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Consultative document on the Standardised Measurement Approach for Operational Risk

Dear Mr. Adashi,

Thank you for providing us with the opportunity to comment on the Basel Committee for Banking Supervision (BCBS) proposals on the Standardised Measurement Approach (SMA) for Operational Risk.

The BCBS aims to address several goals with this proposal. This proposal intends to enhance transparency, improve comparability, reduce complexity and better balance risk sensitivity. This should lead to a better reflection of the capital requirements for banks. Deutsche Bank (DB) supports these objectives and the focus on greater standardisation of Operational Risk given some of the challenges associated with the Advanced Measurement Approach (AMA).

We are concerned that as drafted, the current proposals will not achieve the objectives set. DB's view is also clear that the use of internal models to assess an institution's risk profile constitutes a fundamental part of strong risk management. Variance in risk management practices and outcomes of internal modelling does not imply that internal models are flawed. The variance reflects genuine differences in banks' risk profiles, their client behaviours and banks' strategy which we believe is a positive sign that models are accurate and risk sensitive. Applying internal models will furthermore contribute to continuous improvements and enhancements of the measurement and management of operational risk.

Concerns with the Standardised Measurement Approach

Although the proposal does not provide details on the background of designing the current SMA, DB has performed thorough analysis on the approach. Based on this analysis, the following points would need to be addressed before the SMA is able to reflect operational risks appropriately:

- **Input difference remains - leading to incomparable outcomes:** A key driver of differences in AMA results was the lack of consistency in the input data used by different institutions¹. We expect that this will continue under the SMA as loss event definitions for SMA allow a broad range in interpretation of input data between banks and between local regulators.
- **SMA methodology results in a significant increase in volatility, thereby decreasing the ability to compare outcomes:** Our analysis shows that the SMA component metrics are subject to a significant level of volatility. Due to the sporadic, infrequent nature of large operational losses the metric will be unstable over time for an individual institution and provide very different capital

¹ Based on feedback received by the industry from supervisors



requirements for institutions with a similar level of underlying risk at a given point in time. The key driver of this outcome is the Loss Component and the reliance on a small loss sample (10 years history) as its input.

- **Lack of risk sensitivity:** While the Loss Component makes the SMA sensitive to losses it does so in a purely ex post manner. This framework simply takes the output it is trying to measure as an input. Risk sensitivity requires the identification of factors which drive or are correlated to the relevant output and can be measured on a timely basis. Against this background, the framework cannot be seen to be risk sensitive but merely loss sensitive on a purely historical basis.
- **SMA increases pro-cyclicality:** The proposal is significantly pro-cyclical because at an individual institution level the capital requirement will increase at exactly the same time that its capital is being drawn down. At the system level, large operational losses commonly occur after the onset of distress and not prior to systemic shocks. Hence, under the SMA capital will not be built up when banks can afford it and buffers will be eroded to a greater degree after the onset of stress, weakening the system's resiliency.

Addressing the Concerns: recommendations to improve the SMA

In light of these observations we would propose to enhance the SMA approach with additional features and undergo a significant recalibration based on a thorough assessment of the Quantitative Impact Study (QIS) results. In this context we recommend the following:

- **Increase guidance on model inputs:** As pointed out above, a key driver of differences in AMA results was the lack of consistency in the input data used by different institutions. Therefore, in our view, further guidance on data inputs and definitions, such as on "loss data sets", are necessary to contribute to attaining more comparability (see Annex 1).
- **Amend OpCaR methodology to reduce volatility and increase comparability:** An improved version of the OpCaR methodology, as published by the BCBS in 2014², could replace the SMA. This would substantially improve the quality of its calibration, leading to a reduction of volatility of its results and increase their comparability across banks. The OpCaR model of 2014 provides a direct and conceptually sound approach to measuring an institution's capital demand for operational risk based on loss histories as it applies key features of modern portfolio modeling within a standardised algorithm. However, a number of amendments to this approach would be required to navigate pitfalls inherent to single loss approximation-based approaches, which we provide solutions for in Annex 1.
- **Include risk mitigation to increase risk sensitivity:** Risk mitigation is a fundamental element of risk management. It incentivizes the continuous improvement of risk models and risk management techniques. To limit the SMA's disconnect with risk management, we consider a clearly defined historic loss exclusion process, a phasing-out of loss events to smooth the cliff effects given the ten year average, and the recognition of insurance as a risk mitigant as indispensable characteristics. In addition to reviewing the calibration of the Loss Component, the recalibration should look to understand the extent to which the rank ordering of the Loss Component is stable, particularly if losses in benign times are correlated with larger losses in stressed times.
- **Recalibration should address the procyclical effect:** We recommend that this effect is further assessed through a time series analyses on an institutional level during the recalibration. The Loss Component parameterisation should also be reviewed based upon its impact on the evolution of the rank ordering of the capital requirements in the recalibration over time.
- **Conduct a complete QIS:** DB is not aware of a full QIS being conducted for the SMA proposal. We strongly urge the BCBS to reconsider this view, especially given the inability of the SMA proposal to achieve its own goals. We believe that there is a need for a significant recalibration of

² Basel Committee on Banking Supervision: Operational risk – Revisions to the simpler approaches. October 2014



the SMA proposal, after which a second consultation period would be essential before a final standard is published.

In the Annex 1 we provide more detailed views on the draft SMA standard and we would be happy to share our full analysis on the instability of the SMA proposal with the committee. An excerpt of this analysis is included in Annex 2 and 3. Please do not hesitate to contact us if you have questions or wish to discuss these issues further.

Yours Sincerely,

A handwritten signature in black ink, appearing to read 'MH', with a horizontal line underneath.

Matt Holmes
Head of Group Regulatory Policy



Annex 1: Detailed comments on the SMA proposal

Concerns with the Standardised Measurement Approach

The BCBS aims to address several goals with this proposal. This proposal intends to enhance transparency, improve comparability, reduce complexity and better balance risk sensitivity. This should lead to a better reflection of the capital requirements for banks.

In order to achieve this, the BCBS has replaced all current approaches for operational risk management with one single method, i.e. with the Standardised Measurement Approach (SMA). By combining the Business Indicator with internal loss experience the BCBS has produced a methodology, which it believes contains an appropriate amount of risk sensitivity.

We support these goals and the aim of the BCBS to introduce more risk sensitivity with this second consultation on operational risk. However, these goals will not be achieved by implementing the current proposal of the SMA for the following reasons:

- **Input difference remains - leading to incomparable outcomes:** Feedback from supervisors showed that a key driver of differences in AMA results was the lack of consistency in the input data used by different institutions. We expect that this will continue under the SMA. Loss definitions for SMA still allow for a broad range in interpretation of input data between banks and local regulators. For instance, the requirements to include material pending or timing losses (para 43 (d) and (e)) and to group losses with a joint root cause (para 45) are extremely vague, while two materially different options for loss reference dates are given (para 45).
- **SMA methodology results in a significant increase in volatility, thereby decreasing the ability to compare outcomes:** Due to the sporadic and infrequent nature of large operational losses the methodology will be unstable over time for an individual institution. It will furthermore provide very different capital requirements for institutions with a similar level of underlying risk at a given point in time. This is because idiosyncratic events occur over the ten year measurement period. The direct combination of linear or log-linear functions amplifies the embedded conservatism in each element and magnifies the cliff effects caused by fixed time windows for input data.

The Internal Loss Multiplier (ILM) is driven by the ratio of the Loss Component (LC) with the Business Indicator (BI) Component, which can be interpreted as a loss absorption ratio. We can follow the argument that a bank with a loss absorption ratio of 1 (i.e., where anticipated losses match the bank's capital) should have their capital requirement unchanged. However, our opinion is that the conservatism embedded in the LC moves this point of ILM neutrality too far to the right, making it too conservative. It is this interaction which turns the ILM into a major driver of the volatility of the SMA as new losses have an immediate and strong impact on LC, ILM and the total capital requirement. These calibration issues (including the steepness of the proposed logarithmic function for the ILM) should to be addressed holistically as part of a QIS in-line with our suggestion for the LC.

Our views are the result of a series of analyses we have performed (see Annex 2) which we would be interested in discussing in detail with the BCBS. We would also respectfully recommend that the BCBS perform similar analyses as part of the recalibration. Focus should be on reviewing the LC and ILM calibrations in light of actual one year loss experience for banks of similar size (i.e., in the same BI bucket, not just at the system aggregate).

- **SMA proposal lacks risk sensitivity, focuses only on loss sensitivity:** While introducing historical losses provides some risk sensitivity in the method, it effectively becomes more loss sensitive than risk sensitive. Its sole reliance on historic data without any recognition of changes to the business model and risk mitigation activities makes this risk sensitivity completely backward-looking. Moreover, the uniform calibration of the framework does not take into account the sizes of



operational losses, in particular for conduct risk. The approach to conduct risk differs materially depending on the jurisdiction under which the respective businesses are conducted.

- **SMA increases pro-cyclicality:** The proposal is significantly pro-cyclical because at an individual institution level the capital requirement will increase at exactly the same time that its capital is being drawn down. The additional penalty for large losses embedded in the LC (factor: 19) and the rather low sensitivity of the Business Indicator Component (BIC) offset from a loss (factor: 0.29) further adds to this issue. At the industry level, large operational losses commonly occur after the onset of distress and not prior to systemic shocks. Hence, under the SMA capital will not be built up when banks can afford it and buffers will be constrained to a greater degree after the onset of stress, weakening the resilience of the banking system. We recommend that this effect is further assessed through a time series analyses on an institutional level as part of the recalibration. The ILM parameterisation should also be reviewed based on its impact on the evolution of the rank ordering of the capital requirements over time.

Against the background we strongly recommend to recalibrate the SMA approach and to perform a full impact study. As stated above, our analysis shows that most of the volatility which leads to a lack of comparability is caused by the approach of the ILM with the LC as its core component. This should be a central element of attention in the recalibration by the BCBS.

Addressing the Concerns: Recommendations to improve the SMA

a) Increasing comparability focusing on input to the model

A key driver of differences in AMA results was the lack of consistency in the input data used by different institutions. We expect that this will continue under the SMA as loss definitions for SMA allow for a broad range in interpretation of input data between banks and local regulators. Therefore, further guidance on data input and definitions are necessary to achieve comparability:

- **Loss data standards need further harmonisation and guidance:** We appreciate the general consistency of the proposed minimum standards for loss data with previous guidance but see the need for further standardisation to avoid the SMA falling behind current AMA standards. In the proposal, many aspects are left to be defined in individual bank policies, e.g. inclusion of losses in the “SMA loss data set”, which creates the risk of broadening the range in interpretation of input data between banks and between local regulators.

Furthermore no guidance is provided on the criteria to be used for the removal of historic losses from SMA (e.g. to reflect acquisitions, business closures or decommissioning). Specifically, the limited guidance on grouped losses will create significant divergence between banks results due to the materially differing multipliers applied to large losses within the LC. In order to maintain at least the current AMA standards and foster consistency, we recommend a cross-reference in the SMA minimum loss data standards to loss data standards in existing regulation, clearly highlighting changes and intended simplifications.

- **Scope of application is unclear:** We would appreciate a clarification on the framework’s scope of application and specific guidance on how the super- and sub-additive features of the SMA should be combined to produce only one consistent capital requirement at the group level. Para 4 of the proposal states that “the proposed SMA framework would be applied to internationally active banks on a consolidated basis”. Chapter 5, however, provides guidance on how the SMA shall be calculated for subconsolidated or subsidiary banks. These reference points seem to be at odds with each other.
- **Loss data definitions would benefit from further clarity:** Several definitions in the loss data specification provided in the proposal lack sufficient clarity. For instance, clear guidance should be provided that losses for SMA purposes are defined as net after direct recoveries as is currently defined in AMA rules and grouped to the date of accounting. Similar to our recommendation on risk



mitigation, we suggest that insurance recoveries be subtracted from loss amounts. If necessary, these also could be assigned to the date of the recovery to reflect the time delay between loss and insurance recovery. Finally, the rules for event grouping should be elaborated to ensure consistent application across jurisdictions and banks. We suggest applying the ORX Standards definitions as a starting point for the groupings, which have a substantial impact on the application of the multipliers used within the LC.

b) Improving comparability and reducing volatility of the model

DB acknowledges the decision taken by the BCBS to discontinue the use of AMA models under Pillar 1. However, the replacement of AMA by the proposed SMA is not without alternatives and proper calibration is essential.

Including a (constant) linear scalar to the BI Component (BIC) addresses several issues: We understand that the BIC represents an unexpected loss of a risky portfolio of the Business Indicator as a variable representing an amount for size. This resembles the conversion of Risk Weighted Assets (RWA) into a capital requirement for credit risk. As the risk sensitivity of the SMA is driven by the ILM, this conversion should be linear rather than step-wise linear to avoid double-counting the inherent risk. Using a constant linear scalar would also eliminate the superadditivity of the SMA when applied to low subconsolidation levels. In the current proposal superadditivity is an inadequate property as the combination of two standalone losses cannot produce a higher total joint loss than their sum. Furthermore, portfolio risk assessments should always contain some level of subadditivity to reflect diversification.

Recalibrate the Loss Component using an improved OpCaR model: We recommend that the multipliers used within the calculation of the LC are recalibrated based on a broad sample of loss distributions collected from the participating banks. For this purpose an improved OpCaR model as described below should be used. We interpret the LC as an estimate for an unexpected loss driven by tail risk. In this context, the proposed multipliers 7, 14 and 19 can be interpreted as the unexpected loss / expected loss ratios of the underlying loss distribution. Doubling or almost tripling the base multiplier 7 for larger losses is excessively punitive and not in-line with the behaviour of common portfolio models.

Applying an improved OpCaR methodology increases comparability: We propose to enhance the SMA methodology by improving the underlying OpCaR methodology³. The OpCaR has materially impacted the calibration of the BIC as well as the LC.

The current OpCaR implementation will produce strongly distorted results impacting reliability and quality of LC and BIC, leading to volatility in SMA capital figures. The single-loss approximation (SLA) which provides the basis for the OpCaR approach has a sound theoretical foundation, however, the implementation described in the BCBS publication exhibits significant weaknesses (some of which are listed below). Due to lack of documentation it also remains unclear how or if unintended consequences of these weaknesses (e.g. mis-calibrated outliers driving average results) have been circumvented.

Our first impression was substantiated by an application of OpCaR to DB data as well as simulated test data for hypothetical banks (see Annex 3). As a result of this exercise, we identified a number of issues which lead to significant mis-calibration and most often to significant overestimation of OpCaR results compared to actual loss data:

- Mixing of high frequency/low severity and low frequency/high severity data, e.g. no separation of data from different event types
- Calibration of heavy-tailed distributions is based on body-focused moment/frequency conditions
- Convergence is used as the only criterion to select certain distributions - goodness-of-fit is completely neglected
- There is a dependence on start values
- Infinite mean models are not used, but close to infinite mean models are accepted

³ Operational risk –Revisions to the simpler approaches, BCBS 2014, <http://www.bis.org/publ/bcbs291.pdf>



We strongly recommend adjusting the calibration methodology to make the LC a better proxy for the capital requirements calculated by the single loss approximation and also to improve the BIC calibration. This involves considering the following elements:

- **Increased modelling granularity**, i.e. event type-specific application of OpCaR. The respective data is available from QIS submissions
- **Better usage of QIS data** to ensure stability and reliability of results. Model calibration should not be restricted to a subset of available information (e.g. currently only frequencies above 10,000 and 20,000 and average loss above 20,000 are used)
- **Consider usage of additional alternative conditions for calibration** to stabilize results based on QIS data, e.g. quantile matching for QIS thresholds
- **Use "goodness-of-fit" measures/proxies to carefully select relevant models** to be considered for calibration e.g. based on Cumulative Distribution Functions, conditional averages from QIS data, backtesting against maximum loss from QIS data
- **Cautious usage of models close to infinite mean** and infinite variance models
- **All adjustments require careful testing** on full set of QIS data as well as using hypothetical data from simulations

Our own analyses (see Annex 3) highlight the issues described above and demonstrate that an improved OpCaR model could produce significantly less volatile results than the current SMA.

DB would also like to point out that an improved OpCaR model could be directly used as the LC in the ILM, using the bank's individual OpCaR results instead of an empirical LC fitted to industry averages, leading to more stable results.

c) *Risk mitigation contributes to continuous improvement of operational risk management, thereby increasing risk sensitivity*

Risk mitigation is a component of risk management, which in essence contributes to the continuous improvement of risk models and risk management. We would support including risk mitigation elements in the SMA proposal. This would certainly reduce the current lack of risk sensitivity. The following points should be considered:

Recognition of insurance will increase risk sensitivity: An easy and objective first step to improving risk sensitivity would be to consider recoveries and insurance receipts in the definition of loss applied in the Loss Component. Disallowance of insurance recognition is likely to have banks reduce their external risk mitigation activities. Recognising recoveries and insurance receipts would at least acknowledge loss reduction from the past. An additional forward looking recognition (e.g., through a multiplier derived from the bank's current insurance portfolio) is even more desirable.

Recognise appropriate adjustments in business models following operational losses: The Loss Component will dull the SMA's response to rapid changes in an institution's size despite the fact that these will have a material effect on an institution's risk profile:

- **Business reduction:** Businesses actively pulling out of markets and products, particularly where these decisions are motivated by past operational issues, will have a Loss Component relevant to a much larger business, not reflecting such risk management decisions. This will increase the operational risk capital intensity of their remaining businesses despite there being no change in the risk profile of the remaining businesses.
- **Business increase:** Where a business undertakes rapid expansion, it will maintain a Loss Component relevant to an institution of much smaller size. This will cause operational risk capital to



increase less than pro-rata with the BI increase despite the fact that rapid expansion is a risk factor for operational risk.

d) Using ten year internal loss history as proposed disincentivises risk management

Internal Loss Data should use a decay function and forward looking information: Slow loss roll-off and invariance of the SMA to a bank's control environment results in a less responsive benefit to changes compared to AMA. Reliance on a ten year internal loss history disincentivises the introduction of better controls as their mitigating effects will gradually impact capital requirements only over a multiyear period and the introduction of new controls will not change this. Similarly, strict data requirements to keep losses relating to decommissioned business activities and their capital requirements will cause banks to decrease risk-sensitive business model development.

For the same reason, banks may try to settle open litigation at high, uneconomical costs to accelerate their exclusion from the ten year history. To at least partially address this issue, a decay function could be added to the loss data to avoid cliff effects at the ten year point. To mitigate the effective shortening of the observation window and address the backward looking nature of the LC the loss data could be enhanced with forward looking estimates (e.g., the base scenario impact from regulatory stress testing exercises) weighted as two or three year periods.

Long term events should be based on accounting date: We suggest to either consistently apply the "first accounting date" concept or, if specific treatment of long term (e.g., legal) events is warranted, segment these events into annual components and assign the components to the respective years. Adding event components from up to ten years before the current ten year history for SMA leads to undue data collection and processing burden, and potential double counting of loss components.

Also, defining the "date of accounting" as the date when a reserve is first established inappropriately extends the time until the loss event drops from the loss history. This definition also results in unclear and difficult to understand treatment of payments before the accounting date given they are either double counted or ignored.

e) Wider implications of focusing only on Pillar 1 proposals should be considered

Removing the AMA from the overall operational risk management framework and proposing only one model to replace it triggers necessary amendments to other regulations as well. The impact of these indirect changes also needs to be taken into account when reviewing the comments and SMA methodology. Key areas of focus should be on:

Clarity needed on amending other BCBS principles and standards: In the previous consultation on operational risk, the BCBS stated that:

*"The Committee's Principles for the Sound Management of Operational Risk (PSMOR or the "Principles") set expectations for the management of operational risk. All internationally active banks should implement policies, procedures and practices to manage operational risk commensurate with their size, complexity, activities and risk exposure, and seek continuous improvement in these areas as industry practice evolves. In order to enhance operational risk management, the Principles provide comprehensive guidance regarding the qualitative standards that should be observed by large internationally active banks. The Committee considers it appropriate to achieve more definitive, rigorous and comprehensive implementation of the Principles by setting out specific guidance under Pillar 2 to be observed by large internationally active banks"*⁴.

DB would like to understand if this statement remains the position of the Committee and how it should be interpreted in light of the introduction of SMA. Subsequently, we would be able to include the revision of these principles into the building of our SMA and AMA approaches. The same holds true for the

⁴ Operational risk –Revisions to the simpler approaches, BCBS 2014, page 4,
<http://www.bis.org/publ/bcbs291.pdf>



“Operational Risk – Supervisory Guidelines for the Advanced Measurement Approaches⁵”. We would also seek guidance from the BCBS on how this should be taken into account given the SMA approach.

Guidance on interaction with Pillar 2: As the consultation paper remains silent on the use of AMA models for other internal purposes, we assume that these will continue to be eligible to calculate internal (“economic”) capital within a bank’s ICAAP framework. While we intend to use the AMA model for this purpose, other market participants may decide to exit internal modelling of operational risk completely. Moreover, fewer banks will be interested in pooling their loss data, which in turn will destabilise the remaining AMA models and reduce industry collaboration to better understand and manage operational risks.

Implications outside of capital: The discontinuation of AMA has implications beyond the assessment of capital demand. For instance, the exemption for AMA banks from the calculation of additional valuation adjustments (AVA) for operational risks⁶ requires a revision if additional cost to the banks are to be avoided.

Assessment of the impact of different accounting standards required: By construction of the BI, the SMA capital requirement will differ according to the accounting standard chosen by the institution (e.g., US GAAP, IFRS, German HGB). This also impacts the interpretations of the balance sheet, and profit and loss positions relevant for the BI calculation. We recommend that the magnitude of this sensitivity should be thoroughly assessed as part of the recalibration to avoid a further adverse impact on the level playing field.

BCBS Pillar 3 consultation should refrain from finalising SMA disclosures templates: The BCBS is currently also conducting a consultation on Pillar 3 disclosures in which templates on SMA are included. Given the reservations of the wider industry on the current provisions of the SMA, we believe it is premature to consult on templates directly linked to the SMA. We would propose to postpone this part of the Pillar 3 consultation until the proper level of granularity of disclosures in the templates for operational risk is available.

f) Comments on Alternatives in Annex 2 of the consultation paper

Alternative method is difficult to properly assess: We appreciate that the BCBS is seeking views on alternative options for the ILM function. However, it is difficult to comment on the proposed alternative as its key parameter m is not specified. In our view the only distinguishing feature between the logarithmic ILM and the function defined in para 48 is that the logarithmic function is not bounded. However, this is hardly relevant as the boundedness only matters for banks whose LC and historic losses massively exceeds their capability to generate capital (represented by the BIC). Such a bank would be bankrupt. In our view, a generalised logarithmic function similar to the maturity adjustment for credit risk can also be derived to almost perfectly fit the alternative function in the range relevant for the ILM, making the latter obsolete.

In any case, the alternative loss multiplier does not reduce any of issues related to the proposed specification of the LC, which is the key source of the SMA’s volatility as explained above.

⁵ <http://www.bis.org/publ/bcbs196.htm>

⁶ EBA Regulatory Technical Standards on prudent valuation. January 2015



Annex 2: Analysis of the SMA model

In this annex we provide further insight into some of our analyses which shows that the SMA model and especially the LC requires additional work in order to meet the goals the BCBS intends to achieve. The main two results we would like to focus on here are as follows:

(1) Dispersion across similar banks amplifies lack of comparability and of level playing field:

- The LC, in its current parameterisation, is too volatile and too sensitive with respect to specific internal 10-year loss data histories. This induces potentially large divergences between capital requirements for banks with similar business and risk profiles. The key SMA characteristic causing this problem is the sole reliance on actual realisations of loss profiles (i.e. own historic losses). In this respect, the SMA is neither sensitive to risk exposure nor sufficiently taking into account industry (peer) profiles.
- This can be illustrated by simple examples: The SMA produces (a) a large capital difference for having a large rogue trading event 11 years ago vs. having it eight years ago; or (b) a large capital difference for having seen a large rogue trading event in one's own recent history vs. only having the same trading business / control environment, i.e. same exposure, as a bank who actually suffered such a loss.
- The undue punishment of specific loss histories and underestimation of peer / industry profiles also has a significant impact on whether comparable banks start with a high or low SMA capital.

(2) Time dynamics of SMA distort incentives for risk management:

- Large loss events have an immediately significant impact on the SMA capital level which – after this loss-driven shock – remains almost stable for ten years (assuming no further significant events enter or drop off the 10-year time window).
- An introduction of a phasing in / phasing out of loss events can smooth the SMA time profile but would not change the inherent automatism. Meaning there is still no impact of risk management on the capital requirements but dynamics are solely driven by pre-determined model behaviour.
- Furthermore, time weighting would probably increase the peak effect or enlarge the relevant time window for SMA (depending on implementation). Therefore discounting loss amounts over time would be a more sensible approach.

We recommend to either adjust the methodology to remove the described behaviour or dampen its impact by re-parameterisation of the LC. In the following section we illustrate our findings by two scenario analyses:

Scenario 1 – Comparison of identical banks

Description:

- In this scenario we compare the SMAs of 10,000 hypothetical identical banks, i.e. banks which have the same business and risk profile with losses being drawn from identical loss distributions.
- We make several assumptions, which are reflected in the following calibrations:
 - The Business Indicator (BI) of all banks is €35bn, leading to a Business Indicator Component (BIC) of around €7.8bn.
 - We assume that the total number of yearly internal loss events has a fixed frequency of $\lambda = 2,000$.
 - We further assume that the severity is log-normally distributed with $\mu = 9$ and $\sigma = 2.8$. **In this case the 99.9th percentile of the aggregate loss distribution (true RC/VaR) is around €8.0bn.** (Average Single Loss around €400k, Expected Aggregate Loss around €800mn).
 - We simulate loss samples for 10,000 banks (sample size = 20,000 = 10 years with 2,000 losses for each) with equal Business Indicator, severity and frequency. For each of these bank samples the SMA estimate is calculated and in order to compare with a LDA-type model the parameters of the severity are estimated. It is assumed that the distribution class is known (Lognormal) and only the parameters are unknown (mean and variance). We proceed by computing the corresponding LDA estimate for each of these banks to illustrate the differences.
 - The LDA estimation for each single simulated bank is performed as follows:



- For each bank's 20,000 loss realisations the log-mean and log-standard deviation are computed. Based on the estimated mean and standard deviation, 50,000 annual loss profiles of size 2,000 (annual losses) are generated from a log-normal distribution with the estimated log-mean and log-standard deviation in a Monte-Carlo simulation.
- The aggregate losses are computed by calculating the sum of these 2,000 losses. This process yields, for each of the simulated banks, a distribution of 50,000 aggregate losses.
- The 99.9th percentile of these simulated aggregate losses is then computed to obtain the LDA estimate for one single bank. This process is repeated for each single simulated bank (i.e. 10,000 times).
- Note: No truncation is performed, we thus allow any loss realization from the underlying distribution and do not truncate below 10,000.

Conclusion: *SMA exhibits a large divergence of capital estimates for identical banks*

- Comparing the LDA estimate to the SMA estimate of the RC we observe that **the SMA estimate is significantly more volatile than the one-cell LDA estimate** (see Figure 1).
- Thus, in an example in which the BIC (€7.8bn) is already close to the true RC (€8.0bn) **the Loss Component associated with the SMA generates additional noise.**
- For this representative example in which the BIC is similar to the RC the **SMA generates actually less comparable RC estimates than the LDA although the banks are identical in terms of their underlying risk profiles.**

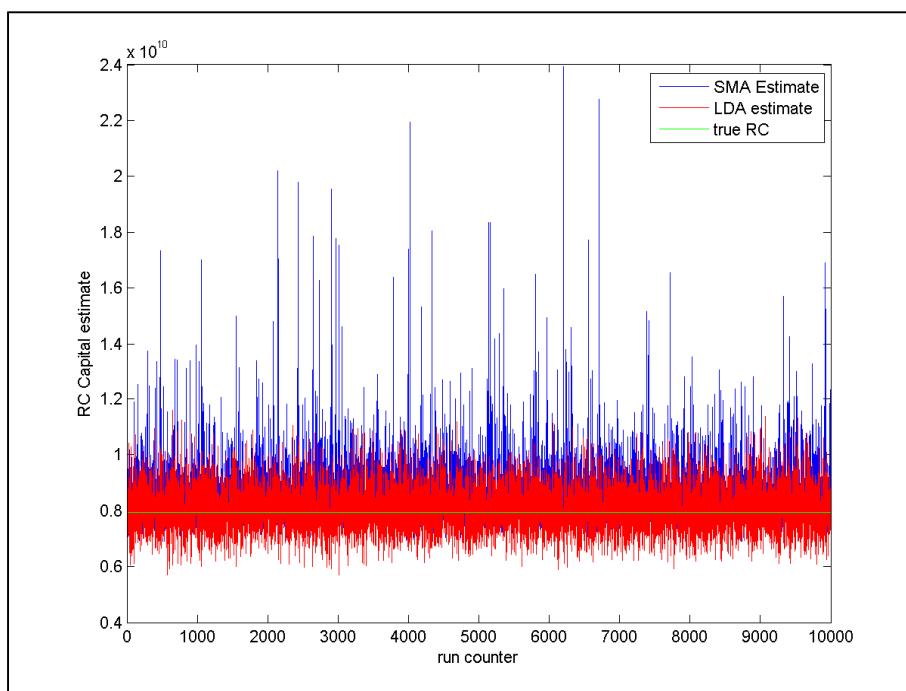


Figure 1: Simulated SMA (blue) and LDA (red) capital estimates (in €) for 10,000 hypothetical identical banks (run counter on x-axis). The true capital of €8.0bn (represented by the 99.9th percentile of the aggregate loss distribution) is shown in green.

Scenario 2 – SMA time evolution

Description:

- In this scenario we compare the SMA time evolution of a simulated hypothetical large bank over a 20 year time horizon. We again make several assumptions, which are reflected in the following calibrations:



- The Business Indicator (BI) of the bank we are interested in is €35bn, leading to a Business Indicator Component (BIC) of €7.8bn.
- We assume that the total number of yearly internal loss events has a fixed frequency of $\lambda = 2,000$.
- We further assume that the severity is log-normally distributed with $\mu = 9$ and $\sigma = 2.8$. **In this case the 99.9th percentile of the aggregate loss distribution (true VaR/RC) is around €8.0bn.** (Average Single Loss around €400k, Expected Aggregate Loss around €800mn).
- We simulate 10,000 loss sample time paths for our bank, starting with the same initial loss vector. We then compute in every year the SMA capital requirements using the 10 year rolling loss history according to the SMA proposal (note that this means, in our context, that we always drop the 2,000 oldest losses). The resulting SMA RC time paths are shown below in Figure 2.

Conclusion: *SMA exhibits erratic behavior over time*

- Starting with an SMA of around €8.4bn, the paths show that the **SMAs can easily double and even triple** within one year although the bank's actual risk profile has not changed.
- The **paths progress asymmetrically** and show that the SMA tends to overstate the true VaR for the hypothetical bank (using the true VaR@99.9% as reference).
- **One bad year has a significant impact on risk management for 10 years**, and the SMA provides no viable option for improvement, thus distorting incentives for banks and their risk management. Phasing in/out of losses over time would smoothen the lines but neither would it reduce the dynamic volatility nor would it allow for risk management actions.
- We observe similar behavior for different starting points.

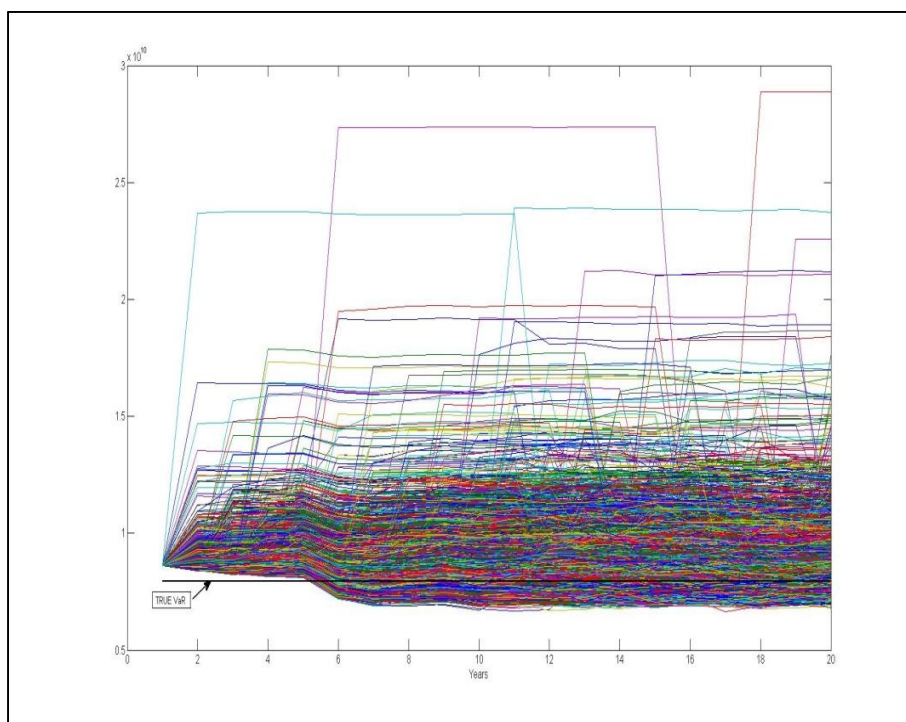


Figure 2: Time evolution of the SMA capital requirements (in €) of a hypothetical bank depicted by 10,000 simulated time paths over a time period of 20 years (x-axis). SMA capital start value slightly above the true capital of €8.0bn represented by the 99.9th percentile of the aggregate loss distribution.



Annex 3: Analysis of improvements to the current SMA calibration using OpCaR

In this annex we provide further insight into some of our analyses which show that the calibration of the SMA model and especially the LC based on the OpCaR approach needs further work in order to meet the goals the BCBS intends to reach. The main outcome of our scenario analysis is as follows:

Calibration of LC cannot be understood from loss data or other obvious exposure indicators:

- The LC calibration is too extreme and biased leading to a substantial capital increase for a number of banks, specifically penalizing large banks with well-populated mid to large loss event history (assuming that such banks carry higher risk than similar banks which - purely by chance - did experience fewer large events in the last ten years).
- The calibration of the LC based on the OpCaR approach is very likely distorted by Single Loss Approximation (SLA) capital requirements from OpCaR which are too high (i.e. not justifiable by loss data). This may to some extent be due to the nature of the SLA but is also driven by the specific OpCaR procedure used for calibration (e.g. neglecting any goodness-of-fit measures). Please see section on OpCaR in Annex 1 for more details.

We recommend to adjust the calibration methodology (see also section on OpCaR in Annex 1) and parameterisation to make the LC a better proxy for the capital requirements calculated by an appropriate Single Loss Approximation.

In the following we illustrate our findings by means of two scenarios⁷: —

Scenario 3 – Dispersion of OpCaR results

Description:

- In this scenario we test the power of the OpCaR approach to detect the correct severity distribution and analyse the dispersion of results from fitting different distributions to a hypothetical simulated data set generated from a known distribution.
- We make several assumptions, which are reflected in the following calibrations:
 - We simulate 1,000 loss profiles for a 10 year time horizon, using an annual frequency of $\lambda = 2,000$.
 - We assume that the losses are drawn from a log-normal distribution with mean $\mu = 9$. We run several simulations, each with 1,000 simulation runs, in which we gradually increase the underlying standard deviation σ of the loss data sample from 1.4 to 2.8.
 - Based on the simulated samples we solve the OpCaR system of equations (see Appendix BCBS 291⁸) for the parameters of the distribution as suggested in the document.
 - Next we compute the number of times the OpCaR methodology accurately identified that the loss-sample was drawn from a log-normal distribution and also compute the number of times OpCaR suggests that the loss sample was drawn from the remaining distributions as suggested in BCBS 291(Pareto, Pareto-Medium, Pareto-Heavy, Log-Logistic, Log-Gamma).
 - We finally compare the SLA estimates that stem from each of the distributions suggested in the methodology whenever a solution to the system of equations existed, again following the OpCaR methodology as close as possible.

Conclusion: *Significant dispersion across distributions may distort average OpCaR results for a bank*

- Our insights suggest that the method has difficulties in identifying accurate distributions for given data: For several parameterizations (in particular as the variance increases) the likelihood of suggesting that the underlying loss-sample was drawn from a distribution which differed from the true log-normal distribution was substantial. In some cases the method is more likely to suggest that the sample was drawn from a much **heavier** distribution than the true log-normal.

⁷ Please note that our OpCaR analyses are based on our own implementation of the OpCaR as we understand the procedure from the available documentation of the two Basel consultation papers. Due to lack of more detailed information, we cannot judge whether our model is in line with the regulatory OpCaR model in all details and standard numerical disclaimers prevail (e.g. differences in numerical solvers etc.).

⁸ <http://www.bis.org/publ/bcbs291.pdf>



- In our implementation the solutions to the OpCaR moment conditions do, in various cases, depend on the initial conditions with potentially strong effects on the Single Loss Approximations.
- The SLAs across the six different distributions can vary quite substantially – sometimes even by factors of up to 8 for this example. Given that the method tends to have difficulties in identifying the accurate underlying distribution, such a dispersion of outcomes gives rise to concerns in particular if the resulting (average) SLAs were used to calibrate the LC.
- We suggest to conduct more detailed calibration analyses, e.g. testing the adequacy of the OpCaR-identified distributions across banks (without parameters), to review the resulting volatility in SLAs across distributions and to provide a reasonable goodness-of-fit overview for each of these distributions.

Scenario 4 – OpCaR for mixed loss profiles

Description:

- In this scenario we analyse the impact of applying OpCaR on aggregate level (e.g. mixing loss data from all event types) vs. application on more granular levels (e.g. separately for each event type) using hypothetical simulated loss data from two different distributions: high frequency/low severity and low frequency/high severity.
- We make several assumptions, which are reflected in the following calibrations:
 - First, we simulate loss data from a log-normal distribution with mean $\mu = 7$ and standard deviation $\sigma = 2.4$. We use an annual loss frequency of $\lambda = 2,000$ and simulate losses for a 10 year horizon.
 - We then use the simulated loss sample as an input to the OpCaR methodology and compute the underlying parameters and the SLAs. For each simulation run we compute the average SLA across distributions, whenever a solution to the OpCaR moment conditions existed.
 - We compute the average SLA across all simulation runs. We denote the resulting average SLA as SLA_1.
 - Next, we redo this exercise with simulated loss data which was drawn from a log-normal with $\mu = 9$ and $\sigma = 3$ assuming an annual loss frequency of 100. We again simulate a 10 year loss history and solve for the underlying parameters and the SLAs, using the OpCaR methodology. For each simulation run we compute the average SLA across distributions, whenever a solution to the OpCaR moment conditions existed. Lastly, we compute the average SLA across these simulation runs and denote the resulting SLA as SLA_2.
 - Subsequently, we rerun the previous exercise but this time we simulate 2,000 annual losses from a log-normal distribution with $\mu = 7$ and $\sigma = 2.4$ **and** 100 annual losses stemming from a log-normal with $\mu = 9$ and $\sigma = 3$. We again simulate a 10 year loss history. We follow the same methodology as before and compute the average SLA per simulation across distributions whenever a solution existed and formed the average SLA across simulations given this merged loss sample. We denote the resulting SLA as SLA_merge.

Conclusion: *Application of OpCaR on aggregate level may lead to significant distortion of results*

- We observe that SLA_merge is larger than SLA_1 + SLA_2 for this example (20% increase for the merged setup). This tends to suggest that fitting one single distribution with one single parameter set can inflate the SLA (in particular if a subset of these losses follow a more heavy tailed distribution) which in turn could also inflate the Loss Component calibration (assuming that the OpCaR was used for this purpose). One improvement could thus be to calibrate OpCaR on a more granular level.
- The problem could be exacerbated if the underlying loss data were drawn from entirely different families of distributions.