

Standardized Measurement Approach for Operational risk: Pros and Cons

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This response has been put together by academics and in total independence of any corporate or individual interests. Our results are solely driven by scientific analysis and presented in the interest of the financial and business community, both the regulated entities and the regulators alike. The response addresses the Standardised Measurement Approach (SMA) proposed in the Basel Committee for Banking Supervision consultative document “Standardised Measurement Approach for operational risk” (issued in March 2016 for comments by 3 June 2016) [BCBSd355,2016]; and closely related Operational risk Capital-at-Risk (OpCar) model proposed in the Committee consultative document “Operational risk – revisions to the simpler approaches”, October 2014 [BCBSd291,2014].

The structure of this response involves a collection of summary results and comments for studies performed on the proposed SMA model which include:

- Capital instability;
- Capital sensitivity;
- Reduction of risk responsivity and interpretability;
- Incentivized risk taking;
- Discarding key sources of Operational risk data;
- Possibility of super additive capital under SMA.

The detailed analysis of these points is developed in the manuscript [Peters *et al*, 2016].

The response then concludes with suggestions relating to maintaining the AMA internal model framework with standardization recommendations that could be considered to unify internal modelling of Operational risk.

SMA Introduces Capital Instability

Our analysis of the SMA and OpCar model shows that SMA fails to achieve the objective of capital stability. Consider a simple representative model for a bank's annual Operational risk loss process comprised of the aggregation of two generic loss processes, one high frequency with low severity loss amounts and the other corresponding to low frequency and high severity loss amounts given by Poisson-Gamma and Poisson-Lognormal models respectively. We set the business indicator (BI) constant to Euro 2 billion at half way within the interval for bucket 2 of the SMA, we kept the model parameters static over time and simulated a history of 1,000 years of loss data for three differently sized banks (small, medium and large) using different parameter settings for the loss models to characterize such banks. For a simple analysis we set a small bank corresponding to capital in the order of Euro 10's of million average annual loss, a medium bank in the order of Euro 100's of million average annual loss and a large bank was set to have in the order of Euro 1 billion average annual loss. We then studied the variability that may arise in the capital under the SMA formulation, under the optimal scenario that models did not change, model parameters were not recalibrated and the business environment did not

change significantly, in the sense that BI was kept constant. In this case we observe the core variation that arise just from loss history experience of many banks of the three different sizes over time.

Our analysis shows that, a given institution can experience the situation in which its capital can more than double from one year to the next, *without any* changes to the parameters, the model or the BI structure. Annual variation can be as large as 2 times the long-term average capital (Figure 1).

It follows from the results in this sections analysis that ***two banks, with the same risk profile, can produce SMA capital numbers differing by a factor of more than 2.***

Details of the analysis are available on the complete paper posted on ssrn.com (see [Peters et al, 2016]) and the code used is available upon request. In summary, the simulation takes the case of BI fixed over time, the loss model for the institution is fixed according to two loss processes given by Poisson(λ)-Gamma(α, β) and Poisson(λ)-Lognormal(μ, σ). In this example, Gamma(α, β) is the distribution of the loss severities with the mean equal to $\alpha\beta$ and the variance $\alpha\beta^2$, and the Lognormal(μ, σ) is the distribution of severities with the mean of the log severity equal to μ and the variance of the log severity equal to σ^2 .

The total institutions losses are set to be on average around 1,000 per year with 1% coming from heavy tailed loss process Poisson-Lognormal component. We perform two case studies, one in which the shape parameter of the heavy tailed loss process component, LogNormal is with $\sigma = 2.5$ and the other with $\sigma = 2.8$. We summarize the settings for the two cases below in Table 1 and Table 2.

The ideal situation that would indicate that SMA was not producing capital figures which were too volatile would be if each of the sub-figures below in Figure 1 and Figure 2 were very closely constrained around 1. However, as we see from the analysis, the variability in capital from year to year, in all size institutions can be significant. In particular medium to large size institutions both demonstrated that in any given year under SMA, the capital required to be held could double.

Table 1. Case 1: $\sigma = 2.5$.

MODEL	Parameters	Mean Annual Loss (Euro Million)	Annual Loss Capital (99.9% VaR) (Euro Million)
Poisson-Lognormal Loss Component	$(\lambda, \sigma, \mu) =$ (10, 2.5, {10; 12; 14})	15 (small) 136 (medium) 769 (Large)	260 (small) 1,841 (medium) 14,610 (Large)
Poisson-Gamma Loss Component	$(\lambda, \alpha, \beta) =$ (990, 1, {10,000;100,000; 500,000})		

Table 2. Case 2: $\sigma = 2.8$.

MODEL	Parameters	Mean Annual Loss (Euro Million)	Annual Loss Capital (99.9% VaR) (Euro Million)
Poisson-Lognormal Loss Component	$(\lambda, \sigma, \mu) =$ (10, 2.8, {10; 12; 14})	21 (small) 181 (medium) 1,101 (Large)	772 (small) 5,457 (medium) 41,975 (Large)
Poisson-Gamma Loss Component	$(\lambda, \alpha, \beta) =$ (990, 1, {10,000;100,000; 500,000})		

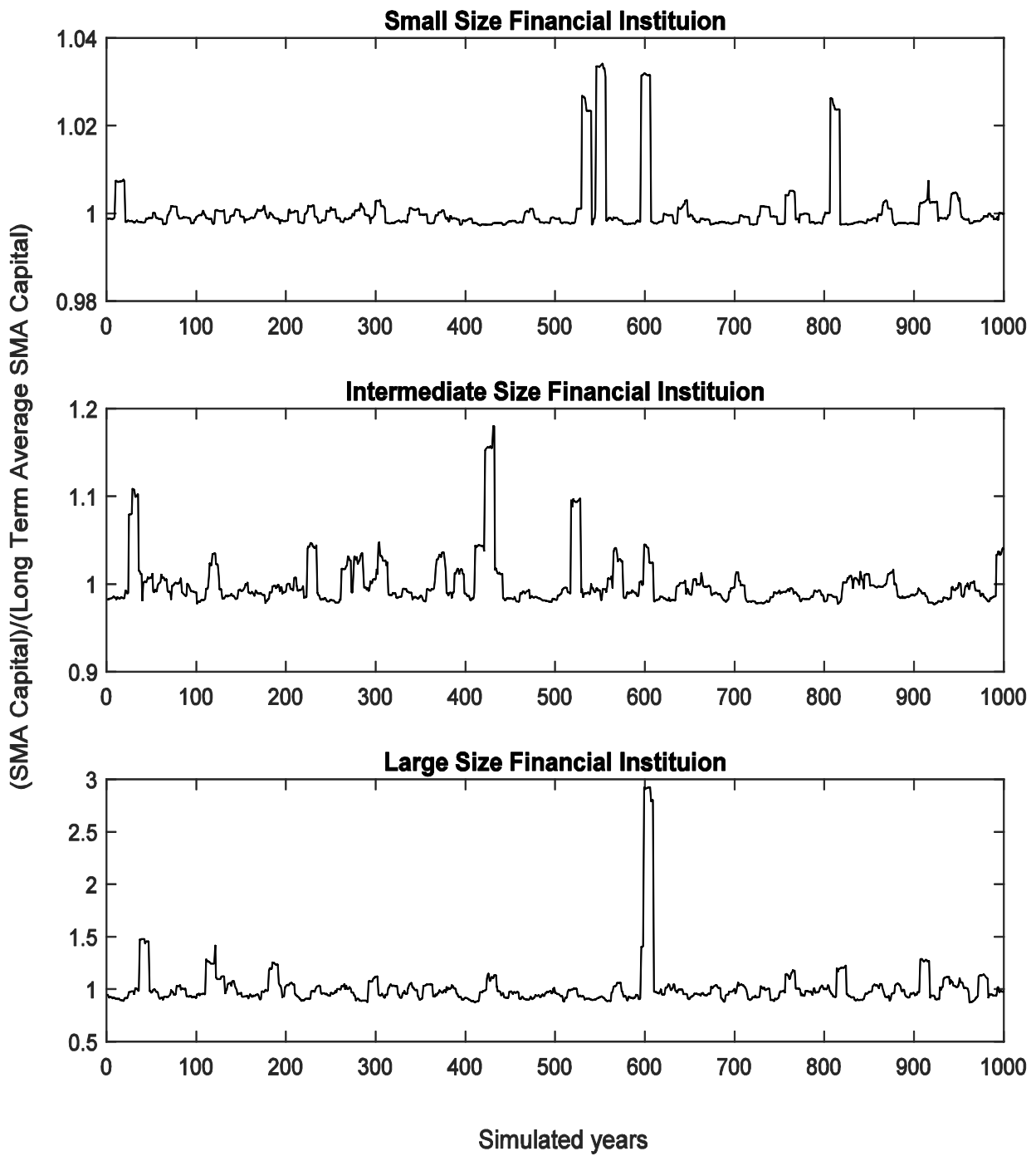


Figure 1. Ratio of the SMA capital to the long term average (Case 1)

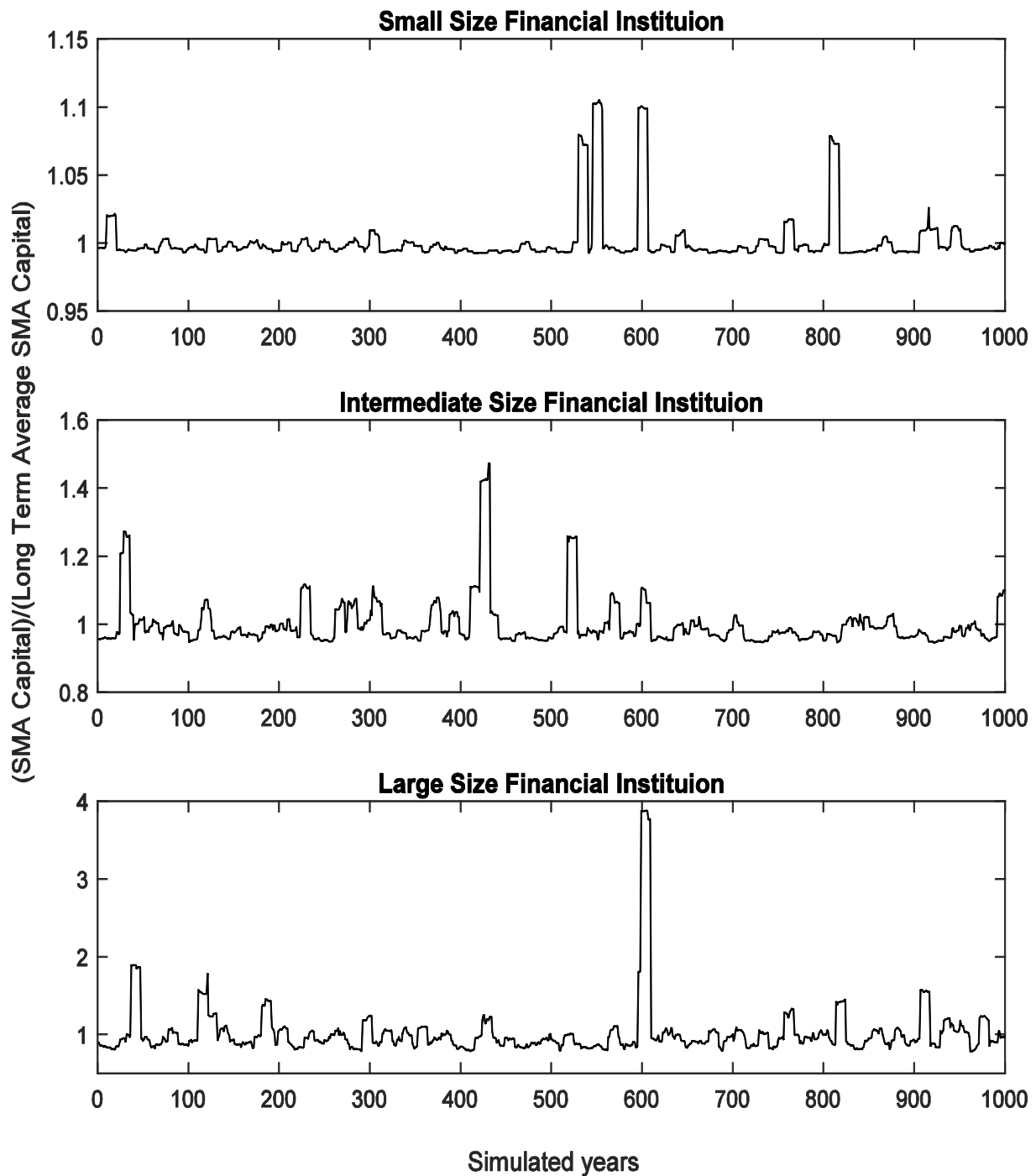


Figure 2. Ratio of the SMA capital to the long term average (Case 2)

These results demonstrate examples of typical variability in capital that can be experienced with the new SMA formulation.

Understanding Variability in BI when SMA matches AMA

As a second study of the SMA capital instability we again consider a Poisson-Lognormal loss process model $\text{Poisson}(\lambda)\text{-Lognormal}(\mu, \sigma)$. Except in this case, instead of fixing the BI to the midpoint of Bucket 2 of the SMA formulation, we instead numerically solve for the BI that would match the SMA capital to the Value-at-Risk for a Poisson-LogNormal Loss Distributional Approach (LDA) model at the annual 99.9% quantile level.

In other words, for these simulations we obtain the BI such that the LDA capital will match SMA capital in the long term. This is achieved by solving the following non-linear equation numerically via root search for the BI. That is we solve for the BI such that $\text{SMA}(\text{BI}) = \text{VaR}(0.999)$.

For this experiment we took 0.999 VaR under Poisson-Lognormal model according to the single loss approximation given by

$$\text{VaR}(0.999) = \exp\left(\mu + \sigma \times \Phi^{-1}\left(1 - \frac{1-0.999}{\lambda}\right)\right) + \lambda \times \exp\left(\mu + \frac{1}{2}\sigma^2\right)$$

where $\Phi^{-1}(\cdot)$ is the standard Normal cdf.

The results of this analysis are presented in Table 3 for $\lambda = 10$ and the results for the LogNormal σ and μ parameters are varied in the table to present different BI values.

Table 3. **Implied BI in billions** $\lambda = 10$

$\mu \setminus \sigma$	1.5	1.75	2	2.25	2.5	2.75	3
10	0.06	0.14	0.36	0.89	2.41	5.73	13.24
12	0.44	1.05	2.61	6.12	14.24	32.81	72.21
14	2.52	5.75	13.96	33.50	76.63	189.22	479.80

In addition, we consider a second capital instability study where we use the BI obtained from matching the long term average SMA capital with the long term LDA capital, as described above for an example generated by $\text{Poisson}(10)\text{-Lognormal}(\mu = 12, \sigma = 2.5)$ and corresponding solved BI=14.714 bln (bucket 4). In this case SMA capital (ideal where averaging over many years rather than 10 years) is 1.87 bln is about the same as LDA 0.999 quantile = 1.87 (calculated through Monte Carlo). Then the year on year variability in the capital with this combination of implied BI and Poisson-LogNormal loss model is given in Figure 3. It shows that again we get capital instability with capital doubling from year to year compared to the long term average SMA capital.

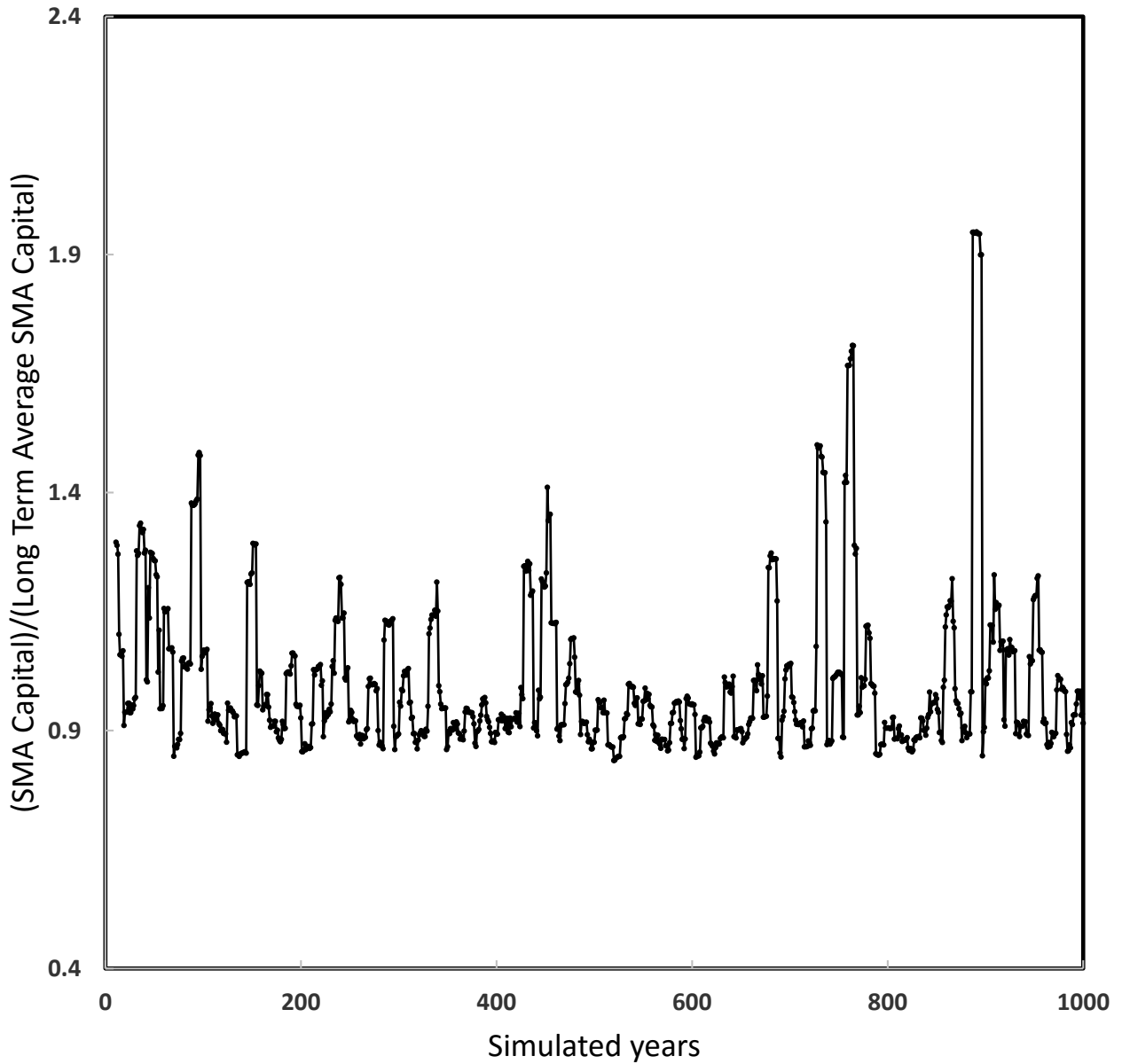


Figure 3. Ratio of the SMA capital to the long term average.

SMA is Excessively Sensitive to Behaviour of Dominant Loss Process

In this section we consider an institution with a wide range of different types of Operational risk loss processes present in each of its business units and risk types. As in our first study above, we again consider in a stylized manner to split these loss processes into two categories, high frequency and low severity, and low frequency high severity types. As in the previous illustration we consider a simplified banking structure with two loss processes given by $\text{Poisson}(\lambda)\text{-Gamma}(\alpha, \beta)$ and $\text{Poisson}(\lambda)\text{-Lognormal}(\mu, \sigma)$. In this study we consider the sensitivity of SMA capital to the dominant loss process. More precisely, we study the sensitivity of SMA capital to the parameter that dictates how heavy the tail of the most extreme loss process will be. This analysis is based on the simulation setup presented in Table 4 with simulations performed over 1,000 years.

Table 4. Case 3: Varying σ .

MODEL	Parameters
Poisson-Lognormal Loss Component	$(\lambda, \sigma, \mu) = (10, \{2; 2.25; 2.5; 2.75; 3\}, 14)$
Poisson-Gamma Loss Component	$(\lambda, \alpha, \beta) = (990, 1, 500,000)$

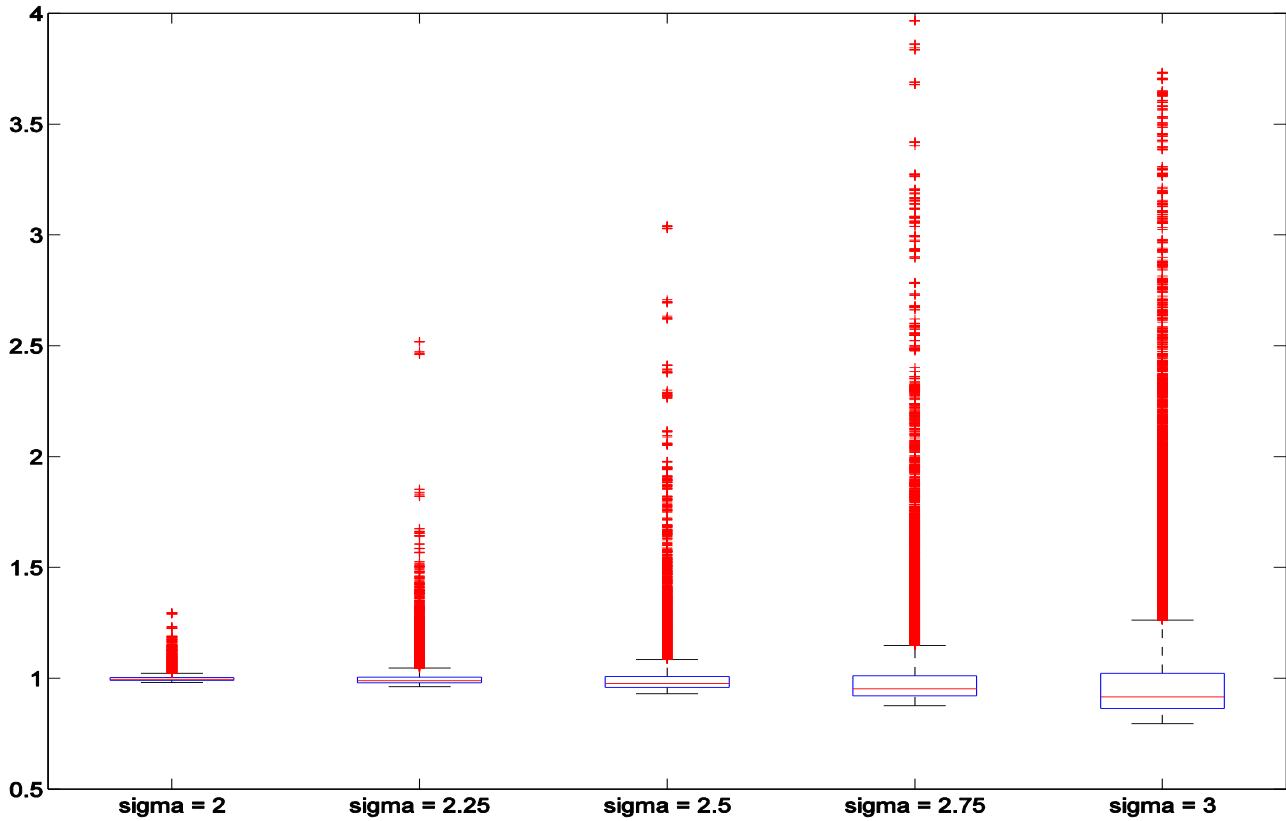


Figure 4. Ratio of the SMA capital to the long term average (Case 3 – SMA sensitivity)

These results in Figure 4 can be interpreted to mean that banks with more extreme loss experiences as indicated by heavier tailed dominant loss processes (increasing σ) tend to have significantly greater capital instability compared to banks with less extreme loss experiences. Importantly, these findings demonstrate how non-linear this increase in SMA capital can be as the heaviness of the dominant loss process tail increases. For instance, banks with relatively less heavy tailed dominant loss processes ($\sigma=2$) tend to have capital variability year on year of between 1.1 to 1.4 multipliers of long term average SMA capital. Already this is not a good outcome. However, banks with relatively heavy tailed dominant loss processes ($\sigma = 2.5, 2.75$ or 3) tend to have excessively unstable year on year capital figures, with variation in capital being as bad as 3 to 6 times multipliers of the long term average SMA capital. Furthermore, it is clear that when one considers each boxplot as representing a population of banks with similar dominant loss process characteristics, then as the tail-heaviness of the dominant loss process in each population increases the population distribution of capital becomes increasingly skewed and demonstrates increasing kurtosis in the right tail, with our findings demonstrating that this can result in excessive variability in capital year on year for banks with heavy tailed dominant loss processes.

Therefore, SMA fails to achieve the claimed objective of robust capital estimation. Capital produced by the proposed SMA approach will be neither stable nor robust with worsening robustness as the severity of Operational risk increases. In other words, banks with higher severity Operational risk exposures will be substantially worse of in SMA approach with regard to capital sensitivity.

SMA Reduces Risk Responsivity and Interpretability

One can consider that the SMA capital is less responsive to risk drivers and the variation in loss experience that is observed in a bank at granularity of the Basel II 56 Business Unit Risk Type units of measure.

This is due to the naive approach of modeling at the level of granularity assumed by the SMA which is only capturing variability at the institution level and not the intra-variability within the institution at division or business unit levels explicitly. Choosing to model at institution level, rather than the units of measure or granularity of the 56 Basel categories reduces model interpretability and reduces risk responsivity of the capital.

Conceptually, it relates to the simplification of the Advanced Measurement Approach (AMA) to instead the SMA adopting a top down formulation that reduces Operational risk modelling to a single unit of measure, as if all operational losses were following a single generating mechanism. This is equivalent to considering that earthquakes, cyber-attacks and human errors are all generated by the same drivers and manifest in the loss model and loss history in the same manner as other losses that are much more frequent and have lower consequence, such as credit card fraud, when viewed from the institution level loss experience. It follows quite obviously that the radical simplification and aggregation of such heterogeneous risks in such a simplified model cannot claim the benefit of risk-sensitivity, even remotely.

Therefore, SMA fails to achieve the claimed objective of capital risk sensitivity. Capital produced by the proposed SMA approach will be neither stable nor related to the risk profile of an institution.

SMA Incentivizes Enhanced Risk-Taking

Besides extreme conceptual flaws, **the SMA induces risk-taking behaviors, failing to achieve the Basle committee objectives of stability and soundness of the financial institutions.**

Moral hazard and other unintended consequences are:

- **More risk-taking:** without the possibility of capital reduction for better risk management, in the face of increased funding costs due to the rise in capital, it is predictable that financial institutions will raise their risk-taking to a level sufficient enough to pay for the increased cost of the new fixed capital. The risk appetite a financial institution would mechanically increase. This effect goes against the Basel Committee objective of a safe and secured financial system.
- **Denying loss events:** whilst incident data collection is a constant effort for over a decade in every institutions, large or small, the SMA is the most formidable disincentive to report losses. There are many opportunities to compress historical losses such as ignoring, slicing, transferring to other risk categories. The wish expressed in the consultation that "*Banks should use 10 years of good-quality loss data*" is actually meaningless if the collection can be gamed. Besides, what about new banks or BIA banks which do not have any loss data collection process as of today?
- **Hazard of reduced provisioning activity:** provisions, which should be a substitution for capital, are vastly discouraged by the SMA, as they are penalized twice, counted both in the BI and in the losses, and not accounted for as a capital reduction. The SMA captures both the expected loss and the unexpected loss, when the regulatory capital should only reflect the unexpected loss. We believe that this confusion might come from the use of the OpCar model as a benchmark because the OpCar captures both equally.

The SMA states in the definition of "Gross loss, net loss, and recovery definitions" on page 10 Section 6.2 of [BCBSd355,2016] under item (c) that the loss data set gross loss and net loss should

include “Provisions or reserves accounted for in the P&L against the potential operational loss impact”. This clearly indicates the nature of the double counting of this component since they will enter in the BI through the PnL and in the loss data component of the SMA capital.

- **Ambiguity in provisioning and resulting capital variability:** the new guidelines on provisioning under SMA framework follow similar general concept as those that recently came into effect in credit risk with the International Financial Reporting Standard (IFRS9) set forward by the International Accounting Standards Board (IASB), who completed the final element of its comprehensive response to the financial crisis with the publication of IFRS 9 *Financial Instruments* in July 2014. The IFRS9 guidelines explicitly outline in Phase 2 an impairment framework which specifies in a standardized manner how to deal with delayed recognition of (in this case) credit losses on loans (and other financial instruments).

IFRS9 achieves this through a new “...expected loss impairment model that will require more timely recognition of expected credit losses. Specifically, the new Standard requires entities to account for expected credit losses from when financial instruments are first recognised and it lowers the threshold for recognition of full lifetime expected losses.”

However the SMA Operational risk version of such provisioning concept for Operational risk losses fails to provide such a standardized and rigorous approach. Instead the SMA framework simply states that loss data bases should now include

“Losses stemming from operational risk events with a definitive financial impact, which are temporarily booked in transitory and/or suspense accounts and are not yet reflected in the P&L (“pending losses”). Material pending losses should be included in the SMA loss data set within a time period commensurate with the size and age of the pending item.”

However, unlike the more specific IFRS9 accounting standards, under the SMA there is a level of ambiguity. Furthermore, this ambiguity can propagate now directly into the SMA capital calculation causing potential for capital variability and instability.

For instance, there is no specific guidance or regulation requirements to standardize the manner in which a financial institution decides what is to be considered as “definitive financial impact” and what they should consider as a threshold for deciding on existence of a “material pending loss” nor what is specifically the guidance or rules relating to time periods related to inclusion of such pending losses in an SMA loss data set and therefore into the capital. The current guidance simply states “Material pending losses should be included in the SMA loss data set within a time period commensurate with the size and age of the pending item”. This is too imprecise and may lead to manipulation of provisions reporting and categorization that will directly reduce the SMA capital over the averaged time periods in which the loss data component is considered.

Furthermore, if different financial institutions adopt differing provisioning rules, the capital obtained for two banks with identical risk appetites and similar loss experience could differ substantially just as a result of their provisioning practices.

- **Imprecise Guidance on Timing Loss Provisioning:**

The SMA guidelines also introduce an aspect of “Timing Loss Provisioning” in which they state:

“Negative economic impacts booked in a financial accounting period, due to operational risk events impacting the cash flows or financial statements of previous financial accounting periods (timing losses). Material “timing losses” should be included in the SMA loss data set when they are due to operational risk events that span more than one financial accounting period and give rise to legal risk.”

However, we would argue that for standardization of a framework there needs to be more explicit guidance as to what constitutes a “Material timing loss”. Otherwise, different timing loss provisioning approaches will result in different loss databases and consequently can result in differing SMA capital just as a consequence of the provisioning practice adopted. In addition, the

ambiguity of this statement doesn't make it clear as to whether such losses may be accounted for twice.

- **Grouping of Losses:** Under previous AMA internal modelling approaches the unit of measurement or granularity of the loss modelling was reported according to the 56 Business Unit and Risk Type categories specified in Basel II. However, under the SMA the unit of measure is just at the institution level so the granularity of the loss processes modelling and interpretation is lost. This has consequences when it is considered in light of the new SMA requirement that

"Losses caused by a common operational risk event or by related operational risk events over time must be grouped and entered into the SMA loss data set as a single loss."

Previously, in internal modelling losses within a given Business Unit Risk Type would be recorded as a random number (frequency model) of individual independent loss amounts (severity model). Then, for instance under an LDA model such losses would be aggregated only as a compound process and the individual losses would not be "grouped" except on the annual basis and not on the per-event basis. However, there seems to be a marked difference in the SMA loss data reporting on this point, under the SMA it is proposed to aggregate the individual losses and report them in the loss database as a "single grouped" loss amount. This is not advisable from a modelling or an interpretation and practical risk management perspective.

Furthermore, the SMA guidance states

"The bank's internal loss data policy should establish criteria for deciding the circumstances, types of data and methodology for grouping data as appropriate for its business, risk management and SMA regulatory capital calculation needs."

One could argue that if the aim of SMA was to "Standardize" Operational risk loss modelling in order to make capital less variable due to internal modelling decisions, then one can fail to see how this will be achieved with imprecise guidance such as the one provided above. One could argue that the above generic statement on criteria establishment basically removes the internal modelling framework of AMA and replaces it with internal heuristic (non-model based, non-scientifically verifiable) rules to "group" data. This has the potential to result in even greater variability in capital than was experienced with non-standardized AMA internal models. At least under AMA internal modelling, in principle the statistical models could be scientifically criticized.

- **Ignoring the future:** all forward-looking aspects of risk identification, assessment and mitigation such as scenarios and emerging risks have disappeared in the new consultation. This in effect introduces the risk of setting back the banking institutions in their progress towards a better understanding of the threats, even though such threats may be increasing in frequency and severity and the bank exposure to such threats may be increasing due to business practices, this cannot be reflected in the SMA framework capital. In that sense, the SMA is only backward looking.

SMA Fails to Utilize Range of Data Sources and Fails to Provide Risk Management Insight

Both Basel II and Basel III regulations emphasize the significance of incorporating a variety of loss data into Operational risk modelling and therefore ultimately into capital calculations. The four primary data sources to be included are Internal Loss Data, External Loss Data, Scenario Analysis and Business Environment and Internal Control Factors (BEICF), where only the first data source is in SMA and the others are not.

To understand the importance of BEICF data in the form of Key Risk Indicators (KRIs), Key Performance Indicators (KPIs) and Key Control Indicators (KCIs) we first briefly recall their properties.

A KRI is a metric of a risk factor. It provides information on the level of exposure to a given operational risk of the organization at a particular point in time. KRIs are useful tools for business lines managers, senior management and Boards to help monitor the level of risk taking in an activity or an organization, with regard to their risk appetite.

Performance indicators, usually referred to as KPIs, measure performance or the achievement of targets. Control effectiveness indicators, usually referred to as KCIs, are metrics that provide information on the extent to which a given control is meeting its intended objectives. Failed tests on key controls are natural examples of effective KCIs.

KPIs, KRIs and KCIs overlap in many instances, especially when they signal breaches of thresholds: a poor performance often becomes a source of risk: poor technological performance such as system downtime for instance becomes a KRI for errors and data integrity. KPIs of failed performance provide a good source of potential risk indicators. Failed KCIs are even more obvious candidates for preventive KRIs: a key control failure always constitutes a source of risk.

Indicators can be used by organizations as a means of control to track changes in their exposure to operational risk. When selected appropriately, indicators ought to flag any change in the likelihood or the impact of a risk occurring.

For financial institutions that calculate and hold operational risk capital under more advanced approaches such as the previous AMA internal model approaches, KPIs, KRIs and KCIs are advisable metrics to capture BEICF. While the definition of BEICF differs from one jurisdiction to another and in many cases is specific to individual organizations, these factors must:

- be risk sensitive (here the notion of risk goes beyond incidents and losses);
- provide management with information on the risk profile of the organization;
- represent meaningful drivers of exposure which can be quantified; and
- should be used across the entire organization.

While some organizations include the outputs of their risk and control self-assessment programs under their internal definition of BEICF's, indicators are an appropriate mechanism to satisfy these requirements, implying that there is an indirect regulatory requirement to implement and maintain an active indicator program, see discussion in [*Chapelle, 2013*].

For instance, incorporating BEICF's into Operational risk modelling is a reflection of the modelling assumption that one can see Operational risk as a function of the control environment. If the control environment is fair and under control, large operational losses are less likely to occur and Operational risk can be seen as under control. Therefore, understanding the firm's business processes, mapping the risks on these processes and assessing how the controls implemented behave is the fundamental role of the Operational risk manager. However, the SMA does not provide any real incentive mechanism firstly for undertaking such a process and secondly for incorporating this valuable information into the capital calculation.

In terms of using pieces of information such as BEICF's and Scenario data, since under the SMA framework the level of model granularity is only at institution level, it does not easily lend itself to incorporation of these key Operational risk data sources.

To business lines managers, KRIs help to signal a change in the level of risk exposure associated with specific processes and activities. For quantitative modellers, key risk indicators are a way of including BEICF into operational risk capital. However, since BEICF data does not form a component of required data for the SMA model, there is no longer a regulatory requirement or incentive under the proposed SMA framework to make efforts to develop such BEICF data sources. Therefore, this not only reduces the effectiveness of the risk models through the loss of a key source of information, but in addition the

utility of such data for risk management practitioners and managers is reduced as this data is no longer collected with the same required scrutiny, including validation, data integrity and maintenance and reporting that was previously required for AMA internal models using such data.

These key sources of Operational risk data are not included in the SMA and furthermore cannot easily be incorporated into an SMA framework even if there were a desire to do so due to the level of granularity implied by the SMA. This makes capital calculations less risk sensitive. Furthermore, the lack of scenario based data incorporated into the SMA model makes it less forward looking and anticipatory as an internal model based capital calculation framework.

SMA can be a super additive capital calculation
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The SMA seems to have the unfortunate feature that it may produce capital at a group level compared to the institutional level in a range of jurisdictions which has the property that it is super additive. To understand this, the following two examples should be helpful.

In each case, consider two banks with identical BI and identical Loss Component (LC). However, the first bank has only one entity where as the second has two entities. The two entities of the second bank have the same BI and the same LC, and those are equal to both half the BI and half the LC of the first joint bank.

In case one (Table 1) we consider the situation of a bucket shift, where the SMA capital obtained for the joint bank is 5,771 million while the sum of the SMA capital obtained for the two entities of the second bank is only 5,387 million. In this example, the SMA does not capture a diversification benefit, on the contrary, it assumes that the global impact of an incident is larger than the sum of the parts.

In the second case (Table 2) we consider no bucket shift between the joint bank and the two entity bank. Again in this case we see that the joint bank has an SMA capital of 11,937mil, whereas the two entity bank has an SMA capital of 10,674mil capital. Again there is a super additive property.

Table 5: Super-additivity issue illustrated (in million)

Bucket Shift

Bank 1	Component	Group	BI=32,000
	BIC	6920	
	LC	4000	
	SMA	5771	

Bank 2	Component	Entity 1	Entity 2	BI=32,000
	BIC	3120	3120	
	LC	2000	2000	
	SMA	2694	2694	
Sum SMA		5387		

Table 6: Super-additivity issue illustrated (in million)

Same Bucket

Bank 1	Component	Group	BI = 70,000
	BIC	17940	
	LC	4000	
	SMA	11937	

Bank 2	Component	Entity 1	Entity 2	BI=70,000
	BIC	7790	7790	
	LC	2000	2000	
	SMA	5337	5337	
Sum SMA		10674		

To conclude this section we state a mathematical expression that a bank could utilize in business structure planning to decide in the long term if it will be advantageous under the new SMA framework to split into two entities (or more) or remain in a given joint structure, according to the cost of funding Tier I SMA capital.

For illustration we can assume the joint institution is simply modelled by a Poisson-Lognormal model $\text{Poisson}(\lambda_J)\text{-Lognormal}(\mu_J, \sigma_J)$ with parameters sub-indexed by J for the joint institution and a BIC_J for the joint institution denoted by BIC_J . Furthermore, we assume that if the institution had split into two separate entities for Tier I capital reporting purposes then each would have its own stylized annual loss modelled by two independent Poisson-Lognormal models: Entity 1 denoted $\text{Poisson}(\lambda_1)\text{-Lognormal}(\mu_1, \sigma_1)$; and Entity 2 denoted by $\text{Poisson}(\lambda_2)\text{-Lognormal}(\mu_2, \sigma_2)$ with BIC_1 and BIC_2 , respectively.

Consider the long term SMA capital behavior averaged over the long term history of the SMA capital for each case, joint and disaggregated business models. Then, according to a long term analysis of these stylized Poisson-Lognormal models, the following expressions can be used to determine the point at which the SMA capital would be super additive. If it is super additive in the long term, it would indicated that there is therefore an advantage to split the institution in the long-run into disaggregated separate components. Furthermore, the expression provided allows one to maximize the long term SMA capital reduction that can be obtained under such a partitioning of the institution.

Note: the following calculations are based on truncated Poisson expected loss expressions for Lognormal models, see details in [Peters and Shevchenko, 2015].

Joint Institution (Long term behavior):

Long Term Average Loss Component (LTALC) is given by

$$\begin{aligned}
 \text{LTALC}(\lambda_J, \mu_J, \sigma_J) = & 7\lambda_J \exp\left(\mu_J + \frac{1}{2}\sigma_J^2\right) + 7\lambda_J \exp\left(\mu_J + \frac{1}{2}\sigma_J^2\right) \times \Phi\left(\frac{\sigma_J^2 + \mu_J - \ln L}{\sigma_J}\right) \\
 & + 5\lambda_J \exp\left(\mu_J + \frac{1}{2}\sigma_J^2\right) \times \Phi\left(\frac{\sigma_J^2 + \mu_J - \ln H}{\sigma_J}\right)
 \end{aligned}$$

Where $\Phi(\cdot)$ denotes the Normal CDF, L is Euro 10 million and H is Euro 100 million.

Therefore the Long term ILM (LTILM) is given by

$$LTIM(\lambda_J, \mu_J, \sigma_J) = \ln \left(\exp(1) - 1 + \frac{LTALC(\lambda_J, \mu_J, \sigma_J)}{BIC_J} \right)$$

These are then used to calculate the Long Term SMA (LTSMA) which will be an explicit function of LDA model parameters $(\lambda_J, \mu_J, \sigma_J)$ according to

$$LTSMA(\lambda_J, \mu_J, \sigma_J) = \begin{cases} BIC_J, & \text{if Bucket 1} \\ 110M\ln + (BIC_J - 110M\ln) \times LTILM(\lambda_J, \mu_J, \sigma_J), & \text{if Buckets 2 - 5} \end{cases}$$

Disaggregated Institution {i=1 or i=2} (Long term behavior):

Long Term Average Loss Component (LTALC) is given by

$$LTALC(\lambda_i, \mu_i, \sigma_i) = 7\lambda_i \exp\left(\mu_i + \frac{1}{2}\sigma_i^2\right) + 7\lambda_i \exp\left(\mu_i + \frac{1}{2}\sigma_i^2\right) \times \Phi\left(\frac{\sigma_i^2 + \mu_i - \ln L}{\sigma_i}\right) \\ + 5\lambda_i \exp\left(\mu_i + \frac{1}{2}\sigma_i^2\right) \times \Phi\left(\frac{\sigma_i^2 + \mu_i - \ln H}{\sigma_i}\right)$$

where $\Phi(\cdot)$ denotes the Normal CDF, L is Euro 10 million and H is Euro 100 million.

Therefore the Long term ILM (LTILM) is given by

$$LTIM(\lambda_i, \mu_i, \sigma_i) = \ln \left(\exp(1) - 1 + \frac{LTALC(\lambda_i, \mu_i, \sigma_i)}{BIC_i} \right)$$

These are then used to calculate the Long Term SMA (LTSMA) which will be an explicit function of LDA model parameters $(\lambda_i, \mu_i, \sigma_i)$ according to

$$LTSMA(\lambda_i, \mu_i, \sigma_i) = \begin{cases} BIC_i, & \text{if Bucket 1} \\ 110M\ln + (BIC_i - 110M\ln) \times LTILM(\lambda_i, \mu_i, \sigma_i), & \text{if Buckets 2 - 5} \end{cases}$$

Hence, **the SMA Super Additive Capital Condition becomes:**

$$LTSMA(\lambda_J, \mu_J, \sigma_J) - LTSMA(\lambda_1, \mu_1, \sigma_1) - LTSMA(\lambda_2, \mu_2, \sigma_2) > 0$$

Using this stylized condition, banks may be able to determine for instance if in the long term it would be economically efficient to split their institution into 2 or more separate entities. Furthermore, they can use this expression to optimize the capital reduction for each of the individual entities, relative to the combined entities SMA capital. Hence, what we show here is the long term average behavior which will be the long run optimal conditions for split or merge.

We also note that due to the volatility of the loss experience, and the BI figures over time it could also be the case that a given institution could have an SMA capital which would be switching between super vs sub-additivity of the capital over time. This would imply that SMA model could provide a time varying incentive and disincentive in merge and split depending on the current environment for capital funding.

Proposition: a Standardization of AMA

In the following section the recommendations made are based on detailed discussions proposed in [Cruz, Peters, Shevchenko, 2015], [Peters and Shevchenko, 2015] and the preprint [Peters et al, 2016].

SMA cannot be considered as an alternative to AMA models. We suggest that **AMA should not be discarded, but instead could be improved by addressing its current weaknesses. It should be standardized!** Details of how a rigorous and statistically robust standardization can start to be considered, with practical considerations, are provided below.

Rather than discarding all Operational risk modelling as allowed under the AMA, instead the regulator could make a proposal to standardize the approaches to modelling based on the accumulated knowledge to date of Operational risk modelling practice.

We propose one class of models that can act in this manner and allow one to incorporate the key features offered by AMA LDA type models which involve internal data, external data, BEICF's and Scenarios, with other important information on factors that the SMA method and OpCar approaches have tried to achieve but failed. As noted in this response, one issue with the SMA and OpCar approaches is that they try to model all Operational risk processes at the institution or group level with a single LDA model and simplistic regression structure, this is bound to be problematic due to the very nature and heterogeneity of Operational risk loss processes. In addition it fails to allow for incorporation of many important Operational risk loss process explanatory information sources such as BEICF's which are often no longer informative or appropriate to incorporate at institution level, compared to individual Business Line/Event Type (BL/ET) level.

We propose a standardization of the AMA internal models to remove the wide range of heterogeneity in model type. Our recommendation involves a bottom up modeling approach where for each BL/ET Operational risk loss process we model the severity and frequency components in an LDA structure which is comprised of a hybrid LDA model with factor regression components, allowing to include the factors driving operational risks in the financial industry, at a sufficient level of granularity, while utilizing a class of models known as the Generalized Additive Models for Location, Shape and Scale (GAMLSS) in the severity and frequency aspects of the LDA framework. The class of GAMLSS models can be specified to make sure that the severity and frequency families are comparable across institutions, allowing both risk-sensitivity and capital comparability. We recommend in this regard Poisson and Generalized Gamma classes for the family of frequency and severity model as these capture all typical ranges of loss model used in practice over the last 15 years in Operational risk, including Gamma, Weibull, Lognormal, Pareto type severities.

Standardizing Recommendation 1:

This leads us to the first standardizing recommendation relating to the level of granularity of modelling in Operational risk. The level of granularity of the modelling procedure is important to consider when incorporating different sources of Operational risk data such as BEICF's and scenarios and this debate has been going for the last 10 years, with discussion on bottom-up versus top-down based Operational risk modelling, see overview in [Cruz, Peters, Shevchenko, 2015] and [Peters and Shevchenko, 2015]. We advocate that a bottom-up based approach be recommended as the standard modelling structure as it will allow for greater understanding and more appropriate model development of the actual loss processes under study. Therefore, we argue that sticking with the 56 BL/ET structure of Basel II is in our opinion best for a standardizing framework with a standard aggregation procedure to institution level / group level. We argue that alternatives such as the SMA and OpCar approaches that are trying to model multiple different featured loss processes combined into one loss process at the institution level will be bound to fail as they need to capture high frequency events, as well as high severity events, this in principle is very difficult if not impossible to capture with a single LDA model at institution level and

should be avoided. Furthermore, such a bottom-up approach allows for greater model interpretation and incorporation of Operational risk loss data such as BEICF's.

Standardizing Recommendation 2:

This brings us to our second recommendation for standardization in Operational risk modelling. Namely, we propose to standardize the modelling class to remove the wide range of heterogeneity in model type. We propose a standardization that involves a bottom up modelling approach where each BL/ET level of Operational risk loss process we model the severity and frequency components in an LDA structure which is comprised of a hybrid LDA model with factor regression components. The way to achieve this is to utilise a class of GAMLSS regression models for the severity and frequency model calibrations.

That is two GAMLSS regression models are developed, one for the severity fitting and the other for the frequency fitting. This family of models is flexible enough in our opinion to capture any type of frequency or severity model that may be observed in practice in Operational risk data whilst incorporating factors such as BEICF's (Key Risk Indicators, Key Performance Indicators, Key Control Indicators) naturally into the regression structure. This produces a class of hybrid factor regression models in an Operational risk LDA family of models that can easily be fit, simulated from and utilised in Operational risk modelling to aggregate to the institution level. Furthermore, as more data years of history become available, the incorporation of time-series structure in the severity and frequency aspects of each loss process modelling can be naturally incorporated in a GAMLSS regression LDA framework.

Standardizing Recommendation 3:

The class of models considered for the conditional response in the GAMLSS severity model can be standardized. There are several possible examples of such models that may be appropriate [*Chavez-Demoulin, 2015*] and [*Ganegoda and Evans, 2013*], however we advocate for the severity models that the class of models be restricted in regulation to one family, the Generalized Gamma family of models, see details in [*Peters et al, 2016*] where these models are developed in an LDA hybrid factor GAMLSS model. This work shows that such models are appropriate for Operational risk as they admit special members which correspond to the LogNormal, Pareto, Weibull and Gamma. All of these models are popular Operational risk severity models used in practice and represent the range of best practice by AMA banks as observed in the recent survey [*BCBS160b*]. Since the Generalized Gamma family contains all these models as special sub-cases it means that banks would only have to ever fit one class of severity model to each BL/ET LDA severity profile, and the most appropriate family member would be resolved in the fitting through the estimation of the shape and scale parameters, in such a manner that if a LogNormal model was appropriate it would be selected, where as if a Gamma model were more appropriate it would also be selected from one single fitting procedure.

Furthermore, the frequency model could be standardized as a Poisson GAMLSS regression structure as the addition of explanatory covariates and time varying and possible stochastic intensity allow for a flexible enough frequency model for all types of Operational risk loss process.

Standardizing Recommendation 4:

The fitting of these models should be performed in a regression based manner in the GAMLSS framework, which incorporates truncation and censoring in a penalized maximum likelihood framework, see [*Stasinopoulos and Rigby, 2007*]. We believe by standardizing the fitting procedure to one that is statistically rigorous, well understood in terms of the estimator properties and robust when incorporating a censored likelihood appropriately, will remove the range of heuristic practices that has arisen in fitting models in Operational risk. The penalized regression framework, based on L1 parameter penalty will also allow for shrinkage methods to be used to select most appropriate

explanatory variables in the GAMLSS severity and frequency regression structures.
Standardizing Recommendation 5:

The standardization in form of Bayesian versus Frequentist type models be left to the discretion of the bank to decide which version is best for their practice. However, we note that under a Bayesian formulation, one can adequately incorporate multiple sources of information including expert opinion and scenario based data, see discussions in [Cruz, Peters and Shevchenko, 2015] and [Peters, Shevchenko and Wuthrich, 2009] and [Shevchenko, 2011].

Standardizing Recommendation 6:

The sets of BEICF's and factors to be incorporated into each BL/ET LDA factor regression model for severity and frequency should be specified by the regulator. There should be a core set of factors to be incorporated by all banks which include BEICF's and other factors to be selected. The following types of KRI's categories can be considered in developing the core family of factors (see [Chapelle, 2013]):

Exposure Indicators: *any significant change in the nature of the business environment and in its exposure to critical stakeholders or critical resources. Flag any change in the risk exposure.*

Stress Indicators: *any significant rise in the use of resources by the business, whether human or material. Flag any risk rising from overloaded humans or machines.*

Causal Indicators: *metrics capturing the drivers of key risks to the business. The core of preventive KRIs.*

Failure Indicators: *poor performance and failing controls are strong risk drivers. Failed KPIs and KCIs.*

In this approach, a key difference is that instead of fixing the regression coefficients for all banks (as is the case for SMA and OpCar) pretending that all banks have the same regression relationship as the entire banking population, instead one should standardize the class of factors. Specify explicitly how they should be collected, the frequency and then specify that they should be incorporated in the GAMLSS regression. This will allow each bank to then calibrate the regression model to their loss experience through a rigorous penalized Maximum Likelihood procedure. With strict criterion on cross validation based testing on the amount of penalization admitted in the regression when shrinking factors out of the model. This approach has the advantage that banks will not only start to better incorporate in a structured and statistically rigorous manner the BEICF information into Operational risk models, but they will be forced to better collect and consider such factors in a principled manner.

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