



EUROPEAN CENTRAL BANK
BANKING SUPERVISION

Instructions for reporting the validation results of internal models

AMA Pillar I models for operational risk

BANKENTOEZICHT

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1 Background and rationale

1.1 Introduction

Regulators and supervisors attribute a crucial role to the assessments conducted by internal validation functions throughout the life cycle of internal models. The term “internal validation function” encompasses the personnel of a credit institution who are responsible for validating internal models and reporting the results of the internal validation process.

In accordance with the requirements set out in Regulation (EU) No 575/2013¹ (the Capital Requirements Regulation or CRR), credit institutions must ensure that their Pillar I internal models for credit, market, counterparty and operational risk are subject to a validation process with the aim of verifying the overall adequacy, robustness and reliability of the internal estimates used to calculate own funds requirements (OFR).

The review carried out by the internal validation function is the first point of reference for supervisors when performing internal model-related tasks such as model approvals (initial approval, model changes, extensions and roll-outs) and ongoing model monitoring.

The instructions in this document shall assist significant credit institutions supervised by the European Central Bank (ECB) under the Single Supervisory Mechanism (SSM) in complying with the decisions² requiring the reporting of additional supervisory information from the validation function for operational risk models (hereinafter: Decisions). To this end the instructions (i) describe the background for the requested reporting of the significant credit institutions' validation results and (ii) explain the supplementary validation reporting using common metrics to assess Pillar I models for operational risk introduced by the Decisions. This supplementary reporting is without prejudice to credit institutions' own methods for validating internal models.

These instructions do not constitute a legal act, and they do not have any binding legal effect. Nothing within their wording, context or substance should be construed otherwise. These instructions are neither intended to replace or overrule applicable European Union (EU) law nor national law.

¹ Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012.

² Decisions were sent by the ECB in May 2018 to institutions applying AMA for the calculation of OFR.

1.2 Regulatory framework

The CRR lays down minimum requirements with respect to the validation of Pillar I models for different risk categories³.

In accordance with the requirements set out in the CRR, the European Commission published, on 14 March 2018, the delegated Regulation (EU) 2018/959 regarding regulatory technical standards on the specification of the assessment methodology under which competent authorities permit institutions to use Advanced Measurement Approaches for operational risk ("RTS on AMA").

The above-mentioned RTS on AMA attribute considerable importance to the assessments conducted by internal validation functions and provide the competent authorities (CAs) with detailed instructions on how to examine the governance, methods and procedures of internal validation functions, as well as the soundness of the reporting process in terms of validation results.

1.3 The role of credit institutions' validation reporting in the ECB's ongoing monitoring of internal models

A sound validation function is crucial to ensure the reliability of internal models and their ability to accurately compute capital requirements. It is the responsibility of the credit institution to ensure that its internal models are fully compliant with all regulatory requirements.

The ongoing assessment of permission to use internal approaches is governed by Article 101(1) of Directive 2013/36/EU (the Capital Requirements Directive or CRD),⁴ which requires CAs to review credit institutions' compliance with the applicable requirements on a regular basis, and at least every three years.

For the purposes of Article 101(1) of the CRD, ongoing supervision of models includes analysis of credit institutions' model validations, as stated in the ECB guide to banking supervision⁵, as well as the SSM supervisory manual.⁶

Each credit institution produces validation reports on internal models in accordance with the scope and standards set out in the applicable regulation (such as the CRR) and the relevant RTS. The ultimate goal of those validation reports is to allow the credit institution's senior management to understand the performance and weaknesses of their internal models.

³ For the main requirements for operational risk, please see Articles 321(e), 321(f), 322(2)(d), 322(5) and 322(6)(d) of the CRR.

⁴ Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directives 2006/48/EC and 2006/49/EC.

⁵ See the "[Guide to banking supervision](#)", as published on the ECB Banking Supervision website in November 2014.

⁶ See the "[SSM Supervisory Manual - European banking supervision: functioning of the SSM and supervisory approach](#)", as published on the ECB Banking Supervision website in March 2018.

All individual validation reports should be shared with the ECB in accordance with the Decision, ideally no later than one month after the validation reports are finalised and have been approved by the credit institution's management in accordance with the institution's internal policies.

2 Supplementary validation reporting on operational risk

Credit institutions are required to develop validation processes to validate their internal models.⁷ While all validation processes must comply with the same regulatory requirements, the ability to perform comparisons across models and institutions remains limited.

Against this background, supplementary validation reporting requested by an ECB decision enables the ECB to carry out ongoing model monitoring mandated by Article 101(1) of the CRD by allowing an initial assessment of the performance of different models on the basis of a common set of statistical tests and analyses (validation tools) for Pillar I models relating to operational risk. The internal validation function within each credit institution is responsible for implementing this validation reporting.

Most of the validation tools focus on quantitative aspects of internal models. To provide clarity and facilitate the implementation of the validation tools and reduce the room for interpretation, detailed instructions on their implementation are provided below.

Under no circumstances should the validation tools referred to in this document be regarded as the minimum set of analyses needed to prove compliance with the applicable requirements set out in the relevant legislation. The validation of internal models remains the responsibility of the institution in question, which should determine the level of sophistication needed, taking into account the complexity and materiality (both current and prospective) of the internal models and their range of application.

This chapter is organised as follows: Section 2.1 defines the scope of application of the validation tools, Section 2.2 provides instructions on the reporting process, Section 2.3 contains definitions valid for all validation tools and Section 2.4 describes each validation tool in detail. More specifically, Section 2.4.1 describes validation tools for the composition of own fund requirements for operational risk, while Sections 2.4.2 and 2.4.3 describe the validation tools for the quality of the outputs and inputs of the AMA models, respectively. Section 2.4.4 describes validation tools for the appropriateness of modelling assumptions and Section 2.4.5 describes the inputs of the new Standardised Approach (SA) for operational risk envisaged by the Basel III reform⁸: these inputs are collected with the main purpose of monitoring the impact of the new SA and ensuring a smooth transition from AMA to the SA in the future. Finally, the Annex provides guidance on compiling the templates for submitting the results of the validation tools.

⁷ For details of the main requirements, see Articles 321(e), 321(f), 322(2)(d), 322(5) and 322(6)(d) of the CRR and Articles 16 and 17 of the RTS on AMA.

⁸ See the document "Basel III: Finalising post-crisis reforms", published by the Basel Committee on Banking Supervision in December 2017.

The following tools should be based on the institution's loss data history, including the most recent data since the validation framework was approved (see Section 2.2).

2.1 Scope of application

The following validation tools should be applied at a consolidated level in the institution, considering that, in most cases, an AMA model is created at the highest level of consolidation in order to benefit from the availability of data. If the model is also applied at lower consolidation levels (e.g. legal entity, sub-consolidated level) and used at a solo level to calculate regulatory capital requirements, the validation tools could be also applied at these levels if they add value.⁹

With the exception of some information requested in Sections 2.4.1 and 2.4.5, analyses should only refer to the parts of the group which use AMA (i.e. excluding parts of the group which use the Basic Indicator Approach (BIA), the Standardised Approach (TSA) or the Alternative Standardised Approach (ASA)).

2.2 Reporting instructions

Using a predefined template, the credit institutions should submit the results of the validation tools to the ECB together with the report documenting the outcomes of the internal model validation.

The validation tools should be implemented in accordance with the scope clarified in Section 2.1 and the observation period used by the institution for its most recent internal model validation. Without prejudice to the implementation period for the internal validation, the recommended reference dates for the observation period are either end-June or end-December.

Credit institutions are invited to use the general comments field in Template 1.1 to comment on the results of the validation tools and to highlight any related analyses documented in the internal validation report that is submitted together with the results of the validation tools.

The template for reporting the results of the validation tools is available as an attachment to this document. The template should be submitted under the naming convention "[LEICode]_OP1_[ReferenceDate]_[VersionNumber]", where:

- [LEICode] is the LEI code of the institution submitting the template according to the scope of application described in the previous section;
- [ReferenceDate] is the reference date on which the validation tools are implemented, to be expressed as DDMMYYYY, e.g. 31122018;

⁹ It is not necessary to perform analyses at lower levels if, for instance, such levels are determined by an allocation of consolidated figures.

- [VersionNumber] is the number indicating the order in which the results for a given reference date are submitted, e.g. "1" for the first submission of 31122018 and "2" for the second submission.

2.3 Definitions

The **definitions** below apply to the entire set of validation tools for operational risk (unless explicitly stated otherwise).

- (a) *Relevant indicator*: this refers to the indicator as defined by Article 316 of the CRR.
- (b) *Observed losses*: losses due to operational risk suffered by the institution during a specific time period. Two different types of observed losses are requested: those stemming from the institution's calculation dataset (see item (j)) and those based on an accounting impact view (see Section 2.4.2 for further details and implementation examples).
- (c) *Recovery except insurance or Direct recovery*: in line with Article 21(b) of the RTS on AMA, this refers to the recovery not originated from insurance and other risk transfer mechanism.
- (d) *Pending losses*: in line with Article 22(1)(d) of the RTS on AMA, this refers to losses stemming from operational risk events, which are temporarily booked in transitory or suspense accounts and are not yet reflected in the Profit and Loss (P&L), and which are planned to be included within a time period commensurate to the size and age of the pending item.
- (e) *Uncollected revenues*: in line with Article 22(1)(e) of the RTS on AMA, this refers to material uncollected revenues, related to contractual obligations with third parties, including the decision to compensate a client following the operational risk event, rather than by a reimbursement or direct payment, through a revenue adjustment waiving or reducing contractual fees for a specific future period of time.
- (f) *Timing losses*: in line with Article 2(14) of the RTS on AMA, this refers to 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.
- (g) *The four elements*: in line with Article 20 of the RTS on AMA, this refers to the use of internal loss data (or ILD), external loss data (or ELD), scenario analysis and business environment and internal control factors (or BEICFs).
- (h) *Operational risk category (ORC)*: in line with Article 2(8) of the RTS on AMA, this refers to the level (such as the institution's organisational unit, operational risk event type, business line) at which the institution's operational risk measurement system generates separate frequency and

severity distributions for estimating operational losses. Consistent with Article 30(b) of the RTS on AMA, losses belonging to the same ORC must be:

- (i) *homogeneous*: all data occur from the same basic random model;
 - (ii) *independent*: there is no form of link, either deterministic or statistic, between data;
 - (iii) *stationary*: the characteristics of the data do not change when shifted in time or space.
-
- (i) *Major ORCs*: this refers to the set of ORCs which are the top contributors to the risk-weighted assets (RWAs) for operational risk. This set should represent at least 80% of the gross AMA RWAs, taking into account up to a maximum of 15 ORCs.
 - (j) *Calculation dataset*: in line with Article 2(2) of the RTS on AMA, this refers to the portion of gathered data, either actual or constructed, that fulfils the necessary conditions to serve as input into the operational risk measurement system to generate the AMA Own Funds Requirements (OFR).
 - (k) *Data collection threshold*: in line with Article 2(3) of the RTS on AMA, this refers to the loss value from which an institution identifies and collects operational risk losses for management and measurement purposes.
 - (l) *De minimis (or “Minimum”) modelling threshold*: in line with Article 2(5) of the RTS on AMA, this refers to the institution's choice of the loss value starting from which the frequency and severity distributions, either empirical or parametrical, are fitted to the operational risk losses.
 - (m) *Body-tail modelling threshold*: in line with Article 2(1) of the RTS on AMA, this refers to the loss value that separates the body from the tail of the loss distributions.
 - (n) *Core source*: this refers to the AMA element (or pooling of AMA elements) among the four elements used directly for the selection of the frequency and severity distributions (see Sections 2.4.2.1 and 2.4.4 for further details and implementation examples).
 - (o) *Last N years*: the time period from T - N years to T, where T is the reference date for the purposes of this exercise.

2.4 Validation tools

The validation tools for significant supervised entities with an approved internal model for operational risk focus on the following areas of investigation:

- composition of OFR;
- outputs of the AMA model;
- inputs of the AMA model;
- modelling assumptions;
- inputs of the Basel III Standardised Approach (SA).

Owing to the high level of heterogeneity in AMA models, the validation tools required for each area have been designed to be applicable to the majority of AMA models. If the validation tools are not applicable to a certain credit institution, the institution should provide a sound explanation for this in Template 1.1.

To ensure the efficient treatment of the outputs of the validation tools, the institutions are encouraged to provide any necessary explanations of their analyses. The validation tools aim to provide information useful for creating a general picture of the AMA models' performance; however, they are not intended to be exhaustive.

In the following sections, each validation tool is specified using the same structure. Firstly, the objective of the analysis is described, followed by a description of the tool. Detailed guidance on implementing the tool and the scope of its application are subsequently provided. Lastly, details are given on the reporting of the results.

2.4.1 Composition of OFR

The following validation tools aim to evaluate the composition of OFR for operational risk by looking at the use of AMA combined with or replaced by other approaches and at the breakdown of the scope of AMA into ORCs.

2.4.1.1 Combined use of approaches

Objectives of the tool

To collect general information on the composition of OFR for operational risk.

Description / implementation

Specifically, for each of the approaches used by the institution to calculate the minimum capital requirements for operational risk (BIA, TSA, ASA and AMA), the institution reports on:

- OFR;
- total assets (TA) for the previous year¹⁰;
- relevant indicator (RI) for the previous year;

¹⁰ The splitting of the TAs by approach should be based on the contribution of TAs to the consolidated figure. This equals the sum of the contributions to the consolidated TAs of the legal entities using the approach. The same splitting criterion should be considered for the relevant indicator.

- figures obtained in parallel-running exercises (for the AMA scope only):
 - (i) OFR, as if under the BIA;
 - (ii) OFR, as if under the TSA or ASA.

Reporting of the results

Results are reported in Template 1.1.

2.4.1.2 ORC details

Objectives of the tool

To define the major ORCs making up the scope of the AMA.

Description

As is well known, there are no common criteria used by AMA institutions to set up the ORCs. However, the most common drivers of the ORCs are the regulatory event types and/or the business lines and the products. Other drivers are used (such as legal entities and organisational units), but these are less common.

Implementation

The total number of ORCs used in the AMA model should be provided in Template 1.2.

To identify the major ORCs, the institution sorts the ORCs according to their contribution to the consolidated RWAs for operational risk (i.e. the value at risk (VaR) amounts of the ORCs), before the application of any offset (i.e. insurance, expected loss and diversification), and then selects the top ORCs from this list¹¹ to reach a coverage of at least 80%, up to a maximum of 15 ORCs.

Where, in some ORCs, the granularity associated with the frequency distribution is different to that associated with the severity distribution, the latter is used to identify the major ORCs.

In the template, the most common drivers and a residual item ("Other") are listed as rows. For each major ORC, the institution:

- inserts an "x" into the cells of the drivers considered in the AMA model and, where necessary, inserts an "x" into the "Other" cell,¹² leaving the remaining cells empty¹³;
- writes the institution's internal name for the ORC in the relevant cell at the end of the table.

Reporting of the results

Results are reported in Template 1.2.

¹¹ This criterion may involve selecting ORCs driven by different sources, for instance the top three ORCs that are driven by ILD/ELD, the ORCs from four to ten driven by the scenario analyses and the last five ORCs on the list still driven by ILD/ELD.

¹² For example, an institution that has a Level 3 event type (business line) classification for its ORCs fills in both rows 001-018 (101-120) in the event types (business lines) section – corresponding to a Level 2 classification – and the cell "Other". The name of the ORCs in cell 300 should provide information about the characteristics of the Level 3 drivers.

¹³ For example, if an institution only uses event types to classify the ORCs, it should not insert an "x" next to any business lines, but leave these cells empty since they do not constitute a driver that is explicitly used in the AMA.

2.4.2 Outputs of the AMA model

The following validation tools aim to evaluate the plausibility of the output of the AMA model by looking at consistency with observed losses and the model's ability to adequately reflect a given institution's operational risk profile:

- comparison of the AMA model estimations with observed losses;
- development of the risk figures over time.

Types of observed losses

Two types of observed losses should be considered for these validation tools: *from the calculation dataset* and *with an accounting impact view*. Both refer to the institution's internal loss datasets (i.e. they do not encompass ELD or other elements of the AMA).

Observed losses from the calculation dataset

In line with the definition in Section 2.3, the observed losses from the calculation dataset are the institution's ILD, which are entered into the operational risk measurement system to generate the AMA OFR.

The reference threshold for reporting this type of observed losses is the de minimis modelling threshold. The observed losses from the calculation dataset are reported in Templates 2.1 and 2.2.

Observed losses with an accounting impact view

This type of observed losses is based on an accounting impact view, meaning that the institution's ILD stemming from new events or loss adjustments¹⁴ of older events have to be assigned to the loss amounts of the years in which they produced an accounting impact. For example, if an event was accounted for in 2012 for the first time with a loss amount in the form of provisions of €1 billion ("new event"), and then the provisions were increased by €2 billion in 2013 ("positive loss adjustment") and, finally, €500 million in provisions was released in 2014 ("negative loss adjustment"), the institution will assign €1 billion to the loss amount in 2012, assign €2 billion to the loss amount for 2013, and subtract €500 million from the loss amount for 2014.

Operational risk losses that are related to credit risk and are subject to OFR for credit risk (boundary credit-related operational risk events) are not included among the observed losses with an accounting impact view.

Consistent with the accounting impact view, the maximum single loss in each year equates to one of the following (whichever is greatest):

¹⁴ If more than one loss adjustment is made for an event within a certain year, the amounts of all these loss adjustments are added together, taking into account the sign of adjustment (positive, negative). This sum is considered as the loss adjustment for that event in that year.

- the greatest loss amount net of direct recoveries related to a new event in that year;
- the greatest loss adjustment net of direct recoveries in that year related to an event first accounted for in a previous year.

The reference threshold for reporting this type of observed losses is the data collection threshold. Observed losses with an accounting impact view are reported in Template 2.2 only.

2.4.2.1 Comparison of the AMA model estimates with observed losses from the calculation dataset

Objectives of the tool

To check the adequacy of the AMA model's estimates against the previous year's observed losses from the calculation dataset.

Description

The most relevant figures provided by the AMA model (i.e. expected frequency, expected severity and total annual loss at different quantiles) are compared against the observed losses from the calculation dataset and/or summary statistics based on these.

For the frequency and severity, at ORC level, the loss values net of direct recoveries are compared with the corresponding frequency and severity estimates provided by the AMA model (expected frequency and expected severity).

For the total annual loss distribution:

- at ORC level, loss values net of direct recoveries are compared with the corresponding estimates provided by the model. If the institution recognises, at ORC level, insurance and/or other risk transfer mechanisms (ORTM) in the AMA model, as set out in Article 323 of the CRR, losses net of all recoveries are compared with the insurance and ORTM-mitigated estimates. If the institution uses an ORC that is determined solely by a scenario analysis, the empirical loss values to be considered should be all losses belonging to the Basel event type (Level 1) that most closely matches the type of scenario analysis determining the ORC;
- at the institution's overall level, loss values net of direct recoveries (or net of all recoveries (see the previous bullet point)) are compared with the corresponding estimates provided by the model. If the institution recognises correlations in the AMA model, as set out in Article 322(2)(d) of the CRR, the diversification effects are reflected in the estimates at the institution's overall level only.

Moreover, the institution provides, at ORC level, the relevant figures of the core source annual loss distribution. These figures shed light on the extent to which the core sources contribute to the total annual loss distribution for each ORC.

The core source annual loss distribution of an ORC is the total annual loss distribution obtained from the convolution of:

- the frequency distribution selected and fitted on the basis of the core source identified for the frequency distribution of the ORC in the AMA model (as reported in Template 4.0);
- the severity distribution selected and fitted on the basis of the core source identified for the body and for the tail severity distributions of the ORC in the AMA model, or identified for the entire severity distribution of the ORC in the AMA model should no spliced modelling be applied (as reported in Template 4.0).

More details on identifying the core source are provided in Section 2.4.4.

Implementation

For frequency and severity figures:

- calculate the summary statistic M/N , where M denotes the previous year's frequency of observed losses and N the expected frequency given by the AMA model;¹⁵
- calculate the summary statistic M/N , where M denotes the previous year's average single observed loss and N the expected severity given by the AMA model. If the expected severity is not directly computable, it can be determined by means of methodological approximations.¹⁶

For the total annual loss distribution:

- calculate the summary statistic M/N , where M denotes the greatest annual observed loss of the last five years and N the 80th percentile of the total annual loss distribution given by the AMA model;
- calculate the summary statistic M/N , where M denotes the greatest annual observed loss in the calculation dataset and N the corresponding percentile of the total annual loss distribution. If t is the length of the observation period of the calculation dataset in months¹⁷, the corresponding percentile is determined using:

$$p = 100 * \left(1 - \frac{1}{t/12}\right)$$

For example, if the length of the observation period equals $t = 60$ months or five years, then $p = 80$ and, hence, the 80th percentile of the total

¹⁵ Where a Poisson is used for the frequency distribution, the expected frequency at ORC level can be estimated considering its additive property. For instance, if the institution determines two frequency distributions in an ORC based on different sources, e.g. the first from ILD/ELD and the second from scenarios, the expected frequency at ORC level is an expected frequency weighted in accordance with the mixture of the two sources.

¹⁶ For instance, the expected severity can be determined as the ratio of the expected loss of the total annual loss distribution (column 030) and the expected frequency.

¹⁷ If the observation period differs according to frequency and severity, the severity period is taken into account.

annual loss distribution should be in the denominator (N). For an observation period of ten years, i.e. $t = 120$, the corresponding percentile would be the 90th percentile of the total annual loss distribution. Once the observation periods at ORC level have been entered into Template 2.1, the template will automatically calculate the observation period to be considered at the overall level in order to identify the corresponding percentile and the maximum annual loss in the observation period;

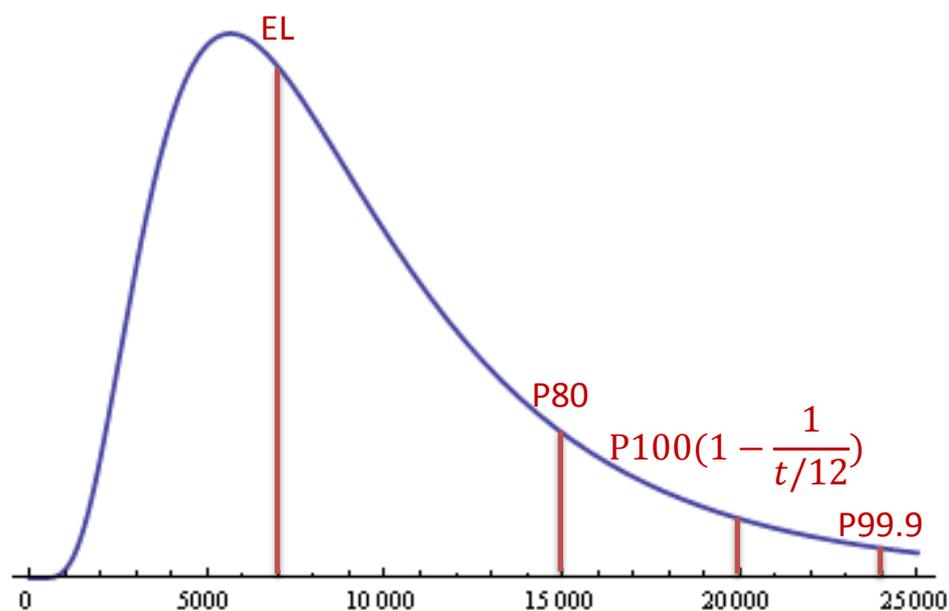
- calculate the summary statistic M/N , where M denotes the previous year's total observed loss and N the expected loss of the total annual loss distribution. The expected loss is the value used by the institution to deduce the EL offset for AMA regulatory purposes, provided the institution recognises EL in its AMA, or a proxy statistic otherwise;
- calculate the summary statistic M/N , where M denotes the 99.9th percentile of the total annual loss distribution and N the expected loss of the total annual loss distribution;
- calculate the summary statistic M/N , where M denotes the previous year's total observed loss and N the 99.9th percentile of the total annual loss distribution.

Chart 1

Probability density for the annual loss distribution

Overall level or ORC level

(EUR, horizontal axis: annual loss amounts, vertical axis: probability density)



Notes: EL indicates the Expected Loss, P80 indicates the 80th percentile of the distribution

Additionally, on the basis of the frequency and severity distributions of the core source, the institution computes, at ORC level, the expected loss and the 80th and 99.9th percentiles of the core source annual loss distribution. The expected loss of

the core source annual loss distribution refers to the statistical measure involved as part¹⁸ of the methodology used by the institution to deduce the EL offset for AMA regulatory purposes, provided the institution recognises EL in its AMA, or a proxy statistic otherwise. The 99.9th percentile of the core source annual loss distribution can be computed by means of methodological approximations such as the single loss approximation (SLA). The institution is not obliged to compute the 80th percentile and EL of the core source annual loss distribution if it can provide strong evidence that these computations are objectively burdensome; this evidence is documented in Template 1.1.

Moreover, the computational error and the calculation method, in the sense clarified in the next section, are to be provided in the template.

Scope

The measure summary statistics for the frequency and severity figures are calculated at ORC level for the major ORCs.

The measure summary statistics for the total annual loss distribution are calculated at ORC level for the major ORCs and at the overall level (considering all ORCs and not just the subset of the major ORCs).

The measure summary statistics for the core source annual loss distribution are calculated at ORC level for the major ORCs.

The measure computational error for the total annual loss distribution is calculated at ORC level for the three major ORCs and at the overall level (considering all ORCs and not just the subset of the major ORCs). The calculation method is provided for all major ORCs and at the overall level. It is mandatory to comment on the methodological details whenever the calculation method "Other" is selected; this is otherwise optional.

Reporting of the results

Results are reported in Template 2.1. The frequency, severity and total loss figures of the observed loss, i.e. M, the corresponding estimates provided by the model, i.e. N, as well as the M/N ratios are reported. Moreover, the relevant annual loss distribution figures related to the core source, the relevant computational error figures and calculation methods are reported.

Computational errors

Since the distribution of the total annual loss suffered by an institution is hard to represent in analytic form, estimates of the 99.9th percentile of this distribution are usually derived via computation methods that approximate the true value of this percentile. Knowing the magnitude of the computation errors caused by the approximation sheds light on the accuracy of the computed risk figures.

¹⁸ For example, if the EL of an ORC in the AMA model is determined as the minimum value between the median of the total annual loss distribution and the loss provision of the ORC, only the median is taken into account when computing the EL of the *core source* annual loss distribution of that ORC.

Against this background, details regarding the computational methods applied should be reported for all major ORCs and at the overall level. An estimate of the computational error should be provided only for the three major ORCs and at the overall level. Computational errors should be understood within the meaning of the RTS on AMA (Article 32(c)); the estimate provides a measure of the magnitude of these errors (e.g. due to the approximation method, sampling, discretisation of the severity distribution and numerical constraints). The computational error calculated therefore strongly depends on the chosen calculation method for the total annual loss distribution and its implementation. The value ε to be reported should correspond to

$$|P99.9 - \hat{P}99.9| < \varepsilon$$

with a confidence¹⁹ of at least 90% on a best-effort basis, where $P99.9$ denotes the true, unknown, percentile of the total annual loss distribution and $\hat{P}99.9$ denotes the percentile of the total annual loss distribution provided in column 050 of Template 2.1. In the comments cell for methodological details in column 330, institutions are encouraged to briefly describe the main features of the computational error provided.

2.4.2.2 Development of the risk figures over a period of time

Objectives of the tool

To check the stability and consistency of the output of the AMA model against the development of the institution's operational risk profile.

Description

Empirical analyses of risk estimates and observed losses both from the calculation dataset and with an accounting impact view over the last five years at the overall level. Both the AMA model figures and the observed losses to be reported in each year refer to the actual AMA framework and scope in that year (e.g. considering AMA changes, AMA extensions, and divestiture of businesses or legal entities). Figures are reported starting from the year, if more recent, in which the institution was authorised to use the AMA for regulatory purposes.

The following chart further clarifies the way in which risk estimates and observed losses should be determined over the last five years based on the following assumptions: the reference date for the implementation of validation tools is end-December 2017 and the observation period considered for the AMA is six years. In this example, the last year (LY) is 2017, the AMA risk estimates for the LY are those computed at end-December 2017 from the calculation dataset covering the period 2012-2017, the observed losses from the calculation dataset for the LY are the subset of losses relating to 2017 taken from the calculation dataset covering the period 2012-2017 and the observed losses for the LY with an accounting impact view are the losses accounted for in 2017 after applying the accounting impact view to the internal loss dataset as at end-December 2017. Figures relating to LY – 1, i.e. 2016, are determined in the same way, but the calculation dataset and internal dataset to

¹⁹ The notion of confidence should be interpreted in light of the calculation method applied. For example, if the Monte Carlo simulation is applied, the confidence can be assessed from the distribution of errors by identifying the value ε such that $Prob(|P99.9 - \hat{P}99.9| < \varepsilon) > 90\%$.

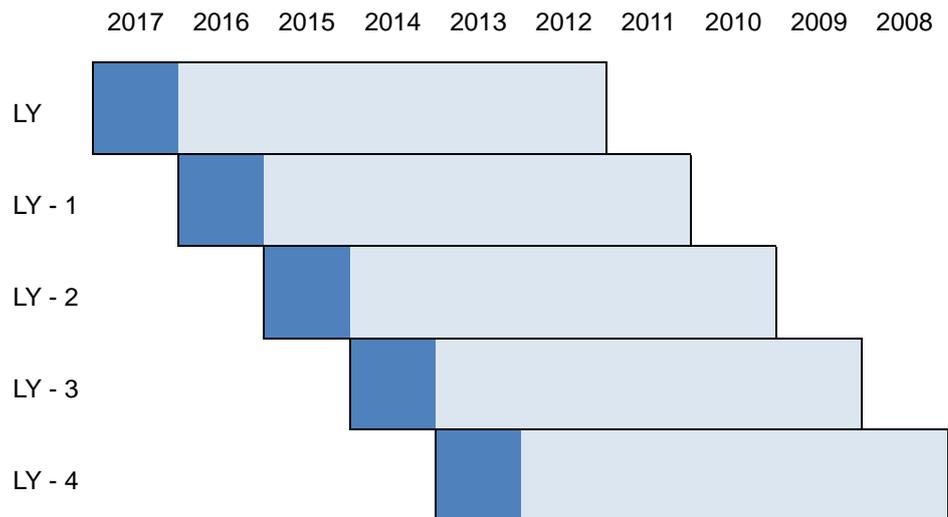
be considered are those as at end-December 2016. The same logic also applies to the preceding years.

Chart 2

Risk estimates and observed losses over the last five years

Years and datasets to be considered

(horizontal axis: actual years, vertical axis: years to be covered in the template)



Note: this chart assumes that the reference date for the validation tools is end-December 2017.

All analyses are conducted at the overall level and in a consistent way, accounting for any diversification effects, where these are recognised in the AMA model. If the institution recognises in the model insurance and/or ORTM in the AMA, comparisons of estimates both gross and net of insurance and/or ORTM are provided.

Implementation

Analyse the development, at the overall level, over the last five years of:

- the observed losses net of direct recoveries from the calculation dataset and with an accounting impact view. "Maximum of the ORCs de minimis modelling threshold" and "Number of losses" are reported for the calculation dataset only. Insurance recoveries are reported only if the institution recognises insurance in the AMA model; otherwise a value of 0 should be provided;
- the gross figures at the 99.9th percentile of the total annual loss distribution of the AMA model (gross VaR amount), net of direct recoveries only, the expected loss and, where applicable, diversification effects and insurance and/or ORTM offsets (if no insurance offsets are used, the EL before insurance should equal the EL after insurance). The VaR amount net of, where applicable, diversification and insurance and/or ORTM offset is also reported;
- the summary statistic M/N, where M denotes the VaR estimate at the 99.9th percentile (taking into account diversification effects where

applicable) and N the expected loss (where applicable, gross and net of insurance and/or ORTM);

- the summary statistic M/N, where M denotes the total observed losses from the calculation dataset and with an accounting impact view, respectively, and N the VaR estimate at the 99.9th percentile (where applicable, gross and net of insurance and/or ORTM);
- the summary statistic M/N, where M denotes the total observed losses from the calculation dataset and with an accounting impact view, respectively, and N the expected loss (where applicable, gross and net of insurance and/or ORTM).

Moreover, the institution provides the following information on the characteristics of the calculation dataset over the given time period:

- type of date used to build the calculation dataset, e.g. discovery, accounting;
- if and how loss adjustments, as set out in Article 29(j) of the RTS on AMA, are included in the calculation dataset;²⁰
- if pending losses, uncollected revenues and timing losses²¹, as defined in Section 2.3, are included in the calculation dataset.

Scope

The observed losses and summary statistics are calculated at the overall level of the annual loss distribution.

Reporting of the results

Results are reported in Template 2.2. The observed losses and recoveries both from the calculation dataset and with an accounting impact view, the estimates provided by the model, i.e. M and N, as well as the M/N ratios specified above, are reported. Moreover, information on the calculation dataset is reported.

2.4.3 Inputs of the AMA model

The following validation tools aim to evaluate qualitative aspects and the sensitivity of the AMA model to changes in the underlying sources of data.

2.4.3.1 Materiality of data adjustments

Objectives of the tool

To assess the significance and relevance of the input data adjustments.

²⁰ Here, loss adjustments in the calculation dataset in line with Article 29(j) of the RTS on AMA are being referred to. They relate to events with a reference date preceding the institution's observation period; hence, they do not have an own reference date. Depending on the institution's AMA model, it could, however, be necessary – for the model to be run – to assign a conventional reference date to such loss adjustments. Some possible dates are the rolling starting (or ending) year of the observation period, or the first (or last) year of the observation period during which loss adjustments were identified.

²¹ where those timing losses span more than one financial accounting year and give rise to legal risk.

Description

A series of summary statistics is calculated in order to assess the significance of filters and adjustments applied to (internal and external) input data to build the calculation dataset. If different datasets are used for the fitting of frequency and severity distributions, the analyses are conducted using the severity data samples.

Implementation

Assess the relevance of quality issues for ILD:

- calculate the summary statistic M/N , where M denotes the total amount of observed losses excluded from the calculation dataset due to data quality issues and N the total amount of observed losses included in the calculation dataset during the time period. Data quality issues strictly depend on the practices applied to ensure the quality and accuracy of the data included in the calculation dataset; examples of reasons to exclude observed data from the calculation dataset due to data quality issues are reconciliation issues²² and delays in the data quality assurance process²³.

Assess the relevance of the filtered-out internal and external data:

- calculate the summary statistic M/N , where M denotes the total amount of the observed losses filtered out from the calculation dataset due to inconsistency with the institution's operational risk profile (e.g. discontinued activities²⁴) and N the total amount of observed losses included in the calculation dataset;
- calculate the summary statistic M/N , where M denotes the total loss amount of the external data filtered out from the calculation dataset due to inconsistency with the institution's operational risk profile and N the total loss amount of the external data included in the calculation dataset. This analysis does not aim to evaluate the portion of external losses excluded using the filtering methodology approved by the CA: for the purposes of the ongoing monitoring of the AMA model framework and performance, the institution reports the portion of external data that are exceptionally filtered out, even if, according to the institution's methodology, they should have been included in the calculation dataset. For instance, if an institution filters out, according to the CA's approval, US data for particular event types/business lines because it does not have any relevant business in this area, the US losses in question are not considered for the purposes of this analysis. On the other hand, if some external data are categorised among the potential relevant data for the institution according to the

²² For instance, reconciliation issues between the loss data used for management purposes and loss data in the calculation dataset.

²³ For instance, an institution can apply a data quality process that foresees different subsequent stages of data approvals: in this case, data that are in the second-to-last stage of approval when the calculation dataset is being built could be considered as excluded due to delays in the data quality process and should therefore be taken into account for the purposes of this analysis.

²⁴ In this case, the total amount of losses relating to discontinued activities recorded in the calculation dataset at the most recent applicable reference date should be considered (for example, if at period t an activity has been discontinued and the corresponding portion of losses has been excluded from the calculation dataset, the institution can reconstruct the portion of excluded losses by considering the losses related to this activity as included in the calculation dataset at period $t-1$).

approved methodology (e.g. for geography, business lines, event types), but the institution does not deem these to be representative of its specific risk profile, for instance based on the event description or loss amount, then those data are considered in the scope of this analysis.

Assess the relevance of the data scaling adjustments:

- calculate the summary statistic $1-M/N$, where M denotes the amount of the portion of losses from the ELD after scaling and N the amount of the same portion of losses before scaling (i.e. if an institution does not use any scaling, both M and N are set to 0). Adjustments to amounts of specific observed losses, excluding those applied to account for inflation, and loss weighting, meaning the application of a weight to reduce loss amounts in a systematic way, should both be considered as data scaling.

Scope

The measure summary statistics are calculated at the overall level.

Reporting of the results

Results are reported in Template 3.0. The figures used to calculate the ratio under analysis, i.e. M and N, as well as the ratios are reported.

2.4.3.2 Sensitivity to the underlying data

Objectives of the tool

To assess the sensitivity of the AMA model to significant changes in each category of inputs (i.e. potential changes in the operational risk profile).

Description

Sensitivity analyses applied to internal data, external data and scenario components.

Specifically, owing to the heterogeneity of scenario analyses, the most feasible ways for supervised institutions to conduct tests are listed under this tool. These tests can be conducted irrespective of whether the scenario data are used to evaluate high-severity events (small number of data) or the institution's overall operational risk profile (usually a large number of data). These tests are also applicable in cases where the judgemental loss-related estimates are used as data points in the AMA model or used to fit some parametric distributions.

Implementation

For the sensitivity analyses listed below, calculate the summary statistic M/N , where N denotes the impact on the loss amount of the calculation dataset (be it internal, external, or scenario) and M the corresponding impact on the risk estimate for the 99.9th percentile of the total annual loss distribution gross²⁵ of direct and insurance recoveries.

In order to implement a sensitivity analysis, the institution changes the underlying data accordingly and then runs its AMA model as if performing a new (future) calculation on the dataset incorporating the changes. Depending on the type of sensitivity analysis, the change to the underlying data will trigger an update of the

²⁵ Note that the calculation of the 99.9th percentile of the total annual loss distribution in this section is different from that in Chapter 2.4.2, which only takes into account insurance-mitigated estimates if the institution recognises insurance or other mitigation techniques in the AMA model.

total annual loss distribution due to a change in the frequency and/or severity distribution.

The 99.9th percentile can be derived by means of computational approximations, such as SLA. Approximations, if used, are applied to the computation of the 99.9th percentile before and after the changes are made to the underlying data in order to measure the impact in a consistent way; an appropriate comment explaining the approximation method applied is provided in Template 1.1.

- Sensitivity analyses for internal data: evaluate the impacts on the capital calculation for the top three ORCs contributing to the RWAs for operational risk as well as at the overall level (diversification offsets are only considered when calculating the risk estimates at the overall level, if applicable), by applying the following tests:
 - (i) increase the amount of the greatest internal loss by 10% and 50%;
 - (ii) increase the observed annual frequencies of internal losses by 10%;
 - (iii) increase the amount of the three greatest internal losses by 10%;
 - (iv) add one loss with an amount 10% higher than the maximum loss in the internal loss dataset. At the overall level the new loss is added to the ORC containing the maximum loss;
 - (v) add one loss with an amount 50% higher than the maximum loss in the internal loss dataset. At the overall level the new loss is added to the ORC containing the maximum loss;
 - (vi) if applicable, include the five greatest excluded internal losses into the analysis. In cases of fewer than five losses in a given ORC, all data are considered;
 - (vii) exclude the five greatest internal losses from the internal loss dataset.
- Sensitivity analyses for external data: evaluate the impacts on the capital calculation for the top three ORCs contributing to the RWAs for operational risk as well as at the overall level, by applying the following tests:
 - (i) increase the amount of the greatest external loss by 10% and 50%;
 - (ii) add one loss with an amount 10% higher than the maximum loss in the external loss dataset. At the overall level the new loss is added to the ORC containing the maximum loss;
 - (iii) add one loss with an amount 50% higher than the maximum loss in the external loss dataset. At the overall level the new loss is added to the ORC containing the maximum loss;

- (iv) exclude the five greatest external losses from the external loss dataset.
- Sensitivity analyses for the scenario component: evaluate the impacts on the capital calculation for the top three ORCs²⁶ contributing to the RWAs for operational risk as well as at the overall level, by applying the following tests:
 - (i) increase the judgemental loss-related estimates of the highest scenario by 10% and 50% in the ORC/at the overall level;
 - (ii) if applicable, add one scenario with loss-related estimates 10% and 50% higher than the highest hypothesised scenario in the ORC/at the overall level.

Scope

The measure summary statistics are calculated for the top three ORCs contributing to the RWAs for operational risk and at the overall level.

Reporting of the results

Results are reported in Template 3.0. The increase in the total underlying loss amount (N), the increase in the risk estimate for the 99.9th percentile (M), as well as the M/N ratio are reported.

Further details on computation of impacts

The impact on the risk estimate ($\Delta P99.9$) is calculated in the same way for all sensitivity analyses:

$$\Delta P99.9 = P99.9^{stressed} - P99.9^{as\ is}$$

where $P99.9^{as\ is}$ denotes the 99.9th percentile of the total annual loss distribution gross of direct and insurance recoveries estimated from the original input data and $P99.9^{stressed}$ denotes the 99.9th percentile of the total annual loss distribution estimated from the input data stressed according to the sensitivity analysis. The same computational approximations, if any, should be applied to $P99.9^{stressed}$ and $P99.9^{as\ is}$ to ensure harmonised computational errors.

The calculation of the impact on the loss amount (Δ Loss amount) depends on the type of sensitivity analysis and, in particular, on the data source involved in the analysis.

The following table summarises the calculation of the Δ Loss amount for the sensitivity analyses with respect to ILD and ELD.

Sensitivity analysis	Δ Loss amount
----------------------	----------------------

²⁶ If the AMA methodology does not allow the scenario component to be linked to the ORCs, the sensitivity analysis on scenarios will be only performed at the overall level. In this case, an explanation should be provided in Template 1.1.

Increase max. loss by 10%	= 10% of the greatest internal (external) loss in the calculation dataset (at the appropriate level, i.e. ORC or overall).
Increase max. loss by 50%	= 50% of the greatest internal (external) loss in the calculation dataset (at the appropriate level, i.e. ORC or overall).
Increase top three losses by 10%	= 10% of the greatest internal loss + 10% of the second-greatest internal loss + 10% of the third-greatest internal loss (at the appropriate level, i.e. ORC or overall). The value is expected to be greater than that for "Increase max. loss by 10%" but smaller than that for "Increase max. loss by 50%".
Increase observed frequencies by 10%	= 10% of the average total annual loss amount over the last five years (at the appropriate level, i.e. ORC or overall).
Add one loss 10% higher than max. loss	= 110% of the greatest internal (external) loss in the calculation dataset (at the appropriate level, i.e. ORC or overall).
Add one loss 50% higher than max. loss	= 150% of the greatest internal (external) loss in the calculation dataset (at the appropriate level, i.e. ORC or overall).
Excluding top five included losses	= -100% of the five greatest internal (external) losses in the calculation dataset (at the appropriate level, i.e. ORC or overall). Hence, a negative value is expected here.
Including top five excluded losses	= 100% of the five greatest excluded internal losses in the calculation dataset (at the appropriate level, i.e. ORC or overall). If an institution does not exclude any losses, the sensitivity analysis cannot be performed and the corresponding cells should be left blank.

Although the scenarios are defined via fairly heterogeneous methodologies, they are often represented by frequencies of loss intervals which have been chosen by experts. As a result, sensitivity analyses with respect to scenario data can be still conducted in a harmonised way by:

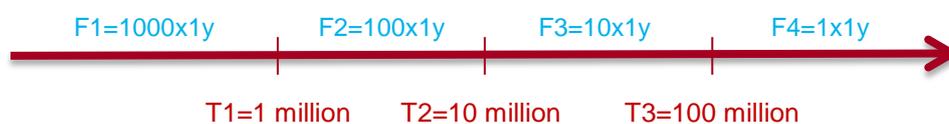
- identifying the most severe scenario in terms of the resulting VaR

- stressing the lower boundary of the interval covering the greatest losses for this scenario

The chart below represents an illustrative scenario with four frequency ranges (F1, F2, F3, F4) and three boundaries for loss intervals (T1, T2, T3). According to this scenario, only one loss above €100 million is expected to occur each year, while lower losses are expected to occur more frequently during the year.

Chart 3
Representation of scenarios

Frequencies of loss intervals
(EUR)



Note: Depending on specific methodologies, more than four loss intervals may be considered.

Assuming that this illustrative scenario is the most severe scenario in terms of the resulting VaR, the sensitivity analyses "Increase max. loss by 10% (or 50%)" should be implemented by increasing the T3 directly in this scenario, irrespective of the estimation method used in the scenario assessment (i.e. even if experts only choose frequencies and the T3 is fixed in the scenario estimation method). The sensitivity analyses "Add one loss 10% (or 50%) higher than max. loss" should be implemented by adding a copy of the illustrative scenario to the collection of considered scenarios and then increasing the T3 of the new scenario added. In the situation described, the Δ Loss amount is to be calculated according to the table below.

Sensitivity analysis	Δ Loss amount
Increase max. loss by 10%	= 10% of the T3
Increase max. loss by 50%	= 50% of the T3
Add one loss 10% higher than max. loss	= 110% of the T3. If the institution's methodology only permits one scenario for the ORC, the cells for this sensitivity analysis should be left blank.
Add one loss 50%	= 150% of the T3. If the institution's methodology only

higher than max. loss | permits one scenario for the ORC, the cells for this sensitivity analysis should be left blank.

The table above is applicable also to other scenarios represented by frequencies of loss intervals by considering the lower boundary of the interval covering the greatest losses rather than the T3 of the illustrative scenario.

2.4.4 Modelling assumptions

The validation tools described in this section are designed taking into account the AMA models based on the loss distribution approach. However, they are also applied, wherever possible, to the models based on scenario approaches.

The tools aim to gather information on the modelling of frequency and severity distributions for the relevant ORCs and evaluate the reliability of the model assumptions regarding the choice of frequency and severity distributions for the relevant ORCs:

- goodness-of-fit of the frequency distribution (if applicable);
- goodness-of-fit of the severity distribution.

In order to obtain clearer, more consistent information from the institutions, drop-down lists are provided in Template 4.0 for the relevant variables to be collected: core source, distribution²⁷ and parameter types, and fitting methods. A reference guide for the common interpretation of the distributions and parameters types as well as for the fitting methods is included in Annex 1.

Identification of the core source

As known, different methods can be adopted by the institutions by combining the four elements (ILD, ELD, scenario analysis, BEICF) to deduce the total annual loss distribution.

Under certain methods, separate frequency and severity distributions are first estimated for each element or a combination of elements (e.g. ILD, ELD, scenario analysis or ILD&ELD and scenario analysis), and then combined to deduce the total annual loss distribution.

In these cases, the tests described in the following sections refer to the core source, as defined in Section 2.3, because their goal is to assess the goodness of the fitting of the selected distributions; therefore, the institution evaluates the tests on the basis of the source(s), among the four elements, taken into account in the fitting. Where

²⁷ If the distribution used is not available in the list, please select "Other" and provide an explanation in Template 1.1. For the family of truncated distribution, please choose the family from the list, if available, specifying the truncation threshold in the "body-tail modelling threshold" field.

separate distribution models are selected and fitted based on different sources, an additional materiality criterion is included to ensure the core source is the source with the total annual loss distribution VaR that comes closest to the ORC's VaR according to the AMA model.

The core source is identified for each distribution to be tested. Therefore, for each ORC, up to three core sources are identified: one for the frequency distribution, one for the body of the severity distribution and one for the tail of the severity distribution (if the severity distribution is spliced); otherwise, only one core source is identified for the entire severity distribution.

The core source is identified based on the methods applied for selecting and fitting distributions in each AMA model. As these methods can be fairly heterogeneous, please find below some example-based guidance on how to identify the core source in the most common cases.

Example 1

A distribution model is selected and fitted based on a unique data source. The other data sources are used to update the parameters without changing the selected distribution model. In this example, the core source is the unique data source used for distribution selection.

Example 2

A distribution model is selected and fitted based on a combination of data sources (e.g. ILD and ELD). The other data sources are used to update the parameters without changing the selected distribution model. In this example, the core source is the combination of data sources used for distribution selection.

Example 3

Separate distribution models are first selected and fitted based on different sources e.g. LogNormal from ILD and Pareto from ELD. The final distribution is then a mixture of the distribution models identified in the first stage, the parameters of which are further updated based on the remaining data sources, if any. In this example, the core source is one of the sources used to select the distribution models in the first stage. To identify which of these sources is the core source, the materiality criterion is taken into account. In the case of severity distributions, the materiality criterion is implemented as follows: for each separate severity distribution model, a total annual loss distribution is built keeping the frequency distribution equal to that used in the AMA for the analysed ORC, and then the core source is identified as the data source with a total annual loss distribution that has a 99.9th percentile closest to that of the total annual loss distribution for the analysed ORC according to the AMA model. SLA can be used for the computation of 99.9th percentiles in order to streamline the

application of the criterion. The materiality criterion is implemented in a similar way for the frequency distribution.

Example 4

The distribution model is predefined and not selected from any data source. Only the parameterisation of the distribution is based on data sources. In this example, the core source is one of the sources that contribute to the parameterisation of the predefined distribution model. To identify which of these sources is the core source, the materiality criterion is applied (see Example 3) to the parameterisations of the predefined model that are based on each contributing data source.

Data points for the frequency distribution

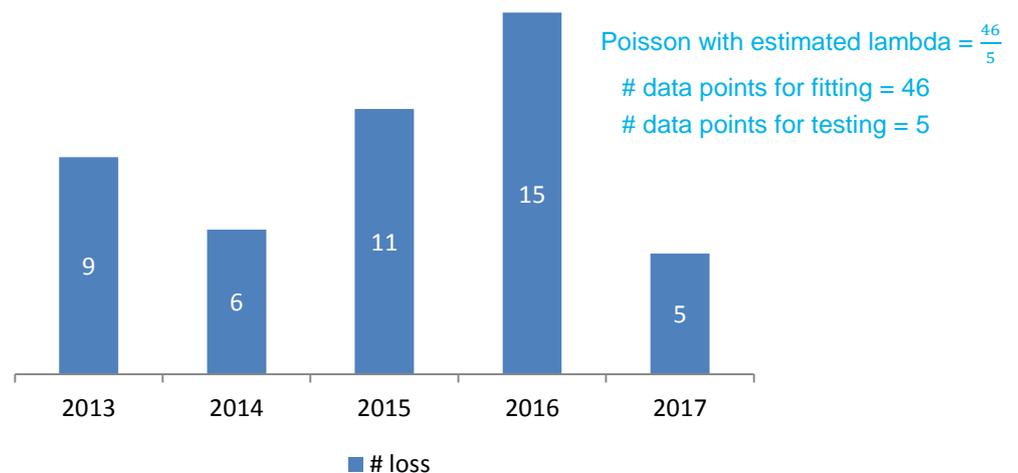
In Template 4.0, the number of data points from the core source and the number of data points from the core source for testing have to be provided for the frequency distributions. To clarify these two notions of data points, please consider the following example: the core source dataset for one ORC consists of five years of data with a total of 46 loss events, which are used to estimate a Poisson distribution. As such, the number provided in column 030 (Data points) should be 46. To test the fitting of the annual frequency distribution, the institution then divides these 46 losses into five buckets – one bucket for each year – to obtain five annual loss frequency values. Hence, in column 040 (Data points for testing), the value five should be provided. The following chart illustrates the example.

Chart 4

Data points for the frequency distribution

Data points for fitting and for testing

(#, horizontal axis: years, vertical axis: frequency)



Note: Poisson model is assumed only for illustrative purposes.

Using the above example as a basis, if the institution were to test the frequency based on quarterly data, i.e. check the fitting of the quarterly frequency distribution, the data points to be reported in column 030 would still equal 46, but the data points for testing to be reported in column 040 would be 20. To sum up, the data points depend on the number of losses in the calculation dataset used to estimate the frequency distribution, while the data points for testing depend on the binning chosen when executing the goodness-of-fit test. Institutions should choose the binning in line with their validation approach taking into account that, although the annual binning perfectly matches the modelled frequency in the AMA, it also leads to the lowest number of data points for testing, thus reducing test reliability.

Execution of tests

The tests detailed in the following sections are executed according to the following general steps. The core source of the distribution to be tested is identified and then the distribution is parameterised on the basis of this core source. Lastly, the fitting of the distribution is evaluated by means of statistical testing using the empirical data from the core source as a basis.

2.4.4.1 Goodness-of-fit of the frequency distribution

Objectives of the tool

To gather information about the chosen frequency distribution and, where applicable, verify its appropriateness.

Description

This validation tool aims to assess the goodness-of-fit of the selected frequency distribution and thus the extent to which the parametric distribution reflects the information given by the loss data in the observation period. The test is applicable in cases where the chosen model does not coincide with the empirical distribution and the ORC is not solely based on scenarios analysis as the core source. In this validation tool the Kolmogorov-Smirnov test is applied: this test quantifies a distance between the empirical distribution function of the loss dataset and the cumulative distribution function of the reference parametric distribution.

Implementation

The Kolmogorov-Smirnov is run on the frequency distribution²⁸ from the core source, wherever possible.

The Kolmogorov-Smirnov test is based on the null hypothesis that the sample is drawn from the reference parametric distribution.

Considering the empirical cumulative distribution function (cdf)

$$F_n(x) = \frac{1}{n} \sum_{i=1}^n I_{[-\infty, x]}(X_i)$$

²⁸ If the frequency distribution is split into two or more intervals for modelling purposes, the analysis should be conducted for the entire ORC frequency wherever possible, e.g. in the case of Poisson modelling given its additive property, and otherwise for the region corresponding to the body.

where $I_{[-\infty, x]}(X_i)$ is the indicator function equal to 1 if $X_i \leq x$ and equal to 0 otherwise, the Kolmogorov-Smirnov statistic for a given cumulative distribution function $F(x)$ is:

$$D_n = \sup_x |F_n(x) - F(x)|$$

From the Glivenko-Cantelli theorem, if the sample comes from distribution $F(x)$, then D_n will almost certainly converge to 0 when n goes to infinity. The critical values of the test can be calculated using simulations²⁹: the null hypothesis regarding the distributional form is rejected if the test statistic D_n is greater than the critical value.

Scope

The test is performed on the frequency distribution from the core source for all major ORCs provided the distribution is not empirical and the core source is not based on scenario analysis only.

Reporting of the results

Results are reported in Template 4.0. The report includes results on the following:

- Information about the core source of the frequency distribution:
 - (i) the relevant core source as described above;
 - (ii) the *de minimis* modelling threshold;
 - (iii) the number of data points in the calculation dataset for the frequency distribution;
 - (iv) the number of frequency data points generated from the calculation dataset for testing the goodness-of-fit of the distribution.
- The frequency model from the core source:
 - (i) the distribution chosen;
 - (ii) the value, the type (e.g. location, scale, shape) and the fitting method adopted (e.g. MLE, PME) for the parameters (up to four) estimated from the core source.
- The goodness-of-fit measure for the frequency model from the core source:
 - (i) the statistic and the p-value of the test described above.

²⁹ As the parameters of the frequency distributions are usually estimated from the sample, the calculation of the critical values of the statistical test should also reflect the method chosen for estimating the parameters. This can be done by calculating the p-values using simulations: each simulated sample should be used to estimate the parameters of the distribution, using the chosen method, and then to compute the simulated statistic. However, many analytical approximations of test statistic distributions do not take into account methods for estimating parameters as they consider the parameters as given rather than estimated. Therefore, analytical approximations can be used only when consistent with the estimation method of the distributions' parameters.

2.4.4.2 Goodness-of-fit of the severity distribution

Objectives of the tool

To gather information about the chosen severity distribution and verify its appropriateness.

Description

This validation tool aims to assess the goodness-of-fit of the selected severity distribution and thus the extent to which the parametric distribution reflects the information given by the loss data in the observation period. The test is applicable in cases where the empirical distribution is not used and the ORC is not solely based on scenarios as the core sources. In this validation tool the Anderson-Darling (AD) and the Anderson-Darling upper tail tests are applied: these tests quantify a distance between the empirical distribution function of the loss dataset and the cumulative distribution function of the reference parametric distribution respectively by weighting equally the observations in the lower and upper tails of the sample or by giving more relevance to the points in the upper tail only.

Implementation

AD and AD upper tail tests of equality of probability distributions are run for the chosen distribution assumption.

- If the severity is modelled with a single distribution, the AD upper tail test is reported.
- If the severity is modelled separately³⁰ for the body and the tail area, the AD is run for the body distribution and the AD upper tail is run for the tail distribution.

The AD test is based on the null hypothesis that the sample is drawn from the reference parametric distribution.

Calculate the AD test statistic as follows:

$$D_n = \sup_x \left| \frac{F_n(x) - F(x)}{\sqrt{F(x)(1 - F(x))}} \right|$$

The test statistic can be compared against the critical values of the theoretical distribution. The critical values of the test can be calculated using simulations³¹: the null hypothesis regarding the distributional form is rejected if the test statistic D_n is greater than the critical value.

Calculate the AD upper tail test statistic as follows:

³⁰ If the severity distribution is split into more than two intervals for modelling purposes, the last interval to the right is considered for the tail and the last but one interval to the right is considered for the body.

³¹ As the parameters of the severity distributions are usually estimated from the sample, the calculation of the critical values of the statistical test should also reflect the method chosen for estimating the parameters. This can be done by calculating the p-values using simulations: each simulated sample should be used to estimate the parameters of the distribution, using the chosen method, and then to compute the simulated statistic. However, many analytical approximations of test statistic distributions do not take into account methods for estimating parameters as they consider the parameters as given rather than estimated. Therefore, analytical approximations can be used only when consistent with the estimation method of the distributions' parameters.

$$D_n = \sup_x \left| \frac{F_n(x) - F(x)}{1 - F(x)} \right|$$

This formulation of the AD test gives more weight to the observation in the upper tail of the sample.

Scope

The test is performed on the severity distribution from the core source for all major ORCs, except in cases where the empirical distribution is used or the ORC only uses scenario analysis as the core source.

Reporting of the results

Results are reported in Template 4.0. The report includes similar information to that described in Section 2.4.4.1, i.e. information about the core source of the severity distribution, the severity model from the core source and the goodness-of-fit measures of the severity model from the core source.

Moreover, if a distribution is spliced into a body and a tail part, the report includes the body-tail modelling threshold and its selection method.

2.4.5 Inputs of the new Standardised Approach

The following validation tools aim to provide information on the inputs used to calculate the minimum capital requirements for operational risk under the new SA, as described in the document "Basel III: Finalising post-crisis reforms", published by the Basel Committee on Banking Supervision in December 2017 ("Basel III paper").

Following the finalisation of the Basel III reform, these data help to ensure a smooth transition between the current and the future framework for measuring operational risk capital requirements³². Collecting these data helps institutions to understand whether there are any gaps with respect to the target framework as well as the expected impact on processes and capital requirements. At the same time, this information enables the ECB to more appropriately oversee the transition to the new SA for AMA institutions.

2.4.5.1 Business Indicator

Objectives of the tool

To provide all inputs for the Business Indicator (BI) of the new SA.

Description

This tool aims to provide all P&L or balance sheet items underlying the "Interest, lease and dividend", the "Services" and the "Financial" components of the BI over recent years.

Implementation

Institutions should provide the P&L or balance sheet items for each year in Template 5.0. All of these items should be interpreted and computed in line with the provisions set out in the Basel III paper and, in particular, in the "Annex: Definition of Business Indicator components".

³² Please note that the Basel III reform will be subject to the European legislative process.

Irrespective of the reference date chosen for the other validation tools and the internal validation report, figures in Template 5.0 should always be as at end-December for each year.

In line with the Basel III paper, the following items are to be provided.

- Interest, lease and dividend component:
 - (i) interest income;
 - (ii) interest expenses;
 - (iii) interest-earning assets (balance sheet item);
 - (iv) dividend income.
- Services component:
 - (i) fee and commission income;
 - (ii) fee and commission expenses;
 - (iii) other operating income;
 - (iv) other operating expenses.
- Financial component:
 - (i) net profit (loss) in the trading book;
 - (ii) net profit (loss) in the banking book.

Scope All data are provided for the last five years and should refer to the entire institution's scope (not only the AMA scope). Data should be provided on a best-effort basis. However, the institution is recommended to at least provide data covering the most recent three years.

Reporting of the results All data are to be provided in Template 5.0 in euro.

2.4.5.2 Loss component

Objectives of the tool To provide all inputs for the Loss Component (LC) of the new SA.

Description This tool aims to analyse the total annual operational risk losses based on different thresholds: the threshold foreseen in the new SA, €20,000 or, under the national discretionary option, €100,000 as well as the data collection threshold currently used in the AMA.

Implementation Institutions should report annual operational risk losses from the last 12 years in Template 5.0, based on the following thresholds:

- including all losses equal to or above the data collection threshold. The data collection threshold should also be provided in column 200;
- including all losses equal to or above €20,000;
- including all losses equal to or above €100,000.

Please refer to the Basel III paper for the relevant criteria for creating the loss dataset to be reported here. The figures provided should meet all of the criteria specified, especially the criteria provided in "5. General criteria on loss data identification, collection and treatment" and "6. Specific criteria on loss data identification, collection and treatment".

Irrespective of the reference date chosen for the other validation tools and the internal validation report, figures in Template 5.0 should always be as at end-December for each year.

Scope

Data should be provided for the last 12 years and should refer to the entire institution's scope (not only the AMA scope). Data should be provided on a best-effort basis. However, the institution is recommended to at least provide data covering the most recent ten years.

If the institution does not have historical data for the last few years, or the dataset for older years does not meet the Basel III paper requirements for the general and specific criteria on loss data identification, collection and treatment, the institution should only provide data from the years that meet these requirements, providing an explanation for the lack of data from the other years in Template 1.1.

Reporting of the results

All data are to be provided in Template 5.0 in euro.

3 Annex

3.1 Reference guide for Template 4.0

3.1.1 Frequency distributions

Poisson

$$\text{pmf: } P(n; \lambda) = \frac{\lambda^n \cdot e^{-\lambda}}{n!},$$

where $\lambda > 0$.

Parameter1 = λ

TypeParameter1 = scale

Binomial

$$\text{pmf: } P(n; p, \nu) = \binom{\nu}{n} p^n (1 - p)^{\nu - n},$$

where $0 \leq p \leq 1$; $\nu > 0$, integer.

Parameter1 = p

TypeParameter1 = shape

Parameter2 = ν

TypeParameter2 = shape

Geometric

$$\text{pmf: } P(n; \beta) = \frac{\beta^n}{(1 + \beta)^{n+1}},$$

where $\beta > 0$.

Parameter1 = β

TypeParameter1 = location

Negative binomial (Pascal)

$$\text{pmf: } P(n; p, \nu) = \binom{n + \nu - 1}{n} p^n (1 - p)^\nu,$$

where $0 \leq p \leq 1$; $\nu > 0$, integer.

Parameter1 = p

TypeParameter1 = shape

Parameter2 = ν

TypeParameter2 = shape

Empirical (Heaviside)

$$\text{cdf: } F(n; n_1, n_2, \dots, n_m) = \frac{1}{m} \sum_{i=1}^m \Theta(n - n_i),$$

where $\{n_1, n_2, \dots, n_m\}$ denotes the sample, Θ the Heaviside (step) function.

$$\text{Parameter1} = \frac{1}{m} \sum_{i=1}^m n_i [= \bar{n}], \quad \text{TypeParameter1} = \text{location}$$

$$\text{Parameter2} = \sqrt{\frac{1}{m} \sum_{i=1}^m (n_i - \bar{n})^2} \quad \text{TypeParameter2} = \text{scale}$$

$$\text{Parameter3} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left[\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right]^{\frac{3}{2}}} \quad \text{TypeParameter3} = \text{shape}$$

$$\text{Parameter4} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left[\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right]^2} \quad \text{TypeParameter4} = \text{shape}$$

Other

Generic (i.e, not presented above) distribution

$$\text{Parameter1} = \text{mean} \quad \text{TypeParameter1} = \text{location}$$

$$\text{Parameter2} = 1^{\text{st}} \text{ quartile} \quad \text{TypeParameter2} = \text{shape}$$

$$\text{Parameter3} = \text{median} \quad \text{TypeParameter3} = \text{shape}$$

$$\text{Parameter4} = 3^{\text{rd}} \text{ quartile} \quad \text{TypeParameter4} = \text{shape}$$

3.1.2 Severity distributions

Lognormal

$$\text{cdf: } F(x; \mu, \sigma) = \Phi\left(\frac{\ln(x) - \mu}{\sigma}\right),$$

where Φ denotes the std. normal cdf; $\sigma > 0$.

Parameter1 = μ

TypeParameter1 = shape

Parameter2 = σ

TypeParameter2 = shape

Pareto

$$\text{cdf: } F(x; \theta, \alpha) = 1 - \left(\frac{\theta}{x+\theta}\right)^\alpha,$$

where $\theta, \alpha > 0$.

Parameter1 = θ

TypeParameter1 = scale

Parameter2 = α

TypeParameter2 = shape

LogLogistic

$$\text{cdf: } F(x; \theta, \gamma) = \frac{(x/\theta)^\gamma}{1+(x/\theta)^\gamma},$$

where $\theta, \gamma > 0$.

Parameter1 = θ

TypeParameter1 = scale

Parameter2 = γ

TypeParameter2 = shape

Inverse Gaussian

$$\text{cdf: } F(x; \mu, \sigma) = \Phi\left(\frac{x-\mu}{\sigma\sqrt{\theta\cdot\mu}}\right) + e^{\frac{2}{\sigma^2}} \cdot \Phi\left(-\frac{x+\mu}{\sigma\sqrt{\theta\cdot\mu}}\right),$$

where Φ denotes the std. normal cdf; $\mu, \sigma > 0$.

Parameter1 = μ

TypeParameter1 = location

Parameter2 = σ

TypeParameter2 = scale

Empirical (Heaviside)

$$\text{cdf: } F(x; x_1, x_2, \dots, x_n) = \frac{1}{n} \sum_{i=1}^n \theta(x - x_i),$$

where $\{x_1, x_2, \dots, x_n\}$ denotes the sample, θ the Heaviside (step) function.

$$\text{Parameter1} = \frac{1}{n} \sum_{i=1}^n x_i [= \bar{x}], \quad \text{TypeParameter1} = \text{location}$$

$$\text{Parameter2} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{TypeParameter2} = \text{scale}$$

$$\text{Parameter3} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left[\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2\right]^{3/2}} \quad \text{TypeParameter3} = \text{shape}$$

$$\text{Parameter4} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left[\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2\right]^2} \quad \text{TypeParameter4} = \text{shape}$$

Weibull

$$\text{cdf: } F(x; \theta, \tau) = 1 - e^{-\left(\frac{x}{\theta}\right)^\tau},$$

where $\theta, \tau > 0$.

$$\text{Parameter1} = \theta \quad \text{TypeParameter1} = \text{scale}$$

$$\text{Parameter2} = \tau \quad \text{TypeParameter2} = \text{shape}$$

Gamma

$$\text{pdf: } p(x; \alpha, \beta) = \frac{\alpha^\beta}{\Gamma(\beta)} x^{\beta-1} e^{-\alpha x},$$

where $\alpha, \beta > 0$.

$$\text{Parameter1} = \alpha \quad \text{TypeParameter1} = \text{scale}$$

$$\text{Parameter2} = \beta \quad \text{TypeParameter2} = \text{shape}$$

LogGamma

$$\text{pdf: } p(x; \alpha, \beta) = \frac{\alpha^\beta}{\Gamma(\beta)} (\log x)^{(\beta-1)} x^{-(\alpha+1)},$$

where $\alpha, \beta > 0$.

$$\text{Parameter1} = \alpha \quad \text{TypeParameter1} = \text{rate}$$

$$\text{Parameter2} = \beta \quad \text{TypeParameter2} = \text{shape}$$

Transformed Beta

$$\text{rv: } Y_{TB} \sim \theta \cdot \left(\frac{x}{1-x}\right)^{\frac{1}{\gamma}},$$

where $X \sim B(\tau, \alpha)$; θ, γ, τ and $\alpha > 0$.

Parameter1 = θ	TypeParameter1 = location
Parameter2 = γ	TypeParameter2 = shape
Parameter3 = τ	TypeParameter1 = shape
Parameter4 = α	TypeParameter2 = shape

g-and-h

$$\text{rv: } Y_{g\text{-and-h}} \sim A + B \cdot \frac{(e^{gZ} - 1) \cdot e^{\frac{h}{2}Z^2}}{g},$$

where $Z \sim N(0,1)$; A, B, g and $h > 0$.

Parameter1 = A	TypeParameter1 = location
Parameter2 = B	TypeParameter2 = scale
Parameter3 = g	TypeParameter1 = shape
Parameter4 = h	TypeParameter2 = shape

Other

Generic (i.e., not presented above) distribution

Parameter1 = mean	TypeParameter1 = location
Parameter2 = 1st quartile	TypeParameter2 = shape
Parameter3 = median	TypeParameter3 = shape
Parameter4 = 3rd quartile	TypeParameter4 = shape

3.1.3 Fitting methods

Method	Description
UMVUE	Uniformly minimum-variance unbiased estimator
MLE	Maximum likelihood estimator (including penalised and weighted MLEs)
MME	Moment matching estimator (including probability-weighted MMEs)
PME	Percentile matching estimator
MDE	Minimum distance estimator (including least-squares estimators)
Bayes	Bayesian estimator (including Bayesian credibility estimators)
Judgemental	Non-Bayesian estimator based on expert assessments
Other	Any estimator type not considered above

3.1.4 Methods for selecting body-tail modelling thresholds

Method	Description
Judgemental	Threshold based on expert assessments (e.g. pre-defined threshold applied to all ORCs)
Graphical	Threshold selected by graphical assessment (e.g. mean excess plot)
Deterministic	Threshold selected by application of an algorithm (e.g. decision tree, statistical criteria)
Other	Any other selection method not considered above

NB: Institutions are kindly invited to provide comments in Template 1.1 whenever "Other" is selected or the proposed options do not perfectly match the model-specific features.

Abbreviations

AD	Anderson-Darling	MLE	Maximum Likelihood Estimator
AMA	Advanced Measurement Approach	OFR	Own Funds Requirements
ASA	Alternative Standardised Approach	ORC	Operational Risk Category
BEICF	Business Environment and Internal Control Factors	ORTM	Other Risk Transfer Mechanisms
BIA	Basic Indicator Approach	PME	Percentile Matching Estimator
CA	Competent Authority	RI	Relevant Indicator
CRD	Capital Requirements Directive (Directive 2013/36/EU)	RTS	Regulatory Technical Standards
CRR	Capital Requirements Regulation (Regulation (EU) 575/2013)	RWA	Risk-Weighted Assets
EBA	European Banking Authority	SA	New Basel III Standardised Approach
ECB	European Central Bank	SLA	Single Loss Approximation
EL	Expected Loss	SSM	Single Supervisory Mechanism
ELD	External Loss Data	TA	Total Assets
EU	European Union	TSA	Standardised Approach
ILD	Internal Loss Data	VaR	Value at Risk
JST	Joint Supervisory Team		