



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

This module should be read in conjunction with the [Introduction](#) and with the [Glossary](#), which contains an explanation of abbreviations and other terms used in this Manual. If reading on-line, click on blue underlined headings to activate hyperlinks to the relevant module.

Purpose

To set out the HKMA approach to the validation of Als' internal rating systems, and the requirements that the HKMA expects Als to follow, in order to qualify for using the internal ratings-based approach ("IRB approach") to measure credit risk for capital adequacy purposes.

Classification

A non-statutory guideline issued by the HKMA as a technical note.

Previous guidelines superseded

CA-G-4 "Validating Risk Rating Systems under the IRB Approaches" (V.1) dated 14.02.06.

Application

To all locally incorporated Als which use, or intend to use, the IRB approach to measure credit risk for capital adequacy purposes.

Structure

1. Introduction
 - 1.1 Terminology
 - 1.2 Minimum requirements for use of IRB approach
 - 1.3 Scope
2. HKMA approach to validation
3. Factors to be considered in the validation process
 - 3.1 Logic and conceptual soundness of a rating system
 - 3.2 Systems and controls



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- 3.3 Data quality
- 3.4 Accuracy of a rating system
- 3.5 Benchmarking
- 3.6 Stress-testing
- 4. Corporate governance and oversight
- 5. Other systems of control
 - 5.1 Independence
 - 5.2 Transparency
 - 5.3 Accountability
 - 5.4 Use of internal ratings
 - 5.5 Internal audit function and external audit
 - 5.6 Treatment of external vendor models
- 6. Data quality
 - 6.1 Overview
 - 6.2 Management oversight and control
 - 6.3 IT infrastructure and data architecture
 - 6.4 Data collection, storage, retrieval and deletion
 - 6.5 Data processing
 - 6.6 Reconciliation
 - 6.7 Data quality assessment
 - 6.8 Use of external and pooled data
 - 6.9 Statistical issues
- 7. Accuracy of PD
 - 7.1 Overview
 - 7.2 Validation of discriminatory power
 - 7.3 Validation of calibration
- 8. Accuracy of LGD
 - 8.1 Overview
 - 8.2 Methods for assigning LGD to non-default facilities



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- 8.3 Issues specific to workout LGD
- 8.4 LGD estimation process
- 8.5 Validation of LGD estimates
- 9. Accuracy of EAD
 - 9.1 Overview
 - 9.2 Construction of a development data set
 - 9.3 Estimation of EAD
 - 9.4 Validation of EAD estimates
- 10. Issues on LDPs
 - 10.1 Types of LDPs
 - 10.2 Implications for risk quantification and validation
- 11. Benchmarking
 - 11.1 Overview
 - 11.2 Use of benchmarking
 - 11.3 Types of benchmarking
 - 11.4 Selection of a benchmark
 - 11.5 Mapping to a benchmark
- 12. Stress-testing

Annex A: Quantitative techniques in validating discriminatory power

Annex B: Statistical methodologies in validating calibration

Annex C: Risk factors in estimation of EAD

Annex D: Flowchart depicting HKMA requirement on benchmarking

Annex E: Minimum requirements for internal rating systems under IRB approach



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

1. Introduction

1.1 Terminology

1.1.1 Unless otherwise specified, abbreviations and terms used in this module follow those used in the Banking (Capital) Rules (“BCR”).

1.1.2 For the purpose of this module:

- “Als”, unless indicated otherwise, means locally incorporated authorized institutions which use, or intend to use, the IRB approach to measure credit risk for capital adequacy purposes;
- “Basel II” means the document entitled “International Convergence of Capital Measurement and Capital Standards — A Revised Framework (Comprehensive Version)” published by the Basel Committee in June 2006;
- “bootstrapping” means a resampling technique with replacement of the data sampled, aiming to generate information on the distribution of the underlying data set;
- “certainty-equivalent cash flow” means the cash payment required to make a risk-averse investor indifferent between receiving that cash payment with certainty at the payment date and receiving an asset yielding an uncertain payout whose distribution at the payment date is equal to that of the uncertain cash flow;
- “credit risk exposure”, unless otherwise specified, means a credit risk exposure that is not a securitization exposure;
- “data architecture” means the underlying set of rules and descriptions of relationships that govern how the major kinds of data support the business processes of an organisation;
- “data cleansing” means the act of detecting and removing and/or correcting a database’s data that



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

are incorrect, out-of-date, redundant, incomplete, or of improper format. The goal of data cleansing is not only to clean up the data in a database but also to bring consistency to different sets of data that have been merged from separate databases;

- “in-sample validation” means validation of a rating system employing observations that have been used for developing the rating system;
- “IRB recognition process” means the process through which the HKMA evaluates an AI’s internal rating systems and the systems of controls surrounding these systems, before deciding whether the AI is allowed to use the IRB approach to measure credit risk for capital adequacy purposes;
- “IT” means information technology which encompasses automated means of originating, processing, storing and communicating information, and covers recording devices, communication networks, computer systems (including hardware and software components and data) and other electronic devices;
- “k-fold cross validation” means a kind of test employing resampling techniques. The data set is divided into k subsets. Each time, one of the k subsets is used as the validation data set and the other k-1 subsets are put together to form the development data set. By repeating the procedures k times, the targeted test statistic across all k trials is then computed;
- “LDPs” means low-default portfolios;
- “out-of-sample validation” means validation of a rating system employing observations that have not been used for developing the rating system;
- “out-of-time validation” means validation of a rating system employing observations that are not contemporary with the data used for developing the rating system;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- “IRB system” has the same meaning as “rating system” as defined in the BCR;
- “reconciliation” means the process of comparing data from multiple sources for the purpose of correcting one or both sources or of enhancing the usability of the data; and
- “UR”, in relation to a non-derivative off-balance exposure of an AI, means the utilisation rate of the exposure.

1.2 Minimum requirements for use of IRB approach

1.2.1 Part 6 and Schedule 2 of the BCR set out the capital adequacy framework for an AI to calculate its credit risk for non-securitization exposures using the IRB approach where it has the MA’s prior approval under the BCR to do so. AIs are therefore advised to read this module in conjunction with the BCR. In case of any discrepancy between the two documents, the BCR prevail.

1.2.2 In addition, the module should also be read in conjunction with [the Completion Instructions for the return MA\(BS\)3](#), [Questions and Answers on Banking \(Capital\) Rules](#), and other relevant documents issued by the HKMA.¹

1.2.3 An AI may submit an application under §8(1) of the BCR to use the IRB approach to calculate its credit risk for non-securitization exposures. The MA may grant approval to an AI under §8(2)(a), subject to any conditions the MA thinks proper in any particular case (see §33A of the BCR), to use the IRB approach for credit risk, provided that the AI demonstrates to the satisfaction of the MA that the minimum requirements specified in Schedule 2 to the BCR applicable to the AI are met. In the IRB recognition process, the HKMA

¹ For ease of reference and maintenance, the requirements set out in the two HKMA documents, “Minimum Requirements for Internal Rating Systems under IRB Approach” and “Minimum Requirements for Risk Quantification under IRB Approach”, referred to in version 1 of this module by way of hyperlinks, have been updated and incorporated into this module (in the main text and Annex E) as appropriate.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

evaluates how the relevant requirements as set out in the BCR and other applicable regulatory or supervisory requirements or provisions² are met to assess the AI's eligibility to use the IRB approach. These regulatory or supervisory requirements and provisions that are applicable to an AI's use of the IRB approach are collectively referred to as "applicable HKMA requirements" in this module.

- 1.2.4 An AI which has made an application under §8(1) to use, or which uses, the IRB approach for credit risk may apply to the MA to exempt an IRB class or subclass of exposures, or the exposures falling within a business unit of the AI, from the scope of IRB calculations in accordance with §12 of the BCR. Where the MA grants approval under §12(2)(a) for such an application, the AI must use the standardized (credit risk) approach ("STC approach") to calculate its credit risk for the exempted exposures and comply with §12(5) of the BCR. The circumstances under which the IRB exemption will be revoked are set out in §13 of the BCR.
- 1.2.5 IRB systems are the cornerstone for calculating regulatory capital charges under the IRB approach, as they form the basis of determining probability of default ("PD") and, in the case of the retail IRB approach and the advanced IRB approach, two additional credit risk components, namely a facility's loss given default ("LGD") and exposure at default ("EAD"). As a consequence, validation of an AI's estimates of these three credit risk components, which are key inputs to the calculation of regulatory capital using the IRB approach, and the underlying internal rating systems, is a major part of both the initial IRB recognition process and the on-going review process of the IRB systems to ensure

² The HKMA may issue additional regulatory or prudential requirements applicable to the IRB approach, such as the revised capital floor requirements as set out in the HKMA circular dated 20 December 2013, and the prudential measures relating to property-related exposures. Where appropriate, the HKMA may also require an AI to comply with certain supervisory actions relating to the AI's use of the IRB approach, e.g. to take remedial actions to address any IRB-related prudential concerns identified during the HKMA's on- or off-site reviews.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

continual compliance with applicable HKMA requirements.

- 1.2.6 To be eligible for the IRB approach, an AI should demonstrate to the MA that it meets the minimum requirements described in Annex E, any condition attached pursuant to §33A of the BCR to the AI's IRB approval, and other applicable HKMA requirements, at the outset and on an ongoing basis. The AI's overall credit risk management practices should also be consistent with the relevant provisions in the BCR, and the guidelines and sound practices issued by the Basel Committee and the HKMA.
- 1.2.7 Where an AI adopting the IRB approach is not in full compliance with the minimum requirements, or it has contravened a condition attached to its IRB approval, the MA may take one or more of the measures set out in §10 of the BCR. These include a requirement for the AI (i) to use the STC approach (instead of the IRB approach) to calculate the credit risk for all or part of the AI's non-securitization exposures; (ii) to submit to the MA a plan which satisfies the MA that if it were implemented by the AI, this would allow the AI a timely return to compliance with the minimum requirements or the attached condition(s); (iii) to be subject to revised capital requirements or capital floor; and (iv) to reduce its credit exposures.³
- 1.2.8 During the period when the AI is in the course of taking the required actions to rectify its non-compliance, the HKMA will consider the need for the AI to hold additional capital under the supervisory review process, or to take other appropriate supervisory action, depending on the circumstances of each case.

³ Provisions under §10(5) of the BCR are applicable to cases where an AI is non-compliant with applicable BCR requirements to the extent that if the AI were to make a fresh application to the MA under §8(1) of the BCR to use the IRB approach, the application would be refused by virtue of §8(3) (but insofar as Schedule 2 to the BCR is concerned, only §1 of the Schedule is to be taken into account). In other cases of non-compliance, the AI concerned will normally be required to rectify the issues, as discussed and agreed with the HKMA, within a reasonable period.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

1.3 Scope

1.3.1 This module:

- sets out the HKMA approach to the validation of the internal rating systems of AIs for the purposes of using the IRB approach to measure credit risk for capital adequacy purposes;
- provides further explanation and elaboration in relation to the applicable HKMA requirements that AIs must follow in respect of the validation of their internal rating systems to ensure accuracy, consistency and reliability, including the systems of controls surrounding these systems; and
- sets out guidance and best practices for the validation of IRB rating systems, taking account of the HKMA's experience in connection with the IRB recognition process since Basel II and relevant developments in both industry practices and regulatory regimes.

1.3.2 The requirements set out in this module apply to AIs that estimate one or more of the credit risk components (i.e. PD, LGD, EAD, expected loss ("EL") and maturity ("M")) for the purposes of using the IRB approach to measure credit risk⁴.

1.3.3 The scope of the applicable HKMA requirements in respect of an AI's use of the IRB approach, and the scope and intensity of the IRB recognition process involved, will depend on the circumstances of the AI's case, for instance, whether the AI is seeking the HKMA's approval to use the IRB approach for the first time, or to modify an approved IRB model in response to changes in business activities. The applicable HKMA requirements will also depend on the IRB calculation approaches applied for, and the nature and scale of the exposures to be covered.

1.3.4 In the case of AIs that are subsidiaries of foreign banking groups, all or part of their IRB systems may be centrally

⁴ See Table 17 under §147 of the BCR for the IRB calculation approaches available in respect of the IRB classes / subclasses of exposures.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

developed and monitored on a group basis. In assessing whether these AIs meet the applicable HKMA requirements for use of the IRB approach, the HKMA will co-ordinate with the home supervisors of the banking groups regarding the group-wide internal rating systems adopted by their subsidiaries in Hong Kong. To minimise duplication and overlap in the validation process of the home and host supervisors of an AI, the HKMA will, to the extent practicable and reasonable, take into account the assessment of the home supervisor as to the accuracy, verifiability, internal consistency and integrity of the rating system, and the appropriateness of the system for assessing the credit risk characteristics of the AI's exposures. This is, however, on condition that the HKMA is satisfied that the capital adequacy standards adopted by the AI's home supervisor for assessing credit risk under the IRB approach are not materially different from those laid down in the BCR. In addition, AIs are expected to conduct their own internal validation at both the group level and the level of those subsidiaries that use the rating systems. The validation should include an evaluation of the local applicability of the group-wide rating systems.

2. HKMA approach to validation

- 2.1 The Basel Committee has stated that “banks must have a robust system in place to validate the accuracy and consistency of ratings systems, processes, and the estimation of all relevant risk components”⁵. In the context of internal rating systems, the term “validation” encompasses a range of processes and activities that contribute to an assessment of whether ratings adequately differentiate risk, and whether estimates of the credit risk components appropriately characterise the relevant aspects of risk.

⁵ Basel II paragraph 500.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

2.2 The Basel Committee has expanded on the concept of validation in the form of six principles⁶ (“Basel IRB validation principles”). These are as follows:

- (i) Validation is fundamentally about assessing the predictive ability of an AI’s risk estimates and the use of ratings in credit processes;
- (ii) AIs have primary responsibility for validation;
- (iii) Validation is an iterative process;
- (iv) There is no single validation method;
- (v) Validation should encompass both quantitative and qualitative elements; and
- (vi) Validation processes and outcomes should be subject to independent review.

2.3 The HKMA approach to IRB validation is closely aligned with these principles. In particular, consistent with the second Basel IRB validation principle, and as required by the BCR (§1 of Schedule 2), it will be an AI’s responsibility to demonstrate to the satisfaction of the MA that its internal rating systems meet the minimum requirements laid down in the BCR and any other applicable HKMA requirements⁷. Thus an AI is required to conduct its own internal validation of its rating systems, estimates of the credit risk components, and the processes by which internal ratings are generated. The processes and results of the internal validation should be clearly documented and shared with the HKMA. The Board⁸ of Directors and senior management of an AI should ensure that validation is performed by individuals who are qualified and trained to do so and are independent of the parties that have been involved in developing

⁶ The Basel IRB validation principles are set out in the document, Working Paper No. 14 – Studies on the Validation of Internal Rating Systems, issued by the Basel Committee in May 2005.

⁷ The Basel Committee also places the responsibility on each bank to “demonstrate to its supervisor that the internal validation process enables it to assess the performance of internal rating and risk estimation systems consistently and meaningfully” (see Basel II paragraph 500).

⁸ Unless indicated otherwise, “the Board” may mean its specialized committee in cases deemed to be appropriate by an AI with reference to applicable requirements set out in section 5 of [CG-1](#) “Corporate Governance of Locally Incorporated Authorized Institutions” and taking account of the individual circumstances of the case.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

the rating systems (see paragraphs 5.1.6 to 5.1.8 below). Where the HKMA considers appropriate, it will require an AI to commission a report from its external auditors or other independent experts with the relevant expertise, experience and track record in such work to review the AI's compliance with the applicable HKMA requirements.

- 2.4 In line with the fourth Basel IRB validation principle, the HKMA recognises that there is no universal tool that can be used for the validation of all portfolios. It therefore expects the design of a validation methodology to depend on the type of rating system and the underlying portfolio. For example, back-testing may be useful for the validation of the credit risk component estimates for the retail portfolio in general. It may however be less applicable to portfolios with a low level of historical defaults where benchmarking may be a more useful validation tool.
- 2.5 The HKMA also notes that the techniques, especially the quantitative techniques, that are being used for validating the robustness, reliability and accuracy of internal rating systems, and the estimates of the credit risk components, are very diverse, portfolio-specific and evolving. Therefore, this module only serves to provide some high level guidance rather than precise quantitative minimum standards that should be employed for IRB systems.
- 2.6 In the absence of precise quantitative minimum standards for IRB systems, the HKMA's approach to validation will be twofold. First, it will review the processes, procedures and controls that are in place for IRB systems. This will include, for example, ensuring that these systems are subject to adequate Board and senior management oversight, both before and during use; that procedures are in place to ensure the integrity and reliability of the data used in IRB systems; and that independent internal reviews of the performance of IRB systems are conducted at an appropriate frequency. Internal and external auditors of the AI should also be involved in the processes. The expectations of the HKMA in these areas are set out in sections 4 to 6.
- 2.7 The second component of IRB validation will be to ensure that AIs make regular use of at least some of the generally accepted quantitative techniques in assessing the performance of their IRB systems. The quantitative techniques presented in sections



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

7 to 9 reflect current market practice in the estimation and validation of the credit risk components.

- 2.8 While the HKMA has not established minimum quantitative standards for IRB systems beyond those specified in, or in conditions on approvals granted under, the BCR, AIs should be able to demonstrate (i) the rationale and the appropriateness of their chosen quantitative techniques, and to understand the limitations, if any, of such techniques; and (ii) the appropriateness of the internal parameters they employ in assessing a rating system's accuracy and reliability.
- 2.9 As noted in paragraph 2.4 above, the HKMA recognises that no one validation technique can necessarily be applied to all portfolios and that it is a common industry practice to apply different validation techniques to different types of portfolios. The HKMA, however, generally expects AIs to apply the validation techniques and practices⁹ that are commonly used in the industry for specific portfolio types. When an AI employs a validation technique which differs from that in widespread use by its peers, the HKMA expects it to be able to justify its choice of approach. Where the HKMA considers appropriate, it may require the AI to apply the validation technique(s) recommended by the HKMA to a portfolio and to submit the validation results for review.
- 2.10 AIs should have in place processes for benchmarking and stress testing their IRB systems, as described in sections 11 and 12 respectively. While the HKMA recognises that benchmarking may be difficult to apply on some portfolios (e.g. retail and SME) due to the current lack of reliable external benchmarks, it nonetheless encourages AIs actively to develop suitable internal benchmarks for the full range of their portfolios and to use relevant external benchmarks should these become available in future.
- 2.11 The HKMA believes that this approach to validation is consistent with the Basel IRB validation principles, and in particular with the fifth principle which emphasises both the quantitative and

⁹ For example, those set out in Chapter 3 of the document, Regulatory consistency assessment programme (RCAP) – Analysis of risk-weighted assets for credit risk in the banking book, issued by the Basel Committee in April 2016.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

qualitative aspects of validation. However, the guidance contained in the module will be subject to further revision and refinement if there is greater convergence in the quantitative techniques for the validation of internal rating systems.

3. Factors to be considered in the validation process

3.1 Logic and conceptual soundness of a rating system

3.1.1 Developing an IRB system requires an AI to adopt methods, choose risk factors, screen candidate systems and, where necessary, make adjustments to the chosen system. The validation process should therefore include an evaluation of the logic and conceptual soundness of the IRB system. An AI is expected to conduct a thorough review of the developmental evidence for the IRB system to ensure that the AI's judgements are plausible, well-founded and reflect the latest industry practice in the risk management field.

3.1.2 An important aspect in the assessment of the IRB system's logic and conceptual soundness is the rating system's economic plausibility. The risk factors that are included in the rating system should be well founded in the relevant economic and financial theory and in established empirical relationships, rather than spurious relationships which are purely driven by the underlying data. AIs should be able to provide valid explanations on why particular risk factors are included in the rating system. Where possible, AIs should assess the discriminatory power and predictive ability of individual risk factors, and analyse how individual factors behave and interact with other factors in the multivariate context in order to justify their inclusion. Other important aspects include the relevancy of data used to calibrate the rating system, and whether the criteria for system screening in the developmental stage are well supported in theory and evidence and are applied consistently.

3.2 Systems and controls

3.2.1 The HKMA's review of IRB systems places substantial emphasis on the systems and controls environment in



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

which the IRB systems are operated. It includes the extent of Board and senior management oversight and review of the design, implementation and performance monitoring of IRB systems.

3.2.2 The HKMA does not require an AI's directors and senior management to have a thorough in-depth knowledge of all of the technical aspects of the IRB systems. They must however take a leading role in determining the design of the internal rating systems that the AI plans to adopt based on the technical support of internal staff expertise and/or external parties. AIs' directors and senior management therefore must ensure the adequacy of the skills and knowledge of their staff. They also need to clearly delineate and assign responsibilities, and establish the necessary policies, procedures and organisational structures to safeguard the independence of the rating system review work. To determine the adequacy of Board and senior management oversight, the HKMA also assesses the effectiveness of the rating system review staff in bringing issues to the attention of the Board and senior management as appropriate, and the adequacy of the response.

3.2.3 AIs should be able to demonstrate that (i) their IRB systems are subject to an independent rating approval process; (ii) the systems are transparent and fully documented; (iii) there are clear lines of accountability for all aspects of rating accuracy and performance; and (iv) the use test for IRB systems is met. Applicable HKMA requirements in these aspects, including the roles of the AIs' internal and external auditors, and the treatment of vendor models in validation, are set out in sections 4 and 5.

3.3 Data quality

3.3.1 The quality of data maintained by an AI for its IRB systems is key to whether the systems are able to produce accurate and reliable information. The HKMA's assessment of data quality includes an evaluation of the systems and controls that an AI has in place to produce estimates of the credit risk components. Details on



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

provisions relating to data management process and validation are discussed in section 6.

3.4 Accuracy of a rating system

3.4.1 Another important factor in the HKMA's recognition of an AI's IRB systems is whether the rating systems are suitable for the purposes of identifying, measuring and controlling the AI's credit risk taking into account the characteristics and extent of the AI's credit risk exposures, and whether they are capable of generating reasonably accurate, consistent and verifiable credit risk components and calculating the AI's regulatory capital for credit risk. AIs should have a robust system in place to back-test and validate the accuracy of the estimates of the credit risk components, and the discriminative power of the rating systems. AIs should be able to demonstrate the rationale for, and the appropriateness of, adopting any one or more of the quantitative techniques presented in sections 7, 8 and 9. Issues specific to the treatment of LDPs are set out in section 10.

3.4.2 In general, estimates of PD, LGD and EAD are likely to involve unpredictable errors. In order to avoid undue optimism, AIs should add to their estimates a margin of conservatism that is related to the likely range of errors. Where methods and data are less satisfactory and the likely range of errors is larger, the margin of conservatism should be larger.

3.5 Benchmarking

3.5.1 Benchmarking is another key validation activity to assure both the AI and the HKMA that the AI's IRB systems and the resulting estimates of the credit risk components are likely to be accurate. This is particularly the case at the early stages of IRB implementation when data to perform comprehensive back-testing are unlikely to be available. Details on the HKMA's approach to benchmarking and its uses in the validation process are discussed in section 11.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

3.6 Stress-testing

3.6.1 The regular application of a comprehensive stress-testing programme to its IRB systems is essential for an AI to assess its potential vulnerability to “stressed” business conditions. In the validation process, an AI will be required to demonstrate that the stress tests it has conducted are appropriate and effective for assessing the AI’s capital adequacy in, and its ability to withstand the unfavourable impact of, stressed business conditions. The stress-testing provisions on validation are highlighted in section 12.

4. Corporate governance and oversight

- 4.1 Effective oversight by an AI’s Board of Directors and senior management is critical to a sound internal rating system including the estimation processes for the credit risk components. In addition to the provisions set out in this module, AIs should also refer to [CG-1](#) “Corporate Governance of Locally Incorporated Authorized Institutions” and [IC-1](#) “Risk Management Framework” for details of their risk management responsibilities. Many of the provisions and practices cited have a general application.
- 4.2 The HKMA expects the Board and senior management of an AI to be actively involved in the implementation of the IRB approach at inception and on an ongoing basis, although the degree of attention and the level of detail that the Board and senior management need to comprehend will vary depending on their particular oversight responsibilities. At a minimum, the Board and senior management of an AI must approve all the key elements of, and any material changes to, the AI’s rating system; possess an adequate understanding of the design and operation of, and the management reports generated by, the AI’s rating system; and exercise oversight sufficient to ensure the AI’s compliance with applicable HKMA requirements on use of the IRB approach. The approval for the key elements of an internal rating system to be adopted by the AI should normally rest with the Board, or the regional or head office in the case of AIs that are subsidiaries of foreign banking groups.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- 4.3 For the initial adoption of the IRB approach or any subsequent significant overhauls of the constituent rating systems, the Board of an AI may delegate an appropriate party (e.g. a project steering committee or implementation team comprising senior management from the relevant business, credit, finance, IT, operations, and other support or control functions) to oversee and ensure the proper implementation of the IRB approach or any significant changes to it according to a pre-defined plan. Where the AI is a subsidiary of a foreign banking group, such delegation may come directly from the regional or head office.
- 4.4 The Board should ensure that sufficient resources are provided for the purposes of implementing the project and that it is regularly kept informed of progress in implementation and any slippages. If the AI is a subsidiary of a foreign banking group, efforts must be made locally to meet this requirement.¹⁰ Where slippages in the project implementation plan are likely to have a significant effect on the AI's ability to comply with the applicable HKMA requirements, the Board and the HKMA should be informed as soon as possible.
- 4.5 After the IRB approach is implemented, AIs are expected to conduct a comprehensive and independent validation of their internal rating systems at least annually, or when there are material changes in the market environment or business activities of the institutions that might have a significant impact on the use of the rating systems. Nonetheless, it will be acceptable for an AI to conduct the validation exercise on a rolling basis, provided that the arrangements are justified by valid operational considerations, approved by the senior management, and the validation cycle for each portfolio (or component of a rating system, depending on the AI's design of its validation programme) is initiated no more than 12 months and finished within 18 months after the completion of the previous cycle. An AI should be able to demonstrate to the

¹⁰ Depending on the complexity and scale of an IRB approach implementation project, individual AIs may need to appoint a full-time manager to take charge of the project. Also, the project implementation plan may need to be divided further into smaller parts or work streams for easier project management and accomplishment of the required tasks. The responsibilities of the respective committee, project manager and staff taking charge of individual work streams should, as the case may be, be clearly defined and documented in the form of committee terms of reference or job descriptions.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

HKMA that the performance of its rating systems is robust and stable over time. If the HKMA is satisfied with the integrity of the AI's IRB systems including the surrounding controls, it may consider permitting the AI to conduct the comprehensive validation exercise less frequently (e.g. every two years). Regardless of how an AI implements its validation programme to meet this annual requirement, reports containing adequate information on the validation results should be reviewed and subject to deliberation by the Board.

- 4.6 Senior management are responsible for the day-to-day operations of an AI, and should have a good general understanding of the internal rating systems employed by the AI. Except in the case of AIs that are subsidiaries of foreign banks, which may need to follow group-developed internal rating systems, senior management should take a leading role in determining the internal rating systems that the AI plans to adopt based upon the technical support of internal staff and/or external parties with the relevant expertise.
- 4.7 To ensure that the internal rating systems will work consistently and as intended on an ongoing basis, senior management of an AI should:
- allocate and maintain sufficient resources (including IT) and internal staff expertise for the development, implementation, support, review and validation of the internal rating systems to ensure continuing compliance with the applicable HKMA requirements for using the IRB approach;
 - clearly delineate and assign the responsibilities and accountabilities for the effective operations and maintenance of the internal rating systems to the respective business, credit, finance, IT, operations and other support or control functions, or personnel;
 - ensure that adequate training on the internal rating systems is provided for staff in the relevant business, credit, finance, IT, operations and other support or control functions;
 - make necessary changes to the existing policies and procedures as well as systems and controls in order to integrate the use of the internal rating systems into an AI's credit risk management processes and culture;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- ensure that the internal rating systems are put to use properly;
 - ensure that the usage of the internal rating systems extends beyond purely regulatory capital reporting to decision-making and monitoring processes including credit approval, limits setting, credit monitoring and reporting, pricing, internal capital allocation, provisioning, etc. (see paragraphs 5.4.1 and 5.4.2);
 - approve and track material differences between the established policies and actual practice (e.g. policy exceptions or overrides);
 - review the performance and predictive ability of the internal rating systems at least quarterly through MIS reports;
 - meet regularly with staff in the relevant business, credit, finance, IT, operations and other support or control functions to discuss the performance and operations of the rating systems, areas requiring improvement, and the status of efforts to improve previously identified deficiencies; and
 - advise the Board of material changes or exceptions from established policies that may materially impact the operations and performance of the AI's internal rating systems.
- 4.8 As regards the applicable HKMA requirements for quarterly review of the performance and predictive ability of the internal rating systems, the HKMA recognises that an increase in the number of defaulted cases over a three-month period may not be significant, especially for certain portfolios with low frequency of default events. In this case, it will be sufficient for senior management to examine only the default and rating migration statistics in the quarterly review exercise, provided that the AI is able to justify its approach with empirical evidence. In addition, the quarterly review of the default and rating migration statistics should include comparisons with expectations and historical figures.
- 4.9 Information on the internal ratings should be reported to the Board and senior management regularly. The depth and frequency of reporting may vary with the significance and the



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

oversight responsibilities of the recipients. The reports should, at a minimum, cover the following information:

- risk profile of the AI's obligors by grade;
- risk rating migration across grades and comparison with expectations;
- estimates of the relevant credit risk components per grade;
- comparison of realized default rates (and LGD and EAD where applicable) against estimates;
- changes in regulatory and economic capital, and identification of sources of the changes;
- results of credit risk stress-testing; and
- reviews on the effectiveness of the internal rating systems and processes (including the results of validation, and reports on policy exceptions and overrides) by internal audit function and other independent control functions.

4.10 The HKMA will look for evidence of the Board and senior management involvement in IRB implementation, and their understanding of the internal rating systems during both the initial IRB recognition process and, where appropriate, the on-going review process of the IRB systems to ensure continual compliance with applicable HKMA requirements.

5. Other systems of control

5.1 Independence

5.1.1 Als should have a credit risk control unit that is functionally independent of the AI's staff and management responsible for credit initiation and that has a direct reporting line to the AI's senior management to be responsible for the design, selection, testing and implementation, oversight of the effectiveness, as well as related monitoring and review, of an internal rating system. Als should also ensure sufficient independence in the rating approval process and in the review of the IRB system and risk quantification.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Independent rating approval process

- 5.1.2 An independent rating approval process is where the parties responsible for approving ratings and transactions are separate from those responsible for credit initiation (such as sales and marketing). The purpose is to achieve more objective and accurate risk rating assignment.
- 5.1.3 Rating processes vary by AI and by portfolio but generally involve a rating “assignor” and a rating “approver”. In an expert judgement-based rating process, the HKMA expects that credit officers should normally be the party responsible for approving ratings. Their independence should be safeguarded through independent and separate functional reporting lines, and well-defined performance measures (e.g. adherence to policy, rating accuracy and timeliness).
- 5.1.4 In some cases, ratings are assigned and approved within sales and marketing by staff (although at perhaps different levels of seniority) whose compensation is tied to the volume of business they generate. The HKMA does not normally consider that such arrangements are consistent with an adequate degree of independence in the rating approval process. However, the HKMA may, in both the initial IRB recognition process and the on-going review process of the IRB systems, take into account the size and nature of the portfolio to which these arrangements are applied, and the compensating controls in place to mitigate the inherent conflict of interest (such as limited credit limits, independent post-approval review of ratings, and more frequent internal audit coverage, to prevent any bias in the rating assignment and approval process).
- 5.1.5 The above requirements are primarily intended to apply to cases where expert judgement forms part of the inputs to the rating assignment or approval process. If the rating assignment and approval process are highly automated and all the rating criteria are based on objective factors (i.e. expert judgement does not form part of the rating process), the independent review



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

should at a minimum include a process for verifying the accuracy and completeness of the data inputs.

Independent validation of IRB system and risk quantification

5.1.6 To ensure the integrity of the IRB systems and risk quantification, Als should have a comprehensive and independent validation process. The unit(s) responsible for validation should be functionally independent from the staff and management functions responsible for developing the underlying IRB systems and performing risk quantification activities, and have sufficient stature in the organisational hierarchy to challenge effectively the work of the model developers. The activities of this validation process may be distributed across multiple areas or housed within one unit. Als may choose a structure that fits their management and oversight framework. However, to maintain the independence of the validation process, cross-validations, whereby two or more separate units validate the IRB models developed by one another, should be avoided. Individuals performing the validations should possess the requisite technical skills and expertise. The validation of the IRB systems should encompass the following aspects:

- compliance with the applicable HKMA requirements for using the IRB approach;
- compliance with established policies and procedures;
- quantification process and accuracy of the credit risk component estimates¹¹;
- rating system development, use¹² and validation¹³;

¹¹ Including an evaluation of model risk (i.e. incorrect estimation of IRB risk parameters), together with an evaluation of the appropriateness of margins of conservatism to cope with model and data imperfections.

¹² Including an evaluation of model use, such as whether there are limitations on input data, how overrides are documented, how model users are trained and feedback received from model users.

¹³ The performance test and back-testing should take place at the aggregate model level as well as at more granular grade or segment levels.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- review and documentation of changes to the rating process and rating system, including the reasons for changes;
 - adequacy of data systems and controls; and
 - adequacy of staff skills and experience.
- 5.1.7 The independent validation unit(s) should formulate a plan to define the validation activities and review processes to be performed. The plan should be modified as appropriate having regard to findings identified in the validation processes. The independent validation unit(s) should perform its own tests of all material aspects of the models, including model performance, quality of databases used, and data cleaning. These tests should also cover tests already performed by the model developers, to check their reliability.
- 5.1.8 The validation processes should seek to identify any weaknesses, make recommendations and ensure that corrective actions are taken. Significant findings of the validations must be reported to the Board and senior management.
- 5.1.9 Als that at present lack sufficient in-house expertise to be able to perform the validation function adequately should make appropriate use of external support that is independent and suitably qualified. Those Als that already have the needed skills and resources in-house should nonetheless consider the benefits of supplementing their internal processes with external reviews. External reviewers are likely to possess a broader perspective on the use of rating systems in different jurisdictions and in different institutions, and they may possess more comprehensive data sets to support the cross-testing of rating systems. Notwithstanding that some validation activities are outsourced to external parties, the Al's internal independent validation unit(s) should retain full and ultimate responsibility for the validation activities and results.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

5.2 Transparency

- 5.2.1 Als' internal rating systems should be transparent to enable third parties, such as rating system reviewers, internal or external auditors, and the HKMA, to understand the design, operations and accuracy of the rating systems, and to evaluate whether the internal rating systems are performing as intended. Transparency should be an ongoing requirement and be achieved through documentation as stipulated in the BCR and explained further in Annex E. In particular, the HKMA expects Als to update their documentation in a timely manner (e.g. as and when modifications are made to the rating systems).
- 5.2.2 Where Als adopt an expert judgement-based internal rating system, the personal experience and subjective assessment used in rating credits are less transparent. Als should offset this shortcoming by applying greater independence in the rating approval process and an enhanced rating system review.
- 5.2.3 Whilst ratings produced by models are more transparent, a model's performance depends on how well the model was developed, the model's logic, the quality of data used to develop the model and the data fed into it during use. Als that use models to assign ratings should implement a system of controls that addresses model development, testing and implementation, data integrity and overrides. These activities should be covered by ongoing spot checks on the accuracy of model inputs. Other control mechanisms such as accountability, and internal or external audit are also required.

5.3 Accountability

- 5.3.1 To ensure proper accountability, Als should have policies that identify individuals or parties responsible for rating accuracy and rating system performance, and establish performance standards in relation to their responsibilities.
- 5.3.2 The responsibilities (including lines of reporting and the authority of individuals) must be specific and clearly defined. The performance standards should be



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

measurable against specific objectives, with incentive compensation tied to these standards.

- 5.3.3 For example, performance measures of personnel responsible for rating assignment may include number and frequency of rating errors, significance of errors (e.g. multiple downgrades), and proper and consistent application of criteria, including override criteria.
- 5.3.4 Staff who assign and approve ratings, derive the credit risk component estimates, or oversee rating systems must be held accountable for complying with internal rating system policies and ensuring that those aspects of the internal rating systems under their control are unbiased and accurate. For accountability to be effective, these staff must have the knowledge and skills, and tools and resources necessary to carry out their responsibilities.
- 5.3.5 If AIs use models in the rating assignment process, a mechanism should be in place to maintain an up-to-date inventory of models¹⁴, and an accountability chart of the roles of the parties within the AIs responsible for every aspect of the models including the design, development, use, data updating, data checking, and validation of the models.
- 5.3.6 A specific individual at sufficiently senior level should have responsibility for the overall performance of the internal rating systems. This individual must ensure that the internal rating systems and all of their components (rating assignments, estimation of the credit risk components, data collection, control and oversight mechanisms etc.) are functioning as intended. When these components are distributed across multiple units of the AI, this individual should be responsible for ensuring that the parts work together effectively and efficiently.

¹⁴ The inventory of models should include a comprehensive list of models used by the AI, their scopes, materiality, and brief descriptions of modelling methodologies and approval conditions.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

5.4 Use of internal ratings

Areas of use

5.4.1 An AI which makes an application to the MA under §8(1) of the BCR for approval to use the IRB approach is required to demonstrate to the satisfaction of the MA that it meets the minimum requirements set out in Schedule 2 of the BCR relating to the use of the AI's rating systems. In particular, the rating systems, and estimates of credit risk components generated by the rating systems (e.g. ratings and default and loss estimates), should play an essential role in the ongoing credit approval, risk management, internal capital adequacy assessment, and corporate governance functions of the AI to the extent that they relate to exposures covered by the IRB approach.

5.4.2 Internal rating systems from which ratings and estimates of the credit risk components are generated for regulatory capital calculation should be used in such a way as to exert a direct and observable influence on an AI's decision-making and actions. In particular, the HKMA expects AIs to apply their internal ratings and estimates of the credit risk components to credit approval, credit monitoring, analyses and reporting of credit risk information (including to the AI's Board of Directors and senior management), and the majority of the following uses:

- pricing;
- setting of limits for individual exposures and portfolios;
- determining provisioning¹⁵;
- modelling and management of economic capital;

¹⁵ There are differences in the requirements governing estimation of credit losses under the IRB approach and under accounting standards (e.g. IFRS 9). The HKMA does not intend to mandate an AI to use the IRB parameters to determine provisions for the purposes of IFRS 9. Where an AI uses IRB parameters to inform its provisioning decisions, the application must be in a meaningful way in order to qualify towards satisfying the use test requirements (e.g. the rank ordering of obligors or exposures should remain the same as that for the purposes of IRB calculations).



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- assessment of total capital requirements in relation to credit risks under the AIs' Capital Adequacy Assessment Process ("CAAP");
- assessment of risk appetite;
- formulating business strategies (e.g. acquisition strategy for new exposures and collection strategy for problem loans);
- setting of, and assessment against, profitability and performance targets;
- determining performance-related remuneration (e.g. for staff responsible for rating assignment and/or approval); and
- other aspects of AIs' risk management (e.g. information technology systems, skills and resources, and organisational structure).

Justifications for using different estimates

5.4.3 AIs may not necessarily use exactly the same estimates for both regulatory capital calculation and internal purposes. Where there are differences, however, AIs should document the differences and their justifications. The justifications should include:

- a demonstration of consistency amongst the risk factors and rating criteria used in generating the estimates for regulatory capital calculation and those for internal purposes;
- a demonstration of consistency amongst the estimates used in regulatory capital calculation and those for internal purposes; and
- qualitative and quantitative analysis of the logic and rationale for the differences.

5.4.4 The justifications should be reviewed by the credit risk control unit and approved by senior management.

5.4.5 The HKMA notes that some AIs may maintain more than one rating model for the same portfolio. For example, one model might be used for the purpose of calculating



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

regulatory capital and another for the purpose of benchmarking. These models may all have been developed in-house, or obtained from external sources, or a combination of both. In all such cases, the HKMA expects an AI to provide documented justification for its application of a specific model to a specific purpose, and for the role it has assigned to that model in its credit management process. In its assessment of whether the "use test" for IRB systems has been met, the HKMA will consider the extent to which an AI makes internal use of the system as a whole, rather than applying the test on an individual model basis.

5.5 Internal audit function and external audit

Internal audit function¹⁶

- 5.5.1 Internal audit function should review at least annually an AI's internal rating systems (including the validation process and the estimation of the credit risk components) and the operations of the related credit risk control unit. The purpose is to verify whether the control mechanisms over the internal rating systems are functioning as intended and the AI is in compliance with the applicable HKMA requirements for using the IRB approach. Internal audit function should document the findings and report them to the Board and senior management.
- 5.5.2 The areas of review should include the independence of the credit risk control unit and the depth, scope and quality of work conducted by it in respect of the AI's use of the IRB approach.
- 5.5.3 Internal audit function should give an opinion on the continuing appropriateness, relevance and comprehensiveness of the existing control mechanisms, the adequacy of expertise of staff responsible for the operations of the credit risk control unit, the resources available to these staff, and an assessment of the AI's compliance with the applicable HKMA requirements, and

¹⁶ The independent review or audit in respect of an AI's IRB systems can be conducted by independent external parties which are qualified to do so.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

any conditions attached to the HKMA's approval, for the AI's use of the IRB approach.

5.5.4 In reviewing an AI's application for using the IRB approach, the HKMA will evaluate, amongst others, the adequacy of the internal audit function. In particular, the AI should be able to demonstrate to the HKMA that:

- the required skill sets of internal audit staff and resources have been suitably strengthened within a definite timeframe before the AI's implementation of the IRB approach; and
- the internal audit scope and programme have been revised such that compliance with the applicable HKMA requirements for using the IRB approach is an area to be covered in the annual audit plan.

5.5.5 Under the IRB recognition process, AIs are required to submit self-assessment questionnaires and relevant supporting documents for review by the HKMA. The HKMA expects internal audit function to be one of the parties signing off on the completed self-assessment as evidence that it has verified an AI's adherence to all applicable HKMA requirements.

External audit

5.5.6 As part of the process of certifying financial statements, external auditors should gain comfort from an AI that its IRB systems are measuring credit risk appropriately and that its regulatory capital position is fairly presented. External auditors should also seek to assure themselves that the AI's internal controls relating to the calculation of regulatory capital are in compliance with applicable HKMA requirements.

5.6 Treatment of external vendor models

5.6.1 AIs commonly make use of outside expertise to develop models for decision-making or risk management purposes. In the context of the IRB approach, an external vendor model is a model developed by an external third party and used by an AI to assign its



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

exposures to rating grades or to estimate the credit risk components of its exposures.

- 5.6.2 As specified in Annex E, the use of a model obtained from an external vendor that claims proprietary technology is not a justification for exemption from documentation, or any other, applicable HKMA requirements in respect of the model. Thus, these models generally have to fulfil the same applicable HKMA requirements as models produced in-house. In addition, senior management should ensure that the outsourced activities performed by external vendors are supported by sufficient quality control measures to ensure that applicable HKMA requirements for using the IRB approach are met on a continuous basis. AIs may refer to [SA-2](#) “Outsourcing” for further guidance.
- 5.6.3 The burden is on the AI to satisfy the HKMA that it complies with these applicable HKMA requirements. The HKMA assessment regarding an external vendor model will focus on the transparency of the model and on its linkage to the internal information used in the rating process. Where the HKMA considers appropriate, it may request an AI and its external vendor to provide detailed information for the HKMA’s assessment.
- 5.6.4 AIs should demonstrate that they have the in-house knowledge to understand the key aspects of the external vendor models. In particular, they should be able to demonstrate a good understanding of the development (e.g. the overarching design, assumptions, data used, methods and criteria for risk factor selection and determination of the associated weights) and the appropriate use of external vendor models. This requires external vendors to document the development of models and the fundamentals of their validation processes in a way that permits third parties to understand the methodologies applied, and to assess whether the models perform adequately on the AI’s current portfolios. AIs should identify and consider in the course of monitoring their models all the limitations of the models and the circumstances in which the models do not perform as expected.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- 5.6.5 Where AIs make use of external vendor models, they should ensure that they possess sufficient in-house model expertise to support and assess these models. Staff who are model users should be provided with adequate training on the use of these models.
- 5.6.6 Where parts of the model developed externally are used simultaneously with parts developed in-house, AIs need to be clear about the nature and content of the information (data) that is processed in the external model. They should ensure that this information is appropriately linked to information that is processed by the parts developed in-house, so that the aggregation of the different parts of the model does not result in an inconsistent rating method.

6. Data quality

6.1 Overview

- 6.1.1 An AI should have an effective system to collect, store, process, retrieve and utilize data on obligor and facility characteristics and default and loss information in respect of the AI's exposures in a reliable and consistent manner. An AI should ensure that the internal or external data it uses in estimating PD, and, where relevant, LGD and EAD, are representative of the AI's long run default and loss experience and are based on relevant economic or market conditions. A process should be in place for vetting data inputs into the internal rating systems. The process should include an assessment of the accuracy, completeness and appropriateness of data.
- 6.1.2 The HKMA recognises that the approach to data management varies by AI and, on many occasions, by type of exposures within an AI. However, regardless of the approach they adopt, AIs should adhere to the provisions in this section in respect of the following aspects:
- management oversight and control;
 - IT infrastructure and data architecture;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- data collection, storage, retrieval and deletion;
- data processing;
- data quality assessment;
- reconciliation between the data used for the IRB calculations and the accounting data;
- use of external and pooled data; and
- application of statistical techniques.

6.1.3 An AI should provide the HKMA with a summary of its approach to data management in relation to the above aspects. The summary should include a diagram of the data architecture covering the collection and storage of data, all data flows between systems, and how relevant data are collated for regulatory capital calculation purposes.

6.2 Management oversight and control

6.2.1 Senior management of an AI have the responsibility for establishing and maintaining a consistent standard of sound practices for data management across the AI. In particular, senior management are responsible for:

- establishing policies, standards and procedures for the collection, maintenance, delivery, updating and use of data, and ensuring their effective implementation;
- establishing a clear organisational structure specifying the accountability for data collection and management so as to ensure proper segregation of duties amongst and within various business units to support data management tasks;
- assessing on an ongoing basis the risks arising from potential poor quality data and ensuring that appropriate risk mitigation measures have been undertaken;
- ensuring sufficient staffing with relevant expertise and experience to handle present and expected work demand;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- formalising internal audit programmes, the scope of which should include assessments of both the numbers produced and the processes used in data management; and
- ensuring that outsourced activities performed by external vendors are supported by sufficient quality control measures to ensure that applicable HKMA requirements for using the IRB approach are met on a continuous basis.

6.2.2 Where data management-related activities are performed on behalf of the AI by another entity in the same banking group, such as an overseas office, the management of the AI are responsible for ensuring that the standards of data management employed by the group entity are consistent with applicable HKMA requirements, and that the respective responsibilities of the entity and the AI are documented (e.g. policies, procedures or service agreements) and properly implemented.

6.3 IT infrastructure and data architecture

6.3.1 An AI should have an adequate IT infrastructure (e.g. data warehouse or data mart) in place to support the management of data. In particular, AIs should store data in electronic format so as to allow timely retrieval for analysis and validation of internal rating systems. The infrastructure should also support comprehensive data quality control measures including data validation and error detection, data cleansing, reconciliation and exceptions reporting.

6.3.2 AIs' data architecture should be scalable, secure and stable¹⁷. Scalability ensures that growing needs due to lengthening data history and business expansion can be met. AIs should test systems' security and stability in the development of data architecture and IT systems. The HKMA expects AIs to have policies, standards and

¹⁷ For ensuring the stability and security of IT systems, AIs should follow the guidance set out in [TM-G-1](#) "General Principles for Technology Risk Management".



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

measures, including audit trails, in place to control access to the data. AIs should also have complete back-up, recovery and contingency planning to protect data integrity in the event of emergency or disaster¹⁸.

6.4 Data collection, storage, retrieval and deletion

6.4.1 AIs should have clear and documented policies, standards (including IT standards) and procedures regarding the collection and maintenance of data in practice, such that data availability can be ensured over time to meet the anticipated demands in the medium and long run, and the data stored include sufficient detail so as to enable the AIs to comply with applicable HKMA requirements in relation to data management.

6.4.2 Data should be updated at least annually or more frequently as required in accordance with the relevant minimum updating requirement for estimation of the credit risk components¹⁹. AIs should be able to demonstrate that their procedures to ensure that the frequency with which data items are updated are sufficient to reflect the risk inherent in their current portfolios. For example, data for higher risk obligors or delinquent exposures should be subject to higher updating frequency.

6.4.3 The HKMA also expects AIs to:

- establish clear and comprehensive documentation for data definition, collection and aggregation, including data sources, updating and aggregation routines;
- establish standards and conduct relevant tests for the accuracy, completeness, timeliness and reliability of data;
- ensure that data collected have the scope, depth and reliability to support the operations of the

¹⁸ The guidance set out in [TM-G-2](#) “Business Continuity Planning” is applicable here.

¹⁹ For example, §186(2)(e) of the BCR requires data updates at least every 3 months in respect of the internal models method for equity exposures and a reassessment of the data whenever market prices change materially.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

internal rating systems, overrides, back-testing, capital requirement calculation and relevant management and regulatory reporting;

- in cases where the necessary data items are absent in the collection process (i.e. data gaps), identify and document such gaps, specify the interim solutions in respect of the rating assignment and risk quantification processes and set up a plan to fill the gaps;
- establish standards, policies and procedures around the cleansing of data, and ensure consistent applications of the techniques;
- establish procedures for identifying and reporting data errors and problems in data transmission and delivery;
- ensure that data collection, storage and retrieval are secure, and at the same time not forming unnecessary obstacles to data users (including the HKMA for supervisory purposes);
- ensure that access controls and data distribution have been validated by internal audit function; and
- establish documented policies and procedures addressing storage, retention and archival, including the procedures for deletion of data and destruction of data storage media.

6.5 Data processing

6.5.1 Data processing covers a wide range of manual or automated activities including data conversion through multiple systems, transmissions, validation and reconciliation. In this regard, the HKMA expects AIs to:

- limit reliance on manual data manipulation in order to mitigate the risk related to human error;
- establish standards and data processing infrastructure for life-cycle tracking of credit data including, but not limited to, relevant history covering features of obligors and facilities, ratings



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

and overrides, repayments, rollovers and restructuring;

- ensure that data are validated and cleansed, and reconciled with accounting data (see subsection 6.6), such as sample checking on manually input financial statements information;
- establish adequate controls to ensure processing by authorized staff acting within designated roles and authorities;
- modify the control procedures when there are changes in the processing environments, conduct testing and parallel processing, and obtain sign-offs by staff at appropriately senior level before full implementation; and
- provide back-up, process resumption and recovery capabilities to mitigate loss of data and/or data integrity in the event of emergency or disaster²⁰.

6.6 Reconciliation

6.6.1 The HKMA expects AIs to conduct reconciliation, where possible, between accounting data and the data used in the risk quantification process under the IRB approach. This would require AIs to identify from the risk quantification data set those data items that can be reconciled with accounting data, and establish the procedures for doing so.

6.6.2 Both an AI's internal rating systems and its accounting systems take data inputs and transform them into data outputs. Therefore, reconciliation between these systems may focus on inputs, outputs (e.g. expected loss under the IRB approach and relevant accounting provisions) or both. At a minimum, AIs should conduct reconciliation on data inputs.

6.6.3 AIs should document the reconciliation process and results (i.e. the amount of the difference between the

²⁰ The guidance set out in [TM-G-2](#) "Business Continuity Planning" is applicable here.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

two data sets). The documentation should also include explanations for why and how the difference arises. The explanations should be sufficiently detailed and supported by sufficient evidence to facilitate internal audit function in verifying enterprise-wide consistency in the use of data and assessing data accuracy, completeness and appropriateness.

6.6.4 For example, for on-balance sheet exposures, the outstanding amount used as the EAD input for regulatory capital calculation could be substantially lower than that for accounting. This is because on-balance sheet netting between loans to and deposits from the same obligor is allowed in the former but not in the latter. The HKMA expects AIs to document such explanations, and the amount of difference accounted for by each of the explanations.

6.6.5 AIs should document the treatment of non-reconciled items (i.e. the amount of difference that cannot be fully explained). In addition, as non-reconciliation may be an indication of deficiency in data quality, AIs should establish standards to address this, and enhance their data management process and apply conservatism in regulatory capital calculation when there are discrepancies. The HKMA may not approve an AI's rating systems if, in its opinion, the discrepancies are of such significance as to cast doubt on the reliability of the systems.

6.7 Data quality assessment

6.7.1 In addition to qualitative assessments on the adequacy of the aspects described in subsections 6.2 to 6.6, the HKMA expects AIs to apply quantitative measures in assessing data accuracy (e.g. error rates in sample checking of data accuracy), completeness (e.g. proportion of observations with missing data) and timeliness (e.g. proportion of data updated later than scheduled).

6.7.2 The data quality assessment should be included as part of the independent review and validation of the rating assignment and risk quantification processes. While the



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

reviewers may either be internal or external parties, they must not be accountable for the work being reviewed.

- 6.7.3 The data quality assessment should be conducted at least annually, matching the minimum frequency of validation of internal estimates by independent validation unit(s) and the review of adherence to all applicable HKMA requirements by internal audit function.
- 6.7.4 The methods employed and analyses conducted in the assessment should be fully documented. The assessment results should be reported to senior management, and further investigation and follow-up action should be fully documented.
- 6.7.5 To facilitate quality assessment and identification of problems, Als should ensure that there are clear audit trails on data (information on where the data are collected, how they are processed and stored, and used in the rating assignment and risk quantification processes etc.).

6.8 Use of external and pooled data

- 6.8.1 Als that use external or pooled data in rating system development and validation, rating assignment and/or risk quantification processes must be able to demonstrate that the data are applicable and relevant to the portfolio to which they are being applied. Als should be able to demonstrate that data definitions are consistent between the external or pooled data, and Als' internal portfolio data, and that distributions of the key risk characteristics (e.g. industry and size) are similar.
- 6.8.2 Als should be able to demonstrate that arrangements for data management by external vendors in relation to external or pooled data used by Als meet the same standards required for data management by Als. In addition, Als should have policies and procedures in place to assess and control the risk arising from the use of external or pooled data. In particular, Als are expected to:
- understand how the third parties collect the data;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- understand the quality control programmes used by the third parties and evaluate the adequacy thereof;
- establish explicit data cleansing procedures for the external or pooled data;
- check the external or pooled data against multiple sources regularly (no less than once every 12 months) to ensure the accuracy, completeness and timeliness of data; and
- conduct regular reviews (no less than once every 12 months) to assess the appropriateness of continuing the use of the external or pooled data.

6.8.3 The process of managing the use of external or pooled data, including the activities described above, should be documented and subject to review by the AI's internal audit function.

6.8.4 When outsourcing activities are involved in the data management process, AIs should follow the guidance set out in [SA-2](#) "Outsourcing" and section 7 of [TM-G-1](#) "General Principles for Technology Risk Management".

6.9 Statistical issues

6.9.1 Where AIs use statistical techniques (e.g. sampling, smoothing and sample truncation to remove outlying observations) in the preparation of the development and validation data sets, and in the operations of internal rating systems, their application should be justified and based on sound scientific methods. AIs should be able to demonstrate a full understanding of the properties and limitations of the statistical techniques they use, and the applicability of these techniques to different types of data.

6.9.2 AIs should be able to demonstrate that the occurrences of missing data are random and that they do not have systematic relationships with default events or credit losses. Where it is necessary to remove observations with missing data, AIs should provide sound justifications, as these observations may contain important information on default events or credit losses. The HKMA does not normally consider that an AI has a



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

valid internal rating system if a large number of observations with missing data have been removed from the system.

7. Accuracy of PD

7.1 Overview

- 7.1.1 There are two stages in the validation of PD: validation of the discriminatory power of an internal rating system and validation of the calibration of an internal rating system (accuracy of the PD quantification). For each stage, the HKMA expects AIs to be able to demonstrate that they employ one or more of the quantitative techniques listed in subsections 7.2 and 7.3²¹ respectively. The procedures and assumptions used in applying the techniques must be documented and consistently applied.
- 7.1.2 If an AI intends to use techniques not included in subsections 7.2 and 7.3, such as proprietary or customised tests, or techniques with ideas borrowed from other fields, it should be able to demonstrate to the HKMA that the techniques are theoretically sound, well-documented, consistently applied and able to meet the requirements applicable to the generally accepted quantitative techniques.
- 7.1.3 The HKMA expects AIs to validate both the discriminatory power and calibration of their internal rating systems regularly (no less than once every 12 months). Such validations should be conducted based on the definition of default under the IRB approach in the BCR, notwithstanding any alternative definitions for default AIs may employ for their own internal risk management purposes. If an AI considers that the status of a previously defaulted exposure is such that the trigger of the definition of default no longer applies, the AI should rate the obligor and estimate LGD as it

²¹ Technical details and properties of the methodologies of validation of discriminatory power and calibration are given in Annexes A and B respectively.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

would for a non-default facility. Should the prescribed definition of default be subsequently triggered, a second default would be deemed to have occurred.

- 7.1.4 An AI must also have a set of procedures to evaluate the appropriateness of the method or data used in making the PD estimates (and also other risk estimates), and there is a mechanism for increasing the estimates to improve the accuracy of the estimates used by the AI (e.g. by adding a margin of conservatism for any likely range of errors).

7.2 Validation of discriminatory power

- 7.2.1 The HKMA expects AIs to demonstrate that they use one or more of the following methodologies in assessing the discriminatory power of an internal rating system:

- Cumulative Accuracy Profile (“CAP”) and its summary index, the Accuracy Ratio (“AR”);
- Receiver Operating Characteristic (“ROC”) and its summary indices, the ROC measure, the Pietra Index and Kolmogorov-Smirnov (“KS”) test statistic;
- Bayesian error rate (“BER”);
- Conditional entropy, Kullback-Leibler distance, and Conditional Information Entropy Ratio (“CIER”);
- Information value (“IV”);
- Kendall’s τ and Somers’ D (for shadow ratings);
- Brier score (“BS”); and
- Divergence.

- 7.2.2 AIs should be able to demonstrate the rationale and the appropriateness of their chosen quantitative techniques, and to understand the limitations, if any, of such techniques.

Stability analysis

- 7.2.3 The HKMA expects AIs to demonstrate that their internal rating systems exhibit stable discriminatory power. Therefore, in addition to in-sample validation, AIs should



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

be able to demonstrate their internal rating systems' discriminatory power on an **out-of-sample** and **out-of-time** basis. This is to ensure that the discriminatory power is stable on data sets that are cross-sectionally or temporally independent of, but structurally similar²² to, the development data set. If out-of-sample and out-of-time validations cannot be conducted due to data constraints, AIs will be expected to employ statistical techniques such as k-fold cross validation or bootstrapping for this purpose. When an AI uses these statistical techniques, it should be able to demonstrate the rationale and the appropriateness of the chosen techniques, and understand the limitations, if any, of these techniques.

Establishment of internal tolerance limits and responses

- 7.2.4 The HKMA expects AIs to establish internal standards for assessing the discriminatory power of their internal rating systems. Breaches of these standards, together with the associated responses, should be fully documented. The HKMA expects to see a range of responses from increase in validation frequency to redevelopment of the internal rating systems, depending on the results of the assessments.
- 7.2.5 The HKMA expects an AI's internal standards for its rating systems' discriminatory power, and its responses to breaches of these standards, to be commensurate with the potential impact on the AI's financial soundness of a failure of its internal rating systems to discriminate adequately between defaulting and non-defaulting obligors. In setting its standards and determining the response to a breach of those standards, an AI should take into account factors including, but not limited to, the relative sizes of the portfolios to which the internal rating systems are applied, its risk appetite relating to the

²² "Structurally similar" means that distributions of obligors' key characteristics (e.g. industry and company size) in the independent data set for validation are similar to those in the development data set.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

portfolios, and the inherent risk characteristics of the portfolios.

7.3 Validation of calibration

7.3.1 The HKMA expects AIs to demonstrate the use of one or more of the following methodologies in assessing an internal rating system's calibration:

- Binomial test with assumption of independent default events;
- Binomial test with assumption of non-zero default correlation; and
- Chi-square test.

Establishment of internal tolerance limits and responses

7.3.2 The HKMA expects AIs to establish internal tolerance limits for the differences between the forecast PD and the realized default rates. AIs should have a clearly documented policy that requires remedial actions to be taken when tolerance limits are exceeded, and any remedial actions should also be documented.

7.3.3 AIs should construct the tolerance limits (and the associated policy on remedial actions) around the confidence levels used in the tests in paragraph 7.3.1²³.

7.3.4 AIs should be able to demonstrate that the internal tolerance limits and remedial actions are commensurate with the risk that the computed capital requirement would not be adequate to cover the default risk incurred. In setting its internal standards, and determining any remedial actions, an AI should be able to demonstrate that it has taken into account a range of factors, including, but not limited to, the relative sizes of the

²³ For example, if a Binomial test is used, AIs can set tolerance limits at confidence levels of 95% and 99.9%. Deviations of the forecast PD from the realized default rates below a confidence level of 95% should not be regarded as significant and remedial actions may not be needed. Deviations at a confidence level higher than 99.9% should be regarded as significant and the PD must be revised upward immediately. Deviations which are significant at confidence levels between 95% and 99.9% should be put on a watch list, and upward revisions to the PD should be made if the deviations persist.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

portfolios to which the internal rating systems are applied, the AI's risk appetite in respect of the portfolios, the distribution of the portfolios amongst rating grades, and the inherent risk characteristics of the portfolios.

8. Accuracy of LGD

8.1 Overview

- 8.1.1 The estimation and quantitative validation methodologies of LGD are generally less advanced than those of PD. As such, for the validation of LGD estimates, the HKMA puts relatively more emphasis on the qualitative assessment of the measurement and estimation process than the use of quantitative techniques.
- 8.1.2 Methods for assigning LGD to non-default facilities and the relevant validation issues are discussed in subsection 8.2. Issues specific to workout LGD, the most commonly-used method, are discussed in subsection 8.3. The elements of the LGD estimation process and validation of LGD estimates are outlined in subsections 8.4 and 8.5 respectively.
- 8.1.3 AIs should be able to meet, among others, the following provisions regarding the estimation of downturn LGD²⁴:
- (i) an AI should have a rigorous and well-documented process for assessing the effects of economic downturn conditions on recovery rates and for producing LGD estimates consistent with these conditions;
 - (ii) in discounting the cash flows used in LGD estimation, the measurement of recovery rates should reflect the cost of holding defaulted assets over the workout period, including an appropriate risk premium; and

²⁴ For example, see "[Guidance on Paragraph 468 of the Framework Document](#)", Basel Committee, July 2005.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- (iii) the AI should provide the HKMA with the long-run default-weighted average loss rate given default for every relevant facility type unless the AI can demonstrate to the HKMA that:
- its estimate of loss rate given default under downturn conditions is consistent with (i) and (ii) above; and
 - reporting a separate estimate of long-run default-weighted average loss rate given default would not be practical.

8.2 Methods for assigning LGD to non-default facilities

8.2.1 The HKMA expects AIs to use one of the following methods to assign LGD to non-default facilities:

- **workout LGD** which is based on observations of the discounted cash flows resulting from the workout process for the defaulted facilities;
- **market LGD** which is derived from observations of market prices on defaulted bonds or marketable loans soon after default;
- **implied historical LGD** which is inferred from an estimate of the expected long-run loss rate (which is based on the experience of total losses) of a portfolio (or a segment of a portfolio) and the PD estimate of that (segment of) portfolio. This method is only allowed for deriving the LGD of retail exposures; and
- **implied market LGD** which is derived from non-default risky bond prices through an asset-pricing model.

8.2.2 For both the workout LGD and market LGD methods, AIs should be able to demonstrate to the HKMA that they have:

- (i) determined which defaulted facilities are to be included in the development data set;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- (ii) established articulated methods to determine and measure the realized LGD of the defaulted facilities in the development data set; and
- (iii) established articulated methods to assign LGD to the non-default facilities in the Als' current portfolios based on the information obtained from the process in (ii).

8.2.3 For the implied historical LGD method for retail exposures, the validity of a LGD estimate will depend on that of the estimate of the expected long-run loss rate and that of the PD estimate. Therefore, Als should be able to demonstrate to the HKMA that the estimates of the expected long-run loss rate and the PD are appropriate.

8.2.4 For the implied market LGD method, credit spreads of the non-default risky bonds (versus realized LGD of the defaulted facilities for the workout LGD and market LGD methods) are used. The credit spreads, among other things, are decomposed into PD and LGD with an asset-pricing model. The Als should therefore be able to demonstrate to the HKMA:

- the appropriateness of the non-default facilities that are included in the development data set; and
- how credit spreads are decomposed (i.e. the soundness of the asset-pricing model used).

8.2.5 The HKMA expects Als to be able to justify their choice of method for LGD estimation. Als should be able to demonstrate a full understanding of the properties and limitations of the methods they use, and the applicability of these methods to different types of facilities.

8.3 Issues specific to workout LGD

8.3.1 Workout LGD is the most commonly-used method in the industry. The definition of when a workout ends, measurements of recoveries and costs, and the assumption on discount rates are crucial to computing the realized LGD for the defaulted facilities in the development data set.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Definition of the end of a workout

8.3.2 The HKMA expects Als to define when a workout is finished using one of the following four options:

- (i) a recovery threshold (e.g. when the remaining non-recovered value is lower than 5% of the EAD);
- (ii) a given time threshold (e.g. one year from the date of default);
- (iii) an event-based threshold (e.g. when repossession occurs); and
- (iv) a combination of (i), (ii) and/or (iii) (e.g. the earlier of one year from the date of default or when repossession occurs).

When formulating the definition, Als should consider the resulting impact on the development data set²⁵, and be able to justify their choice.

Measurement of recoveries

8.3.3 Recoveries from a workout process can be **cash recoveries** and/or **non-cash recoveries**.

- Cash recoveries are relatively easy to measure and incorporate into the LGD calculations.
- Non-cash recoveries, especially those resulting from repossessions, are more difficult to track and are typically treated on a case-by-case basis for individual defaulted facilities in the development data set.

8.3.4 There are two options for Als to measure non-cash recoveries resulting from repossessions.

- The first option is to consider the recovery process complete at the time of the repossession.

²⁵ For example, if only data of completed workouts are included in the development data set, a 10-year time threshold may result in exclusion of many defaulted facilities in more recent years.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- The second option is to consider the recovery process complete only when the repossessed asset has been sold to a third party.
- 8.3.5 If Als choose to adopt the first option, they should apply a haircut coefficient to the book value of the repossessed asset to convert the associated non-cash recovery into an artificial cash recovery. Als should calibrate the haircut coefficient based on historical experience (e.g. historical volatility of asset value and time required for selling the asset to a third party).

Measurement and allocation of costs

- 8.3.6 Als must include all the costs, including both **direct costs** and **indirect costs**, of the workout process in the calculation of LGD, taking account of the possibility that Als will have to incur unexpected losses during the debt recovery period.
- Direct costs are those associated with a particular facility (e.g. a fee for an appraisal of collateral).
 - Indirect costs are those necessary to carry out the recovery process but not associated with individual facilities (e.g. overheads associated with the office space for the workout department).
- 8.3.7 The HKMA generally expects Als to identify the key recovery costs for each product, to model them using a sample of defaulted facilities for which the true costs (both direct and indirect costs) are known, and to allocate costs of recoveries out of the sample using the model.

Choice of discount rate

- 8.3.8 To calculate the economic loss of a defaulted facility, it is necessary to discount the observed recoveries and costs back to the date of default using some discount rates. The HKMA recognises two options that can be used by Als: **historical discount rates** and **current discount rates**.
- Historical discount rates are fixed for each defaulted facility, regardless of the date on which



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

the LGD is being estimated. All of the cash flows associated with a defaulted facility are discounted using a rate determined at a particular date in the life of the defaulted facility. Alternatively, at the date of default a discount rate curve can be constructed with rates for each date over the expected life of the workout and the cash flows can be discounted using the curve. Typically, the discount rate is defined as either the risk-free rate plus a spread at the default date for the average recovery period, a suitable rate for an asset of similar risk at the default date, or a zero-coupon yield plus a spread at the default date.

- Current discount rates are fixed on each date on which LGD is being estimated. All the cash flows associated with a defaulted facility are discounted by using a rate, or a curve, that is determined at the current date. These rates can be either average rates computed at the moment when the LGD is being calculated (such as the average risk-free rate plus a spread during the last business cycle or the average rate of similar risky assets over the last business cycle) or spot rates plus a spread existing at that moment.

8.3.9 The HKMA expects AIs to use either method of calculating discount rates in a consistent manner. The guiding principle is that the selected discount rates should be commensurate with the risks of the recovery. Specifically, the higher the uncertainty about the recovery in respect of a defaulted facility, the higher the discount rate that will be expected.

8.3.10 The discount rate applied should reflect the underlying risk of the transaction and the type and nature of the security available to the AI. A risk-free rate should only be used when the recovery is:

- expected to come from liquidation of cash collateral with certainty; or
- converted to a certainty-equivalent cash flow.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

8.3.11 In cases where the recovery is expected to arise from entering a new contract to pay (e.g. restructuring) or from enforcing the existing contract, the discount rate should be higher than the original contractual rate. This is to reflect the heightened risk evidenced by the default. When possible, reference should be made to yields on defaulted facilities of similar structure.

8.3.12 When the recovery is expected to come from a third party (e.g. a guarantor), the discount rate should reflect the risk associated with that third party.

8.3.13 The HKMA does not generally expect AIs to use the cost of capital or the cost of equity as the discount rates, as these rates do not reflect the risk of recovery of a defaulted facility. The HKMA generally expects that the discount rate used by an AI will vary by type of product/facility in order to reflect the differences in the risk of recovery. However, the HKMA may consider permitting an AI to use the same discount rate across different products/facilities, provided that it should be able to demonstrate to the HKMA that:

- such rate is sufficiently conservative as regards the products/facilities to which the rate is applied; or
- the products/facilities share a similar level of risk in their recoveries.

8.4 LGD estimation process²⁶

8.4.1 AIs should be able to demonstrate that all the components that are needed to produce LGD estimates satisfy the provisions set out in this module. The components include:

²⁶ The estimation process outlined in this subsection is directly related to market LGD and workout LGD methods. Where applicable, however, AIs using the implied historical and implied market LGD methods should follow the guidance set out in this subsection. For example, an AI using the implied market LGD method should ensure that there are no potential biases in selecting the non-default bonds for constructing the development data set, and that the transaction characteristics of these bonds are similar to those of the AI's portfolio. Similarly, an AI using the implied historical LGD method should ensure that the estimate of the expected long-run loss rate is consistent with the concept of economic loss under which all the aspects discussed in subsection 8.3 should be taken into account.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- (i) construction of a development data set of defaulted facilities;
- (ii) calculation of the realized LGD for the defaulted facilities in the development data set; and
- (iii) generating LGD estimates for the non-default facilities based on information obtained from the defaulted facilities in the development data set (i.e. item (ii)).

Construction of a development data set

8.4.2 To produce LGD estimates, the first step is to construct a development data set containing loss and recovery information on defaulted facilities. An AI will need to satisfy the HKMA with respect to the following:

- there are no potential biases in selecting the defaulted facilities for constructing the development data set;
- data for years with relatively frequent defaults and high realized LGD are included in the development data set;
- the risk factors/transaction characteristics in the development data set and the risk factors/transaction characteristics used by the AI in assigning facility rating or segmentation are similar;
- the definition of default used in the development data set for generating the LGD is consistent with the one used to estimate PD; and
- appropriate techniques are used for identifying and assessing the effects of economic downturn conditions on realized LGD.

Measuring the realized LGD for the defaulted facilities

8.4.3 After constructing the development data set, the realized LGD for each defaulted facility included in the development data set must be measured. For workout LGD, this should involve all the aspects discussed in subsection 8.3, specifically the measurement of cash and non-cash recoveries, measurement and allocation



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

of direct and indirect costs, and selection of discount rates. For market LGD, the primary aspects on which the AI will need to satisfy the HKMA concern the liquidity of the market and the comparability of the instruments in the development data set to the AI's portfolio.

Generating LGD estimates for non-default facilities

8.4.4 AIs should be able to demonstrate that they have conducted an analysis of the empirical distribution of realized LGD to detect problems related to data outliers, changes in segmentation, and temporal homogeneity of the facilities included in the development data set.

8.4.5 In assigning LGD estimates to non-default facilities, the HKMA expects AIs to choose a statistic of the empirical distribution, such as mean or median, of the realized LGD of similar but defaulted facilities. However, if there were adverse dependencies between the realized LGD and economic downturn conditions (i.e. realized LGD increased when there were economic downturns), the HKMA expects AIs to incorporate this factor into their LGD estimates. There are two options available to AIs.

- The first option is to use an average of loss severities observed during periods of high credit losses.
- The second option is to use a higher percentile of the distribution appropriate to the degree of adverse dependency instead of the mean (or median) as a more conservative LGD estimate.

8.4.6 The HKMA expects AIs to construct confidence intervals for the LGD estimates, by either:

- using the empirical percentiles if the development data set is large enough; or
- applying statistical techniques (e.g. bootstrapping).

AIs should closely monitor these confidence intervals. The LGD assigned to the non-default facilities should be adjusted upward if the confidence interval is wide, for instance, relative to the mean.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- 8.4.7 Als may use modelling techniques (e.g. a regression model) to directly derive, or to refine the LGD estimates. When models are used, the HKMA expects Als to perform both out-of-time and out-of-sample tests in order to assess their true predictive power.
- 8.4.8 Expert judgement should only be used to fine-tune the LGD estimates to the extent that the reasons for adjustments have not been taken into account in the estimation process. The process of exercising expert judgement should be transparent, well-documented and closely monitored.
- 8.4.9 Als should compare the LGD estimates with the long-run default-weighted average loss rate given default for every relevant facility type to ensure that the former is not lower than the latter.

8.5 Validation of LGD estimates

- 8.5.1 Als should be able to demonstrate that they have performed the following analyses and tests on their estimates of LGD:
- **Stability analysis:** Als should analyse how changes in the development data set (e.g. use of sub-samples) and changes in the assumptions made for determining the realized LGD and/or parameters of the model impact the LGD estimates. Als should analyse the volatility of the LGD estimates when the timeframe of the development data set changes. These analyses are to ensure that Als' LGD estimates are stable and robust.
 - **Comparisons between internal LGD estimates and relevant external data sources:** Als should compare their internal LGD estimates with relevant external data sources. When conducting such comparisons, Als should take into account the differences in default definition, potential biases in the external data sample, and different measures of recoveries/losses and discount rates. The HKMA may require Als to provide the relevant data



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

for comparison amongst Als' internal LGD estimates for similar facilities in order to identify potential outlying predictions.

In cases where relevant external data sources are not available, the HKMA expects Als to develop the benchmarks internally (e.g. LGD estimates based on alternative methods).

- **Comparisons between realized LGD of new defaulted facilities and their LGD estimates:** Als should compare the actual outcomes with their internal estimates. In particular, Als should develop statistical tests²⁷ to back-test their internal LGD estimates against the realized LGD of the new defaulted facilities, establish internal tolerance limits for the differences between the estimates and the realized LGD, and have a policy that requires remedial actions to be taken when policy tolerances are exceeded²⁸. The general requirements for Als in establishing their internal tolerance limits and remedial actions for PD (outlined in paragraphs 7.3.2 to 7.3.4) are also applicable to LGD.

9. Accuracy of EAD

9.1 Overview

- 9.1.1 Estimation and quantitative validation methodologies of EAD are generally less well developed than those of PD. Therefore, validation of EAD estimates will need to rely more on the qualitative assessment of the estimation process than quantitative techniques.

²⁷ Als are permitted to develop their own statistical tests, provided that they are theoretically sound, well-documented and consistently applied.

²⁸ For example, Als can assume a parametric distribution on the LGD estimate for a certain type of facilities. Based on this distribution, Als can establish confidence intervals around the LGD estimate. The tolerance limits and remedial actions then can be constructed on different confidence intervals in which the realized default-weighted average LGD of the new defaulted facilities may fall.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

9.1.2 Compared with LGD, measuring EAD for defaulted facilities is simpler as it is readily observable. In constructing the development data set for EAD estimation, the HKMA expects Als to use one of the two methods outlined in subsection 9.2. Subsections 9.3 and 9.4 discuss issues related to EAD estimation and validation respectively.

9.2 Construction of a development data set

9.2.1 The HKMA recognises two methods to construct a development data set for EAD estimation, the **cohort method** and the **fixed-horizon method**. Under either method, only information about defaulted facilities should be used. Data of facilities that have defaulted, but have subsequently been recovered, should also be included.

Cohort method

9.2.2 Under the cohort method, Als should group defaulted facilities into discrete calendar periods (of at least 12 months) according to the date of default. For the defaulted facilities in each calendar period, information about the risk factors of these facilities at the beginning of that calendar period and the outstanding amounts at the date of default (i.e. the realized EAD) should be collected. Data of different calendar periods should then be pooled for estimation.

9.2.3 As an example: if a discrete calendar period is defined as 1 November 2003 to 30 October 2004, then information about the risk factors of the facilities on 1 November 2003 (the observation point) should be extracted to construct the development data set. In addition, the outstanding amounts of the facilities upon default should be captured.

Fixed-horizon method

9.2.4 Under this method, Als should collect information about the risk factors for a fixed interval prior to the date of the default (at least 12 months) and the outstanding amount



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

at the date of default, regardless of the actual calendar date on which the default occurred.

- 9.2.5 As an example: assume that the fixed interval is defined as 12 months. If a default event occurred on 15 July 2004, then in addition to the outstanding amount upon default, information about risk factors of the defaulted facility 12 months ago (the observation point is then 15 July 2003) is used.

9.3 Estimation of EAD

The estimation target

- 9.3.1 For on-balance sheet items, the minimum requirement is that the EAD estimate for an exposure cannot be less than the current drawn amount; or the sum of the amount by which the AI's CET1 capital would be reduced if the exposure were fully written off, and any specific provisions and partial write-offs in respect of the exposure. AIs may use the outstanding balance (including accrued but unpaid interest and fees) at the observation points as the EAD estimate. However, if AIs use this method, they should be able to demonstrate its conservatism by demonstrating further that the estimated aggregate EAD amount for a facility type is higher than the realized aggregate EAD amount for that facility type (see subsection 9.4).
- 9.3.2 For off-balance sheet items in respect of derivative contracts and securities financing transactions ("SFTs"), AIs should calculate the default risk exposures according to the calculation approaches and the applicable requirements set out in the BCR.
- 9.3.3 For the estimation of EAD for facilities with off-balance sheet exposures (other than derivative contracts and SFTs) in the banking book, such as the undrawn portion of credit lines, commitments and guarantees, AIs should use one of the following expressions:
- $EAD = \text{current drawn amount} + CCF \times (\text{current limit} - \text{current drawn amount})$; or
 - $EAD = UR \times \text{current limit}$



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

where CCF means credit conversion factor, representing the future draw-down of available but untapped credit, and UR means utilisation rate of the whole facility. In the development data set, “current limit” or “current drawn amount” means the relevant limit and drawn amount respectively at the observation point discussed in paragraphs 9.2.2 to 9.2.5. CCF or UR then becomes the subject variable that requires estimation. Under either expression, the estimated EAD amount of the entire facility cannot be less than the EAD of its on-balance sheet exposure (see paragraph 9.3.1).

- 9.3.4 Als are permitted to take 100% of current limit as the EAD estimate. If Als use this method, they should be able to demonstrate its conservatism by demonstrating further that the estimated aggregate EAD amount for a facility type is higher than the realized aggregate EAD amount for that facility type (see subsection 9.4).

Possible risk factors for EAD estimation

- 9.3.5 The HKMA expects Als to be able to demonstrate that their estimates of the EAD of a facility take into account the following types of factors (there are interactions and overlaps amongst factors of different types):
- factors affecting the obligor’s demand for funding/facilities;
 - factors affecting the Al’s willingness to supply funding/facilities;
 - the attitude of third parties (e.g. other Als, money lenders, trade creditors and owners if the obligor is a company) who can act as alternative sources of funding supply available to the obligor; and
 - the nature of the particular facility and the features built into it (e.g. covenant protection).



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Some possible risk factors that Als may consider in the estimation of EAD are given in Annex C²⁹.

Estimation process

9.3.6 The estimation process of EAD for non-default facilities is similar to that of LGD.

- A development data set storing information (including the relevant risk factors) of the defaulted facilities is first constructed.
- CCF or UR of each of these defaulted facilities is then calculated.
- The relationship between the CCF or UR and the risk factors is established (in the form of, for example, a regression model or classification by risk factors).
- The EAD for the non-default facilities in the current portfolio is then estimated with this relationship.

9.3.7 Expert judgement can be used to fine-tune the EAD estimates to the extent that the reasons for adjustments have not been taken into account in the estimation process. The process of exercising expert judgement should be transparent, well-documented and closely monitored.

9.3.8 For every relevant facility type, Als should compare the estimated CCF or UR with the long-run default-weighted average CCF or UR to ensure that the former is not lower than the latter.

9.3.9 The CCF or UR estimate should reflect the additional draw-downs during periods of high credit losses if they are systematically higher than the default-weighted average. For this purpose, Als should use averages of CCF or UR observed during periods of high credit losses for that product, or forecasts based on conservative assumptions (e.g. at a higher percentile of the

²⁹ The list of risk factors in Annex C is not intended to be exhaustive. The HKMA expects Als to take into account additional factors that may influence EAD.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

distribution of CCF or UR of similar defaulted facilities in the development data set).

- 9.3.10 EAD may be particularly sensitive to changes in the way that Als manage credits³⁰. The HKMA expects Als to have a process in place for ensuring that estimates of EAD take into account these developments. In particular, the process should ensure that Als immediately raise the EAD estimates if policy changes are likely to significantly increase CCF or UR. However, if the policy changes are likely to lower CCF or UR, Als will be expected not to reduce the EAD estimates until a significant amount of actual experience has been accumulated under the new policy to support the reductions.
- 9.3.11 Due consideration should be paid by Als to their specific policies and strategies adopted in respect of account monitoring and payment processing. Als should also consider their ability and willingness to prevent further drawings in circumstances short of payment default, such as covenant violations or other technical default events. Als should also have adequate systems and procedures in place to monitor facility amounts, current outstandings against committed lines and changes in outstandings per obligor and per grade. Als should be able to monitor outstanding balances on a daily basis.
- 9.3.12 The HKMA expects Als to have processes in place to monitor closely the confidence interval of CCF or UR (resulting from the established relationship) in the development data set. The CCF or UR assigned to the non-default facilities should be adjusted conservatively if the confidence interval is wide, for instance, relative to the mean.

³⁰ For example, a significant change in CCF or UR may result from a change in policy regarding covenants for corporate portfolios or a change in policy regarding credit line increases or decreases for particular segments of retail portfolios.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

9.4 Validation of EAD estimates

9.4.1 Als should be able to demonstrate that they have conducted the same types of analyses and tests used for assessing LGD estimates (see paragraph 8.5.1) in their assessment of the accuracy of EAD in terms of UR or CCF. Als should develop statistical tests³¹ to back-test their internal EAD estimates against the realized EAD of new defaulted facilities, establish internal tolerance limits for the differences between the estimates and the realized EAD, and have a policy that requires remedial actions to be taken when policy tolerances are exceeded³². The general requirements for Als in establishing their internal tolerance limits and remedial actions for PD (outlined in paragraphs 7.3.2 to 7.3.4) are also applicable to EAD.

9.4.2 Where available, Als should compare their internal estimates with external benchmarks. Where external benchmarks are not available, the HKMA expects Als to develop internal benchmarks for this purpose. The HKMA may also require Als to provide the relevant data for comparison amongst Als' internal EAD estimates for similar facilities in order to identify potential outlying predictions.

9.4.3 Where Als use 100% UR or CCF for non-derivative off-balance sheet items (see paragraph 9.3.4) and EAD for on-balance sheet items (see paragraph 9.3.1), the HKMA does not normally expect them to conduct the analyses and assessments described in paragraph 9.4.1 for validating the accuracy of the relevant EAD estimates. However, Als should be able to demonstrate, no less than once every 12 months, that these EAD estimates

³¹ Als are permitted to develop their own statistical tests, provided that they are theoretically sound, well-documented and consistently applied.

³² For example, Als can assume a parametric distribution on the CCF or UR estimate for a certain type of product. Based on this distribution, Als can establish confidence intervals around the CCF or UR estimate. The tolerance limits and remedial actions then can be constructed on different confidence intervals in which the realized default-weighted average CCF or UR of the new defaulted facilities may fall.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

are sufficiently conservative³³. In particular, the HKMA expects AIs to:

- compare the estimated aggregate EAD amount for the subject facility type with the realized aggregate EAD amount for that facility type; and
- monitor the safety margin under these approaches, where safety margin can be defined as:

$$\frac{\text{Estimated aggregate EAD amount of the subject facility type}}{\text{Realized aggregate EAD amount of the subject facility type}} - 1.$$

If the estimated aggregate EAD amount is below the realized aggregate EAD amount or the safety margin falls below a predetermined tolerance level, AIs should revise the EAD estimates upwards. In establishing the tolerance level, an AI should have regard to, amongst others, historical volatility of the safety margin, size of the portfolio, its risk appetite relating to the product and economic outlook.

10. Issues on LDPs³⁴

10.1 Types of LDPs

10.1.1 A key characteristic of LDPs is that AIs lack sufficient default and loss data in respect of these portfolios. This presents challenges for risk quantification and validation. In practice, there are several types of portfolios that may qualify as LDPs, including but not limited to:

- (i) portfolios that historically have experienced low numbers of defaults and are generally considered to be relatively low-risk (e.g. sovereigns, banks, insurance companies, large corporations);

³³ There can be situations where the realized UR or CCF would exceed 100% for the non-derivative off-balance sheet items (e.g. upward revision of credit limit after observation point) or the realized EAD is larger than the current outstanding balance for the on-balance sheet items (e.g. accumulation of accrued but unpaid interest and fees).

³⁴ Although the focus of the recommendations is mainly on PD estimation and validation, they can be applied to the estimation and validation of other credit risk components.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- (ii) portfolios that are relatively small in size either globally or at an individual bank level (e.g. project finance, shipping);
- (iii) portfolios for which an AI is a recent market entrant; and
- (iv) portfolios that have not incurred recent losses but historical experience or analysis suggests that there is a greater likelihood of default (or losses) than is captured in recent data (e.g. retail residential mortgages in a number of jurisdictions).

10.2 Implications for risk quantification and validation

10.2.1 An AI should consider whether any of its portfolios have the characteristics of an LDP and design specific appropriate risk quantification and validation methodologies, as each type of LDP has quite different risk characteristics with varying implications for risk quantification and validation. In particular, AIs should be able to demonstrate that they have taken into account the considerations in paragraphs 10.2.3 to 10.2.6, which extend the Basel IRB validation principles.

10.2.2 AIs should note that the techniques outlined in paragraphs 10.2.3 to 10.2.6 are tools to increase the reliability of the credit risk component estimates of LDPs. The applicability of a particular technique is likely to vary between AIs. AIs may also use techniques other than those described in this module. In all cases, AIs will need to justify their chosen techniques, document the limitations and apply conservatism to the results where necessary.

Forward-looking and predictive risk estimates

10.2.3 While estimates of credit risk components are grounded in historical experience, they are intended to be forward-looking for all portfolios. Consequently, relative scarcity of historical default and loss data in some circumstances may not be a serious impediment to developing PD and, where applicable, LGD and EAD estimates. Where, for example, there is a lack of recent loss data, but other analysis suggests that the potential risk of loss in a



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

portfolio is not negligible (type (iv) in paragraph 10.1.1), AIs should base the credit risk component estimates not solely on recent loss data, but also on additional information about the drivers of default and losses. For example, AIs can use default and loss experience of similar asset classes in other geographical locations in risk quantification or validation. Taking a longer run of data would be another option provided that the data are available.

Data-enhancing techniques

10.2.4 Where the problem of limited loss data exists at the level of an individual AI, the HKMA expects the AI to make use of techniques such as pooling of data with other financial institutions or market participants, the use of other external sources, or the use of market measures of risk, to compensate for its lack of internal loss data. An AI would need to satisfy itself and the HKMA that the external or pooled data are relevant to its own situation (see subsection 6.8). This technique is especially relevant to small portfolios (type (ii)) and to portfolios where an AI is a recent market entrant (type (iii)).

10.2.5 For some portfolios, such as type (i) above, there may be limited loss data not just at an individual AI's level, but also industry-wide. In these cases, the HKMA expects AIs to demonstrate the use of some or all of the following techniques to enhance data richness³⁵:

- AIs can combine internal portfolio segments with similar risk characteristics for estimating and validating the credit risk components. For example, an AI may have a broad portfolio with adequate default history that, if more narrowly segmented, may result in the creation of a number of LDPs. In these cases, AIs that use narrower segmentation for internal use might be expected to combine the sub-portfolios for the purposes of estimating or validating the credit risk components

³⁵ These tools are also applicable to other types of LDPs.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

for the calculation of regulatory capital requirements.

- Als can combine different rating grades, and estimate or validate the credit risk components for the combined grade. This technique is especially useful for Als using an internal rating system that maps to a rating agency's grades, for example, to combine AAA, AA, and A-rated credits, or to combine BBB+, BBB, and BBB-rated credits.
- Where defaults are spread out over several years, an AI can calculate a multi-year PD and then annualise the resulting figure.
- If low default rates in a particular portfolio are the result of credit support (e.g. government bailout of distressed state-owned enterprises, banks, investment firms, thrifts, pension funds and insurance firms), Als can use the lowest non-default rating as a proxy for default.
- Als can analyse intra-year rating migrations as separate rating movements to infer the annualised PD.

Effective use of benchmarking tools

10.2.6 When Als do not have sufficient loss data (even if data-enhancing techniques are used) to back-test their internal estimates of the credit risk components, the HKMA expects them to place greater emphasis on the use of benchmarking tools to demonstrate that their estimates are accurate. Section 11 gives details on the use of benchmarking tools in validation.

11. Benchmarking

11.1 Overview

11.1.1 In the context of validation, benchmarking refers to a comparison of an AI's internal estimates of the credit risk components with estimates obtained through other estimation techniques (the "benchmarks").



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

11.1.2 Generally, the HKMA expects AIs to obtain their benchmarks from third parties, provided that relevant external benchmarks for a specific portfolio are available. When external benchmarks are not used, despite being available, the HKMA expects AIs to provide valid justifications and demonstrate that they have other compensating measures (e.g. comprehensive back-testing at a higher frequency than required, such as quarterly, with sufficient default observations to ensure the reliability of the back-testing results) to ensure the accuracy of their rating systems. The HKMA does not accept cost implications as the sole justification for not using external benchmarks.

11.1.3 Where a relevant external benchmark is not available (e.g. PD of SME and retail exposures, LGD and EAD), an AI should develop an internal benchmark. For example, to benchmark against a model-based rating system, an AI might employ internal rating reviewers to re-rate a sample of credits on an expert-judgement basis. If an AI can demonstrate to the HKMA that it has other compensating measures to ensure that the ratings and estimates of the credit risk components are credible, this requirement may, subject to the HKMA's prior agreement, be waived. Notwithstanding the availability of such a waiver, the HKMA would encourage the AI to develop suitable internal benchmarks to supplement its back-testing analyses.

11.1.4 In addition, while the HKMA does not actively initiate data sharing arrangements amongst AIs for the purpose of benchmarking, this could be an approach that AIs may nonetheless wish to consider.

11.1.5 The HKMA's general expectations with regard to benchmarking for validation purposes are set out in Annex D.

11.2 Use of benchmarking

11.2.1 The HKMA believes that benchmarking is one of the key quantitative tools in the validation of an AI's IRB systems and internal estimates of the credit risk components. The HKMA expects an AI to integrate benchmarking into



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

its validation process and conduct benchmarking at least annually on a representative sample of its current portfolio.

- 11.2.2 Als should be able to explain the differences between the internal estimates and benchmarks, and take the necessary actions (e.g. review the rating criteria) when the differences are significantly larger than expected. To achieve the effective use of benchmarking, Als should establish internal tolerance limits against the differences, and the remedial actions when the limits are breached. The form of the tolerance limits will depend on the type of benchmarking. The general provisions for Als in establishing their internal tolerance limits and remedial actions for back-testing (see paragraphs 7.3.2 and 7.3.4) are also applicable to benchmarking.
- 11.2.3 An AI should ensure that the benchmarking results and analysis are reported promptly to senior management and relevant business line managers. The AI should also ensure that Board members are provided with a summary report on the benchmarking results and actions taken, if any.
- 11.2.4 An AI should be able to demonstrate to the HKMA that its use of benchmarking is appropriate and effective on a portfolio-specific basis. In particular, the HKMA will have regard to the following:
- suitability of the types of benchmarking chosen for the portfolio;
 - quality of the benchmarks in terms of their accuracy in predicting default and/or loss;
 - comparability between the benchmarks and the AI's internal estimates in terms of, for example, definition of default and assessment horizon;
 - consistency and appropriateness of the mapping procedures, if these procedures are required in the benchmarking exercise;
 - adequacy of the use of the benchmarking results in relation to the AI's risk management policies;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- level of oversight exercised by the Board and senior management on the benchmarking exercise and the results generated; and
- adequacy of the AI's internal audit of its benchmarking exercise.

11.2.5 The HKMA may also make use of data and results generated from AIs' benchmarking exercises. For example, the HKMA may compare AIs' internal estimates of the credit risk components across a panel.

11.3 Types of benchmarking

11.3.1 Benchmarking can take a variety of forms, generally depending on the relevant types and characteristics of exposures, and the interpretation of "other estimation techniques" in paragraph 11.1.1.

11.3.2 To expand the effective use of benchmarking in validation, AIs may interpret "other estimation techniques" broadly, and this could be in terms of differences in the data used, and methods of rating assignment and risk quantification etc. The following is a list of the types of benchmarking that the HKMA normally expects AIs to use in validating their rating systems and internal estimates:

- comparison of internal estimates with benchmarks with respect to a common or similar set of obligors/facilities;
- comparison of internal ratings and migration matrices with the ratings and migration matrices of third parties such as rating agencies or data pools;
- comparison of internal ratings with external expert judgements, for example, where a portfolio has not experienced recent losses but historical experience suggests that the risk of loss is greater than zero;
- comparison of internal ratings or estimates with market-based proxies for credit quality, such as equity prices, bond spreads, or premiums for credit derivatives;



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- analysis of the rating characteristics of similarly rated exposures; and
- comparison of the average rating output for the portfolio as a whole with actual experience for the portfolio rather than focusing on estimates for individual obligors/facilities.

11.3.3 The above list of benchmarking techniques is not intended to be exhaustive. The HKMA expects an AI to demonstrate the use of a wide variety of benchmarking techniques and their appropriateness for specific portfolios in providing assurance regarding the predictive ability of its internal rating systems.

11.3.4 The HKMA notes that AIs may maintain more than one rating system for the same portfolio, for example one for the purpose of the regulatory capital calculation and another for benchmarking. In such cases, the HKMA expects AIs to provide documented justifications for their application of a specific rating system to a specific purpose (see paragraph 5.4.5 above).

11.4 Selection of a benchmark

11.4.1 AIs should be able to demonstrate that the selection of a benchmark is based on an assessment of its qualities in adequately representing the risk characteristics of the portfolio under consideration. Such qualities include:

- definition of default;
- rating criteria;
- data quality;
- frequency of rating updates; and
- assessment horizon.

11.4.2 To accept an AI's benchmark for validation purposes, it should be able to demonstrate an adequate level of equivalence between the internal rating system and the benchmark rating system in the above aspects. This is to ensure that the ratings or estimates generated from the two rating systems are comparable.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

11.4.3 The HKMA generally recognises a benchmark for validation purposes subject to the following conditions:

- the AI should be able to demonstrate an adequate level of equivalence between the internal and benchmark rating systems;
- both the equivalent properties and differences between the internal and benchmark rating systems are well-documented; and
- any rating system differences should be and are accounted for in the analyses of the benchmarking results.

11.4.4 AIs should also assess the accuracy (including discriminatory power) of the benchmark rating systems in comparison with their internal rating systems.

11.4.5 Before conducting the regular benchmarking exercise, AIs should reassess the appropriateness of the types of benchmarking and methodologies chosen taking into account changes in the AIs' portfolios characteristics and the external environment.

11.5 Mapping to a benchmark

11.5.1 In designing the mapping procedures, where required in conducting the benchmarking exercise, an AI should ensure consistency between the properties of the internal and benchmark rating systems. Examples of such properties for a mapping process based on average PD include:

- definition of default;
- assessment horizon; and
- stressed or unstressed.

11.5.2 The HKMA recognises that there might not be one-to-one mapping between internal ratings and external benchmark ratings. In this case, the AI should be able to demonstrate the rationale and appropriateness for the mapping methodology adopted, and how the mapping methodology would affect the benchmarking results and analyses thereof.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

11.5.3 When designing a consistent mapping to a master scale, Als should be able to demonstrate the appropriateness of the granularity of the master scale. A balance needs to be struck between meaningful risk differentiation and having so many grades that too few exposures will fall into a single grade thus significantly reducing the reliability of the benchmarking results.

12. Stress-testing

- 12.1 Als that use the IRB approach are required to have a comprehensive stress-testing programme with stress-testing being conducted regularly for the assessment of the adequacy of the Als' regulatory capital and internal capital for credit risk, and the institutions' ability to withstand any future events or changes in economic conditions that may have adverse effects on their credit quality.
- 12.2 The guidance on the key elements of an effective stress-testing programme and the HKMA's supervisory approach to assessing Als' stress-testing practices are set out in [IC-5](#) "Stress-testing".
- 12.3 In addition to the applicable provisions set out in [IC-5](#), for the purposes of IRB validation, the HKMA expects Als to:
- conduct a regular (no less than once a year, or more frequently if this is warranted by significant changes in the business strategies of the AI or in the external environment in which it operates) credit risk stress test to assess the effect of specific conditions on their total regulatory capital requirements for credit risk. The test may be chosen by the AI, and would be subject to supervisory review by the HKMA;
 - use either a static or dynamic test to calculate the impact of the stress scenario, with consideration of their own data as well as external ratings for estimation of the migration;
 - ensure that their internal ratings are up to date and valid. Other important data relevant to Als' credit risk exposures include the outstanding volume of each credit facility, and the interest rate, as well as any available collateral values;
 - if an AI uses risk models such as credit portfolio models or credit pricing models, ensure that the assumptions underlying the risk models will also be valid in stress



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

situations, especially regarding default rate volatility, rating migrations, and correlation between individual credit facilities or obligors; and

- take remedial action to reduce risks and/or to hold additional capital/provisions when the results of their stress test indicate a deficiency of capital calculated based on the IRB approach.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Annex A: Quantitative techniques in validating discriminatory power

A1. Generating the data set for validation

- A1.1 In order to generate the data set for validation, an AI needs to define two cut-off dates with an interval of at least 12 months (the assessment horizon). The **rating information** (obligor grade or credit score) on a predefined set of obligors as of the earlier cut-off date is collected. Then the associated **performance information** (i.e. default or not) on these obligors as of the later cut-off date is added.
- A1.2 The set of obligors chosen as the validation data set determines whether the validation is in-sample, out-of-sample or out-of-time. In-sample means the data set for developing the rating system is the same as that for validation. Out-of-sample means the set of obligors in the data set for rating system development is different from that for validation, though the relevant cut-off dates may be the same or overlap. Out-of-time means that the pair of cut-off dates in the development data set is different from that for validation, though the set of obligors may be the same. Regardless of the type of validation, the validation data set should be structurally similar to the AI's actual portfolio in terms of the obligors' characteristics such as industry, company size, residency and income.
- A1.3 Information on obligors that have defaulted before the first cut-off date cannot be used. Cases for which the loans were properly repaid during the assessment horizon should be included and are classified as "non-default". Cases for which no rating information as of the first cut-off date is available (e.g. new accounts) cannot be included in the sample. Updated rating information on the obligors between the cut-off dates cannot be used. Figure A1 depicts how a validation data set is generated.
- A1.4 Based on the information collected, the distributions of defaulters and non-defaulters as per obligor grade (or score or range of scores) can be obtained and used for validation.
- A1.5 Data of different pairs of cut-off dates can be pooled for validation. This is especially necessary when the sample size within each pair of cut-off dates is not large enough. But the resulting measures will be an indication of the average discriminatory power over the relevant period.
- A1.6 Out-of-sample and out-of-time validation to a certain extent can verify the stability of a rating system. Besides, an AI can generate sub-samples from the validation data set or use various assessment



Supervisory Policy Manual

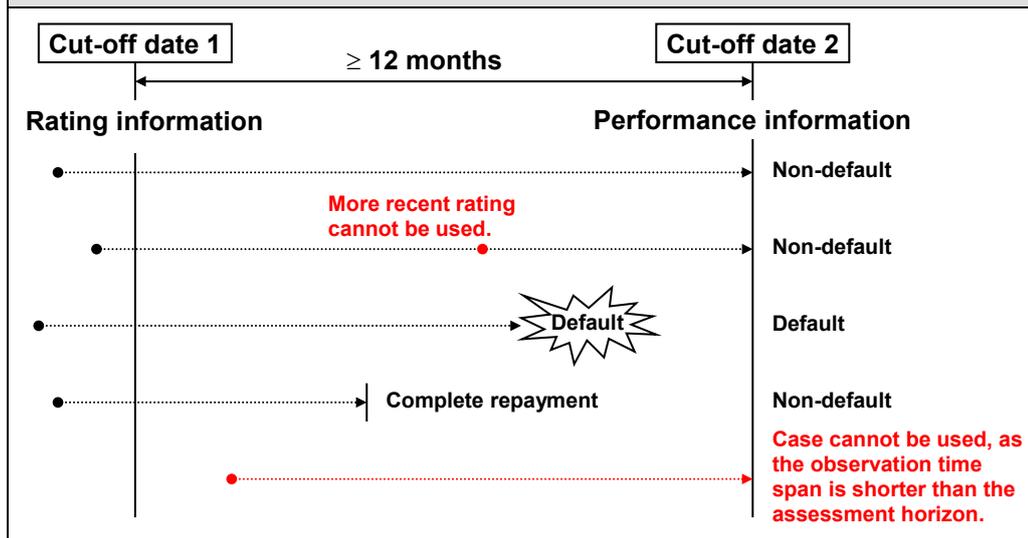
CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

horizons (e.g. two years), and check whether the discriminatory power of a rating system is stable across the sub-samples or different assessment horizons.

Figure A1. Generating the data set for validation



A2. Cumulative Accuracy Profile (“CAP”) and Accuracy Ratio (“AR”)

CAP

A2.1 **CAP** is also known as the **Gini curve**, **Power curve** or **Lorenz curve**. It is a visual tool whose graph can be drawn if two samples of obligor grades (or scores) for defaulters and non-defaulters are available.

A2.2 Consider a rating model that is intended to produce higher rating scores for obligors of lower default probability. To obtain a CAP curve, all obligors are first rank-ordered by their respective scores, from the riskiest to the safest, i.e. from the obligor with the lowest score to the obligor with the highest score. The CAP curve is then constructed by plotting the cumulative percentage of all obligors on the horizontal axis and the cumulative percentage of all defaulters on the vertical axis, as illustrated in figure A2.

A2.3 Concavity of a CAP curve is equivalent to the property that the conditional probabilities of default given the underlying scores form a



Supervisory Policy Manual

CA-G-4

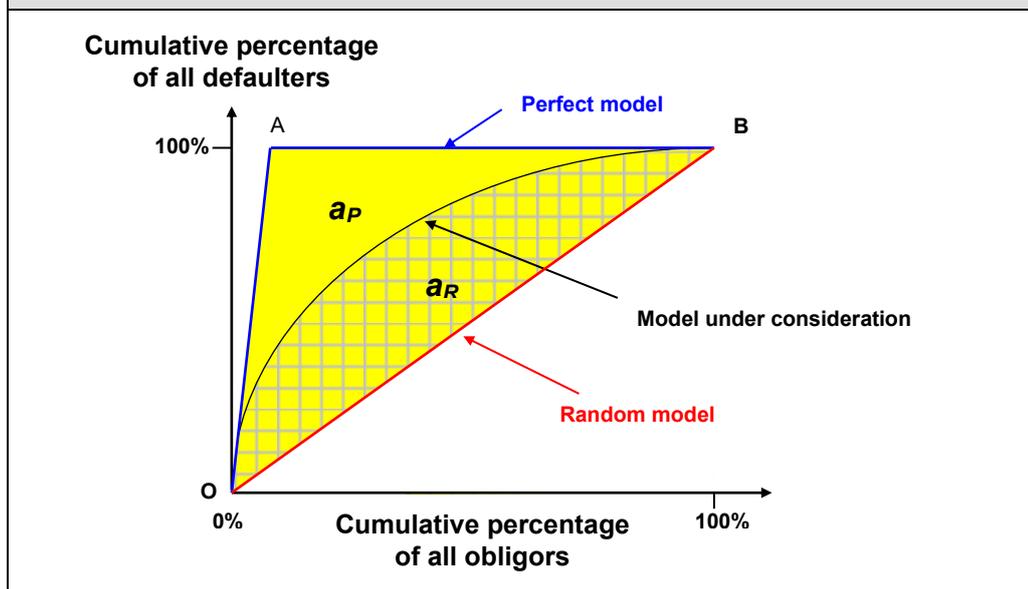
Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

decreasing function of the scores. Non-concavity indicates sub-optimal use of information in the specification of the scoring function.

- A2.4 A perfect rating model will assign the lowest scores to the defaulters. In this case, the CAP curve will increase linearly (i.e. OA in figure A2) and then stay at 100% (i.e. AB). For a random model without any discriminatory power, the percentage of all obligors with rating scores below a certain level (i.e. the X co-ordinate) will be the same as the percentage of all defaulters with rating scores below that level (i.e. the Y co-ordinate). In this case, the CAP curve will be identical to the diagonal (i.e. the straight line OB). In reality, the CAP curve of a rating system will be somewhere in between these two extremes (i.e. the arch OB).

Figure A2. Cumulative Accuracy Profile (CAP)



AR

- A2.5 **AR** (also known as the **Gini coefficient** and **Powerstat**) is a summary index of a CAP. It is defined as the ratio of the area a_R between the CAP of the rating system being validated and the CAP of the random model, and the area a_P (area of triangle AOB) between the CAP of the perfect rating model and the CAP of the random model, i.e.:

$$AR = \frac{a_R}{a_P} .$$



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

A2.6 In practice, there are many approaches to the calculation of the areas. The HKMA does not prescribe a particular method but an AI should apply a theoretically sound method and use the same method consistently.

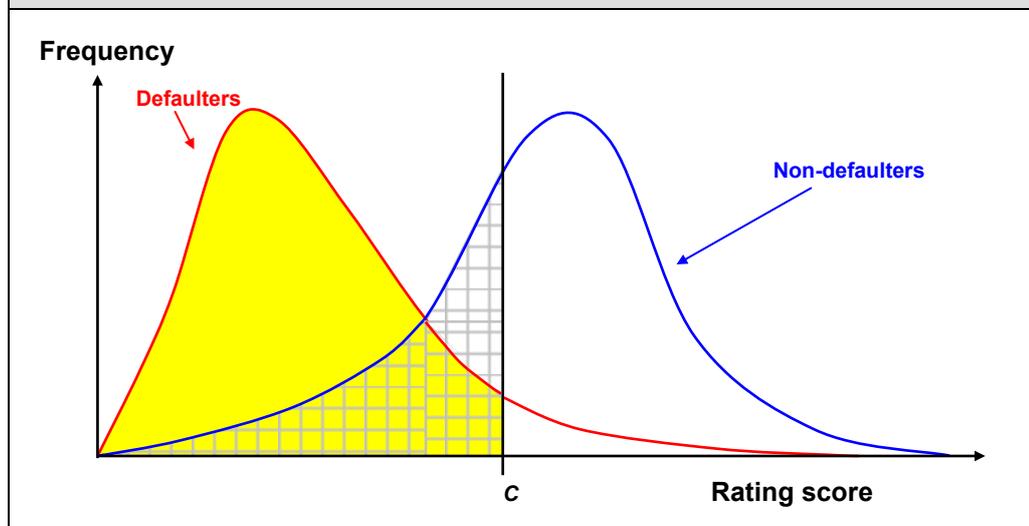
A2.7 AR is always between 0% and 100% for any rating system better than random assignment of ratings. The better the rating system, the closer is AR to 100%.

A3. Receiver Operating Characteristic (“ROC”), ROC measure and Pietra Index

ROC

A3.1 Like CAP, **ROC** is a visual tool that can be constructed if two samples of obligor grades (or scores) for defaulters and non-defaulters are available. To plot this curve, the rating grade or score distribution for defaulters, on the one hand, and for non-defaulters, on the other, is determined.

Figure A3. Distribution of rating scores for defaulters and non-defaulters



A3.2 For a perfect rating model, the left distribution and the right distribution in figure A3 would be separate. In reality, a rating system with perfect discrimination is unlikely, and the two distributions will overlap partially as illustrated in figure A3.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

A3.3 Assume that an AI has to find out from the rating scores which obligors will not default during the assessment horizon and which obligors will default. One possibility for the AI would be to introduce a cut-off value C as in figure A3, and to classify obligors with rating scores lower than C as potential defaulters and obligors with rating scores higher than C as potential non-defaulters. Then four decision results would be possible. If the rating score of an obligor is below the cut-off value C and the obligor defaults subsequently in the assessment horizon, the decision was correct (i.e. “hit”). Otherwise, the AI wrongly classified a non-defaulter as a defaulter (i.e. “false alarm”). If the rating score is above the cut-off value and the obligor does not default, the classification was correct. Otherwise, a defaulter was incorrectly assigned to the non-defaulters’ group.

A3.4 To plot the ROC curve, hit rate $HR(C)$ is defined as:

$$HR(C) = \frac{H(C)}{N_D},$$

where $H(C)$ is the number of defaulters predicted correctly with the cut-off value C , and N_D is the total number of defaulters in the sample. This means that the hit rate is the fraction of defaulters that was classified correctly for a given cut-off value C . The false alarm rate $FAR(C)$ is defined as:

$$FAR(C) = \frac{F(C)}{N_{ND}},$$

where $F(C)$ is the number of false alarms, i.e. the number of non-defaulters that were classified incorrectly as defaulters by using the cut-off value C . N_{ND} is the total number of non-defaulters in the sample. In figure A3, $HR(C)$ is the area to the left of the cut-off value C under the score distribution of the defaulters (the coloured area), while $FAR(C)$ is the area to the left of C under the score distribution of the non-defaulters (the chequered area).

A3.5 The quantities $HR(C)$ and $FAR(C)$ are computed for all cut-off values C that are contained in the range of the rating scores. The ROC curve is a plot of $HR(C)$ versus $FAR(C)$. This is illustrated in figure A4.



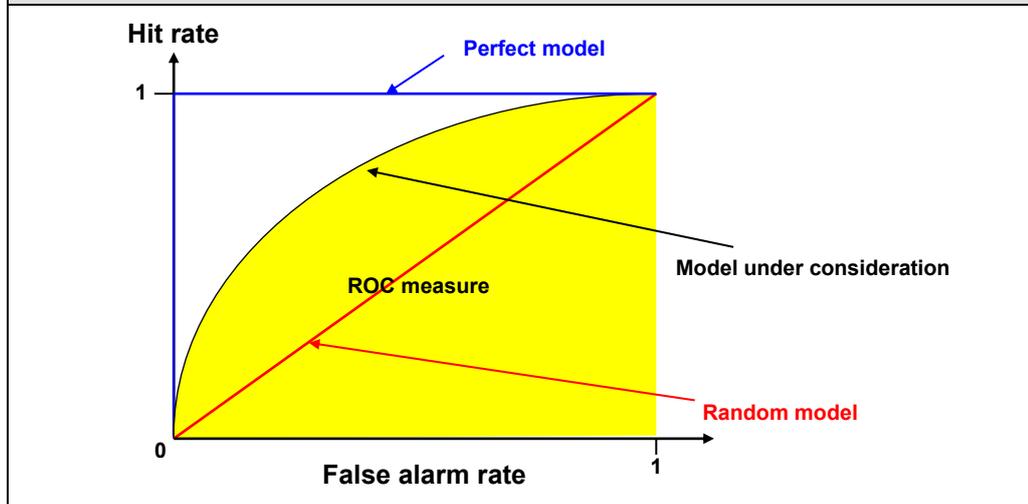
Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Figure A4. Receiver Operating Characteristic (ROC) curve



A3.6 As with CAP, concavity of a ROC curve is equivalent to the conditional probabilities of default being a decreasing function of the underlying scores and non-concavity indicates sub-optimal use of information in the specification of the scoring function. The better a rating model's performance, the steeper is the ROC curve at the left end and the closer is the ROC curve's position to the point (0, 1).

ROC measure

A3.7 The **ROC measure** (also known as the **area under the curve**, "AUC") is defined as the area below the ROC curve, including the triangle below the diagonal of the unit square. A random model without discriminatory power has a ROC measure equal to 50%, and a perfect model would have a ROC measure equal to 100%³⁶.

A3.8 As with AR, there are many approaches to the calculation of the areas in practice. The HKMA does not prescribe a particular method but an AI should apply a theoretically sound method and use the same method consistently.

³⁶ The AR and ROC measure have a linear relationship:

$$AR = 2 (\text{ROC measure}) - 1.$$



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Pietra Index

A3.9 Geometrically, the **Pietra Index** can be defined as the maximum area of a triangle that can be inscribed between the ROC curve and the diagonal of the unit square. In case of a concave ROC, the Pietra Index can be calculated as follows:

$$Pietra\ Index = \frac{\sqrt{2}}{4} \max_c |HR(C) - FAR(C)| .$$

KS test statistic

A3.10 The maximum term $HR(C) - FAR(C)$ in the calculation of the Pietra Index is the **KS test statistic** of the distribution functions $HR(C)$ and $FAR(C)$. The expression $|HR(C) - FAR(C)|$ can take values between zero and one. The better a rating model's performance, the closer is the value to one. This expression can also be interpreted as the maximum difference between the cumulative frequency distribution of defaulters and that of non-defaulters.

Confidence intervals and tests for the ROC measure and Pietra Index

A3.11 The ROC measure has statistical properties coincident with the Mann-Whitney statistic. Therefore, AIs can construct confidence intervals for the ROC measure of a rating system and test the difference between the ROC measures of two rating systems which are validated on the same data set^{37, 38}.

A3.12 As with the ROC measure, testing for the dissimilarity in discriminatory powers between two rating systems can be conducted.

³⁷ The relevant formulas are not given here, as the methods have been integrated into most of the commonly-used statistical software packages. Therefore, this should not be a constraint for AIs in computing the confidence intervals of a ROC measure or conducting a statistical comparison of the ROC measures of two rating systems based on the same data set.

³⁸ With the linear relationship between AR and ROC measure (see footnote 36), AIs using the former in assessing rating systems' discriminatory powers can calculate the confidence intervals and conduct statistical tests as with the ROC measure.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

A4. Bayesian error rate (“BER”)

A4.1 **BER**, also known as the **classification error** or **minimum error**, is the proportion of the whole sample which remains misclassified when the rating system is in the optimal use.

A4.2 Denote with p_D the default rate of the sample, and hit rate $HR(C)$ and the false alarm rate $FAR(C)$ as in section A3 above. For a concave ROC curve, the BER can be calculated as:

$$BER = \min_C \{p_D [1 - HR(C)] + (1 - p_D) FAR(C)\} .$$

A4.3 For a perfect rating model, the BER will have a value of zero. In reality, a model’s BER will depend on p_D (the proportion of default in the sample). In particular, for technical reasons it might sometimes be necessary to develop a scoring function on a sample which is not representative in terms of the proportion of defaulters and non-defaulters. The assumption on p_D and hence the BER will then vary accordingly. In practice, the BER is often applied with a fictitious p_D of 50%. Then, the BER can be expressed as:

$$BER (p_D = 50\%) = \frac{1}{2} - \frac{1}{2} \max_C |HR(C) - FAR(C)| .$$

In this case, the BER is a linear transformation of the Pietra Index and the Kolmogorov-Smirnov test statistic can be applied accordingly.

A5. Conditional entropy, Kullback-Leibler distance, and Conditional Information Entropy Ratio (“CIER”)

A5.1 Entropy is a concept from information theory that is related to the extent of uncertainty eliminated by an experiment. In application to validating a rating system’s discriminatory power, entropy measures assess the information gained (or uncertainty reduced) by using the rating system in predicting default of an obligor.

A5.2 Let information entropy $IE(p)$ of an event with probability p as:

$$IE(p) = -[p \log_2(p) + (1 - p) \log_2(1 - p)] .$$

Figure A5 depicts the relationship between $IE(p)$ and p .



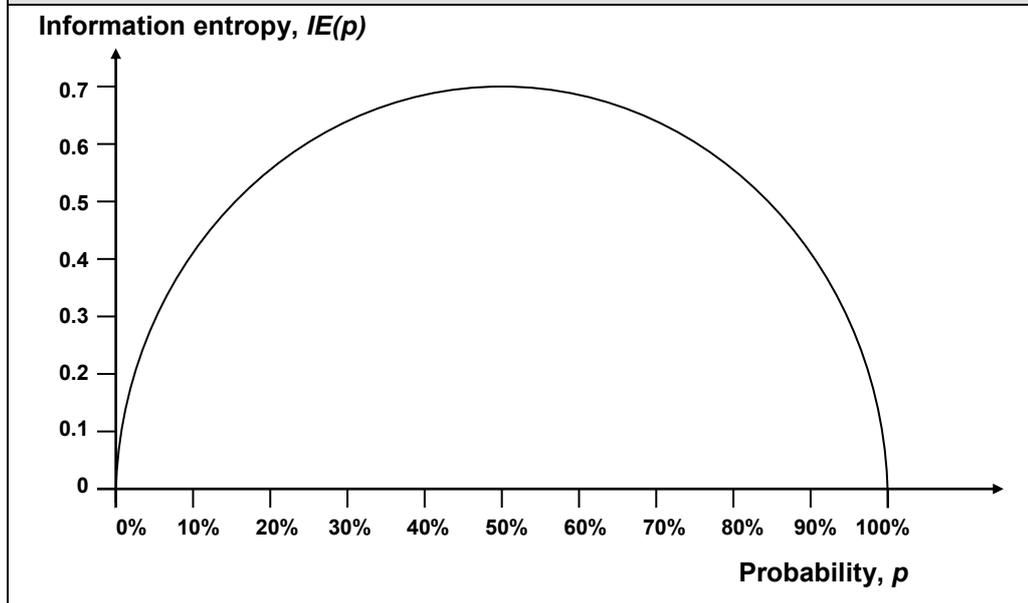
Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Figure A5. Information entropy as a function of probability



A5.3 $IE(p)$ takes its maximum at $p = 50\%$, the state with the greatest uncertainty. If p equals zero or one, either the event under consideration itself or its complementary event will occur with certainty.

Conditional entropy

A5.4 Consider a rating model assigning obligors to a set of k obligor grades (or scores) $K = \{K_1, K_2, \dots, K_k\}$, and define $ce(K_i)$ as the **conditional entropy** that measures the remaining uncertainty conditional on obligor grade K_i , i.e.:

$$ce(K_i) = -\{p(D | K_i) \log_2 [p(D | K_i)] + [1 - p(D | K_i)] \log_2 [1 - p(D | K_i)]\} ,$$

where $p(D | K_i)$ is the probability that an obligor defaults given the rating grade K_i . If there are N_{Di} defaulters and N_{NDi} non-defaulters for obligor grade K_i , $p(D | K_i)$ can be defined as:

$$p(D | K_i) = \frac{N_{Di}}{N_{Di} + N_{NDi}} .$$

A5.5 Across all obligor grades, the conditional entropy $CE(K)$ is defined as the average of $ce(K_i)$ weighted by the observed frequencies of obligors across the rating grades, i.e.:



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

$$CE(K) = \frac{\sum_{i=1}^k (N_{Di} + N_{NDi}) ce(K_i)}{\sum_{i=1}^k (N_{Di} + N_{NDi})} .$$

$CE(K)$ corresponds to the remaining uncertainty with regard to the future default event after application of the rating model.

Kullback-Leibler distance

- A5.6 To derive the amount of information gained (or the uncertainty reduced), $CE(K)$ needs to be compared with the entropy where the rating model is not used. In particular, using the entropy $CE(p)$ defined above with the assumption of p as the default rate of the sample (p_D), the **Kullback-Leibler distance** can be calculated as:

$$\text{Kullback-Leibler distance} = CE(p_D) - CE(K) , \text{ where}$$

$$p_D = \frac{\sum_{i=1}^k N_{Di}}{\sum_{i=1}^k (N_{Di} + N_{NDi})} .$$

- A5.7 The Kullback-Leibler distance is bounded between zero and $CE(p_D)$. The longer the distance, the more is the information gained, and the better is a rating model in differentiating risk.

CIER

- A5.8 The range of values that the Kullback-Leibler distance can take depends on the unconditional probability of default. In order to arrive at a common scale for any underlying population, the Kullback-Leibler distance can be normalised to produce **CIER**:

$$CIER = \frac{CE(p_D) - CE(K)}{CE(p_D)} .$$

- A5.9 CIER will be closer to one when more information on the future default event is contained in the obligor grades K (i.e. the rating model is better). A random model will have CIER equal to zero.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

A6. Information value (“IV”)

A6.1 **IV** is another entropy-based measure of discriminatory power. It measures the difference between the distribution of defaulters and that of non-defaulters across obligor grades (or scores). In this sense, it is similar to the Pietra Index.

A6.2 Consider a rating model assigning obligors to a set of k obligor grades $K = \{K_1, K_2, \dots, K_k\}$. For obligor grade K_i , assume that there are N_{Di} defaulters and N_{NDi} non-defaulters. The distributions (observed frequencies) of defaulters and non-defaulters across the obligor grades are $d = \{d_1, d_2, \dots, d_k\}$ and $nd = \{nd_1, nd_2, \dots, nd_k\}$ respectively, where:

$$d_i = \frac{N_{Di}}{\sum_{i=1}^k N_{Di}}, \text{ and}$$

$$nd_i = \frac{N_{NDi}}{\sum_{i=1}^k N_{NDi}}.$$

A6.3 The IV is defined as the sum of:

- (1) the relative entropy of the non-defaulters’ distribution with respect to the defaulters’ distribution; and
- (2) the relative entropy of the defaulters’ distribution with respect to the non-defaulters’ distribution; i.e.:

$$IV = \sum_{i=1}^k \left[nd_i \log_2 \left(\frac{nd_i}{d_i} \right) + d_i \log_2 \left(\frac{d_i}{nd_i} \right) \right].$$

A6.4 IV takes the value of zero for a random rating model (i.e. the distributions of defaulters and non-defaulters are the same). The higher the IV, the more is the separation of the distributions (see figure A3), and the better is the discriminatory power of a rating model. However, there is no theoretical upper bound to its range.

A7. Kendall’s τ and Somers’ D

A7.1 A **shadow rating system** is one that generates ratings (the shadow ratings) that are intended to duplicate external ratings (e.g. of a rating agency), but can be applied to obligors for which the external rating is



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

not available. On obligors for which both the shadow ratings and external ratings are available, the degree of concordance of the two rating systems can be measured with two rank-order statistics, **Kendall's τ** and **Somers' D**. The shadow rating system will inherit the discriminatory power of the external rating system if:

- (1) there is high concordance of the shadow ratings and the external ratings; and
- (2) the portfolio under consideration and the rating agency's portfolio are structurally similar.

A7.2 For both statistics, tests can be performed and confidence intervals can be calculated³⁹. Statistical inferences can be made on the quality of a shadow rating system or the relative performance of shadow ratings with respect to the reference ratings⁴⁰.

A8. Brier score (“BS”)

A8.1 **BS** is defined as:

$$BS = \frac{1}{N} \sum_{j=1}^N \left(\hat{PD}_j - \theta_j \right)^2,$$

where N is the number of rated obligors, \hat{PD}_j is the forecast default probability of obligor j , and θ_j is defined as one if the obligor defaults and zero otherwise.

A8.2 BS is always between zero and one. The closer BS is to zero, the better is the discriminatory power of a rating model.

A8.3 The value of BS depends on the default frequency of the overall sample (p_D , with the same definition as in paragraph A5.6 above). Therefore, the BS of a rating model can be measured against the BS of a “trivial forecast” of which p_D is assigned to all obligors. In particular, the BS of the trivial forecast (\overline{BS}) is given by:

³⁹ As with the Mann-Whitney test statistic for the ROC measure and Kolmogorov-Smirnov test statistic for the Pietra Index, the relevant formulas for Kendall's τ and Somers' D are not given here. This is because the methods have been integrated into the commonly-used statistical software packages.

⁴⁰ Rank-ordering statistics like Kendall's τ and Somers' D can also be used in benchmarking, for comparing the concordance of rank-ordering of an internal rating system with that of an external rating system.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

$$\overline{BS} = (1 - p_D)p_D .$$

A9. Divergence

A9.1 **Divergence** is defined as:

$$Divergence = \frac{(\mu_{ND} - \mu_D)^2}{\frac{1}{2}(\sigma_{ND}^2 + \sigma_D^2)} ,$$

where μ_{ND} (and μ_D) and σ_{ND}^2 (and σ_D^2) are respectively the mean and variance of an attribute, such as the credit scores, of non-defaulters (and defaulters).

A9.2 The higher the value of divergence, the better is the power of the attribute to discriminate defaulters from non-defaulters. The divergence has a lower bound value of zero but there is no theoretical upper bound to its range.



Supervisory Policy Manual

CA-G-4

**Validating Risk Rating Systems
under the IRB Approach**

V.2 – 17.05.18

Annex B: Statistical methodologies in validating calibration⁴¹

B1. Binomial test with assumption of independent default events

B1.1 Consider a rating model assigning obligors to a set of k obligor grades $K = \{K_1, K_2, \dots, K_k\}$. For obligor grade K_i , assume that there are N_{Di} defaulters and N_{NDi} non-defaulters. For **each obligor grade** (or pool for retail exposures, but not score), the binomial test with assumption of zero default correlation can be conducted based on the following hypotheses:

Null hypothesis (H_0): The PD of an obligor grade is correct.

Alternative hypothesis (H_1): The PD of an obligor grade is underestimated.

B1.2 Given a confidence level q (e.g. 99%), the null hypothesis is rejected if the number of observed defaults N_{Di} in obligor grade K_i is greater than or equal to a critical value N_{Di}^* , which is defined as:

$$N_{Di}^* = \min \left\{ N_{Di} \mid \sum_{i=0}^{N_{Di}} \binom{N_i}{i} (\hat{PD}_i)^i (1 - \hat{PD}_i)^{N_i - i} > q \right\},$$

where \hat{PD}_i is the forecast of default probability for the obligor grade and N_i is the number of obligors assigned to the obligor grade (i.e. $N_{Di} + N_{NDi}$). The critical value N_{Di}^* can be approximated by:

$$N_{Di}^* \approx \Phi^{-1}(q) \sqrt{N_i \hat{PD}_i (1 - \hat{PD}_i)} + N_i \hat{PD}_i,$$

where Φ^{-1} denotes the inverse cumulative distribution function of the standard normal distribution. The critical value can be expressed in terms of an observed default rate PD_i^* that is allowed at maximum:

$$PD_i^* \approx \Phi^{-1}(q) \sqrt{\frac{\hat{PD}_i (1 - \hat{PD}_i)}{N_i}} + \hat{PD}_i.$$

⁴¹ The procedures in generating the data set for validating discriminatory power and for validating calibration are similar. But the data set used in the latter must be out-of-time (i.e. with cut-off dates later than those for calibration) and include all relevant obligors in the AI's actual portfolio.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

B1.3 If the number of observed defaults of the obligor grade is bigger than N_{Di}^* , or the observed default rate of the obligor grade is higher than PD_i^* , it can be concluded with a confidence level q that the PD is underestimated.

B2. Binomial test with assumption of non-zero default correlation

B2.1 In reality, defaults are correlated. Even if the correlation is small, the true Type I error (i.e. the probability of rejecting erroneously the null hypothesis of a correct PD forecast) can be much larger than the normal level. To circumvent this problem, the calculations of critical values N_{Di}^* and PD_i^* above can be modified by taking into account asset correlation ρ as follows:

$$N_{Di}^*(\rho) = N_i \Phi \left(\frac{\Phi^{-1}(q)\sqrt{\rho} + \Phi^{-1}(\hat{PD}_i)}{\sqrt{1-\rho}} \right), \text{ and}$$

$$PD_i^*(\rho) = \Phi \left(\frac{\Phi^{-1}(q)\sqrt{\rho} + \Phi^{-1}(\hat{PD}_i)}{\sqrt{1-\rho}} \right).$$

B2.2 The interpretations of $N_{Di}^*(\rho)$ and $PD_i^*(\rho)$ are the same as those of N_{Di}^* and PD_i^* in section B1 above, except the assumption on correlation.

B2.3 Als have latitude in selecting the assumption of ρ for different asset classes and different obligor grades. But the value should not be higher than that stipulated in the risk-weight functions used in the calculation of regulatory capital requirements under the IRB approach as specified in the BCR.

B2.4 For example, for residential mortgages, the assumption in ρ cannot be higher than 0.15 for all rating grades (or pools) and 0.04 for qualifying revolving retail exposures (“QRRE”). For other retail exposures and small business retail exposures, the upper bound of ρ depends on the PD forecast (i.e. \hat{PD}_i) of a particular obligor grade (pool):



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

$$\text{Max } \rho = 0.03 \left(\frac{1 - e^{-35\hat{PD}_i}}{1 - e^{-35}} \right) + 0.16 \left(1 - \frac{1 - e^{-35\hat{PD}_i}}{1 - e^{-35}} \right).$$

B3. Chi-square test

B3.1 In general, the Binomial test is applied to one obligor grade at a time. To simultaneously test the PD forecasts of several obligor grades, Als can apply the **chi-square** (or **Hosmer-Lemeshow**) test.

B3.2 Let $\hat{PD}_1, \hat{PD}_2, \dots, \hat{PD}_m$ denote the forecasts of default probabilities of obligor grades K_1, K_2, \dots, K_m (m can be smaller than or equal to k as defined in paragraph B1.1 above). Define the statistic:

$$T_m = \sum_{i=1}^m \frac{\left(N_i \hat{PD}_i - N_{Di} \right)^2}{N_i \hat{PD}_i \left(1 - \hat{PD}_i \right)},$$

with N_i and N_{Di} having the same definitions as in section B1 above.

B3.3 The statistic T_m has a chi-square distribution with $m-2$ degrees of freedom. Therefore, the p -value of the chi-square test with $m-2$ degrees of freedom could serve as a measure of the accuracy of the forecasts of default probabilities: the closer the p -value is to zero, the worse are the forecasts.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Annex C: Risk factors in estimation of EAD

C1. Type of obligor

C1.1 The differentiation of obligor types is relevant with regard to varying behaviour in credit line utilisation. For example, for large-scale obligors (such as large corporates and banks), lines of credit are often not completely utilised at the time of default. In contrast, retail customers and SMEs are more likely to overdraw (or fully utilise) the approved lines of credit.

C2. Relationship between an AI and obligor in adverse circumstances

C2.1 When estimating EAD, it is important to recognise that EAD depends on how the relationship between an AI and obligor evolves in adverse circumstances, when the obligor may decide to draw unused commitments.

C3. Alternative sources of funds available to the obligor

C3.1 The more the obligor has access to alternative sources and forms of credit, the lower the EAD is expected to be. For example, retail customers and SMEs in general have less access to alternative sources than large corporate obligors and banks. In cases where this factor cannot be observed, AIs may apply the “type of obligor” factor as a proxy for it.

C4. Covenants

C4.1 Empirical findings indicate that the draw-down of a credit line at the time of default tends to decrease with the quality of the obligor’s credit rating at the time the commitment was granted. The argument behind this observation is that a bank is more likely to require covenants for obligors with lower credit quality which restrict future draw-downs in cases where the credit quality has declined.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

C5. Restructuring

C5.1 If an obligor experiences payment difficulties or is in default, credit restructuring may result in stricter covenants and make the obligor less likely to use the unused portion of a commitment.

C6. Time to maturity

C6.1 The longer the time to maturity, the higher is the probability that the credit quality will decrease, and the obligor has both an increased opportunity and an increased need to draw down the remaining credit line.



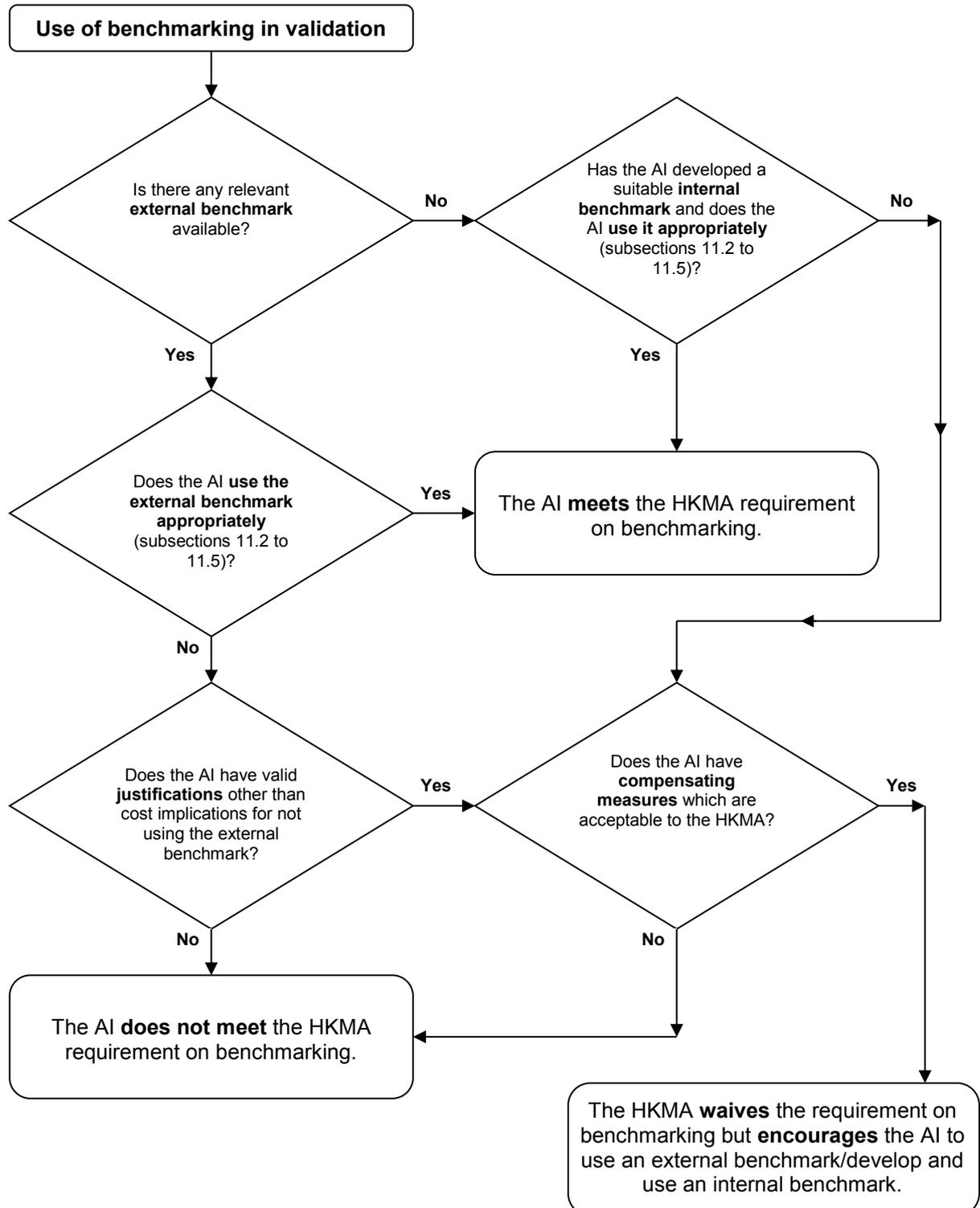
Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Annex D: Flowchart depicting HKMA requirement on benchmarking





Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Annex E: Minimum requirements for internal rating systems under IRB approach⁴²

E1. Introduction

E1.1 An AI which makes an application under §8 of the BCR to use the IRB approach to calculate its credit risk must demonstrate to the satisfaction of the MA that the minimum requirements for use of the IRB approach set out in Schedule 2 to the BCR applicable to the AI are met.

E1.2 The provisions set out herein apply to the foundation IRB approach, advanced IRB approach and retail IRB approach where applicable. The requirements for internal rating systems of equity exposures under the PD/LGD approach are basically the same as those for the foundation IRB approach for corporate exposures except as otherwise specified in Division 7 of Part 6 of the BCR. Where AIs adopt the simple risk-weight method or the internal models method to calculate capital charges for equity exposures, the relevant requirements are set out in the BCR⁴³.

E2. Overview of composition of minimum requirements

E2.1 The minimum requirements on use of the IRB approach focus on an AI's ability to rank order and quantify risk in a consistent, reliable and valid manner, and primarily cover the following aspects:

- (i) Rating system design;

⁴² The document, "Minimum Requirements for Internal Rating Systems under IRB Approach", referred to in version 1 of this module by way of hyperlinks, has been updated with reference to the prevailing Basel capital standards and BCR requirements on the IRB approach and incorporated into this Annex for ease of reference and maintenance.

⁴³ AIs that use the internal models method for equity exposures may refer to [CA-G-3](#) "Use of Internal Models Approach to Calculate Market Risk" for guidance on the use of a value-at-risk-based methodology to estimate the potential loss of AIs' equity exposures; and Basel II (paragraphs 529 to 536) for guidance on related requirements on validation and documentation.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- (ii) Rating system operations;
- (iii) Corporate governance and oversight;
- (iv) Use of internal ratings;
- (v) Risk quantification;
- (vi) Validation of internal estimates;
- (vii) Supervisory LGD and EAD estimates;
- (viii) Requirements for recognition of leasing;
- (ix) Calculation of capital charges for equity exposures – internal models method; and
- (x) Disclosure requirements.

E2.2 This Annex provides explanations on certain of the requirements that are more qualitative in nature, i.e. those under items (i), (ii) and (x), to facilitate understanding and compliance by AIs.

E3. Rating system design

E3.1 Rating dimensions

Corporate, sovereign and bank exposures

E3.1.1 AIs adopting the IRB approach should have a two-dimensional rating system that provides separate assessment of obligor and transaction characteristics. This approach assures that the assignment of obligor ratings is not influenced by consideration of transaction-specific factors.

Obligor rating

E3.1.2 The first dimension should reflect exclusively the risk of obligor default. Collateral and other facility characteristics should not influence the obligor rating.⁴⁴ AIs should assess and estimate the

⁴⁴ For example, in an eight-grade rating system, where default risk increases with the grade number, an obligor whose financial condition warrants the highest investment grade rating should be rated a 1 even if the AI's transactions are unsecured and subordinated to other creditors. Likewise, a



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

default risk of an obligor based on the quantitative and qualitative information regarding the obligor's credit-worthiness (see subsection E3.4 below for rating criteria). Als should rank and assign obligors into individual grades each associated with an average PD.

- E3.1.3 Separate exposures to the same obligor should be assigned to the same obligor grade, irrespective of any differences in the nature of each specific transaction, unless the AI demonstrates to the satisfaction of the HKMA that the risk of default of the obligor in respect of such exposures is different. Once an obligor has defaulted on any credit obligation to an AI (or to any member of the consolidation group of which the AI is a part), all of the facilities of the obligor with that AI (or any member of the consolidation group of the AI) are considered to be in default subject to certain specified exceptions (see §149 of the BCR).
- E3.1.4 There are two typical examples that may result in multiple grades for the same obligor. First, to reflect country transfer risk⁴⁵, an AI may assign different obligor grades depending on whether the facility is denominated in local or foreign currency. Second, the recognition of the credit risk mitigating effect of eligible guarantees to a facility may be reflected in an adjusted obligor grade.
- E3.1.5 In assigning an obligor to an obligor grade, Als should assess the risk of obligor default over a period of at least one year. However, this does not mean that Als should limit their consideration to the outcomes for that obligor that are most likely to occur over the next 12 months. Obligor ratings should take into account all possible adverse events that might increase an obligor's likelihood of default (see subsection E3.5 below).

Facility rating

- E3.1.6 The second dimension should reflect transaction-specific factors (such as collateral, seniority, product type, etc.) that affect the loss severity in the case of obligor default.

defaulted obligor with a transaction fully secured by cash should be rated an 8 (i.e. the defaulted grade) regardless of the remote expectation of loss.

⁴⁵ Country transfer risk is the risk that the obligor may not be able to secure foreign currency to service its external credit obligations due to adverse changes in foreign exchange rates or when the country in which it is operating suffers economic, political or social problems.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

E3.1.7 For Als adopting the foundation IRB approach, this requirement can be fulfilled by the existence of a facility dimension which may take the form of:

- a facility rating system that provides a measure of EL by incorporating both obligor strength (PD) and loss severity (LGD); or
- an explicit quantifiable LGD rating dimension, representing the conditional severity of loss, should default occur, from the credit facilities.

In calculating the regulatory capital requirements, these Als should use the supervisory estimates of LGD.

E3.1.8 For Als using the advanced IRB approach, facility ratings should reflect exclusively LGD. These ratings should cover any and all factors that can influence LGD including, but not limited to, the type of collateral, product, industry, and purpose. Obligor characteristics may be included as LGD rating criteria only to the extent they are predictive of LGD⁴⁶. Als may alter the factors that influence facility grades across segments of the portfolio as long as they can satisfy the HKMA that it improves the relevance and precision of their estimates.

E3.1.9 Als using the supervisory slotting criteria approach for the specialized lending (“SL”) exposures need not apply this two-dimensional requirement to these exposures. Given the interdependence between obligor and transaction characteristics in SL, Als may instead adopt a single rating dimension that reflects EL by incorporating both obligor strength (PD) and loss severity (LGD) considerations in respect of SL subject to the supervisory slotting criteria approach.

Retail exposures

E3.1.10 Rating systems for retail exposures should reflect both obligor and transaction risks, and capture all relevant obligor and transaction characteristics. Als should assign each retail exposure to a particular pool. For each pool, Als should estimate PD, LGD and

⁴⁶ For example, the credit quality of property developers and asset values in the property market are interdependent.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

EAD. Multiple pools may share identical PD, LGD and EAD estimates.

E3.1.11 Als should demonstrate that this grouping process provides for a meaningful differentiation of risk and results in sufficiently homogeneous pools that allow for accurate and consistent estimation of loss characteristics at the pool level.

E3.1.12 Als should have specific criteria for assigning an exposure into a pool that cover all factors relevant to the risk analysis. At a minimum, Als should consider the following risk drivers when assigning exposures to a pool:

- Obligor risk characteristics (e.g. obligor type, demographics such as age/occupation);
- Transaction risk characteristics including product and/or collateral type. One example of split by product type is to group exposures into credit cards, instalment loans, revolving credits, residential mortgages, and small business facilities. When grouping exposures by collateral type, consideration should be given to factors such as loan-to-value ratios, seasoning⁴⁷, guarantees and seniority (first vs. second lien). Als should explicitly address cross-collateral provisions, where present;
- Delinquency status: Als should separately identify delinquent and non-delinquent exposures.

E3.2 Rating structure

Corporate, sovereign and bank exposures

E3.2.1 Als should have a meaningful distribution of exposures across grades with no excessive concentrations, on both obligor-rating and facility-rating scales (also see paragraph E3.2.4). The number of obligor and facility grades used in a rating system should be sufficient to ensure that management can meaningfully differentiate risk in the portfolio. Perceived and measured risk should increase as credit quality declines from one grade to the next.

⁴⁷ Seasoning can be a significant element of portfolio risk monitoring, particularly for residential mortgages which may have a clear time pattern of default rates.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Obligor rating

- E3.2.2 Rating systems should have a minimum of seven obligor grades for non-default obligors and one for defaulted obligors⁴⁸.
- E3.2.3 In defining obligor grades, the grade definition should include both a description of the degree of default risk typical for obligors assigned the grade and the criteria used to distinguish that level of credit risk. Furthermore, “+” or “-” modifiers to alpha or numeric grades will only qualify as distinct grades if the AI has developed complete rating descriptions and criteria for their assignment, and separately quantifies PDs for these modified grades.
- E3.2.4 AIs with loan portfolios concentrated on a particular market segment and a range of default risk should have enough grades within that range to avoid undue concentration of obligors in particular grades⁴⁹. Significant concentration within a single grade or grades should be supported by convincing empirical evidence that the grade or grades cover reasonably narrow PD bands and that the default risk posed by all obligors in a grade falls within that band.
- E3.2.5 For AIs using the supervisory slotting criteria approach for SL exposures, the rating system for such exposures should have at least four obligor grades for non-default obligors and one for defaulted obligors. SL exposures that qualify as corporate exposures under the foundation IRB approach or the advanced IRB approach are subject to the same requirements as those for general corporate exposures (i.e. a minimum of seven obligor grades for non-default obligors and one for defaulted obligors).

Facility rating

- E3.2.6 There is no minimum number of facility grades for AIs using the advanced IRB approach. Such AIs should ensure that the number of facility grades is sufficient to avoid facilities with widely varying LGDs being grouped into a single grade. On the other hand, the number of facilities in each facility grade should be sufficient to allow

⁴⁸ For the purpose of reporting under the HKMA’s loan classification framework, AIs should also be able to identify/differentiate defaulted exposures that fall within different categories of classified assets (i.e. Substandard, Doubtful and Loss).

⁴⁹ In general, a single corporate obligor grade assigned with more than 30% of the gross exposures (before on-balance sheet netting) could be a sign of excessive concentration.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

for validation at grade level. The criteria used to define facility grades should be grounded in empirical evidence.

Retail exposures

- E3.2.7 The level of differentiation in respect of retail exposures should ensure that the number of exposures in a given pool is sufficient to allow for meaningful quantification and validation of the loss characteristics at the pool level. There should be a meaningful distribution of obligors and exposures across pools to avoid undue concentration of an AI's retail exposures in particular pools.

E3.3 Multiple rating methodologies/systems

- E3.3.1 An AI's size and complexity of business, as well as the range of products it offers, will affect the type and number of rating systems it has to employ. However, an AI should only use more than one rating system for exposures within an IRB class if the AI demonstrates to the satisfaction of the HKMA that the rating systems concerned are necessary having regard to the characteristics and complexity of those exposures, and provided that the AI only assigns an exposure to such a rating system if that system accurately reflects the level of credit risk of the exposure, and documents the reason for doing so. Obligors should not be allocated across rating systems inappropriately to minimise regulatory capital requirements (i.e. there should be no cherry-picking by choice of rating system).

E3.4 Rating criteria

- E3.4.1 To ensure the transparency of individual ratings, AIs should have clear and specific rating definitions, processes and criteria for assigning exposures to grades within a rating system. The rating definitions and criteria should be both plausible and intuitive, and have the ability to differentiate risk. In particular:
- The grade descriptions and criteria should be sufficiently detailed and specific to allow staff responsible for rating assignments to consistently assign the same grade to obligors or facilities posing similar risk. This consistency should exist across lines of business, departments and geographic locations. If rating criteria and procedures differ for different types of



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

obligors or facilities, AIs should monitor for possible inconsistency, and alter rating criteria to improve consistency when appropriate.

- Written rating definitions should be clear and detailed enough to allow independent third parties (e.g. the HKMA, internal or external audit) to understand the rating assignments, replicate them and evaluate their appropriateness.
- The criteria should be consistent with an AI's internal lending standards and its policies for handling troubled obligors and facilities.

E3.4.2 AIs should take into account all relevant and material information that is available to them when assigning ratings to obligors and facilities.⁵⁰ Information should be current. The less information an AI has, the more conservative should be its rating assignments. An external rating can be the primary factor determining an internal rating assignment. However, the AI should avoid mechanistic reliance on external ratings and ensure that other relevant information is also taken into account. AIs could refer to List A for the relevant factors in assigning obligor and facility ratings.

SL exposures

E3.4.3 AIs using the supervisory slotting criteria approach for SL exposures should assign these exposures to internal rating grades based on their own criteria, systems and processes, subject to compliance with the applicable HKMA requirements. The internal rating grades of these exposures should then be mapped into the supervisory rating grades specified in the BCR (see §158(2)). The general assessment factors and characteristics exhibited by exposures falling under each of the non-default supervisory rating grades are provided in Annex 6 to Basel II.

⁵⁰ It could be difficult to address the qualitative considerations in a structured and consistent manner when assigning ratings to obligors and facilities. In this regard, AIs may choose to cite significant and specific points of comparison by describing how such qualitative considerations can affect the rating. For example, factors for consideration may include whether an obligor's financial statements have been audited or are merely compiled from its accounts, or whether collateral has been independently valued. Formalising the process would also be helpful in promoting consistency in determining risk grades. For example, a "risk rating analysis form" can provide a clear structure for identifying and addressing the relevant qualitative and quantitative factors for determining a risk rating, and document how grades are set.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

E3.4.4 Als should demonstrate that their mapping process has resulted in an alignment of grades consistent with the preponderance of the characteristics in the respective supervisory category. Als should ensure that any overrides of their internal criteria do not render the mapping process ineffective.

E3.5 Rating assignment horizon

E3.5.1 Although the time horizon used in PD estimation is one year, Als should apply a longer time horizon in assigning ratings. An obligor rating should represent the AI's assessment of the obligor's ability and willingness to contractually perform despite adverse economic conditions or the occurrence of unexpected events. In other words, the AI's assessment should not be confined to risk factors that may occur in the next 12 months.

E3.5.2 Als may satisfy this requirement by:

- basing rating assignments on specific, appropriate stress scenarios (see section 12 of this module); or
- taking appropriate consideration of obligor characteristics that are reflective of the obligor's vulnerability to adverse economic conditions or unexpected events, without explicitly specifying a stress scenario. The range of economic conditions should be consistent with current conditions and those likely to occur over a business cycle within the respective industry/geographic region.

E3.5.3 PD estimates for obligors that are highly leveraged or whose assets are predominantly traded assets should reflect the performance of the obligor's assets based on volatilities calibrated to data from periods of significant financial stress.

E3.5.4 Given the difficulties in forecasting future events and the influence they will have on a particular obligor's financial condition, Als should take a conservative view of projected information. Where limited data are available, Als should adopt a conservative bias to their analysis.

E3.5.5 Als should articulate clearly their rating approaches in their credit policies, particularly how quickly ratings are expected to migrate in response to economic cycles and the implications of the rating approaches for their capital planning process. If an AI chooses a



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

rating approach under which the impact of economic cycles would affect rating migrations, its capital management policy should be designed to avoid capital shortfalls in times of economic stress.

E3.6 Use of models

Risk assessment techniques

E3.6.1 There are generally two basic methods by which ratings are assigned: (i) a model-based process; and (ii) an expert judgement-based process. The former is a mechanical process, relying primarily on quantitative techniques such as credit scoring/default probability models or specified objective financial analysis. The latter relies primarily on personal experience and subjective judgement of credit officers⁵¹.

E3.6.2 Credit scoring models and other mechanical procedures are permissible as the primary or partial basis of rating assignments, and may play a role in the estimation of loss characteristics. Nevertheless, sufficient human judgement and oversight is necessary to ensure that all relevant and material information is taken into consideration and that the model is used appropriately.

Requirements for using models

E3.6.3 Als should meet the following applicable HKMA requirements relating to use of statistical models and other mechanical methods in rating assignments or in the estimation of PD, LGD or EAD:

- Als should demonstrate that a model or procedure has good predictive power and its use will not result in distortion in regulatory capital requirements. The model should be accurate on average across the range of obligors or facilities to which the AI is exposed and should not have material biases. Its input variables should form a reasonable set of predictors and have explanatory capability.
- Als should have in place a process for vetting data inputs into a

⁵¹ In practice, the distinction between the two is not precise. In many model-based processes, personal experience and subjective judgement play a role, at least in developing and implementing models, and in constructing their inputs. In some cases, models are used to provide a baseline rating that serves as the starting point in judgement-based processes.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

statistical default or loss prediction model. This should include an assessment of data accuracy, completeness and appropriateness.

- The data used to build the model should be representative of the population of the AI's actual obligors or facilities.
- When model results are combined with human judgement, the judgement should take into account all relevant and material information not considered by the model. AIs should have written guidance describing how human judgement and model results are to be combined.
- AIs should have procedures for human review of model-based rating assignments. Such procedures should focus on finding and limiting errors associated with model weaknesses and should also include credible ongoing efforts to improve the model's performance.
- AIs should have a regular cycle of model validation that includes monitoring of model performance and stability, review of model relationships, and testing of model outputs against outcomes.

E3.7 Documentation of rating system design

E3.7.1 AIs should document in writing the design of their rating systems and related operations (see section E4 below on rating system operations) as evidence of their compliance with the applicable HKMA requirements.

E3.7.2 The documentation should provide a description of the overarching design of the rating system, including:

- the purpose of the rating system;
- portfolio differentiation; and
- the rating approach and implications for an AI's capital planning process.

E3.7.3 Rating criteria and definitions should be clearly documented. These include:

- the relationship between obligor grades in terms of the level of risk each grade implies, and the risk of each grade in terms of both a description of the probability of default typical for obligors



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

assigned the grade and the criteria used to distinguish that level of credit risk;

- the relationship between facility grades in terms of the level of risk each grade implies, and the risk of each grade in terms of both a description of the expected severity of the loss upon default and the criteria used to distinguish that level of credit risk;
- methodologies and data used in assigning ratings;
- the rationale for choice of the rating criteria and procedures, including analyses demonstrating that those criteria and procedures should be able to provide meaningful risk differentiation;
- definitions of default and loss, demonstrating that they are consistent with the definitions in the BCR; and
- the definition of what constitutes a rating exception (including an override).

E3.7.4 Documentation of the rating process should include the following:

- the organisation of rating assignment;
- responsibilities of parties that rate obligors and facilities;
- parties that have authority to approve exceptions (including overrides);
- situations where exceptions and overrides can be approved and the procedures for such approval;
- the procedures and frequency of rating reviews to determine whether they remain fully applicable to the current portfolio and to external conditions, and parties responsible for conducting such reviews;
- the process and procedures for updating obligor and facility information;
- the history of major changes in the rating process and criteria, in particular to support identification of changes made to the rating process subsequent to the last supervisory review⁵²; and

⁵² The supervisory review could be a review conducted by either the HKMA or the home supervisor of the AI concerned (in the case of a foreign bank subsidiary).



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- the rationale for assigning obligors to a particular rating system if multiple rating systems are used.
- E3.7.5 In respect of the internal control structure, the documentation should cover the following:
- the organisation of the internal control structure;
 - Board and senior management oversight of the rating process;
 - the operational processes ensuring the independence of the rating assignment process; and
 - the procedure, frequency and reporting of performance reviews of the rating system (on rating accuracy, rating criteria, rating processes and operations), and parties responsible for conducting such reviews.
- E3.7.6 AIs employing statistical models in the rating process should document their methodologies. The documentation should include:
- a detailed outline of the theory, assumptions and/or mathematical and empirical basis of the assignment of estimates to grades, individual obligors, exposures, or pools, and the data sources used in assigning the estimates;
 - the guidance describing how human judgement and model results are to be combined;
 - the procedures for human review of model-based rating assessments;
 - a rigorous statistical process (including out-of-time and out-of-sample performance tests) for validating the model; and
 - any circumstances under which the model does not work effectively.
- E3.7.7 Use of a model obtained from an external vendor that claims proprietary technology is not a justification for exemption from documentation or any other applicable HKMA requirements. The burden is on the model's vendor and the AI to satisfy the HKMA.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

E4. Rating system operations

E4.1 Rating coverage

E4.1.1 For corporate, sovereign and bank exposures, each obligor and all recognized guarantors should be assigned a rating and each exposure should be associated with a facility rating as part of the credit approval process. Similarly, for retail exposures, each exposure should be assigned to a pool as part of the credit approval process.

E4.1.2 Each separate legal entity to which an AI is exposed should be separately rated. An AI should demonstrate to the HKMA that it has prudent and reasonable policies regarding the treatment of individual entities in a connected group, including circumstances under which the same obligor grade may or may not be assigned to separate obligors in a connected group, and the definition of a connected group for the purposes of rating assignment. Such policies should also include a process for the identification of specific wrong way risk for each legal entity to which the AI is exposed.

E4.2 Integrity of rating process

Corporate, sovereign and bank exposures

E4.2.1 AIs should ensure the independence of the rating assignment process. Rating assignments and periodic rating reviews should be completed or approved by a party that does not stand to benefit from the extension of credit. AIs should follow the requirements set out in [CR-G-2](#) “Credit Approval, Review and Records” relating to credit approval and review. Credit policies and approval/review procedures should reinforce and foster the independence of the rating process.

E4.2.2 Obligor and facility ratings should be reviewed and updated at least annually. Higher risk obligors or problem exposures should be subject to more frequent review.

E4.2.3 In addition, obligor and facility ratings should be refreshed whenever material information on the obligor or facility comes to light.⁵³ AIs

⁵³ The rating should generally be updated within 90 days for performing obligors and within 30 days for obligors with weakening or deteriorating financial condition.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

should establish an effective process to obtain and update relevant and material information on the obligor's financial condition, and on facility characteristics that affect LGD and EAD (e.g. the condition and value of collateral). Upon receipt of such information, an AI needs to have a procedure to update the obligor's rating in a timely fashion.

Retail exposures

E4.2.4 AIs should review the loss characteristics and delinquency status of each identified risk pool at least on an annual basis. This should include a review of the status of individual obligors within each pool as a means of ensuring that exposures continue to be assigned to the correct pool, e.g. by review of a representative sample of exposures in the pool.

E4.3 Overrides

E4.3.1 AIs should have in place an effective process for identifying, documenting, reviewing and updating the situations where it is appropriate and prudent for human judgement to override the inputs or outputs of the rating process, and for ensuring that all permissible overrides are approved by officers of the AI having delegated credit authority and are applied consistently. AIs should identify overrides and separately track their performance.

E4.4 Data maintenance

E4.4.1 AIs should collect and store data on key obligor and facility characteristics to support their internal credit risk measurement and management process and to enable them to meet the applicable HKMA requirements. The data collection and IT systems should serve the following purposes:

- improve AIs' internally developed data for PD/LGD/EAD estimation and validation;
- provide an audit trail to check compliance with rating criteria;
- enhance and track predictive power of the rating system;
- modify risk rating definitions to more accurately address the observed drivers of credit risk; and



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

- serve as a basis for supervisory reporting.

E4.4.2 The data should be sufficiently detailed to allow retrospective reallocation of obligors and facilities to grades (e.g. if it becomes necessary to have finer segregation of portfolios in future).

E4.4.3 Furthermore, AIs should collect and retain data relating to their internal ratings as required under the Banking (Disclosure) Rules.

Corporate, sovereign and bank exposures

E4.4.4 AIs should maintain complete rating histories on obligors and recognized guarantors, which include:

- the ratings since the obligor/guarantor was assigned a grade;
- the dates the ratings were assigned;
- the methodology and key data used to derive the ratings;
- the person/model responsible for the rating assignment;
- the identity of obligors and facilities that have defaulted, and the date and circumstances of such defaults; and
- data on the PDs and realized default rates associated with rating grades and rating migration.

E4.4.5 AIs adopting the advanced IRB approach should also collect and store a complete history of data on LGD and EAD estimates associated with each facility. These include:

- the dates the ratings were assigned and the estimates done;
- the key data and methodology used to derive the facility ratings and estimates;
- the person/model responsible for the rating assignment and estimates;
- data on the estimated and realized LGDs and EADs associated with each defaulted facility;
- data on the LGD of the facility before and after evaluation of the credit risk mitigating effects of any recognized guarantee/credit derivative contracts; and
- information on the components of loss or recovery for each defaulted exposure, such as amounts recovered, source of recovery (e.g. collateral, liquidation proceeds and guarantees),



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

time period required for recovery, and administrative costs.

E4.4.6 AIs utilizing supervisory estimates under the foundation IRB approach are encouraged to retain relevant data (e.g. data on loss and recovery experience for corporate, sovereign, and bank exposures under the foundation IRB approach; and data on realized losses for SL exposures where the supervisory slotting criteria approach are applied).

Retail exposures

E4.4.7 AIs should collect and store the following data:

- data used in the process of allocating exposures to pools, including data on obligor and transaction risk characteristics used either directly or through use of a model, as well as data on delinquency;
- data on the estimated PDs, LGDs and EADs associated with pools of exposures;
- the identity of obligors and details of exposures that have defaulted; and
- data on the pools to which defaulted exposures were assigned over the year prior to default and the realized outcomes on LGD and EAD.

E5. Disclosure requirements

E5.1 In order to be eligible for the IRB approach, AIs should meet the applicable requirements set out in the Banking (Disclosure) Rules. Failure of an AI to meet the applicable disclosure requirements will lead to the HKMA considering the taking of certain measures as provided for in the BCR (see §10(5)), including requiring the AI to use the STC approach (instead of the IRB approach) to calculate its credit risk for non-securitization exposures.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

Table 1: Summary of Key Aspects of an Internal Rating System

(A) Requirements	(B) Rating Process	(C) Use of ratings
<p>Rating structure:</p> <ul style="list-style-type: none"> • Maintain a two-dimensional system • appropriate gradation • no excessive concentration in a single grade 	<p>Rating assignment:</p> <ul style="list-style-type: none"> • ratings assigned before lending/investing • independent review of ratings assigned at origination • comprehensive coverage of ratings 	<p>Credit risk measurement and management:</p> <ul style="list-style-type: none"> • credit approval • credit monitoring • reporting of credit risk information to board of directors and senior management • loan pricing • analysis of capital adequacy, reserves and profitability of AIs
<p>Key data requirements:</p> <ul style="list-style-type: none"> • probability of default • loss given default • exposure at default • history of obligor defaults • rating decisions • rating histories • rating migration • information used to assign the ratings • party/model that assigned the ratings • PD/LGD estimate histories • key obligor characteristics and facility information 	<p>Rating review:</p> <ul style="list-style-type: none"> • independent review (annual or more frequent depending on loan quality and availability of new information) by control functions such as credit risk control unit, internal and external audit • oversight by senior management and board of directors 	<p>Stress test used in assessment of capital adequacy:</p> <ul style="list-style-type: none"> • stress-testing should include specific scenarios that assess the impact of rating migrations • three areas that AIs could usefully examine are economic or industry downturns, market risk events and liquidity conditions
<p>System requirements:</p> <ul style="list-style-type: none"> • the IT system should be able to store and retrieve data for exposure aggregation, data collection, use and management reporting 	<p>Internal validation:</p> <ul style="list-style-type: none"> • a robust system for validating the accuracy and consistency of rating systems, processes, and risk estimates • a process for vetting data inputs • compare realized default rates with estimated PDs 	<p>Disclosure of key internal ratings information:</p> <ul style="list-style-type: none"> • disclosure of items of information as stated under the Banking (Disclosure) Rules



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

List A : Assessment factors in assigning ratings

1 Obligor ratings

1.1 Relevant factors that AIs should consider in assigning obligor ratings are set out below. However, these factors are not intended to be exhaustive or prescriptive, and certain factors may be of greater relevance for certain obligors than for others:

- the historical and projected capacity to generate cash to repay an obligor's debt and support its other cash requirements (e.g. capital expenditures required to keep the obligor a going concern and to sustain its cash flow);
- the capital structure and the likelihood that unforeseen circumstances could exhaust the obligor's capital cushion and result in insolvency;
- the quality of earnings (i.e. the degree to which the obligor's revenue and cash flow emanate from core business operations as opposed to unique and non-recurring sources);
- the quality and timeliness of information about the obligor, including the availability of audited financial statements and their conformity with applicable accounting standards;
- the degree of operating leverage and the resulting impact that deteriorating business and economic conditions might have on the obligor's profitability and cash flow;
- the obligor's ability to gain additional funding through access to debt and equity markets;
- the depth and skill of management to effectively respond to changing conditions and deploy resources, and the degree of prudence reflected from business strategies employed;
- the obligor's position within the industry and its future prospects; and
- the risk characteristics of the country in which the obligor is operating, and the extent to which the obligor will be subject to transfer risk or currency risk if it is located in another country.



Supervisory Policy Manual

CA-G-4

Validating Risk Rating Systems under the IRB Approach

V.2 – 17.05.18

2 Facility ratings

2.1 Als should look at the following transaction specific factors, where applicable, when assigning facility ratings:

- the presence of third-party support (e.g. owner/guarantor) in respect of a facility. Considerable care and caution should be exercised if ratings are to be improved because of the presence of any third-party support. In all cases, Als should be convinced that the third party is committed to ongoing support of the obligor and the credit protection is permissible under the IRB credit risk mitigation framework. Als should establish specific rules for third-party support;
- the maturity of the transaction. It is recognized that higher risk is associated with longer-term facilities while shorter-term facilities tend to have lower risk. A standard approach is to consider further adjustment to the facility rating (after adjusting for third-party support), taking into account the remaining term to maturity;
- the structure and lending purposes of the transaction which influence positively or negatively the strength and quality of the credit. These may refer to the status of obligor, priority of security, any covenants attached to a facility, etc. Take, for example, a facility that has a lower rating due to the term of a loan. If its facility structure contains very strong covenants which mitigate the effects of its term of maturity (say, by means of default clauses), it may be appropriate to adjust its facility rating to offset (often partially) the effect of the maturity term.
- the presence of recognized collateral. This factor can have a major impact on the final facility rating because of its significant effect on the LGD of a facility. Als should review carefully the quality of collateral (e.g. documentation and valuation) to determine its likely contribution in reducing any loss. While collateral value is often a function of movements in market rates, it should be assessed in a conservative manner (e.g. based on net realizable value or forced-sale value where necessary).