THE RISK MANAGEMENT ASSOCIATION

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Industry Position Paper

AMA Quantification Challenges:

AMAG Range of Practice and Observations on "The Thorny LDA Topics"

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The AMA Group
The Risk Management Association
Operational Risk Advisors LLC

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Table of Contents

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Introduction

This discussion of Quantification Challenges is one in a series of industry position papers (IPPs) by the AMA Group[1] (AMAG) on business practices addressing the implementation of Advanced Measurement Approaches (AMA). It is intended to aid in a continued dialogue between the industry and the regulatory community on effective implementation of AMA in the United States.

Specifically, this paper was developed in response to a series of questions raised by U.S. regulators about the implementation of the Loss Distribution Approach (LDA)[2] in 2012 (dubbed "thorny topics"). It offers industry ranges of practice, and a variety of experience, observations and positions about technical implementation, identifies some additional fundamental concerns about LDA application, and offers solutions.

AMAG continues to believe that the regulatory community should take a principles-based, versus a prescriptive, approach to operational risk measurement by the industry. This is particularly true in view of inherent challenges of the LDA as outlined herein, the state of evolution of operational risk quantification overall, loss data availability, the impact of extraordinarily large losses whether internal or external to an institution, and appropriate quantitative judgment necessary for these models to be effective as capital estimation and risk management tools. Although AMAG has observed signs of convergence[3] on aspects of LDA quantification modeling as described herein, some of this convergence has been involuntary and, in some cases, industry quantitative analysts have not been wholly in agreement with the directives for change.

One concern that has been developing in recent years is that a possible consequence of some regulatory implementation directives is the production of inappropriate results from already unstable LDA models. Some banks have opted for pursuit of methodologies within the AMA framework to overcome this concern together with the associated stability challenges of LDA, including the exploration of alternative and/or supplemental exposure-, factor- and/or scenario-based models, in conjunction with LDA.

As outlined herein, considering data and model instability challenges, an important theme in successful implementation is the need to preserve latitude for flexibility in allowing judgment toward model selection and implementation, as well as in the application of such alternative and/or supplemental models, provided that the decision-making process is balanced by systematic, well-documented and governed approaches.

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[1] The Advanced Measurement Approaches Group (AMAG) was formed in 2005 to share industry views on aspects of Advanced Measurement Approaches (AMA) implementation with the U.S. financial services federal regulatory agencies. Attachment A to this Paper consists of additional information about AMAG, including a list of member firms. They are listed for identification purposes only. Support for the AMAG is provided by RMA and Operational Risk Advisors LLC (ORA). This Paper does not necessarily represent the views of RMA, RMA's institutional membership at large, ORA, or the views of the individual institutions whose staff have participated in the AMAG.

[2] The Loss Distribution Approach under AMA / Basel II.

[3] The AMA Group has observed convergence through its 2006, 2010, 2011, 2012 and 2013 capital quantification range-of-practice survey work in terms of some areas such as general LDA approach, distribution selection and the like, but notes that there is a range of practice with respect to implementation in view of the importance of judgmental factors driven by data challenges and inherent LDA model instability concerns.

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Background

On June 18, 2012, the Federal Reserve Bank of New York hosted an Interagency meeting with the AMA Group for the purposes of discussing some key quantitative topics that have presented particular challenges for both the industry and regulatory community in operational risk Pillar 1 LDA quantification under the AMA approaches. It is anticipated that ultimately the U.S. regulators will issue guidance with respect to these challenging topics to aid the industry in exiting from Basel II parallel run.
The topics[4] are:

- Diversification and Dependence
- Model Selection and Fitting Techniques
- Data Thresholds and Correcting Frequency Estimations
- External Data and Scenario Analysis
- Model Risk, Stability, Benchmarking, and Back testing

The meeting was facilitated by FRBNY and the AMA Group (AMAG). Regulatory agencies represented at the meeting included the Federal Reserve (Board of Governors, New York, Boston, and Richmond), the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC).

In response to the regulatory community's invitation, AMAG presented opening comments for each topic based on recent industry range-of-practice (ROP) survey work involving its membership. The regulators typically responded with further clarification of their concerns. Discussion and dialog generally focused on the findings from the AMAG survey.

Since the discussions in June 2012, the industry has endeavored to explore further the ROP in these areas. This paper presents the result of those efforts. Detailed commentary on the individual topics follows. For each, this paper (1) presents the questions and/or concerns expressed by regulators; (2) recaps findings from AMAG's two recent range of practice surveys (both from 2012); (3) elaborates on industry practices and presents responses to the regulators' concerns; and (4) summarizes some questions and concerns from the industry. Because of the technical nature of the discussion, and for readability, it was the sense of the AMAG that the key points could best be presented in an outline format.

AMAG Observations and Positions

Following is a summary of observations and positions developed by AMAG during the course of collective industry-wide work to date on LDA quantification and ongoing discourse within the membership.

1. Diversification and Dependence

Dependence relationships are estimated with great imprecision. For the most part, banks have not been able to draw very strong conclusions based on a lack of statistically significant findings.

[4] The original 6 topics are presented here, although in a slightly different order, and with a combination of 2 of the topics (I.e., Model Selection and Model Fitting).

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The final quantification of diversification benefit is determined by the complex and non-linear interaction of a number of factors and, hence, judgment is key. In any event, the magnitude of diversification benefit cannot be manipulated readily to benefit each financial institution.

2. Model Selection and Fitting Techniques

Frequency:

- Underlying frequency data should be subject to thorough EDA[5] prior to modeling to develop supporting information for the frequency model specification. A variety of considerations as to the characteristics of the time series should be applied. Banks should be permitted latitude in determining how best to resolve any issues identified in the EDA.

- Selection of the distribution of loss frequency should be supported by sufficient documentation, and subject to model governance policies and procedures, but ultimately left to the discretion of the institution.

- Banks should be permitted the latitude to develop sustainable processes for model and variable selection in loss frequency models that are clearly stated, systematically applied, well documented, and subject to suitable governance and oversight.

Severity:

- Provided that their selection of class of severity model for each unit of measure is well considered, supported, and documented with sufficient justification based on statistical principles or business rationale, judgment is key here as well. The estimation approach should be clearly linked to the underlying methodology and "conceptual soundness" should be demonstrated. Criteria must be multifaceted and, at a minimum, two (2) distributions should be selected.

- Banks should be in a position to define the set of severity distributions that are to be evaluated provided that this set includes some probability distributions that are medium- or heavy-tailed.

- Processes for selection of loss severity models should be clearly stated, systematically applied, well documented, and subject to suitable governance and oversight. Judgment in developing them is key, however, once again.

3. Data Thresholds and Correcting Frequency Estimations

Although the industry generally accepts the existence of operational losses below the data collection threshold, the appropriate treatment of such losses in the context of capital estimation is still widely debated.

4. External Data and Scenario Analysis (SA)

The strength in the use of external data is that it allows financial institutions to leverage the experience of peer firms to assess the riskiness of specific event types / businesses that they are (or may be) engaged in. The treatment of extraordinarily large losses remains a challenge, however, and the industry continues to work toward appropriate principles for representing them in capital estimates.

[5] Exploratory Data Analysis.

Scenarios provide the benefit of a forward-looking assessment of risk as opposed to a backward- looking view that is based largely on historical failures (loss data) that may or may not still be relevant to the organization.

Not all scenarios are designed and used for the capital model. Using SA data for risk management uses help identify control gaps in firms, to understanding plausible op risk events, identifying potential control enhancements or risk mitigation actions and support for other risk management such as stress testing, ICAAP, and understanding a firm's risk profile.

While the AMAG has observed signs of convergence on certain aspects of Scenario Analysis, it believes that there should not be an expectation that all aspects of practice will eventually converge, and hence the supervisory community should continue to apply a principles-based approach, as opposed to a prescriptive one, to the use of SA.

In light of the value demonstrated at institutions in a range of Scenario Analysis processes and practices, the definition of SA should be refined and the rigor and documentation of the process can and should be permitted to vary depending on measurement or management use.

Appropriate use of Scenario Analysis benchmarking should be permitted to result in an upward or a downward adjustment to the operational risk capital amount.

5. **Model Risk, Benchmarking, and Back-testing**

Documented Procedure -- Banks should have a documented procedure for *benchmarking* the capital model results and the overall firm-level capital.

Model results should be *benchmarked* using alternative models. Options may include bootstrapping to an alternative model, benchmarking to scenario models built on scenario analysis information or to exposure-based models

Banks should have a documented procedure for *back-testing* the capital model results and the overall firm-level capital. Distinction between how the loss amount is recorded for the purpose of the LDA model (referred to in this document as Event Basis) and how it is recorded from a P/L perspective (Impact Basis) should be noted.

Alternative Models

LDA provides a rigorous approach for modeling past loss distributions and, therefore, has become the standard practice for modeling operational risks for which historical loss distributions are assumed to be the best predictor of future loss distributions. In fact, LDA works satisfactorily for many risk types. However, for operational risk types with defined risk exposure and identifiable risk drivers, the so-called 'known-unknowns', future loss distributions can be better predicted by alternative models which incorporate available risk factors into capital requirements. In addition, factor models can offer an effective alternative to LDA when data are insufficient to generate stable results. In short, these models could be indispensable in cases where standard approaches fail.

Thus, the industry sees a growing need for pursuing alternative operational risk modeling approaches to support a diverse set of operational risk event types. Operational risk types that would benefit from predictive, factor-based modeling approaches have emerged as material risks over recent years. They include, but are not necessarily limited to: (1) litigation events linked to credit- or market-risk losses that emerged during the recent crisis as material sources of operational risk; and (2) litigation liabilities assumed as a part of acquisitions that are often anticipated and reflected in discounted purchase pricing.

Effective use of factor-based and other alternative modeling to quantify capital requirements for these and possibly other types of events would support improved soundness of operational risk capital calculation and risk management frameworks. For instance, factor-based modeling would incorporate available data pertaining to current risk exposures in quantifying capital to better enable banks to hold capital based on known risks. By linking capital requirements to risk exposure, factor-based models support strong risk management by increasing capital requirements as risks are added and reducing capital in reaction to risk mitigation actions.

Principles-based Regulation

The U.S. Rule allows explicitly for the development and use of various approaches to operational risk quantification, which should include, but not limited to, enhancements to LDA, alternatives to LDA, or models that supplement LDA.

The industry continues to conduct ground breaking research and development in operational risk measurement, including areas such as:

- Exposure- and/or factor-based modeling, scenario modeling and/or hybrid LDA models;
- Customized approaches to the unique characteristics of a financial institution (such as modeling techniques for merged firms, treatment of losses in disposed businesses, changes in existing business mix over observed time period);
- Use of covariate information from loss event databases that explain systematic differences in loss severity within a unit of measure to build more flexible, more stable, and more robust models for operational risk;
- Other approaches or methods that incorporate additional latitude for modeling the severity component of operational risk;
- Development of more robust estimators for loss severity; and
- Techniques to remove or mitigate the systematic overstatement (bias) of capital arising in the context of capital estimation with the LDA methodology.

Principles-based regulatory guidance that promotes a controlled and documented process for model selection and includes expert judgment in evaluating statistical tests, graphical diagnostics, and quantitative metrics such as capital stability would likely be helpful to the industry. This will be the case provided, however, that the language permits institutions to develop customized and sustainable processes that are credible for banks *both internally and in external disclosures*.

In addition, application of a principles-based approach would continue to allow banks to pursue alternative models, especially for event types where specific underlying risk characteristics can be demonstrated. In cases where loss event exposures can be defined prior to loss events occurring, factor-based and/or other alternative models should be considered based on their ability to better quantify the bank's risk exposure. Guidelines should be established to support a range of practice for further work in this area. Principles should be established for model selection, use of data, expert judgment and ongoing validation in order to facilitate development and application of these next generation models.

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AMAG welcomes feedback and a continued dialogue with the regulatory community as both endeavor to evolve these topics, and pursue resolution of these difficult challenges in the quantification of operational risk.

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TOPIC 1: Diversification and Dependence

I. **Regulatory Issues and Concerns** – Following are the issues and questions that were raised by regulators and posed to the industry in 2012:

A. Dependence in operational risk is heavy tailed but data are usually insufficient to calibrate models. What are the different approaches to address this problem?
B. Use of a Gaussian copula does not sufficiently account for tail dependence.
C. Banks must defend chosen degrees of freedom.
D. Regulators are skeptical if the diversification benefit reaches 50% or more.

II. **Industry Approaches and AMAG Range-of-Practice highlights (2012)**

A. Chosen copulas: primarily Student-t or Gaussian
B. Statistical techniques employed: Maximum Likelihood Estimation (MLE) and business judgment.
C. Range of metrics applied: Kendall Tau, Spearman and copula fit, but also Pearson and Tail dependence coefficient.
D. Degrees of freedom: Most banks use 5 or less, with some in the range of 10-20.
E. Annual pools of data do not provide a sufficient sample to evaluate correlation, as a result data are aggregated quarterly or monthly.
F. Reasonableness is demonstrated through comparison to a simple sum (i.e., perfect correlation).

III. Industry Response / Positions

A. The reality of dependence in the current universe of operational risk loss data is that dependence relationships can only be estimated with great imprecision. Banks cannot draw very strong conclusions based on a lack of statistically significant findings.

1. Limited historical data for model estimation.
2. Conversion of monthly/quarterly relationships to annual may ignore lagged dependency relationships and understate annual dependence. There may be a need for a time-scaling relationship to address this challenge.

B. Dependence relationship

1. A non-linear relationship is expected that must have upper tail dependence (i.e. Gaussian copula is unacceptable).
2. Dependence relationships are a function of time and attempts to measure it with only 10 years of data or so are challenging at best.
3. Industry analyses (such as that from ORX[6]) indicate limited evidence of correlation (frequency or severity) with a much larger pool of data.

[6] Operational Riskdata eXchange Association

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4. Degrees of freedom of 5 or less using a Student's-t copula should be viewed as tending toward conservatism. The chosen degrees of freedom should be defended through statistical analysis of actual loss data whenever possible.

5. Assuming the statistical techniques to measure correlation are documented well and a sufficient sample of data is analyzed, negative correlation values should be allowed. Let the data tell the real story.

C. More complete support for a diversification model could be provided with additional sensitivity analysis of:

1. Lagged dependence relationships within monthly/quarterly data.
2. Model estimation using occurrence or discovery date for event timing instead of financial recognition date alone.

D. The magnitude of diversification benefit is not something that can be manipulated readily to the benefit of each financial institution. The final quantification of diversification benefit is determined by the complex and non-linear interaction of a number of factors and, hence, judgment is key.

1. Methodology for the implementation of dependence:
   a. The chosen copula;
   b. Degrees of freedom (when relevant);
   c. Pair-wise dependence factors; and
   d. The type of analysis performed to determine, calibrate or estimate copula parameters.

2. Modeling decisions outside the scope of dependence modeling:
   a. The number of UOMs;
   b. The severity models selected; and
   c. Whether the capital contributions of UOMs are of similar scale or a single UOM has a dominant capital contribution.

IV. Industry Concerns / Uncertainty

A. The decision as to what the reference date should be for dependence (occurrence, discovery, financial recognition).
B. Regulatory (FRB) studies of correlation across data from multiple banks show evidence of correlation in frequency. Previous guidance "required" implementation of correlation on severity and NOT frequency. It is unclear based on the results of recent FRB studies as to whether this guidance will be changed.
C. It is anticipated that it will take a very long time, indeed, before an individual bank would see similar correlation levels in their own data.
D. It is unclear how the homogeneity (and heterogeneity) of the chosen unit of measure effects the study or implementation of dependence across these same units of measure.
E. It is unclear why model risk was included specifically in this topic. Model error is relevant to all of the "thorny topics".

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TOPIC 2: Model Selection and Fitting Techniques[7]

I. Regulatory Issues and Questions

A. Frequency and Severity fitting – What would reasonable rules be? Should statistical best fit be evaluated each year?
B. How should the industry be addressing model stability?
C. What model fitting techniques are being used industry-wide? What are the ranges-of-practice and preferences?

II. Industry ROP Findings – Modeling Fitting Techniques (2012) – Key findings of AMAG ROP surveys:

A. Severity fitting techniques

1. MLE[8] is predominant, by far.
2. Significant number of Banks pursuing GF[9] and Monte Carlo simulations
3. Bayesian approaches included Markov Chain Monte Carlo (MCMC) - Some find that MCMC provides more stability and control than MLE.
4. Quantile matching techniques have also proven to be useful.

B. Variety of tests for Goodness-of-fit

1. AD and KS predominant,
2. but CvM[10] and CS[11] are used as well.

C. Severity distributions for entire support (body & tail combined)

1. Significant Range of practice in selection –
    a. Lognormal is apparently dominant,
    b. but there is significant use of Weibull, GPD[12],
    c. and a variety of others, often driven by considering UoMs

D. It is very common to use a separate distribution for the tail

1. Variety of distributions used, from lognormal and GPD to a variety of others
2. AD[13] and KS[14] tests most common for GF on the tail only
3. Tail severity model techniques – EVT[15] very common, or mixture distributions

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[7] Originally presented by regulators as separate topics
[8] MLE = Maximum Likelihood Estimation
[9] GF = Goodness of Fit
[10] CVM= Cramer-von Mises
[11] CS = Chi Square
[12] GPD = Generalized Pareto Distribution
[13] AD=Anderson Darling
[14] KS = Kolomogorow-Smirnov test
[15] EVT = Extreme Value Theory

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4. If EVT, then a variety of tests are applied in considering the behavior of the tail, including Hill Estimator, MEF[16], GPD shape, etc.

E. When for the body of the distribution only – Lognormal is common; also empirical distributions.

III. Industry Positions – Frequency:

A. Defining the Frequency Time Series

Banks differ as to how loss events are assigned to historical time periods for frequency modeling. There are advantages and disadvantages to using the different date fields typically captured in loss event databases (loss event start date/occurrence date, date of event discovery, or date of financial recognition), but the choice should be left to the institution for these reasons:

1. There is often a time lag between occurrence date and discovery date, only a portion of loss events that occurred within a quarter are discovered by a bank in the same quarter. Some institutions estimate loss frequency excluding the most recent quarters of losses while waiting for undiscovered loss events to be identified. Institutions may apply other adjustments to account for undiscovered losses.
2. At the time a loss event is discovered, there is often incomplete information about its circumstances. In some cases, it is unclear whether the event is even an operational loss at the time of discovery. Because such events may fall out of the loss event database or be subject to reclassification of characteristics needed for modeling (such as business line or event type), some institutions use the date of financial recognition for frequency modeling.
3. A clear complication in analyzing loss frequency is that the business environment and internal control factors that influence the loss event are typically most directly related to event start and/or end date and not to discovery date or date of financial recognition.

B. Sample Selection

Although the final U.S. Rule requires a minimum of five years of loss event data for modeling internal loss data, institutions vary as to how many years of data are used for frequency estimation. Five years is a reasonable sample size in most cases, however exceptions should be allowed (i.e., to use more or less if supported by logic, the business model, etc.) for their risk measurement processes.

1. A rolling window of five years of data is a very common data sample for frequency estimation.
2. Some institutions use frequency time series data over a longer time period arguing that a better long run estimate is obtained with more data. This is particularly true for institutions estimating loss frequency using regression modeling approaches.

[16] MEF = Mean-Excess function

C. Exploratory Data Analysis

The underlying frequency data should be subject to thorough EDA[17] prior to modeling to develop supporting information for the frequency model specification. Key considerations / questions may include:

1. Does the time series appear to be a stationary count process?
2. Does there appear to be over-dispersion, under-dispersion, or excess zeroes?
3. Are there structural breaks in the time series based on graphical plots and/or statistical tests?
4. If a structural break is identified, what underlying changes in BEICFs can explain the change in frequency (e.g. acquisitions/divestitures, changes in business strategy, volume growth, etc.)?
5. Is there a seasonal pattern of variation in loss frequency?

Judgment should be allowed in determining how best to resolve any issues identified in the exploratory data analysis.

D. Distributional Assumptions

For estimating capital requirements, it is most common for institutions to assume a Poisson or Negative Binomial distribution and may account for excess zeroes by applying zero-inflated or zero-modified versions of these distributions. In most cases, very similar estimates of expected operational loss and capital requirements are obtained using either the Poisson or Negative Binomial distribution. Selection of the distribution of loss frequency should be supported_by sufficient documentation, and subject to model governance policies and procedures, but_ultimately left to the discretion of the institution.

E. Estimation Methodology

In general, the choice of estimation methodology does not affect the estimated parameters meaningfully because the estimating equations are the same or nearly the same for the most commonly used estimators such as Maximum Likelihood Estimation (MLE), Generalized Linear Models (GLM), and Generalized Method of Moments (GMM).

1. For estimating the Poisson model with no covariates, estimation with the simple average is equivalent to estimation by MLE, GLM, and GMM.
2. Estimation of the Negative Binomial model with no covariates by MLE or GLM yields equivalent estimates.
3. Estimation of regression-based models that include explanatory variables has typically relied upon MLE, GLM, or GMM estimators.
4. When excess zeroes are suggested in the frequency data, MLE is typically the estimator of choice.

These circumstances will factor into the bank's ultimate decision to select from any estimation methodology. That decision should be well-supported, of course.

[17] Exploratory Data Analysis

F. Selection Criteria

Some institutions use multifaceted selection criteria for evaluating alternative frequency models and estimation techniques. The choice may be informed by:

1. Formal hypothesis testing for goodness-of-fit (e.g. Likelihood Ratio or Chi-squared tests) or comparison of potentially non-nested models (e.g., Vuong's test); and
2. Comparison of model selection criteria or parsimony (such as Aikaike's Information Criterion, Bayesian Information Criterion, or deviance).

When explanatory variables are included in a frequency model, institutions may develop variable selection criteria to guide the model building process. These criteria may include:

1. Statistical significance of estimated coefficient;
2. Business relevance or theoretical justification for the explanatory variable; and
3. Stability of coefficient estimates across historical data samples.

Provided that they are stated clearly, applied systematically, well documented, and subject to suitable governance and oversight, banks should be permitted the latitude to develop sustainable processes for model and variable selection in loss frequency models.

IV. Industry Positions – Severity:

A. Class of Severity Model

In modeling the severity of operational losses, the form of the assumed distribution should have a domain that is unbounded in the right tail and is bounded on the left at the data collection or modeling threshold. Institutions typically select from one of the following classes of distributions:

1. Single parametric distribution -- All losses in the unit of measure are assumed to follow a common parametric probability distribution. The parameters of the distribution are estimated using all losses above the data collection or modeling threshold.
2. Finite mixture model -- The unit of measure is assumed to consist of losses arising from multiple loss generating mechanisms (LGMs), but the mapping of individual losses to specific LGMs is not known with certainty. Each LGM assumed to have a parametric probability distribution and the parameters of these distributions along with probabilities assigning each loss to each LGM are estimated using all losses above the data collection or modeling threshold.
3. Spliced distributions -- The distribution of losses within the unit of measure is assumed to change at certain severity levels (splice points). In the body-tail approach, losses follow one parametric (or empirical) distribution from the data collection threshold up to the splice point, and another parametric distribution in the tail (losses above the splice point). The body-tail approach may be extended to join together more than two distributions to model losses in the unit of measure.

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Provided that their selection of class of severity model for each unit of measure is well considered, supported and documented with sufficient justification based on statistical principles or business rationale, judgment is essential here, too, *in the selection*. Specifically, the estimation approach should be clearly linked to the underlying methodology and "conceptual soundness" should be demonstrated. Criteria must be multifaceted and at a minimum two (2) distributions should be selected.

1. Arguments supporting the selection of a single parametric distribution:

    a. The kernel density plot is unimodal;
    b. The empirical distribution of losses is similar across different subgroups of losses in the unit of measure; and
    c. Simplicity/parsimony.

2. Arguments to justify the selection of a finite mixture model:

    a. The kernel density plot is not unimodal (modality testing);
    b. A single parametric distribution is unable to achieve satisfactory fit in both the body and the left tail of the data;
    c. There is insufficient data to permit precise severity estimation by splitting the unit of measure into smaller subsets of losses; and
    d. Plausible business rationale supports the existence of multiple LGM within unit of measure (for instance, workers compensation to senior exempt and junior non-exempt employees might justify different severity modes).

3. Arguments to justify the selection of a spliced distribution:

    a. Empirical sampling will be used for the body of the severity distribution and modeling will focus on the tail (which drives capital);
    b. Severe losses have a distinct or different distribution than losses below the splice point because of data quality issues – higher quality data are gathered and collected for larger losses while the data quality and accuracy for small losses may be less;
    c. Application of EVT methodology – asymptotic approximation of the tail using extreme value distributions such as GEV, GPD; and
    d. Some business rationale for why large losses have a very different data generating process than smaller losses.

4. Further comments on finite mixture models and spliced distributions:

    a. In a finite mixture model, the mixing proportions should be free parameters that are estimated along with the severity parameters of the components;
    b. The splice point(s) in a spliced distribution can be justified by conducting sensitivity analysis to alternative locations (such as Hill plots, etc.); and
    c. Spliced distributions that combine two or more parametric distributions should incorporate constraints to ensure continuity and smoothness.

Banks should be in a position to define the set of severity distributions that are to be evaluated, provided that the choices include some probability distributions that are medium- or heavy-tailed.

B. Consideration of Several Families of Severity Distribution

For modeling loss severity, an institution should define a consideration set that includes a variety of distributions.

1. The consideration set should include some probability distributions that are considered medium- or heavy-tailed (such as Gamma, lognormal, Weibel, GPD, Loglogistic, etc.)
2. For completeness of analysis, light-tailed distributions (such as Gamma, Weibull, etc.) may be relevant for some units of measure with lower loss sizes.
3. The probability distributions in the consideration set should include distributions with varied but not excessive number of parameters to enable consideration of progressively more flexible and complex distributions.

C. Systematic Process for Estimating and Evaluating Alternative Severity Models

Institutions should develop a systematic and transparent process for estimating and evaluating severity models. The process for specifying the severity distribution in each unit of measure should be subject to clear governance standards, management oversight, and management reporting requirements.

1. The documentation of this process should provide a verifiable and transparent record to support the selection of severity distribution in each unit of measure whenever this modeling choice is re-evaluated.
2. As part of the capital quantification system, institutions should state specifically how often the severity selection process will be conducted and how often severity parameters will be updated to incorporate more recent data. This should be no less frequent than annually. In the event that severity selection is not re-evaluated on a quarterly basis, however, institutions should develop a monitoring program to establish what types of changes in the institution's risk profile, internal loss data, or business environment would require the execution of the severity selection process ahead of the stated schedule.

Banks should have the latitude to balance their design of a severity distribution estimation and selection process. On one hand it must meet internal needs for resource utilization, effective oversight, and business as usual production and reporting of capital results, while also complying with the regulatory requirements to be systematic, transparent, verifiable, and credible.

D. Selection Criteria and Diagnostics

Institutions should use multifaceted selection criteria for evaluating alternative severity models and estimation techniques. Practitioners have evaluated competing severity models using quantitative metrics, graphical diagnostics, and modeler judgment. The process of arriving to final selection includes the analysis of the severity consideration set starting from simpler parametric distributions to more complex distributions. Banks' severity distribution selection processes should be based on a combination of quantitative metrics, graphical diagnostics, and modeler judgment.

Dutta and Perry (2003) suggest the following severity selection criteria:

1. Good Fit - Statistically, how well does the method fit the data?

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2. Realistic - If a method fits well in a statistical sense, does it generate a loss distribution with a realistic capital estimate?
3. Well-Specified - Are the characteristics of the fitted model similar to the loss data and logically consistent?
4. Flexible - How well is the method able to reasonably accommodate a wide variety of empirical loss data?
5. Simple - Is the method easy to apply in practice, and is it easy to generate random numbers for the purposes of loss simulation?

The passing of goodness of fit tests is complicated by fitting the full severity to truncated data and is necessary but not sufficient condition by itself to discriminate between severity choices. Among most used diagnostics are:

1. AD;
2. KS; and
3. Chi Square, etc.

Benchmark comparisons can be useful in selecting the severity distribution, especially in determining whether the model-based capital estimate is realistic. Comparison of the number of breaches of model-based capital estimates and benchmark capital estimates can be a useful metric for severity selection. Relevant benchmarks may be constructed using alternative approaches (such as historical re-sampling or scenario-based methods).

Many institutions rely upon graphical diagnostics and other calculations to inform severity distribution selection:

1. QQ or PP plots
2. Mean Excess plots
3. Hill plots
4. Comparison of ECDF and model CDF
5. Structural assumptions, such as a finite mean, may be necessary when selecting distributions

Based on the sensitivity of capital estimates to minor data changes and the widely noted instability of an institution's unit of measure level capital estimates over time, model stability is an important consideration in a bank's severity distribution selection processes.

1. Structural assumptions, such as a finite mean, may be necessary when selecting distributions. How best to deal with outlier losses when a limited amount of data is the cause for an infinite mean is an open question.
2. Measures of precision or relative precision for capital estimates are valid metrics for informing severity distribution selection.
3. Metrics or tools that assess the stability of severity parameter estimates or capital estimates to minor data changes are valid factors to consider in severity distribution selection (e.g. sensitivity analysis or application of the influence function approach).
4. Stability of severity parameter estimates or capital estimates in historical back-testing are also valid factors to consider in severity distribution selection.

Banks should retain the latitude to state and implement severity selection criteria or modeling principles that are suitable for the institution. These selection criteria or modeling principles should be supported by sound theoretical justification or business rationale and additionally, should be applied equally across all units of measure. With this as a foundation, banks should also be in a position to determine what criteria or evidence will be required to change from one family of severity distribution to another.

Moreover, institutions should also be allowed the latitude to design a severity selection process with any desired level of automation (i.e. a process that has fully automated logic for selecting from alternative models is as valid as another severity selection process that requires careful application and documentation of modeler judgment).

Last, processes for selection of loss severity models should be stated clearly, applied systematically, well documented, and subject to suitable governance and oversight. Banks should retain the authority, however, to design and develop them.

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TOPIC 3: Data Thresholds and Correcting Frequency Estimations[18]

I. Regulatory Issues and Concerns

A. Effect of threshold on frequency and severity.
B. Use of a shifted distribution is unacceptable, with the exception of distributions of the Pareto type.
C. Banks must use truncated distributions to account for data collection or modeling thresholds for all other distributions.
D. Losses "below the threshold" may amount to a material loss exposure in some instances (such as when threshold is high and when a large number (frequency) of losses fall "below the threshold"). When the potential loss exposure to small losses is material, a capital "add-on" for the "losses below the threshold" may be relevant. It is acceptable to estimate the "add-on" by extrapolating the severity and frequency model out-of-sample or by using supplemental data sources.

II. Industry Positions

Although in general the industry accepts the existence of operational losses below the data collection threshold, the appropriate treatment of such losses in the context of capital estimation is still widely debated and inconclusive.

A. The assumption that such losses exhibit behavior similar to what is observed above the threshold is a fundamentally un-testable modeling assumption and may be invalid in many cases. Consider that:

   1. These losses may not even exist in some units of measure (e.g. in a UOM defined for legal events, there may be no losses below a sufficiently small threshold due to the costs of litigation); and
   2. There may be no plausible business rationale to support the assumption that the underlying causal factors or loss generating mechanisms for small losses are well represented by the behavior of losses above the threshold

B. Industry research on the issue …

   1. Finds that the capital contribution of losses below the threshold is a major source of capital estimate instability and imprecision when using the out-of-sample extrapolation approach;
   2. Suggests that supplemental data sources can greatly improve the accuracy and precision of the capital contribution from "losses below the threshold"; and
   3. Suggests that supplemental data sources can greatly improve the accuracy and precision of the severity parameter estimates greatly by imposing non-linear constraints in parameter estimation routines.

C. Because the objective is to determine a capital "add-on" for the enterprise, highly aggregated supplemental information about operational losses is suitable for this purpose.

[18] The issues and considerations underlying topic overlap somewhat with Model Selection and Model Fitting techniques addressed in Topic 2.

1. The most likely sources of relevant supplemental information for this purpose are general ledger entries that represent aggregates of many small adjustments, but typically this information may not map perfectly into Basel Event Types, Basel Business Lines, or bank UOM definitions.
2. An institution should be permitted to rely on historical analysis of such data to form the basis of an estimate of the capital "add-on" due to "losses below the threshold". This analysis may test the historical data for seasonal effects, structural breaks, or trends.

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TOPIC 4: External Data and Scenario Analysis

I. Regulatory Issues and Concerns

A. The industry must resolve the question of effective use of external data.
B. Scenario analysis – same effective use concern.

II. External Loss Data and Quantification

A. External Loss Data (ELD) – Range of Practice Highlights (2012) -_Although External loss data is one of the four basic elements required for AMA, there is inconsistent treatment of ELD in models:

1. Most, but not all, use ELD as a direct input to their model.
2. Most integrate ELD with ILD for use in models.
3. Homogeneity or other statistical tests are generally applied prior to incorporating the ELD into the model.
4. ELD is generally filtered for business lines, products or other risk profile considerations (e.g., business model); relevance is a key consideration.

B. Industry Observations and Practices

1. Challenges of using ELD in models

   a. Direct incorporation into the capital model poses a challenge as to how to compensate for differences between banks in areas like business lines, product offerings, effectiveness of control environments, culture, asset size, etc. This is especially true when estimating severity distributions.
      i. Large banks with a significant volume of internal loss data are typically so large that using external data is of less importance to them
      ii. Smaller banks or banks with limited internal loss data have great difficulty with direct pooling
         - Often fail to demonstrate statistically that internal and external data can be combined
         - Capital estimates are completely driven by severe tail events from other institutions that may have little relevance for the bank

   b. Lack of scaling tools availability.
   c. A primary source of external data for industry is ORX and the anonymity of these data causes concerns of homogeneity regardless of the unit of measure (Basel event type, business line or some combination of both).
   d. Survival bias is inherited in all ELD. Data supplied to consortiums are from banks that continue to operate. ELD usually excludes the types of loss events that cause banks to fail since the banks in question are no longer contributing to the consortiums.
   e. It is important to recognize the heterogeneity of this pool of data and that unique characteristics of each financial institution will influence how these data are captured in the capital models (direct or indirect).

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f. Key questions for resolution -- when combining ELD and ILD, should banks pool the data? If they pool, should they simply combine losses or should they weight ELD differently than ILD?

2. Advantages of using ELD in the models

a. The strength in the use of external data is that it allows financial institutions to leverage the experience of peer firms to assess the riskiness of specific event types / businesses that they are (or may be) engaged in.

3. ELD – Positions and Observations

External loss data definitely should be considered in AMA models.

a. Should filtering of ELD be limited?
   i. Not necessarily; objective is to ensure homogeneity of the data

b. Should ELD only be used in benchmarking models and used for comparative basis?
   i. Quite often ELD is required to ensure sufficient data to predict severity loss distributions

c. Comparison to Peer Institutions is appropriate, but limitations exist
   i. Scaling to size of institution can be problematic
   ii. Business Mix is difficult to account for
   Bank-specific factors (internal controls) are not factored

d. The treatment of extraordinarily large losses remains a challenge and the industry continues to work toward appropriate principles for representing them in capital estimates.

III. Scenario Analysis and Quantification

A. Scenario Analysis Usage

Scenarios provide the benefit of a forward-looking assessment of risk as opposed to a backward-looking view of historical loss data that may or may not still be relevant to the organization.

1. Creation of scenarios

a. Most banks use structured presentations / group workshops to gather scenarios.
b. Participants in the forums / processes are fairly consistent across banks involving Business line, senior or executive management; business line staff; business line control function staff; and / or corporate operational risk management.
c. Of the data provided to scenario development participants, it is most common to provide external loss data, internal loss data or BEICF data.

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d. Scenarios are created at various levels. They maybe at the enterprise-wide level, major business line or business process, by unit of measure, by risk theme, or by other measure.
e. Many banks maintain a scenario library.
f. Most scenarios are refreshed at least annually. Reviews may also be triggered by a benchmarking process to reflect changes in the business environment, significant changes to assumptions, high severity and high risk ratings, etc.
g. Most often the validation of scenarios is the responsibility of ORM. Some banks use independent groups such as corporate ORM or internal audit.

2. Information collected during the creation process

Key information collected during workshops consists of severity, descriptions, severity and causes / drivers. A significant but lesser number of banks also collect frequency data.

3. Scenario Applications

a. Most banks use scenarios as indirect inputs into their capital model.
b. Direct input into the model often combines scenario data points with ILD or ELD.
c. Indirect input uses scenarios to benchmark scenario severity amounts against capital model output. Some banks use scenario data in a benchmark model whose results are compared to the core model. Others benchmark severity and frequency inputs.
d. Not all scenarios are designed and used for the capital model. Using SA data for risk management uses help identify control gaps in firms, to understanding plausible op risk events, identifying potential control enhancements or risk mitigation actions and support for other risk management such as stress testing, ICAAP, and understanding a firm's risk profile.
e. When institutions use only a subset of scenarios in the capital model, their approaches vary in terms of how the input set is determined, such as:

    i. An expert judgment-based process to select the relevant input along with appropriate governance and controls;
    ii. A top-down approach in which the risk management group determines the number of scenarios and identifies risk themes that will be used in capital quantification; or
    iii. A filtering mechanism or other rules-based approaches are used to select specific scenarios from the scenario library for application in capital quantification.

f. Regulators appear inconsistent in recognition of risk management scenarios versus risk modeling scenarios

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B. Scenario Analysis Positions

Following are positions that the AMAG has developed relative to Scenario Analysis practice, and are also based on extensive collective industry experience[19]:

1. Scenario Analysis continues to develop as a very *important and valuable tool* for the management and measurement of operational risk;
2. In order to accommodate the differing needs, objectives, and uses of Scenario Analysis across institutions, flexibility of implementation should continue to be a critical underlying element of SA practice;
3. While the AMAG has observed signs of convergence on certain aspects of Scenario Analysis, the Group believes that there should not be an expectation that all aspects of practice will eventually converge, and hence the supervisory community should continue to apply a principles-based approach, as opposed to a prescriptive one, to the use of Scenario Analysis;
4. To be credible the Scenario Analysis process must meet *standards and rigor* commensurate with its use. That is, in light of the value demonstrated at institutions in a range of Scenario Analysis processes and practices, the definition of Scenario Analysis should be refined and the rigor and documentation of the process can and should be permitted to vary depending on measurement or management use; and
5. Appropriate use of Scenario Analysis benchmarking should be permitted to result in an upward or a downward adjustment to the operational risk capital amount.

[19] These were also among scenario analysis positions that were also presented and supported in AMAG's Scenario Analysis Industry Position Papers released in 2011 and 2012.

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TOPIC 5: Model Risk, Benchmarking and Back-testing

I. Regulatory Issues and Concerns

A. How should Model Risk and Model Error be taken into account?
B. How has the industry addressed model risk and stability from period to period?
C. What is the range of practice in benchmarking and back-testing?

II. Model Risk and Model Stability

A. Model Validation – Range of Practice 2012

Among the findings from the 2012 AMAG Range-of-Practice survey section on model validation was that:

1. Most firms have formal programs to validate data within the risk management function (65%); a significant but lesser number perform informal data validation activities within the business line (35%); at others internal audit validates data as part of their audit plan (30%).

B. Large Losses and LDA Model Stability

Periodic extraordinary losses present significant challenges for the stability of LDA models. When an extremely large loss develops, at least one of the following characteristics is often present. Identifying these characteristics is crucial to understanding and modeling the risk accurately.

1. Losses for which the impacts are realized over an extended time period.
2. Those that are incorporated in a firm's loss dataset through the takeover of another institution.
3. Losses that have occurred (internally or at peer organizations) but are deemed to not be relevant to a firm's current business environment.
4. Others for which their severity is linked to macro-economic factors, which have a significant relationship to size of the exposure and business activity.
5. Due to homogeneity of risk profiles, extremely large internal and external losses may have different criteria to be justified.

C. Challenges Unique to Extraordinary Legal Losses

1. Most operational risk losses fall into the category of a sudden event that produces an immediate financial impact, and therefore a buffer (I.e., capital) is needed. Legal losses, on the other hand, do not fit these characterizes. Although the lawsuit might appear very suddenly, realizing the losses that might result from it are not.
2. There is a disconnect between the 1-year time horizon used for defining capital requirements and the requirement that loss amounts over the number of years are treated as a single loss event (e.g., large legal losses)
3. There is a timing disconnect between the manifestation of very large legal losses and the underlying causative factors that existed often years earlier (e.g., member institutions in 2013 have different risk profiles, and in most cases very different business practice and control structures than they had in 2008).

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4. Other considerations already complicate quantification based on legal losses. Contrary to most non-legal loss events, once a legal case exposure is deemed material, institutions establish reserves for them and adjust those reserves as information about exposure develops. One can argue that because of this, once the reserves are established, those provisions should be deducted from capital estimates, not then factored in as a basis for increasing them even further.

III. Benchmarking

A. Industry Approaches and Range-of-Practice (2012) – Key findings of recent AMAG ROP surveys:

1. Comparing final capital estimates against various benchmark models – A range of practice exists – Results indicated that it is most common to do so 'vs. use of an internal data model alone' (53%). The next most common response was 'comparison to a scenario based model alone' (47%), and then 'to an external data model alone' (24%).
2. Reconciling the differences when (if) generating multiple capital estimates or employing multiple benchmark models -- A range of practice exists here, as well. The most common approach being use of set rules or principles to determine final capital estimate, but with only 36% of members indicating this approach.

B. Documented Procedure -- Banks should have a documented procedure for benchmarking the capital model results and the overall firm level capital. The documentation should discuss:

1. The distinction between benchmarking the model results and benchmarking OR Capital for an entity (Firm / LOB):

   a. Benchmarking model results typically performed using alternative models; and
   b. Benchmarking the Firm Level (or LOB level) OR Capital results typically done using peer comparisons, standard metrics, and ratios.

2. Determining which ORC model results are to be included in the benchmarking exercise (Firm level, LOB Level, or UOM level)

   a. Firm Level should be mandatory – it can be performed:
      i. Using alternative models; and
      ii. External / peer bank information.

   b. LOB level:
      i. External information and metrics are available for benchmarking;
      ii. Alternative models could be used; but
      iii. Should not be mandatory.

   c. UOM Level:
      i. Extremely difficult, if not practically impossible using external benchmarks;
      ii. Should be limited to benchmarking of model results using alternative models
      iii. Benchmarks could be used as part of the model selection criteria (e.g., capital for UOM must be greater than bootstrap results)

3. Deciding how often the benchmarking exercise is refreshed:

    a. Certain metrics are easy to update and should be refreshed as often as capital is refreshed; and
    b. Other metrics could be more challenging and therefore would be refreshed annually (even if the capital is refreshed quarterly).

C. Benchmarking Model Results with alternative models -- Model results should be benchmarked using alternative models. Options might include:

1. Bootstrapping[20] is an alternative model:

    a. Relatively easy to build;
    b. Should be a highly recommended alternative benchmark; and
    c. Regulators have often implied that bootstrapping should be used as a floor, but this is not necessarily valid from a pure statistical perspective.

2. Alternative models built using scenario analysis information typically can be used most effectively to benchmark capital results at UOM level:

    a. Scenario analysis information is not always conducive to be used as benchmark model;
    b. Scenario methodology varies across institutions and, therefore, not all banks are able to use it in the same manner; and
    c. To be performed only if data permit.

3. Exposure-based models for a specific risk or UOM could be used to benchmark model results for a given risk or UOM and, in some cases, at a firmwide level:

    a. Exposure-based models can be difficult to build and resource intensive;
    b. When constructed with representative metrics, however, they can be quite effective;
    c. Usefulness for benchmarking depends on the institution and quality of the model; and
    d. To be performed on a case-by-case basis and, of course,.only if available.

4. Other alternate models – if available

    a. External data only – Issues:
        i. Very challenging to make any sense of results
        ii. Scaling could be a factor
        iii. Relevance of points
        iv. If ORX data – but data points are anonymous
        v. Should NOT be mandatory

D. Benchmarking Firm / LOB Level OR Capital using metrics and external information

1. Basic Indicator Approach (BIA) and The Standardized Approach (TSA)

[20] Bootstrapping involves a method for assigning measures of accuracy to sample estimates.

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a. The operational risk regulatory capital calculated using the AMA model should be in the range of the capital estimates produced using the BIA and TSA
b. Given the current environment and regulatory guidance on AMA models, it appears that the regulatory expectation is that AMA results should actually be higher than BIA or TSA

2. Financial Statement Comparison to Peer Institutions

a. European institutions are publishing their OR Capital in their Financial Statements. This information could be used to compare a bank's AMA capital.

i. Comparison can be difficult at times due to scale and business mix differences
ii. Ratios are often used to attempt to mitigate scale issue
  - OR RWA as a percent of total RWA
  - OR Capital as a percent of total Revenue
iii. Understanding the business mix at a peer institution should be used to ensure that the comparison is made to appropriate internal business unit
  - For instance, if a peer bank is mostly focused on Investment Banking activity, the benchmarking might be more appropriate to a bank's investment banking unit

b. Because US Banks have not exited Basel II parallel run, using information from the financial statement is not readily available as an option

i. Alternative is to rely on informal discussions with peers to benchmark firm-level capital estimate
  - Adjustment for scale might be needed

c. NOTE: Peer comparisons across regulatory jurisdictions should be interpreted with caution as differences in acceptable methodologies and data element usage may create huge differences in capital outcomes

i. The BCBS[21] recently reviewed the consistency of RWA outcomes for *market risk*.
ii. The report found that substantial variation in RWA may not reflect actual differences in risk but arise from:

  - Differences in supervisory decisions across jurisdictions;
  - Differences in supervisory decisions as applied within jurisdictions; and
  - Differences in modeling choices by banks.

iii. A recent review of RWA estimates for market risk exposures in trading book and banking book found very large differences in risk estimates across institutions and regulatory regimes.

[21] Basel Committee on Banking Supervision (BCBS)

iv. Even when RWA estimates were computed with bank models on the same portfolios large differences in results persisted across regulatory jurisdictions.

3. Using AMAG and ORX Benchmarking Surveys

   a. Banks can use the information in these surveys to benchmark certain aspects of the models and/or the actual capital results.
   b. It is difficult to be very precise with the benchmarking as the information is usually anonymous.
   c. Oftentimes the survey requires the use of standard Business Line hierarchy, which is not always easily mapped to the internal Line of Business that a bank is using to report capital.
   d. The objective of this benchmarking should be to identify area(s) where the bank is clearly an outlier relative to its peers.
      i. If it is determined that a bank is an outlier relative to its capital estimate or modeling methods, then it should investigate and either work to remedy the situation or provide clear rationale for why it might be an outlier.

E. Benchmarking – General conclusions/ Positions

1. Benchmarking is a valuable exercise that allows a bank to determine whether OR capital results are within an acceptable range given industry best practices.

   a. Bootstrapping is often considered a floor by regulators:
      i. But it is not necessarily accurate from a mathematical perspective; and
      ii. Also not if there is significant change in internal and/or external factors.

   b. Other models (exposure-based models, scenario analysis models) could also be used as an effective way to validate results:
      i. But the regulatory bias to use the "most conservative" result does not provide incentive for banks to innovate and attempt alternatives; and
      ii. If alternative models are more risk sensitive, then their use should be allowed even if the capital estimate that they produce is lower than that of the LDA approach.

   c. BIA and TSA metrics could be used, but these metrics are not risk- sensitive metrics:
      i. Initially the U.S. Rule "intended" for AMA banks to qualify for a "discount" compared to BIA and TSA; and
      ii. Currently, however, an AMA bank's capital results may be significantly above these metrics.

   d. Comparison to Peer Institutions is appropriate but limitations exists
      i. Scaling to size of institution can be problematical
      ii. Business mix is difficult to account for
      iii. Bank-specific factors (internal controls) are not factored in

   e. It is important to realize that an appropriate risk sensitive benchmark is not readily available

f. One potentially effective way to benchmark each institution's OR capital model would be to perform a benchmarking exercise in which all banks are provided exactly the same input data. The Office of the Superintendent of Financial Institutions (OSFI) in Canada has initiated and completed such an exercise. The exercise appears to have been quite useful for banks.

IV. Back-Testing

A. AMAG Range of Practice Survey findings on Back-testing (2012)

1. Comparing realized operational loss frequency to model estimates from prior periods – Divergent practices observed, in which less than half of members (44%) 'make the comparison', whereas the remaining 56% 'do not or are not yet doing so'. The survey detail appears to indicate some convergence for those that do so at the UOM level or for a combination of UOMs.

2. Comparing realized operational losses (severity) to model estimates from prior periods -- There is clear convergence here, with far more members (72%) comparing severity.

3. How the comparisons are made – Convergence is apparent here with many 'comparing total annual loss to capital estimate' (53%) or 'total annual loss to model-based expected aggregate loss' (60%). More often than not these comparisons are made at the UOM level (73%) or at the top of the house (47%).

4. Actions are taken, if any, when realized losses ($) exceed prior period estimates – It has been observed that there is convergence around either additional investigation prior to any modifications (47%) or that the selection of severity distribution is re-evaluated (27%).

5. Ratios: There is a broad range of results indicated on both 'losses per dollar of Gross Income for the prior 12 months' (i.e., 2011 calendar year) and 'Losses per dollar of Gross Income for the prior 36 months' (i.e., 2009-2011 calendar years)

B. Documented procedure -- Banks should have a documented procedure for back-testing their capital model results and their overall firm-level capital.

1. The distinction between how the loss amount is recorded for the purpose of the LDA model referred to in this document as Event Basis) and how it is recorded from a P/L perspective (Impact Basis) should be noted.

   a. Event Basis is the "true" test of the model
   b. Impact Basis is more a test of the capital adequacy level, not of the MODEL
      i. Under certain circumstances (very unlikely, but possible) a failure of this back-test would not necessarily mean that the model is wrong, but rather an issue with the manner in which the Rule prescribes the treatment of losses.
   c. However, banks should back-test according to both alternatives

2. Event Basis

    a. The estimated Capital for each UOM should be evaluated against the yearly loss total according to the manner in which the data were input into the model.

        i. Any UOM for which the capital is breached should be evaluated carefully.
        ii. Depending on the number of years and UOMs, breaches are possible / should be expected.
        iii. An effective report would show the annual aggregate loss total (input data) as a quantile of the simulated distribution for each UOM.
            - A heat map would be useful and should be generated to highlight that the annual losses are well dispersed when compared to the simulated distributions:
                - If there is an excess of "red" then model is probably underestimating capital (red is high quantile); and
                - If there is an excess of "blue" then model is probably overestimating capital (blue is low quantile).

    b. Testing at the Line of Business Level / Firm Level
        - If the Event Basis back-testing result at the UOM level is satisfactory, then the Line of Business Level and Firm Level back-testing should also pass the test relatively easily (unless there is something significantly wrong with the model's dependence structure).

3. Impact Basis

    a. Estimated Firm Level capital should be greater than the:

        i. Actual annual losses for the Bank looking back as far as possible (likely not available for more than a few years); or
        ii. Actual 4-quarter loss total for the bank based on a consecutive rolling-quarter basis.

    b. There should not be any requirement to perform this type of back testing at the Line of Business or UOM level as the capital adequacy concern is at the Firm Level only

C. Back-testing – General Observations / Positions

1. The distinction between Event Basis and Impact Basis is not viewed consistently by Regulatory Supervisors, and sometimes seemingly overlooked entirely.

    a. Any guidance on this subject should acknowledge the distinction and address it accordingly.
    b. This distinction is most pronounced when dealing with large litigation that spans multiple years, and for which significant losses are accrued over time.

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2. The industry encourages regulators to consider resisting the temptation to set an excessive number of "floors" in guidance

    a. Actual Annual aggregate loss is an obvious floor for firm-level capital.
    b. A rolling 4-quarter aggregate loss would also be reasonable for firm-level capital.
    c. UOM-level back-testing should be performed, and results should be evaluated.
        i. There should not be a floor, however, based on the largest aggregate annual loss for a UOM.
        ii. Instead, institutions should have documented process for evaluating the results of the back-testing.
            - Including more in-depth analysis and documentation of the reason for any historical breaches.
            - Breaches should be random and not systematic.

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Alternative Models Discussion

I. LDA Models – Overcoming Some Fundamental Concerns

LDA provides a rigorous approach for modeling past loss distributions. It has become the standard practice for modeling those operational risks for which historical loss distributions are assumed to be the best predictor of future loss distributions. In practice, LDA works satisfactorily for many risk types, but remains problematical for others.

A. Representation-of-Risk and Timing Concerns

Certain operational risk types have emerged as quite material over recent years and have proven to be problematical for LDA from a representation-of-risk standpoint.

1. Litigation events linked to credit or market risk losses emerged during the recent crisis as material sources of operational risk. Many of these events are related to representations and warranties on sold mortgages that defaulted during the crisis. The risk exposure for these events is defined by the credit or market risk exposure in contrast to standard operational risk types with an undefined exposure, and although operational in nature the losses can be driven by credit events such as defaults. Additionally, predictive factors for the operational risks are not captured in LDA, but could be assigned using a combination of statistical modeling and expert judgment, allowing for factor based quantification of capital requirements.
2. Litigation liabilities assumed as a part of acquisitions are often anticipated and reflected in discounted purchase pricing. LDA does not reflect the risk drivers used in setting purchase price discounts. In contrast, those drivers would also support predictive capital modeling using factor-based models.
3. The use of LDA for these 'predictable' risk types has been observed to undercapitalize known risks before they occur, and overcapitalize for risk after the losses materialize, creating inappropriate capital estimates, including:
    a. Underestimation at the time of manifestation of loss due to lag in "realizing" losses for events that are already known to have been triggered. This is particularly relevant for large litigation losses for which there is a significant lag between the event trigger and the initial reserve. (e.g. PLMBS[22] issues);
    b. Overestimation of capital estimates in a time lag after the manifestation of loss due to extrapolation to the 99.9th percentile and an over-stretched distribution; and
    c. The large data gap is a modeling issue/challenge and capital results are questionable.
4. An unintended consequence of this timing paradox is that it results in disincentives to taking strong risk management steps to mitigate risk. Where LDA models drive capital and risk management, capital will at times increase in tandem with risk mitigation steps, a counterintuitive phenomenon, thus being at odds with strong risk management.

[22] Private Label Mortgage-backed Securities

B. Implications of LDA Model Instability

The industry has observed model instability, and thus capital volatility, due to the non-robust model parameters relative to inclusion of the data or in combination with a methodology change of some type necessitated by the data (e.g. distribution change, fitting routine change). The implications can be:

1. A disconnect with Market and Credit Risk practices, due to not using generally accepted risk measurement techniques.
2. Loss of credibility with Senior Management due to the lack of transparency and inability to apply their intuition to understand the model results.
3. Reaction to public disclosure (Pillar 3) – industry and regulators alike must be sensitive to analyst review and reporting. Important for industry, of course, to deal with undesired market effects on stakeholders, and also important for regulators to deal with undesired consequences.
4. Concern about understanding and modeling an event's risk profile accurately manifests itself especially in the U.S. Generally agencies require LDA and its retrospective-only view and approach to estimating capital, which presents little or no opportunity to modify the capital results through prospective scenarios or other means.

II. AMAG Position on Developing and Applying Alternative Models

The U.S. Rule is explicit in allowing for the development and use of various approaches to operational risk quantification, which should include but not limited to enhancements to LDA, alternatives to LDA, or models that supplement LDA.

III. Examples of Alternative Models

A. Factor-based Models

1. Comprised of a series of exposure and risk factor pairs, where exposures might include but not be limited to business transaction or asset variables and the like. Risk factors are intended to represent likelihood of loss. Control factors may also be a third variable, and may be included to represent additional risk adjustment and information value.
2. Typically presents upwards of ten (10) exposure / risk factor pairs
3. Considers Maximum Possible Loss (MPL) in populating the exposure variable.
4. Draws from publicly-available data, such as from financial reporting (e.g. assets, credit exposure) and non-public data (e.g., legal exposure, reserves).
5. May include certain scenario-based pairs, as well, using maximum possible loss figures there, as well, for the exposure variable.
6. Fits a distribution to results of the series of exposure / risk factor combinations (e.g., Beta distribution), and selects 99.9% confidence level.
7. Effective use of factor-based modeling to quantify capital requirements for the types of events highlighted above (e.g., litigation as an extension of credit or market events and litigation liabilities assumed as part of acquisitions) would support improved soundness of operational risk capital calculation frameworks.

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   a. Factor-based modeling would incorporate available data pertaining to risk exposure in quantifying capital to better enable banks to hold capital based on known risks.
   b. By linking capital requirements to risk exposure, factor-based models support strong risk management by increasing capital requirements as risks are added and allows for reductions in reaction to risk mitigation actions.
8. Major benefit of factor models is their transparency, which results in:
   a. The ability to manage capital by making risk-based decisions
   b. Ability to price individual transactions or expansion into new market segments etc.

   Contrast to LDA black-box methodology which produces a tax with no management control.
9. The industry recognizes that calibration of factor-based models is still an issue and reliant on the availability of relevant loss data, both internal, and more importantly, external.

B. Scenario-based Models

1. Scenario analysis-oriented models are based on a process designed to identify the worst-case losses for each risk class.
2. The process takes into account internal and external data, as well as the business environment and control factors to identify potential scenarios of large losses and their associated financial impacts.
3. The process of scenario analysis yields loss estimates for each risk class along with their associated confidence levels. These estimates then form the inputs to the severity distribution estimator.
4. Internal losses greater than established thresholds are used to derive empirical frequency estimates for each risk class.
5. In the event that there is no internal loss data to determine frequency, expert judgment during the scenario analysis process is used. A minimum frequency or floor may also be applied. Judgment may also be employed to modify empirical frequency to a more forward-looking basis for a given risk class.

C. Hybrid LDA Models

1. LDA Model with Multiplier Approach

   a. The challenge to LDA lies primarily in the fact that banks are asked to make a 1-in-1000 year prediction based on only 10 years or so of operational risk loss data.
   b. Multiplier -- One way to reduce volatility (due to uncertainty in the extreme tail region) is to allow the banks to use LDA to produce capital at a lower confidence level (e.g. 99^{th} percentile), and use a multiplier (could be risk-type based) to scale it up to the 99.9^{th} level.
   c. Definition of Multiplier -- The multiplier can be defined by regulatory community or based on extensive research and/or bootstrap simulation under reasonable distribution and parameter specifications, etc.

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2. LDA Model with Add-ons

   a. Calculation of a core capital figure at a lower confidence level (e.g., 99th percentile)
   b. Development of add-ons using an incentive and factor- or scenario-based approach to represent difficult-to-model events such as those described in Section I.A., above.

IV. Triangulating Model Results

There are no guarantees of precision in modeling, of course. One means of increasing the reliability of capital estimates, however, is by considering several reference points, or findings from different models, in representing final capital estimates. This approach has been suggested in both industry and regulatory discussions alike, and may lay the groundwork for the introduction and broader use of alternative modeling approaches.

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Attachment A

About the AMA Group

The Advanced Measurement Approaches Group (AMAG) was formed in 2005 by the Risk Management Association (RMA) at the suggestion of the U.S. AMA-BQT (formerly the Inter-Agency Working Group on Operational Risk). The RMA is a member-driven professional association whose purpose is to advance the use of sound risk management principles in the financial services industry.

The purpose of the AMAG is to share industry views on aspects of Advanced Measurement Approaches (AMA) implementation with the U.S. financial services federal regulatory agencies. The Group consists of operational risk management professionals working at financial service organizations throughout the United States. The AMAG is open to any financial institution regulated in the United States that is either mandated, opting in, or considering opting in to AMA. A senior officer responsible for operational risk management serves as the primary representative of each member institution on the AMAG. Of the US financial service institutions that are currently viewed as mandatory or opt-in AMA institutions; twenty were members of the AMAG at the time of this writing.

The members of AMAG are listed below. They are provided for identification purposes only. This paper does not necessarily represent the views of RMA's institutional membership at large, or the views of the individual institutions whose staff have participated in the AMAG.

Bank of America / Merrill Lynch
Bank of the West
BMO Financial
BNY Mellon
Capital One Bank
Citizens Bank
Comerica
Deutsche Bank
Goldman Sachs
HSBC
JP Morgan Chase
Keycorp
Morgan Stanley
Northern Trust
PNC
State Street
SunTrust
TD Bank Financial Group
Union Bank
Wells Fargo

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