50}$ and $VaR^{i}_{0.99}$ are comparatively stable due to the overlapping of estimation windows and also, as a consequence, ΔCoVaR. In addition, while additional variables could explain part of the estimated tail-dependency over time, the focus of our analysis is on a comparison of systemic importance in the cross-section, rendering common macro control variables less relevant. Lastly, using a three-year rolling window estimation represents a trade-off between stability in the estimates in the case of longer estimation windows and greater prominence for the most recent data in the case of shorter estimation windows. However, since ΔCoVaR relies on tail events there may also be an argument in favour of using a longer estimation, in order to capture a greater number of such events.

As robustness checks we estimate four additional specifications of ΔCoVaR: (i) using all past information instead of the three-year window, (ii) including macro control variables in the quantile regressions to estimate $\hat{\beta}^{i}_{0.99}$, $VaR^{i}_{0.50}$ and $VaR^{i}_{0.99}$[15], (iii) using a bank index rather than the MSCI world index to proxy for the global financial system rather than the real economy, as in Adrian and Brunnermeier (2016)[16], and (iv) using the 5th (respectively the 95th) instead of the 1st (respectively the 99th) percentile in the quantile regression as well as for the value at risk estimate.

## 2.4 ΔCoVaR across time and banks

Chart 1 shows the evolution of ΔCoVaR and its components from 2007 to 2018 as a simple average across all banks in the sample. Average ΔCoVaR, which is shown by the blue line, spikes around the market turmoil of the crisis years 2008-09. This is followed by a decline, with another peak during the period 2015-17. While high levels of systemic importance appear to be intuitive during crisis times, it is not immediately apparent what drives the high values during the later years, which were generally marked by positive market developments.

To better understand what is driving the evolution of average ΔCoVaR across time, we decompose ΔCoVaR into its three components. To do this we fix two of the three components in equation (2) at their 2007 values and only take into account the variation across time of the third component. The green, orange and yellow lines in Chart 1 show the ΔCoVaR trend for each of the three components. In particular, we observe that the two spikes in our sample period were driven by different components.

The first spike during the crisis years was predominantly driven by increases in $VaR^{i}_{0.99}$ (orange line), reflecting the large losses in banks' equity prices during the

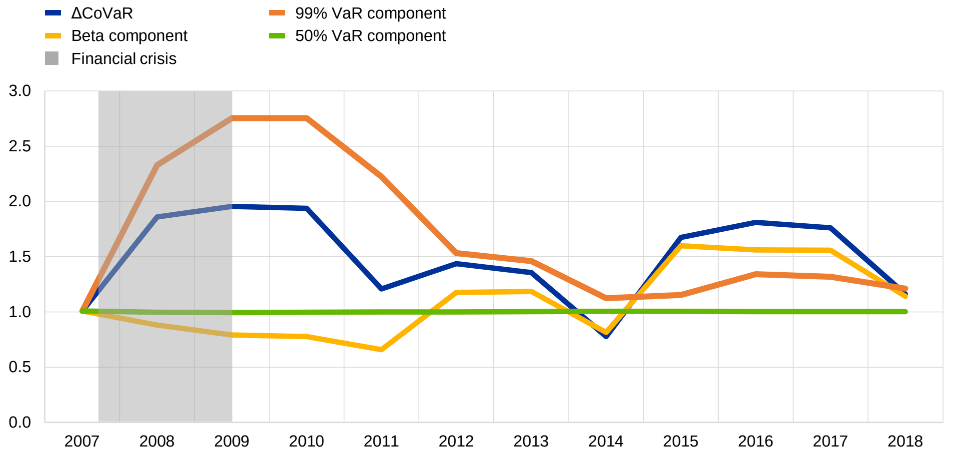
[15] We follow Adrian and Brunnermeier (2016) in constructing the macro controls for the quantile regressions. These refer to market liquidity spread, variation in the three-month Treasury Bill and variation in the slope of the yield curve. (See Chapter III.C).

[16] This index is constructed by summing the returns of all other banks in the sample weighted by their lagged market capitalisation.

great financial crisis. At the same time, we observe a decrease in the average $\widehat{\beta}^{i}_{0.99}$ (yellow line), indicating weaker co-movement between the market index and banks' returns in the tail, which dampens this first ΔCoVaR spike. Meanwhile, the second ΔCoVaR spike for the period 2015-17 is driven by an increase in $\widehat{\beta}^{i}_{0.99}$, the co-movement of extreme return losses between our sample of global banks and the MSCI World index in 2015, and a slight pickup in $VaR^{i}_{0.99}$ in 2016.

## Chart 1

The evolution of ΔCoVaR and its components




Note: Own calculations based on daily equity price and index data from Bloomberg over the period 2005-18. To isolate that component of ΔCoVaR after which the series is labelled, the two remaining components are fixed at their 2007 values. For example, for the red-plotted time-series "99% VaR component", we compute ΔCoVaR using 2007 values for the 50% VaR and the beta component as well as the contemporaneous value for the 99% VaR component.

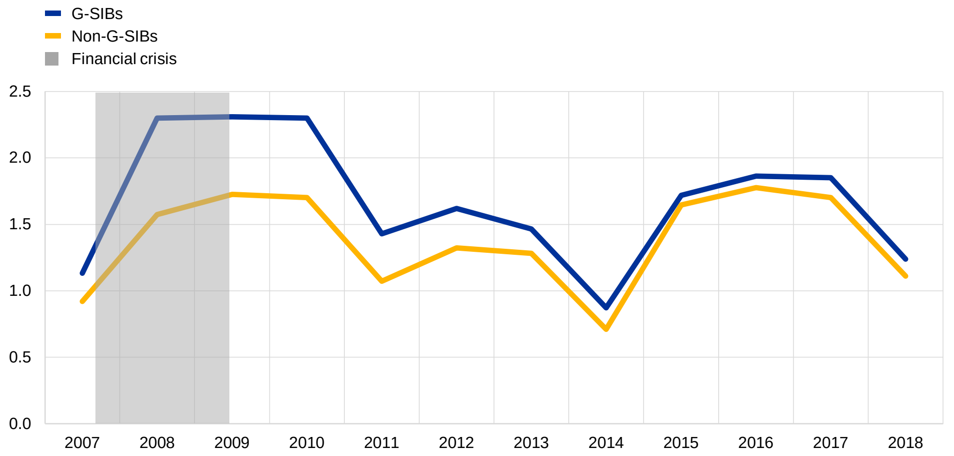
A decomposition of ΔCoVaR is useful when interpreting ΔCoVaR's evolution over time. The increase in average systemic importance in more recent years, as measured by ΔCoVaR, might reflect increasing market integration or commonality between large banks, which would result in a stronger co-movement of returns. Meanwhile, the high levels seen during the financial crisis appear, to some extent, to reflect the severity of distress events and a slight trend towards market disintegration.

This also illustrates the point that market-based measures cumulate different factors of systemic importance. During the first spike the ongoing crisis revealed new information about the potential severity of idiosyncratic stress events, which was captured by ΔCoVaR. Meanwhile, during the later economic upswing, changes in ΔCoVaR were mainly driven by new information on the commonality or spillovers of stress events. Ultimately, both factors play a role in determining whether an idiosyncratic stress event goes hand-in-hand with system-wide stress events.

Chart 2 compares the development of the average ΔCoVaR for G-SIBs and non-GSIBs – we generally observe similar trends in ΔCoVaR for both groups across our sample period. As expected, ΔCoVaR is, on average, higher for G-SIBs (as identified by the Financial Stability Board (FSB)) than for non-GSIBs over the entire sample period. In other words, the distress of a G-SIB is associated with higher losses in the world economy than that of non-GSIBs. Starting from 2011, the year the G-SIB framework was implemented, we observe a convergence of ΔCoVaR for the two groups, which is consistent with the intended effects of the reform aimed at decreasing the difference between G-SIBs and non-GSIBs with regard to the impact of a bank's failure on the economy. The convergence could, however, also reflect other factors.

**Chart 2**

Evolution of ΔCoVaR by (non-)G-SIBs



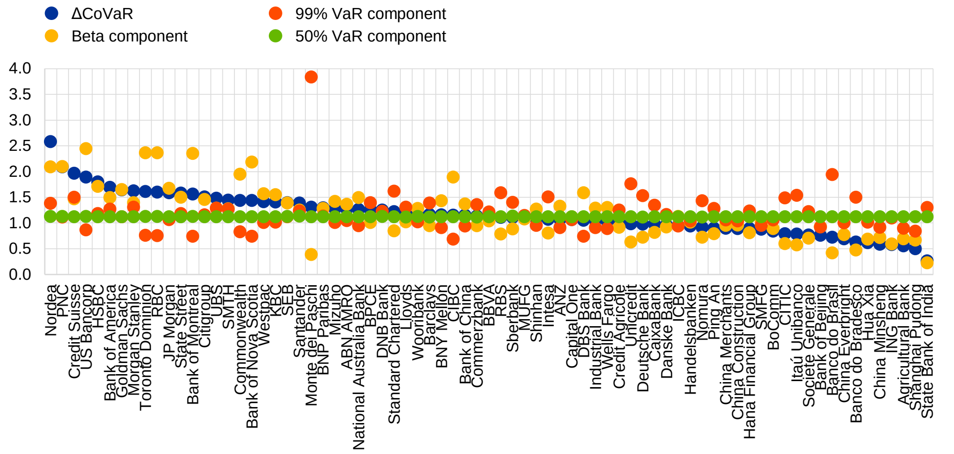

Note: Own calculations based on daily equity price and index data from Bloomberg over the period 2005-18.

We now focus on the cross-sectional variation of ΔCoVaR. This is in line with the recent contribution by Brownlees et al. (2021) who conclude that market-based measures are mostly successful in rank-ordering firms at any point in time, while there is little if any information to be gained from their time series properties. Chart 3 explores the drivers of the cross-sectional variation in ΔCoVaR – the chart depicts ΔCoVaR for different banks in 2018. For each bank we re-compute ΔCoVaR, fixing two of the three components at their median values across banks in 2018. We observe that within the cross-section $\hat{\beta}^i_{0.99}$ is the main driver of the variation in ΔCoVaR, i.e. banks with a high ranking in our sample tend to show strong co-movement of extreme return losses with the MSCI World index. The magnitude of extreme losses, as measured by $VaR^i_{0.99}$, is less relevant for explaining cross-sectional variation and a bank's median return, as measured by $VaR^i_{0.50}$, has the least impact on cross-sectional variation in ΔCoVaR. This is also apparent if we look at the correlation between ΔCoVaR and the different components in 2018: the $\hat{\beta}^i_{0.99}$ component shows a correlation of 0.79, while the correlation for the $VaR^i_{0.99}$, component is 0.24 and for $VaR^i_{0.5}$ it is -0.01.

Intuitively, these results suggest that a bank's systemic importance, as measured by ΔCoVaR, depends more on how strongly the market/economy reacts to a bank being in distress than on the severity of the stress event at that bank. One can therefore conclude that, in particular, the spillover effects associated with a bank in distress drive its systemic importance as measured by ΔCoVaR. The results further indicate that banks with high idiosyncratic risk, as measured by extreme losses, are not categorised as more systemically important. This observation is also corroborated by the observation that a bank's median return has almost no impact on its systemic importance as, ceteris paribus, banks that are considered riskier should offer higher returns.

**Chart 3**

ΔCoVaR and its components in 2018




Note: Own calculations based on daily equity price and index data from Bloomberg over the period 2005-18. To isolate the three components of ΔCoVaR, the two remaining components are fixed at their median values across all banks in 2018. We then re-compute ΔCoVaR allowing only the third component to vary across banks – for example, for the red-plotted data points "99% VaR component" we compute ΔCoVaR using median values for the 50% VaR and the beta component over all banks in the sample in 2018 as well as the bank-specific value for the 99% VaR component.

# 3 Comparing ΔCoVaR and the G-SIB framework

We cannot observe the true systemic footprint of a given bank as the systemic impact of a bank's failure can only be observed once it has defaulted – even then it is still difficult to isolate from other events. In the absence of an accurate benchmark, we compare ΔCoVaR with the observable BCBS indicators which proxy a bank's systemic footprint using balance sheet information.

## 3.1 Overall comparison

Mirroring the BCBS scoring methodology[17] we calculate, for each year, a bank's ΔCoVaR score as the bank's ΔCoVaR share of the total ΔCoVaR of the 75 largest banks for which data are available.[18] Using a relative score rather than absolute values allows us to abstract from overall market movements and to follow an approach resembling the BCBS methodology for computing the G-SIB score. We use this relative ΔCoVaR score, rather than absolute values of ΔCoVaR, throughout the analysis set out in the remainder of this paper. Importantly, we now align the timing of the ΔCoVaR score with the G-SIB so that both are based on data measured at the end of the previous year. This means the 2018 ΔCoVaR score relies on an estimation window that ends at year-end 2017, while the 2018 G-SIB score relies on balance sheet data at year-end 2017.

**Table 1**

Correlation of the ΔCoVaR score with the G-SIB score and categories

| | ΔCoVaR score | G-SIB score | Size | Interconn. | Substitut. | Complexity | Cross-juris. |
|---|---|---|---|---|---|---|---|
| **ΔCoVaR score** | 1.00 | | | | | | |
| **G-SIB score** | 0.24*** | 1.00 | | | | | |
| **Size** | -0.06 | 0.81*** | 1.00 | | | | |
| **Interconnectedness** | 0.13* | 0.93*** | 0.86*** | 1.00 | | | |
| **Substitutability** | 0.25*** | 0.76*** | 0.49*** | 0.67*** | 1.00 | | |
| **Complexity** | 0.25*** | 0.90*** | 0.65*** | 0.81*** | 0.68*** | 1.00 | |
| **Cross-jurisdictional** | 0.32*** | 0.81*** | 0.55*** | 0.69*** | 0.46*** | 0.60*** | 1.00 |

Notes: Own calculations. N = 398; significance levels: *p<0.05, **p<0.01, ***p<0.001.

Table 1 displays the correlations between the ΔCoVaR score and the G-SIB score with its five constituent categories. The market-based score is positively correlated with all categories except for size. It has the lowest correlation at 0.13 with the

17 The G-SIB assessment methodology – score calculation.

18 In a recent contribution by Jiron, Passmore and Werman (2021), the authors compare the supervisory consensus and a surcharge framework based on CoVaR and find that the CoVaR-based approach would, overall, result in declines in G-SIB surcharges, except for the most systemically important banks which would be subject to an increase in a CoVaR-based capital surcharge.

interconnectedness category and the highest at 0.32 with cross-jurisdictional activities. This positive correlation indicates that ΔCoVaR captures, to a certain degree, the systemic importance reflected in those four categories – the correlation with size is insignificant and has a negative sign. This is a rather unintuitive result. A standard outlier analysis based on residuals from regressing ΔCoVaR scores on size identifies three outliers (Industrial and Commercial Bank of China, Agricultural Bank of China and Bank of China), which have a negative market beta for most years in our sample period. In other words, these banks' stock prices correlate negatively with global stocks in the tail, suggesting that their failure would, actually, have positive externalities for the global economy. A negative relation of this type is not, however, in line with the sLGD concept and, therefore, we exclude the three outliers from the sample in the calculations which follow.[19]

Excluding the outliers the correlation between G-SIB and ΔCoVaR scores increases, as shown in Table 2 below. Notably, the correlation of ΔCoVaR with size becomes positive and significant, reaching a level of 0.12. The correlation with the G-SIB scores also increases (from 0.24 to 0.30) mainly due to the correlation with size and, to a lesser extent, because of an increase in the correlation with interconnectedness (from 0.13 to 0.23). Other correlations also increase marginally, although they remain of the same magnitude. Interestingly, the correlations of the G-SIB score with the categories and the correlations between the categories also increase.

**Table 2**
Correlation of the ΔCoVaR score with the G-SIB score and the categories when Industrial and Commercial Bank of China, Agricultural Bank of China and Bank of China are excluded from the sample

| | ΔCoVaR score | G-SIB score | Size | Interconn. | Substitut. | Complexity | Cross-juris. |
|---|---|---|---|---|---|---|---|
| **ΔCoVaR score** | 1.00 | | | | | | |
| **G-SIB score** | 0.30*** | 1.00 | | | | | |
| **Size** | 0.12* | 0.87*** | 1.00 | | | | |
| **Interconnectedness** | 0.23*** | 0.94*** | 0.89*** | 1.00 | | | |
| **Substitutability** | 0.26*** | 0.77*** | 0.57*** | 0.69*** | 1.00 | | |
| **Complexity** | 0.26*** | 0.91*** | 0.75*** | 0.84*** | 0.68*** | 1.00 | |
| **Cross-jurisdictional** | 0.34*** | 0.82*** | 0.66*** | 0.72*** | 0.46*** | 0.61*** | 1.00 |

Notes: Own calculations. N = 380; significance levels: *p<0.05, **p<0.01, ***p<0.001.

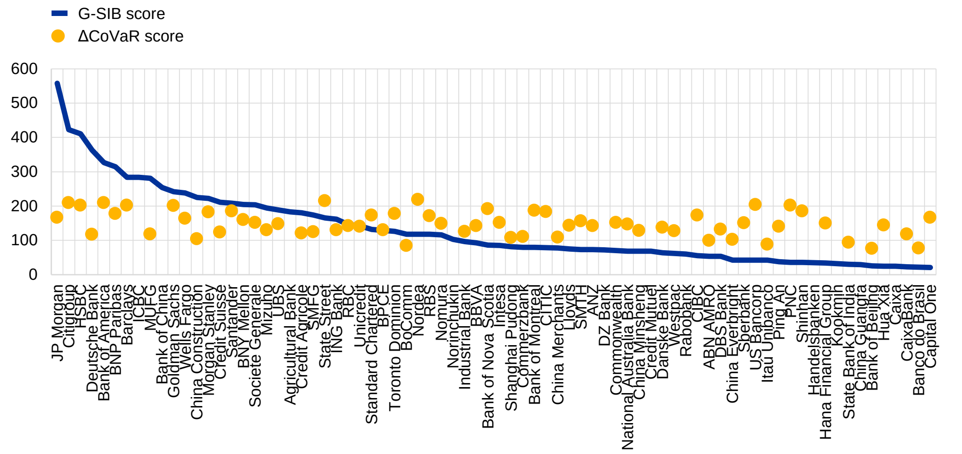
## 3.2 Comparison at bank level

Chart 4 shows the ΔCoVaR score and the G-SIB score across banks for 2018. The chart confirms our earlier observation of a comparatively low correlation between ΔCoVaR scores and G-SIB scores.

19 The negative beta for these three outliers probably stems from using the MSCI World as a benchmark index for the calculation of ΔCoVaR.

**Chart 4**

G-SIB scores and ΔCoVaR scores in 2018




Notes: Own calculations.

We now compare the G-SIB ranking with the market-data-informed ranking based on rank correlations and the share of commonly identified G-SIBs. First, we consider average rank correlations between the G-SIB score and our ΔCoVaR scores for the G-SIB sample for the years 2014 and 2018, as well as for the whole period. Second, we calculate the share of commonly identified G-SIBs based on the regulatory G-SIB score and the market-based ΔCoVaR score. To this end, we conduct a simple counterfactual G-SIB designation: based on each alternative score, the *n* banks with the highest score are considered to be designated G-SIBs, where *n* is set equal to the number of G-SIBs identified by the BCBS in each year (roughly 30 banks).[20]

Table 3 shows rank correlations as well as the share of commonly identified G-SIBs for the two approaches.[21] For the period 2014-18 the rank correlation between the ΔCoVaR score and the G-SIB score is 0.28. Moreover, using ΔCoVaR for G-SIB identification would overlap with actually identified G-SIBs in just over half of all cases.[22]

20 Alternatively, one could use the same threshold for G-SIB designation as that applied in the BCBS methodology (130 basis points) or use cluster analyses to determine those banks which are most different from the others in terms of score.

21 Table A1 in the Appendix provides the corresponding information for the full, not outlier-corrected, sample.

22 The banks which would have been identified at least three times as G-SIBs under the alternative but not the actual designation are Bank of Montreal, Bank of Nova Scotia, CIBC, CITIC, Intesa, PNC, RBC, Toronto Dominion, US Bancorp and Westpac. For 2018, banks identified as G-SIBs under the alternative but not the actual designation are Bank of Montreal, Bank of Nova Scotia, Capital One, CIBC, CITIC, Intesa, Nordea, PNC, RBS, Shinhan, SMTH, Toronto Dominion and US Bancorp. The ΔCoVaR ranking and the score for all banks for 2018 are shown in Chart 4.

**Table 3**

Rank correlations and share of identified G-SIBs when outliers (Industrial and Commercial Bank of China, Agricultural Bank of China and Bank of China) are excluded from the sample

| Market-based measures | Rank correlations with G-SIB score | | | G-SIB coverage | | |
|---|---|---|---|---|---|---|
| | 2014 | 2018 | 2014-18 | 2014 | 2018 | 2014-18 |
| **ΔCoVaR score** | 0.283 | 0.262 | 0.284 | 56% | 54% | 58% |
| **Robustness checks:** | | | | | | |
| **Complete past** | 0.200 | 0.251 | 0.203 | 63% | 58% | 58% |
| **Macro controls** | 0.246 | 0.257 | 0.260 | 59% | 50% | 57% |
| **Bank index** | 0.345 | 0.257 | 0.284 | 59% | 46% | 53% |
| **95$^{th}$ percentile** | 0.198 | 0.310 | 0.317 | 52% | 58% | 62% |

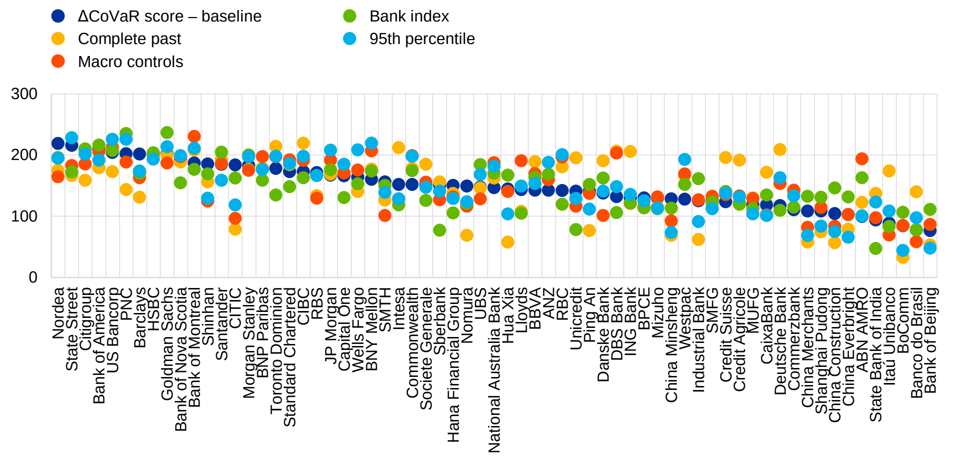
Notes: The year indicated on the time axis refers to the FSB's publication date for the overall score, which is based on end-year data for the previous year. The calculated rank correlation with the market measure is, similarly, based on the previous year's information.

In addition to our baseline specification for ΔCoVaR, Table 3 considers a number of alternative specifications, as outlined in Section 2.3, to evaluate the robustness of our findings. The findings are generally robust to these differences in calculation, i.e. we observe similar rank correlations and shares of commonly identified G-SIBs for all variants. Over the whole period, we observe the highest rank correlations with G-SIB score and the highest share of commonly identified G-SIBs when we measure the value at risk at the 95$^{th}$ percentile. At the same time this variant performs poorly in comparison with the others in 2014. Generally, there is no clear time trend with regard to the similarity of outcomes when compared with the G-SIB score across the different ΔCoVaR specifications.

While the average performance appears to be robust to alternative choices in the computation of ΔCoVaR, we observe that these choices do affect individual banks' ranking. Chart 5 shows the scores resulting from the different variants for individual banks for 2018. For many banks there is a considerable variation in their score, depending on how we compute ΔCoVaR. Consequently, the relative ranking of the individual banks also differs across computation choices. In the absence of an accurate benchmark, the variability in specifications for ΔCoVaR means this market-based measure is difficult for policymakers to use.

## Chart 5

Different specifications of ΔCoVaR score in 2018

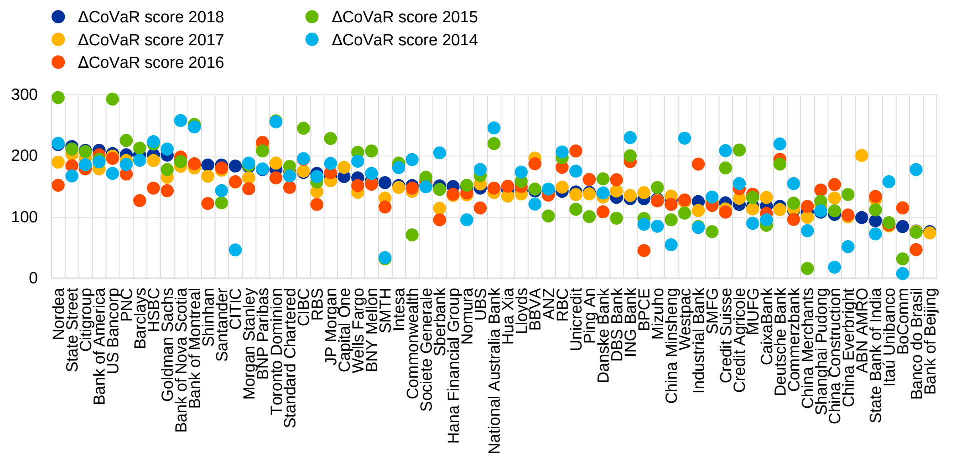



Notes: Own calculations.

Lastly, we assess the robustness of rankings across time. In our baseline specification we use a three-year rolling window in the ΔCoVaR estimation to give prominence to more recent data, while at the same time ensuring there are sufficient data for value-at-risk estimates. Even so, this specification exhibits low autocorrelation in scores of about 0.62, compared with the BCBS G-SIB scores which display an autocorrelation of 0.99. The low autocorrelation can also be seen in Chart 6, where we show the ΔCoVaR score for banks for all years. Unsurprisingly, the issue is alleviated when longer estimation windows are used. For example, when considering all past data to compute ΔCoVaR the autocorrelation of ΔCoVaR scores increases to 0.96. In making a choice of estimation window one essentially needs to weigh the measure's ability to capture changes in market information relatively quickly against having a relatively stable ranking over time. The evidence calls for using a longer estimation time window to mitigate the variability in ΔCoVaR scoring.

## Chart 6

Distribution of ΔCoVaR score 2014-18, ranked by 2018 score




Notes: Own calculations.

# 4 Using market data to inform the weighting of BCBS G-SIB indicators

In the previous chapter we compared the information content of scores based on ΔCoVaR with scores based on balance sheet information. While our analyses reveal that the direct use of ΔCoVaR appears to represent a challenge for policymaking, market information may still provide a useful input into the G-SIB assessment methodology. We now use market information with the aim of capturing the relative importance of the contagion channels considered in the BCBS G-SIB methodology. The importance of these channels is reflected in the weights assigned to the different indicators considered. Currently, these weights have little empirical underpinning – instead indicators are weighted equally within five categories and these five categories are in turn weighted equally to compute the final score.

Passmore and von Hafften (2017) argue that, other than for simplicity, it is difficult to find strong arguments for the weighting of the indicators in the BCBS methodology. They therefore explore alternative weighting schemes which have economic foundations. As a part of this exercise, Passmore and von Hafften (2017) implement an analytical approach that (i) aims to parsimoniously capture the information provided by the indicators using factor analysis and (ii) calibrates weights based on market data using SRISK as a proxy for a bank's sLGD.[23] As discussed in Section 2.1, SRISK measures the capital shortfall of a credit institution conditional on a severe market decline and is a function of its size, leverage and risk. While SRISK, as proposed by Acharya et al. (2017), is a sound indicator in its own right, given that it is based on balance sheet indicators in addition to market indicators and has an economic rational, it does not measure the systemic footprint of an institution, which is the ultimate aim of the BCBS G-SIB framework. For this reason we use ΔCoVaR and we therefore implement the approach used by Passmore and von Hafften (2017) for ΔCoVaR. In this way we aim to place the weighting scheme for the balance-sheet-based indicators on an empirically motivated footing. In work conducted in parallel with ours, Jiron et al. (2021) propose using ΔCoVaR (rather than SRISK) as a market-based measure for social LGD in the BCBS G-SIB methodology.[24]

The underlying rationale for using market information to calibrate weights rests on the premise that market-based measures can be a proxy for the true but unobservable systemic importance of a bank, as advocated by Adrian and Brunnermeier (2016) and others. We also understand the BCBS indicators as a set of relevant transmission channels for systemic importance identified via expert judgement. However, it is difficult to determine the relative importance of these different channels in explaining the true systemic risk via expert judgment (given a

[23] A detailed description of the approach can be found in Appendix 1 of Passmore and von Hafften (2017). Note that this analysis is not included in the 2019 version of the paper published in the International Journal of Central Banking.

[24] In their analysis, Jiron et al. (2021) map a log-linear function of the G-SIB score (with its original weighting scheme) onto ΔCoVaR. By contrast, we are interested in the importance of the different G-SIB indicators or contagion channels with regard to recalibrating the weighting scheme.

lack of information, countervailing effects, etc.). As a result the indicators in the BCBS G-SIB methodology are currently weighted equally within five categories and those five categories are in turn weighted equally to compute the final score. Market data can be helpful in such a situation under the proviso that they are an observable proxy for the true, unobservable systemic importance of a bank (respectively, to be at least as correlated with the true systemic importance). In this case, market data could be useful as they could complement expert judgement and help to determine the relative importance of the different transmission channels.

The analytical approach followed by Passmore and von Hafften (2017) takes total exposures as a prima facie measure of sLGD. As a first step, the remaining G-SIB indicators are regressed on total exposures in order to isolate their information content beyond that of total exposures. Next, the authors perform an orthogonal factor analysis on the residuals of the aforementioned regressions. The resulting orthogonal factors account for the maximum variation of information content of the current G-SIB indicators net of size, while minimising the number of variables. A loading cut-off is employed for indicators with low loadings, i.e. indicators that offer only limited explanatory value beyond what has already been explained by other indicators.[25] As a third step, a measure of sLGD is regressed on total exposures and the constructed factors. The resulting coefficient estimates reflect the importance of the different factors in explaining sLGD. Lastly, the coefficient estimates from the regression in the third step are multiplied by the factor loadings obtained in the second step and the resulting products are transformed into relative weights for the individual indicators. We provide the technical notation for the different steps in the Appendix.

Passmore and von Hafften (2017) use the current G-SIB score itself as a proxy for a bank's sLGD as well as SRISK. Instead of SRISK, we use ΔCoVaR as a proxy for sLGD.[26] The resulting regression estimates then indicate the importance of size as well as the factors in explaining sLGD proxied by ΔCoVaR.

Table 4 reports the factor loadings from our factor analysis. We follow Passmore and von Hafften (2017) and apply a loading cut-off of 0.7.[27] The three identified factors are consistent with their results. They are: one factor related to capital market activities comprising underwriting activity and OTC derivatives, one factor comprising cross-jurisdictional claims and liabilities and one factor related to custodial activities comprising payment activity and assets under custody. Passmore and von Hafften (2017) identify a fourth factor comprising intra-financial assets, which was not the case for our results. Our results imply that intra-financial system assets – as well as the remaining indicators – do not help to explain the variation in the residuals.

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[25] Passmore and von Hafften (2017) exclude the indicators for Intra-financial liabilities, securities outstanding, trading/AFS securities and level 3 assets in this step of their analysis.

[26] By comparison, we also replicate the analysis in Passmore and von Hafften (2017) using the BCBS G-SIB score as a sLGD measure. This allows us to determine to what extent differences in the results are driven by differences in the sample. The results of this analysis are reported in Tables A.2 and A.3 in the Appendix. The main differences compared with the results in Passmore and von Hafften (2017) are that we obtain a higher weight for total exposures and that the indicator for intra-financial assets is dropped as our factor analysis finds that it does not add any unique information.

[27] This cut-off results in dropping the same indicators as in the analysis by Passmore and von Hafften (2017). In addition, the indicator for intra-financial assets is also dropped.

### Table 4

Factor loadings of residuals

| Residuals of | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
|---|---|---|---|---|---|
| **Intra-financial assets** | 0.604 | 0.311 | 0.045 | 0.367 | 0.080 |
| **Intra-financial liabilities** | 0.107 | 0.188 | 0.481 | 0.540 | 0.000 |
| **Securities outstanding** | 0.318 | 0.152 | 0.101 | -0.355 | 0.095 |
| **Payment activity** | 0.239 | 0.050 | **0.840** | 0.014 | -0.066 |
| **Assets under custody** | 0.057 | 0.046 | **0.882** | 0.060 | 0.069 |
| **Underwriting activity** | **0.849** | 0.080 | 0.137 | -0.067 | 0.020 |
| **OTC derivatives** | **0.819** | 0.289 | 0.166 | 0.045 | -0.100 |
| **Trading/AFS securities** | 0.649 | 0.039 | 0.234 | -0.002 | 0.195 |
| **Level 3 assets** | 0.648 | -0.045 | 0.047 | 0.078 | 0.053 |
| **Cross-jurisdictional claims** | 0.120 | **0.952** | 0.001 | 0.060 | -0.023 |
| **Cross-jurisdictional liabilities** | 0.101 | **0.954** | 0.095 | 0.004 | 0.027 |

Notes: Factor loadings for the residual from regressions of each indicator on total exposures using indicator scores for the period 2014-18, excluding outliers (Industrial and Commercial Bank of China, Agricultural Bank of China and Bank of China) from the sample. Following Passmore and von Hafften (2017), we apply a loading cut-off of 0.7.

Next, we use the ΔCoVaR score as a proxy for sLGD to derive market-based weights. Table 5 reports the results of the regression of the ΔCoVaR score on total exposures and the factors. We obtain statistically significant, positive coefficients for all three factors. Factor 2, which captures cross-jurisdictional activities, is the most relevant in explaining our market-based score.[28]

### Table 5

Regression of G-SIB and ΔCoVaR score on total exposures and the factors

| | ΔCoVaR score |
|---|---|
| **Total exposures** | 0.0658*<br>(1.84) |
| **Factor 1** | 0.0504**<br>(2.41) |
| **Factor 2** | 0.107***<br>(4.08) |
| **Factor 3** | 0.0253***<br>(2.95) |
| **Constant** | 142.4***<br>(19.56) |
| **Adjusted R-sq.** | 0.153 |
| **Observations** | 317 |
| **Sample** | Excluding outliers |
| **t statistics in parentheses, * p<0.1 ** p<0.05 *** p<0.01** | |

The weights of the BCBS G-SIB framework and the derived indicator weights are reported in Table 6. Compared with the BCBS weights (column 1), the weighting informed by ΔCoVaR (column 2) places more importance on size and cross-jurisdictional activity as well as, to a lesser extent, underwriting and OTC derivative

28 For total exposure the coefficient is statistically insignificant if we do not exclude the three outlier banks (see Appendix).

activities.[29] Cross-jurisdictional activities are the most important category in our market-based weighting scheme, with a combined weight of 43% compared with a weight of 20% under the BCBS methodology. Total exposure is the most important single determinant, with a weight of 27% compared with a weight of 20% in the BCBS methodology.[30]

Comparing the derived weights with the results of the correlation analysis in Section 3.1, it may to some extent appear counterintuitive that the implied weighting scheme assigns a greater weight to size, for which the correlation with ΔCoVaR was found to be comparatively low. However, the correlation analysis constitutes a univariate analysis and therefore does not control for any other factors. Meanwhile, the weights are based on a multivariate analysis, which controls for the impact of the other indicators. The different G-SIB indicators are all positively correlated with size, and this correlation is stripped out by orthogonalising the indicators on size in the first step of the approach adopted by Passmore and von Hafften (2017). For a positive correlation of size and systemic importance we would therefore expect higher univariate correlations but lower multivariate correlations for the other indicators.

**Table 6**

Indicator weights estimated using ΔCoVaR

| Indicator | Current weight (1) | Using ΔCoVaR as sLGD (2) |
|---|---|---|
| Total exposures | 20 | 26.5 |
| Intra-financial assets | 6.7 | - |
| Intra-financial liabilities | 6.7 | - |
| Securities outstanding | 6.7 | - |
| Payment activity | 6.7 | 5.0 |
| Assets under custody | 6.7 | 5.2 |
| Underwriting activity | 6.7 | 10.3 |
| OTC derivatives | 6.7 | 10.0 |
| Trading/AFS securities | 6.7 | - |
| Level 3 assets | 6.7 | - |
| Cross-jurisdictional claims | 10 | 21.5 |
| Cross-jurisdictional liabilities | 10 | 21.5 |

Notes: BCBS (2013) and own calculation. Column 1 reports current indicator weights in BCBS (2013). Column 2 reports indicator weights derived using the factor analysis approach in Passmore and von Hafften (2013) and ΔCoVaR as a measure for sLGD. Weights are estimated using data for the sample period 2014-18, excluding outliers (Industrial and Commercial Bank of China, Agricultural Bank of China and Bank of China) from the sample.

Chart 7 shows the implied scores based on the derived weights in comparison with the ranking based on the BCBS G-SIB methodology. Overall, using weights informed

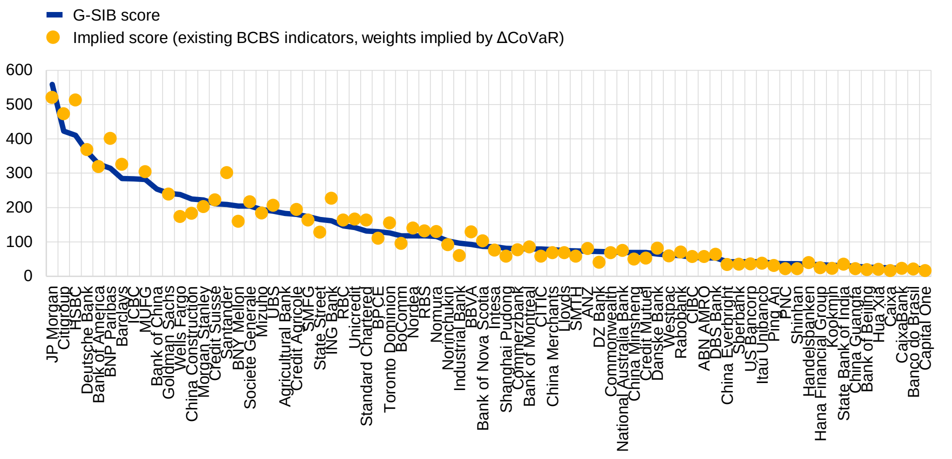
[29] Using SRISK, Passmore and von Hafften (2017) also find that total exposures and the indicators for international activities receive the highest implied weights, while the indicators for market activities receive zero weight and the indicators for payment and custodial activities receive small negative weights. To explain these negative weights, the authors argue that once you control for size, the market views these activities as more robust during a downturn.

[30] For the full sample – not outlier-corrected – cross-jurisdictional claims and activities each receive a weight of 27%. The remaining weights are underwriting activities at 17%, OTC derivatives at 16%, assets under custody at 7% and payment activity at 6%. Notably, total exposures receive zero weight when we derive the weights for the full sample since the regression coefficient is not significantly different from zero.

by market data results in similar outcomes to the BCBS methodology with very few bucket changes. While the implied indicator weights from the factor analysis differ considerably from the current weights in the BCBS methodology, the resulting ranking and designation are very similar: the rank correlation is 0.94 and the share of commonly identified G-SIBs is 89% across the whole period. Passmore and von Hafften (2017) also note in their analysis using SRISK that different weighting schemes would result in only limited changes in terms of G-SIB surcharge buckets. However, the approach would also be expected to result in outcomes that are similar to those produced by the BCBS G-SIB methodology. As is evident in Table 1, the single indicators in the G-SIB methodology are highly correlated, so even material changes to the weights result in comparatively small changes to the overall score.

**Chart 7**

G-SIB scores and implied scores using estimated indicator weights in 2018



# 5 Policy implications

Market-based measures are appealing in many respects, in particular due to their timeliness and the ease with which their data may be collected. However, our analyses show that for ΔCoVaR to be directly usable for policy purposes, policymakers need to overcome a number of challenges. First, while ΔCoVaR is positively correlated with fundamental, balance-sheet-based information, there is considerable information/noise which cannot be attributed to aspects captured in the BCBS methodology. Moreover, it is difficult to identify the relevant contagion channel (as described in the BCBS G-SIB assessment methodology) that determine banks' ΔCoVaR scores. Therefore, further work is needed to identify additional channels of systemic risk which are captured by ΔCoVaR. Second, a bank's ΔCoVaR, and a relative score based on it, exhibit substantial variability over time and across specifications. Lastly, the applicability of the measure is limited to listed banks. While this is less problematic for ranking G-SIBs, market-based measures appear to be unsuitable for assessing domestic systemically important banks due to a lack of return data for some of the more important domestic banks. This drawback is particularly relevant in economies where only a minority of banks are publicly listed.

Despite these findings, ΔCoVaR might provide a useful additional score which could trigger a deeper analysis and discussion by policymakers for banks which might otherwise fall below the supervisor's radar. Another potential application of market information in the context of G-SIB identification would be to inform the weighting scheme used in the BCBS balance-sheet-based indicator approach. Currently, the weights in the BCBS G-SIB framework are derived from equal-weighting within and across categories. Using market information in the context of the weighting scheme would make it possible to use that part of the information which can be clearly attributed to a contagion channel as captured by the balance-sheet-based indicators, placing their relative importance on an empirically motivated footing. However, our analysis also found that alternative weighting schemes are unlikely to lead to materially different outcomes, given the high correlation between the single indicators used in the G-SIB framework.

Based on our analysis we conclude that ΔCoVaR-based indicators cannot replace balance sheet indicators in a policy context. There are considerable challenges, in particular when it comes to interpreting market-based measures and identifying the relevant contagion channel. However, market information could be a useful addition and challenge to the established policy indicators.

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# Appendix

**Table A.1**

Rank correlations and share of identified G-SIBs not outlier-corrected

| Market-based measures | Rank correlations with G-SIB score | | | G-SIB coverage | | |
|---|---|---|---|---|---|---|
| | 2014 | 2018 | 2014-18 | 2014 | 2018 | 2014-18 |
| **ΔCoVaR score** | 0.268 | 0.168 | 0.216 | 50% | 48% | 52% |
| **Robustness checks:** | | | | | | |
| **Complete past** | 0.192 | 0.155 | 0.138 | 57% | 52% | 52% |
| **Macro controls** | 0.230 | 0.166 | 0.199 | 53% | 45% | 52% |
| **Bank index** | 0.327 | 0.233 | 0.266 | 53% | 41% | 50% |
| **95th percentile** | 0.142 | 0.213 | 0.231 | 47% | 52% | 56% |

Notes: The year indicated on the time axis refers to the FSB's publication date for the overall score, which is based on end-year data for the previous year. The calculated rank correlation with the market measure is, similarly, based on the previous year's information.

## Technical notation of the Passmore and von Hafften (2017) approach used to derive indicator weights using factor analysis

Passmore and von Hafften (2017) use a factor analysis to derive an alternative weighting scheme for the G-SIB indicators using market information. Below, we provide the technical notation for each step of their approach, largely following the notation provided in Appendix 1 of the original paper.

*Step 1:* Regress each G-SIB indicator $X_j$ on total exposures to isolate information content beyond what is explained by total exposures.

$$X_{i,j} = \alpha_j * Total\ exposures_i + \varepsilon_{i,j}$$

*Step 2:* Perform an orthogonal factor analysis on the residuals $\varepsilon_{i,j}$ of the regressions performed in Step 1. Each resulting factor is constructed as a linear combination of $n_k$ indicator residuals weighted by $\beta_j$ , where $\beta_j$ is the loading estimated in the factor analysis (see Table 4). There is a loading cut-off of 0.7, so indicators receiving low weights are dropped.

$$Factor_{i,k} = \sum_{j=1}^{n_k} \beta_j * \varepsilon_{i,j}$$

*Step 3:* Regress a measure of sLGD on total exposures and the set of factors constructed in Step 2, to estimate the importance of each regressor in explaining sLGD. We use ΔCoVaR as our measure for sLGD (see Tables 5 and A.2). We also replicate the analysis conducted by Passmore and von Hafften (2017) using the BCBS G-SIB score as the sLGD measure in this step, which we describe in the next section of this appendix. This also allows us to determine the extent to which differences in the results are driven by differences in the sample.

$$\Delta CoVaR\ score_{\ i} = \delta_0 * Total\ exposures_i + \sum_{k=1}^{m} \delta_k * Factor_{i,k} + \gamma_i$$

Step 4: Derive the implied indicator weights using the factor loadings $\beta_j$ obtained in Step 2 and the regression coefficients $\delta_0$ and $\delta_k$ obtained in Step 3 and compute the implied scores using the derived indicator weights (see Tables 6 and A.3).

$$\begin{aligned}\widehat{\Delta CoVaR\ score_{\iota}} &= \delta_0 * Total\ exposures_i + \sum_{k=1}^{m} \delta_k * \sum_{j=1}^{n_k} \beta_j \varepsilon_{i,j} \\ &= \delta_0 * Total\ exposures_i + \sum_{k=1}^{m} \delta_k \\ &* \sum_{j=1}^{n_k} \beta_j \left(X_{i,j} - \alpha_j * Total\ exposures_i\right) \\ &= \left[\delta_0 - \sum_{k=1}^{m} \delta_k * \sum_{j=1}^{n_k} \beta_j \alpha_j\right] * Total\ exposures_i + \sum_{k=1}^{m} \delta_k \\ &* \sum_{j=1}^{n_k} \beta_j X_{i,j}\end{aligned}$$

### Replication of the analysis conducted by Passmore and von Hafften (2017) using the BCBS G-SIB score as a sLGD measure to derive indicator weights

To work out the sample effect, we replicate Passmore and von Hafften's analysis to derive minimum variance regulatory consensus weights. To derive the minimum variance regulatory consensus weights the BCBS G-SIB score is used to proxy for sLGD. While Passmore and von Hafften's analysis is based on end-2014 G-SIB public disclosures, we rely on data for the period 2014-18. Table A.2 reports the results of the regression of the G-SIB score as a measure of sLGD on total exposures and the factors. The resulting weights for the indicators are reported in Table A.3 (column 2). As expected, the most relevant indicator is total exposures at 67%. The remaining indicators are *jurisdictional claims* and *liabilities and OTC derivatives* at around 7% each and *assets under custody* and *payment activity* at around 3%. The main differences compared with the results in Passmore and von Hafften are that we obtain a considerably higher weight for *total exposures* and that *intra-financial assets* are not included, as our factor analysis finds that it does not add unique information. The weights for the other indicators are slightly smaller but our results indicate the same relative order of importance. One potential explanation for the shift in weights towards *total exposures* may be that, overall, business models have converged in recent years. The remaining indicators would, therefore, provide less unique information in addition to *total exposures*.

### Table A.2

Regression of G-SIB and ΔCoVaR score on total exposures and factors

| | G-SIB score (1) | ΔCoVaR score (2) | G-SIB score (3) | ΔCoVaR score (4) |
|---|---|---|---|---|
| **Total exposures** | 0.865*** (53.12) | -0.0261 (-0.82) | 1.058*** (47.22) | 0.0658* (1.84) |
| **Factor 1** | 0.220*** (18.36) | 0.0677*** (3.06) | 0.218*** (17.79) | 0.0504** (2.41) |
| **Factor 2** | 0.225*** (18.08) | 0.109*** (4.65) | 0.226*** (15.46) | 0.107*** (4.08) |
| **Factor 3** | 0.0833*** (6.56) | 0.0260*** (3.17) | 0.0833*** (6.57) | 0.0253*** (2.95) |
| **Constant** | 14.19*** (6.51) | 150.8*** (21.73) | -3.665 (-1.42) | 142.4*** (19.56) |
| **Adjusted R-sq.** | 0.984 | 0.226 | 0.984 | 0.153 |
| **Observations** | 379 | 332 | 364 | 317 |
| **Sample** | Full sample | | Excluding outliers | |
| **t statistics in parentheses, * p<0.1 ** p<0.05 *** p<0.01** | | | | |

### Table A.3

Indicator weights estimated using factor analysis

| Indicator | Current weight (1) | G-SIB score sLGD (2) | Market-based sLGD (3) |
|---|---|---|---|
| **Total exposures** | 20 | 66.7 | 26.5 |
| **Intra-financial assets** | 6.7 | - | - |
| **Intra-financial liabilities** | 6.7 | - | - |
| **Securities outstanding** | 6.7 | - | - |
| **Payment activity** | 6.7 | 2.6 | 5.0 |
| **Assets under custody** | 6.7 | 2.7 | 5.2 |
| **Underwriting activity** | 6.7 | 7.0 | 10.3 |
| **OTC derivatives** | 6.7 | 6.8 | 10.0 |
| **Trading/AFS securities** | 6.7 | - | - |
| **Level 3 assets** | 6.7 | - | - |
| **Cross-jurisdictional claims** | 10 | 7.1 | 21.5 |
| **Cross-jurisdictional liabilities** | 10 | 7.1 | 21.5 |

Notes: BCBS (2013) and own calculation, excluding outliers.

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