Supervisory Policy Manual		
CA-G-4	**Validating Risk Rating Systems under the IRB Approaches**	V.1 – 14.02.06

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 AIs' internal rating systems, and the requirements that the HKMA expects AIs to follow, in order to qualify for using the IRB Approaches to measure credit risk for capital adequacy purposes

Classification

A technical note issued by the HKMA

Previous guidelines superseded

This is a new guideline.

Application

To all locally incorporated AIs which intend to use the IRB Approaches to measure credit risk for capital adequacy purposes

Structure

1. Introduction

1.1 Terminology

1.1.1 For the purpose of this module:

- "IRB Approach" means Internal Ratings-based Approach;
- "Basel II" means the revised regulatory capital adequacy framework to be implemented from 1 January 2007 for locally incorporated authorized institutions;
- "AIs", unless indicated otherwise, means locally incorporated authorized institutions which use the IRB Approaches to measure credit risk for capital adequacy purposes under Basel II;
- "PD" means the probability of default of an obligor over one year. "One year" refers to the next year commencing from the date the PD is estimated;
- "EAD" means exposure at default being the expected amount of an exposure upon default of an obligor measured gross of specific provisions and adjusted for the risk mitigating effects of valid bilateral netting arrangements;
- "LGD" means loss given default being the loss likely to be incurred on an exposure upon default of an obligor relative to the amount outstanding at default;
- "M" means the effective maturity of an exposure being the maturity as measured or specified in "Weighting Framework for Credit Risk (IRB Approach)";
- "dilution risk", in respect of receivables purchased by an AI, means the possibility that the amount of a receivable is reduced through cash or non-cash credits to the receivable's obligor. Examples of such "credits" include offsets or allowances arising from returns of goods sold, disputes regarding product quality, possible debts of the borrower to a

receivable's obligor, and any payment or promotional discounts offered by the borrower;

- "EL" means the expected loss on an exposure arising from the potential default of the obligor, or the dilution risk relative to EAD, over one year. "One year" refers to the next year commencing from the date of calculation of the capital adequacy ratio;
- "CCF", in relation to a non-derivative off-balance exposure of an AI, means the credit conversion factor of the exposure;
- "UR", in relation to a non-derivative off-balance exposure of an AI, means the utilisation rate of the exposure;
- "Foundation IRB Approach" means that, where an AI is using the IRB Approach, the AI provides its own estimates of PD for each of its obligor grades in respect of its corporate, sovereign and bank exposures and uses supervisory estimates for the other credit risk components and M of its corporate, sovereign and bank exposures;
- "Advanced IRB Approach", means that, where an AI is using the IRB Approach, the AI is permitted to provide its own estimates of PD, LGD and EAD and calculate M of its corporate, sovereign and bank exposures;
- "PD/LGD Approach", means an IRB calculation approach which may be used in respect of an AI's equity exposures as set out in "Weighting Framework for Credit Risk (IRB Approach)";
- "IRB Approach for retail exposures", in relation to an AI's retail exposures, means that the AI provides its own estimates of PD, LGD and EAD to measure credit risk of the retail exposures, with no distinction between Foundation IRB Approach and Advanced IRB Approach;
- "LDPs" means low-default portfolios;
- "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;

- "Basel Committee" means the Basel Committee on Banking Supervision;
- "obligor grade" means a risk category (as measured by PD) representing an assessment of risk of obligor default to which obligors are assigned on the basis of a specified and distinct set of internal rating criteria and from which estimates of PD are derived. The obligor rating reflects exclusively the risk of obligor default. Collateral and other facility transaction characteristics should not influence the obligor grade. These factors will be considered in assigning the facility grade;
- "facility grade" means a category of loss severity in the event of default (as measured by LGD or EL) to which transactions are assigned on the basis of a specified and distinct set of rating criteria. The facility grade definition involves assessing the amount of collateral, and reviewing the term and structure of a transaction (such as the lending purpose, repayment structure and seniority of claims);
- "risk components", unless indicated otherwise, means PD, LGD and EAD;
- "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;
- "rating system" or "IRB system" means all of the methods, processes, controls, and data collection and IT systems used by an AI that enable the assessment of credit risk, the assignment of

internal risk ratings, and the quantification of default and loss estimates by the AI;

- "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 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;
- "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;
- "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;
- "bootstrapping" means a resampling technique with replacement of the data sampled, aiming to generate information on the distribution of the underlying data set;
- "in-sample validation" means validation of a rating system employing observations that have been used for developing the rating system;
- "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; and

- "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.

1.2 Background

1.2.1 IRB systems are the cornerstone for calculating regulatory capital charges under the IRB Approaches, as they form the basis of determining a borrower's PD and, in the case of the IRB Approach for retail exposures and the Advanced IRB Approach, two additional risk components, namely a facility's LGD and EAD. As a consequence, validation of an AI's estimates of these three risk components, which are key inputs to the calculation of regulatory capital, and the underlying internal rating systems, is a major part of the IRB recognition process.

1.2.2 Through discussions with AIs and experts in this field, the HKMA understands that the techniques adopted by the banking industry for the validation of IRB systems at present vary from institution to institution. To accommodate such variability and ensure consistency at the same time on the supervisory standards for validation, the HKMA considers it necessary to establish certain essential requirements in line with current industry practice for AIs to follow. In the IRB recognition process, the HKMA will evaluate how these requirements are met to assess AIs' eligibility to use the IRB Approaches.

1.3 Scope

1.3.1 This module sets out:

- the HKMA approach to the validation of the internal rating systems of AIs using the IRB Approaches to measure credit risk for capital adequacy purposes; and
- the requirements that the HKMA expects AIs to follow on the validation of their internal rating

systems to ensure accuracy, consistency and reliability, including the systems of controls surrounding these systems.

1.3.2 All the requirements set out in the module apply to locally incorporated AIs which use the Advanced IRB Approach to measure the credit risk of corporate, sovereign and bank exposures[1]. AIs that use the Foundation IRB Approach to measure the credit risk of corporate, sovereign and bank exposures, and AIs that apply the PD/LGD Approach to equity exposures, must meet the requirements set out in the module with the exception of those in sections 8 and 9. AIs that use the IRB Approach for retail exposures, regardless of the type of IRB Approach they use for corporate, sovereign, bank and equity exposures, must meet all the requirements set out in the module. Unless indicated otherwise, the requirements, techniques and terminology set out and used in the module are applicable to all IRB exposure classes including corporate, sovereign, bank exposures, equity and retail exposures.

1.3.3 In the case of AIs that are subsidiaries of foreign banking groups, all or part of their IRB systems may be centrally developed and monitored on a group basis. In assessing whether these AIs meet the requirements of the module, the HKMA will co-ordinate with the home supervisors of the banking groups regarding the validation of the group-wide internal rating systems adopted by their authorized subsidiaries in Hong Kong. To minimise duplication and overlap in the validation process, the HKMA will rely on the validation work performed by the home supervisors, provided that it is satisfied that the requirements set by the home supervisors are comparable to those laid down in the module, and the relevant rating systems can adequately reflect the specific risk characteristics of the AIs' portfolios.

1.3.4 The module should be read in conjunction with other HKMA guidance papers regarding Basel II implementation, in particular the "Minimum Requirements for Internal Rating Systems under IRB Approach" and

[1] See "Weighting Framework for Credit Risk (IRB Approach)" for definitions of exposure classes (corporate, sovereign, bank, retail and equity exposures).

"Minimum Requirements for Risk Quantification under IRB Approach".

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."[2] 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 risk components appropriately characterise the relevant aspects of risk.

2.2 The Validation Subgroup of the Accord Implementation Group (AIG) of the Basel Committee has expanded on the concept of validation in the form of six 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 principle, it will be an AI's responsibility to demonstrate to the HKMA that its internal rating systems meet the minimum requirements laid down in the module and other relevant HKMA guidance papers[3]. Thus the HKMA will expect an AI to conduct its own internal validation of the rating systems, estimates of the

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[2] "International Convergence of Capital Measurement and Capital Standards", Basel Committee, November 2005, paragraph 500.

[3] 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 reference in footnote 2).

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 Board[4] of Directors and senior management of an AI should ensure that validation is performed by individuals independent of the parties that have been involved in developing the rating systems (see paragraphs 5.1.6 and 5.1.7 below), and that the individuals assigned to conduct the validation work possess the necessary skills and knowledge. 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 academic background, work experience and previous track record in such work to review the AI's compliance with the requirements set out in the module.

2.4 In line with the fourth validation principle, the HKMA recognises that there is no universal tool that can be used for the validation of all portfolios. It therefore will expect 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 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 the absence at present of an industry "best practice" standard concerning validation. One consequence is that the techniques, especially the quantitative techniques, that are being used by AIs to validate the robustness, reliability and accuracy of their internal rating systems, and the estimates of the risk components, are very diverse, portfolio specific and still evolving. In view of the current state of industry practice, the HKMA believes that it would be premature to establish precise quantitative minimum standards and benchmarks for IRB systems, and that to do so at this stage would stifle innovations which may ultimately result in more robust validation techniques. Consequently, the HKMA will continue to review industry practice, and the policies of other supervisors, and anticipates that current trends will permit it to establish minimum quantitative standards at some point in the future.

4 Unless indicated otherwise, "the Board" may mean its delegated committee that is acceptable to the HKMA.

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 management oversight, both before and during use, at appropriately senior levels within an AI; 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 on 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 7 to 9 reflect current market practice in the estimation and validation of the risk components.

2.8 While the HKMA will not establish minimum quantitative standards for IRB systems, it will expect AIs to be able to demonstrate the rationale and the appropriateness of their chosen quantitative techniques, and to understand the limitations, if any, of such techniques. AIs should be able to demonstrate the appropriateness of the internal parameters they employ in assessing a rating system's accuracy and reliability.

2.9 The HKMA recognises that no one validation technique can necessarily be applied to all portfolios, and that it is common industry practice to apply different validation techniques to different types of portfolio. It will, however, generally expect AIs to apply the validation techniques 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 will expect 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 The HKMA will also expect AIs to 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 AIG subgroup principles, and in particular with the fifth principle which emphasises both the quantitative and qualitative aspects of validation. As noted above, 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. The HKMA will expect AIs 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 will place substantial emphasis on the systems and controls environment in which the IRB systems are operated. It will include the extent of Board and senior management oversight and review of the design, implementation and performance monitoring of IRB systems. The HKMA expects the directors and senior management of AIs to have a general understanding of the HKMA requirements under the IRB Approaches, and be able to express views on how their AIs' IRB systems meet those requirements.

3.2.2 The HKMA will not require an AI's directors and senior management to have a thorough knowledge about 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 management oversight, the HKMA will also assess the effectiveness of the rating system review staff in bringing issues to the attention of senior management and the adequacy of the senior management response.

3.2.3 The HKMA also expect AIs to demonstrate that their IRB systems are subject to an independent rating approval process, that the systems are transparent and fully documented, and that there are clear lines of accountability for all aspects of rating accuracy and performance. Under this criterion, AIs will also need to be able to demonstrate that they meet the use test for IRB systems. Requirements on these areas, 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 IRB systems is key to whether the systems are able to produce accurate and reliable information. The HKMA's assessment of data quality will include an evaluation of the systems and controls that an AI has in place to produce estimates of the risk components. Details on the procedures in and the adopted requirements on 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 can adequately differentiate risks, and whether estimates of the risk components are accurately measured such that they can appropriately characterise the relevant aspects of risks. AIs should have a robust system in place to back-test and validate the accuracy of the estimates of the risk components, and the discriminative power of the rating systems. During the IRB recognition process, the HKMA will expect AIs to demonstrate the rationale and the appropriateness for 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.

3.5 Benchmarking

3.5.1 Benchmarking is another key validation activity to assure both the AI and the HKMA that the IRB systems and the resulting estimates of the 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.

3.6 Stress-testing

3.6.1 Scenario testing of the IRB systems is essential for an AI to assess its potential vulnerability to "stressed" business conditions. In the validation process, the HKMA will expect an AI to demonstrate that the stress tests it has conducted are appropriate and effective for assessing the AI's capital adequacy and ability to withstand the unfavourable impact of stressed business conditions. Details of the stress-testing requirements on validation are given 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 risk components.

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.

4.3 At the Board level, the directors should have a general understanding of the HKMA requirements under the IRB Approach and how the AI proposes to meet such requirements according to a defined timeframe. The approval for the key elements of an internal rating system to be adopted by the AI should normally rest with the Board based on information provided by senior management, which should have reviewed the technical aspects with support from internal staff expertise and/or external parties. Such approval may come from the Board of the regional or head office in the case of AIs that are subsidiaries of foreign banking groups.

4.4 The Board may delegate an appropriate party (e.g. a Basel II 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 project according to plan. Where the AIs are subsidiaries of foreign banking groups, such delegation may come directly from the regional or head office.

4.5 Depending on the complexity and scale of the project, individual AIs may need to appoint a full-time manager to take charge of the Basel II project implementation. Also, the project implementation plan may be divided further into smaller parts or work streams by risk or Pillar (under the definitions of Basel II) 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.

4.6 The Board should ensure that sufficient resources are provided to project implementation and that it is regularly kept informed of the project implementation progress and any slippages. If the AI is a subsidiary of a foreign banking group, local efforts must be made to meet this requirement. Where slippages in the project implementation plan are likely to have a significant effect on the AI’s ability to comply with the HKMA minimum requirements on the IRB Approach, the Board and the HKMA should be informed as soon as possible.

4.7 Under the AIG subgroup principles related to validation under Basel II, AIs have primary responsibility for validation and validation is an iterative process. To comply with the principles, AIs are expected to conduct a comprehensive and independent validation of their internal rating systems at least annually. 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. When an AI has gained sufficient experience in validating its IRB systems, it should be able to demonstrate to the 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 prepared and submitted to members of the Board in advance for review and discussion at the Board meetings.

4.8 Senior management are responsible for the day-to-day operations of an AI, and the HKMA expects them to have a good general understanding of the internal rating systems employed by the AI. Except 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 expertise and/or external parties.

4.9 To ensure that the internal rating systems will work consistently and as intended on an ongoing basis, senior management are expected to:

- demonstrate a good understanding of the internal rating system design and operations;
- 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 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;
- 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, pricing, internal capital allocation, provisioning, etc.;

- 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.

4.10 As regards the requirement on 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.

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

- risk profile of the AI by grade;
- risk rating migration across grades and comparison with expectations;
- estimates of the relevant risk components per grade;
- comparison of realised 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 and other independent control functions.

4.12 The HKMA will look for evidence of the Board and senior management involvement in Basel II project implementation, and their understanding of the internal rating systems during the IRB recognition process.

5. Other systems of control

5.1 Independence

5.1.1 In addition to the need for an independent credit risk control unit that is responsible for the design or selection, implementation and performance of an internal rating system, AIs should also ensure sufficient independence in the rating approval process and in the review of the IRB system and risk quantification.

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 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 will not normally consider that such arrangements are consistent with an adequate degree of independence in the rating approval process. However, it will take into account the size and nature of the portfolio to which these arrangements are applied. Where the HKMA approves such arrangements, AIs should mitigate the inherent conflict of interest with compensating controls, 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 should at a minimum include a process of verifying the accuracy and completeness of the data inputs.

Independent review of IRB system and risk quantification

5.1.6 To ensure the integrity of the IRB systems and risk quantification, AIs should have a comprehensive and independent review process. The unit(s) responsible for review should be functionally independent from the staff and management functions responsible for developing the underlying IRB systems and performing risk quantification activities. The activities of this review process could be distributed across multiple areas or housed within one unit. AIs may choose a structure that fits their management and oversight framework. Individuals performing the reviews should possess the requisite technical skills and expertise. The review should be conducted at least annually and should encompass all aspects of the process, including:

- compliance with established policies and procedures;
- quantification process and accuracy of the risk component estimates;

- rating system development, use and validation;
- adequacy of data systems and controls; and
- adequacy of staff skills and experience.

5.1.7 The review process should identify any weaknesses, make recommendations and ensure that corrective actions are taken. Significant findings of the reviews must be reported to the Board and senior management.

5.1.8 AIs that at present lack sufficient in-house expertise to be able to perform the review function adequately should make appropriate use of external support. Those AIs that already have the needed skills and resources in-house should nonetheless consider the benefits of supplementing their internal processes with external reviews. Among these benefits are that external reviewers are likely to possess a broader perspective on the use of rating systems in different jurisdictions and in different institutions, and that they may possess more comprehensive data sets to support the cross-testing of rating systems.

5.2 Transparency

5.2.1 AIs' 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 "Minimum Requirements for Internal Rating Systems under IRB Approach". In particular, the HKMA expects AIs to update their documentation in a timely manner (e.g. as and when modifications are made to the rating systems).

5.2.2 Where AIs adopt an expert judgement-based internal rating system, the personal experience and subjective assessment used in rating credits are less transparent. AIs 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, and the quality of data used to develop the model and the data fed into it during use. AIs that use models to assign ratings must 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, AIs 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 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 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 models, and an accountability chart of roles of 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 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.

5.4 Use of internal ratings

Areas of use

5.4.1 Ratings and default and loss estimates should play a major role in the credit approval, risk management, internal capital allocations, and corporate governance functions of AIs.

5.4.2 Internal rating systems from which ratings and estimates of the risk components are generated for regulatory capital calculation should have a substantial influence on the AIs' decision-making and actions. In particular, the HKMA expects AIs to apply their internal ratings and estimates of the risk components to the following uses over time:

- credit approval;
- pricing;
- individual and portfolio limit setting;
- credit monitoring (e.g. higher rating review frequency for riskier obligors);
- analysis and reporting of credit risk information, including that for the Board and senior management oversight;
- determining provisioning;
- modelling and management of economic capital;

- 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 of new exposures and collection strategy of 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 related to AIs' risk management (e.g. AIs' infrastructure such as IT, 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 such differences, 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 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 will expect 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 and external audit

Internal audit[5]

5.5.1 Internal audit should review at least annually an AI's internal rating systems (including the validation process and the estimation of the 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. Internal audit should document the findings and report them to the Board and senior management.

5.5.2 The areas of review should include the depth, scope and quality of work conducted by the credit risk control unit, as well as adherence by the AI to all applicable HKMA requirements for using the IRB Approach.

5.5.3 Internal audit 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 related credit risk control unit, and the resources available to these staff.

5.5.4 Internal audit should conduct necessary testing to ensure that the conclusions on the credit risk control unit are well founded. In particular, if the requirement on independence regarding the review of rating system and risk quantification (see paragraphs 5.1.6 and 5.1.7) cannot be met, an AI's internal auditors may need to "walk through" or review the validation process. This

[5] Unless indicated otherwise, "internal audit" may mean an equivalent function possessing a similar degree of independence that is acceptable to the HKMA.

may include evaluation of model logic and assumptions, statistical model-building techniques and back-testing the models. In this case, the HKMA expects the AI's internal audit to be staffed by personnel with sufficient expertise and supported with adequate resources.

5.5.5 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 needs 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.

5.5.6 Under the IRB recognition process, AIs are required to submit the self-assessment questionnaires and the pertinent support documents for review by the HKMA. The HKMA expects internal audit to be one of the sign-off parties of the completed self-assessment as evidence that it has verified the AIs' adherence to all applicable HKMA requirements.

External audit

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

5.6.2 As specified in the "Minimum Requirements for Internal Rating Systems under IRB Approach", 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 requirements for internal rating systems. Thus, these models generally have to fulfil the same 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 meet the HKMA requirements for using the IRB Approach. 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 requirements. The HKMA assessment regarding an external vendor model will focus on the transparency of the model and of 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 on a model for IRB recognition purposes.

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 model monitoring all the limitations of the models and the circumstances in which the models do not perform as expected.

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 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 AIs should have a process 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 in many occasions by type of exposures within an AI. Regardless of the approach they adopt, AIs should adhere to the requirements in this section in respect of the following aspects:

- management oversight and control;
- IT infrastructure and data architecture;
- data collection, storage, retrieval and deletion;
- data processing;
- data quality assessment;
- reconciliation between the data used for the IRB Approaches 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 polices, 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 of 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;
- formalising internal audit programmes, the scope of which should include assessments of both the numbers produced and processes of data management; and
- ensuring that outsourced activities performed by third-party vendors are supported by sufficient quality control measures to meet the HKMA requirements for using the IRB Approach.

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 the 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 The HKMA expects an AI to 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 stable[6]. Scalability ensures that the 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 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 from events of emergency or disaster[7].

6.4 Data collection, storage, retrieval and deletion

6.4.1 The HKMA expects AIs to 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.

6.4.2 At a minimum, data should be updated annually, matching the minimum updating requirement for estimation of the risk components. The HKMA expects AIs to demonstrate that their procedures to ensure that the frequency with which data items are updated are

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[6] 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".

[7] The guidance set out in TM-G-2 "Business Continuity Planning" applies here.

sufficient to reflect the risk inherent in their current portfolios. For example, data for higher risk borrowers 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 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; 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 etc. 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 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 events of emergency or disaster[8].

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 Approaches. 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.

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8 The guidance set out in TM-G-2 "Business Continuity Planning" applies here.

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 accounting provisions for incurred loss) 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 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 the internal audit in verifying the 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 treatments 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 on this, and enhance its 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 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 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 and the review of adherence to all applicable minimum requirements by internal audit.

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, AIs 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 AIs that use external or pooled data in the 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. AIs should be able to demonstrate that data definitions are consistent between the external or pooled data, and AIs' internal portfolio data, and that distributions of the key risk characteristics (e.g. industry and size) are similar.

6.8.2 The HKMA expects AIs to be able to demonstrate that arrangements for data management by third parties meet the same standards required for data management by AIs. In addition, AIs should have policies and procedures in place to assess and control the risk arising from the use of external or pooled data. In particular, AIs are expected to:

- understand how the third parties collect the data;
- understand the quality control programmes 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); and
- assess the appropriateness for continuation of using the external or pooled data based on regular review (no less than once every 12 months) of the above aspects.

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

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. The HKMA expects AIs 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 The HKMA will expect AIs 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 will not normally consider that an AI has a 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 7.3[9] respectively. The application procedures and assumptions must be documented and consistently applied.

7.1.2 If an AI intends to use techniques not included in paragraphs 7.2.1 and 7.3.1, such as proprietary or customised tests, or techniques with ideas borrowed from other fields, it needs 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).

7.1.4 The validation of the internal rating systems' discriminatory power and calibration should be conducted according to the definition of "default/non-default" stipulated in the "Minimum Requirements for Risk Quantification under IRB Approach", notwithstanding any alternative definitions AIs may

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

employ for their own internal risk management purposes.

7.2 Validation of discriminatory power

7.2.1 The HKMA will expect 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 and the Pietra Index;
- 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 The HKMA expects AIs 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 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 similar[10] to, the development data set. If out-of-sample and out-of-time validations cannot be conducted due to data

[10] "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.

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 needs 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 will expect 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 will expect 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 borrowers. 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 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 realised default rates. AIs should have a clearly documented policy that requires remedial actions to be taken when policy tolerances 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 7.3.1[11].

7.3.4 The HKMA expects AIs 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 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 significantly less advanced than those of PD. As such, the HKMA regards qualitative assessment of the measurement and estimation process as a more meaningful validation method than the use of quantitative techniques for LGD alone.

[11] 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 realised 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.

8.1.2 Methods 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 The HKMA also expects AIs to adhere to the guidelines in the Basel Committee paper regarding the estimation of downturn LGD[12]. In particular,:

(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 the 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

(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 assigning LGD to non-default facilities

8.2.1 The HKMA will expect AIs to use one of the following methods in assigning LGD to non-default facilities:

[12] "Guidance on Paragraph 468 of the Framework Document", Basel Committee, July 2005. The HKMA will adopt the principles and guidance set out in that paper, and incorporate them as part of the minimum requirements for the quantification of LGD under the IRB Approach.

- **workout LGD** which is based on observations of the discounted cash flows resulting from the workout process of 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 will need to demonstrate to the HKMA that they have:

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

(ii) established articulated methods to determine and measure the realised 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 AIs' current portfolios based on the information obtained 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, AIs will need 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 realised 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 AI will therefore need 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 AIs to be able to justify their choice of method to LGD estimation. The HKMA will expect AIs to 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 realised LGD for the defaulted facilities in the development data set.

Definition of the end of a workout

8.3.2 The HKMA will expect AIs 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, AIs should consider the resulting impact on the development data set[13], and be able to justify their choice.

[13] 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.

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 AIs in measuring non-cash recoveries resulting from repossessions.

- The first option is to consider the recovery process complete at the time of the repossession.
- 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 AIs 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. AIs 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 AIs must include all the costs, including both **direct costs** and **indirect costs**, of the workout process in the calculation of LGD.

- 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 AIs 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 AIs: **historical discount rates** and **current discount rates**.

- Historical discount rates are fixed for each defaulted facility, regardless of the date on which 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 will expect 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 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. 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.

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. The HKMA will 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.

8.3.13 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 will consider permitting an AI to use the same discount rate across different products/facilities, provided that it can 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 process[14]

8.4.1 The HKMA will expect an AI to be able to demonstrate that all the components that are needed to produce LGD estimates satisfy the requirements of the module. The components include:

(i) construction of a development data set of defaulted facilities;

(ii) calculation of the realised 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 the LGD estimates, the first step is to obtain 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 realised 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

[14] The estimation process outlined in this subsection is directly related to market LGD and workout LGD methods. Where applicable, 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.

- appropriate techniques are used for identifying and assessing the effects of economic downturn conditions on realised LGD.

Measuring the realised LGD for the defaulted facilities

8.4.3 After constructing the development data set, the realised 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 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 The HKMA will expect AIs to demonstrate that they have conducted an analysis of the empirical distribution of realised 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 will expect AIs to choose a statistic of the empirical distribution, such as mean or median, of the realised LGD of similar but defaulted facilities. However, if there were adverse dependencies between the realised LGD and economic downturn conditions (i.e. realised LGD increased when there were economic downturns), the HKMA will expect 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 will expect 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.

8.4.7 AIs may use modelling techniques (e.g. a regression model) to directly derive, or to refine the LGD estimates. When models are used, the HKMA will expect AIs 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 above estimation process. The process of exercising expert judgement should be transparent, well-documented and closely monitored.

8.4.9 AIs 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 The HKMA will expect AIs to be able to demonstrate that they have performed the following analyses and tests on their estimates of LGD:

- **Stability analysis**: AIs should analyse how changes in the development data set (e.g. use of sub-samples) and changes in the assumptions made for determining the realised LGD and/or parameters of the model impact the LGD estimates. AIs should analyse the volatility of the LGD estimates when the timeframe of the development data set changes. These analyses are to ensure that AIs' LGD estimates are stable and robust.

- **Comparisons between internal LGD estimates and relevant external data sources**: AIs should compare their internal LGD estimates with relevant external data sources. When conducting such comparisons, AIs 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 AIs to provide the relevant data for comparison amongst AIs' internal LGD estimates for similar facilities in order to identify potential outlying predictions.

  In cases where relevant external data source is not available, the HKMA will expect the AIs to develop the benchmarks internally (e.g. LGD estimates based on alternative methods).

- **Comparisons between realised LGD of new defaulted facilities and their LGD estimates**: AIs should compare the actual outcomes with their internal estimates. In particular, AIs should develop statistical tests[15] to back-test their internal LGD estimates against the realised LGD of the new defaulted facilities, establish internal tolerance limits for the differences between the estimates and the realised LGD, and have a policy that requires remedial actions to be taken when policy tolerances are exceeded[16]. The general requirements for AIs 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.

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

16 For example, AIs can assume a parametric distribution on the LGD estimate for a certain type of facilities. Based on this distribution, AIs 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 realised default-weighted average LGD of the new defaulted facilities may fall.

9. Accuracy of EAD

9.1 Overview

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

9.1.2 Compared with LGD, measuring EAD for the defaulted facilities is simpler as they are readily observable. In constructing the development data set for EAD estimation, the HKMA will expect AIs 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 will recognise two methods to construct a development data set for EAD estimation, **cohort method** and **fixed-horizon method**. Under either method, only information about the defaulted facilities should be used. Data of facilities that defaulted but subsequently recovered should also be included.

Cohort method

9.2.2 Under the cohort method, AIs should group defaulted facilities into discrete calendar periods (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 realised 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, AIs 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 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 a facility cannot be less than the current drawn amount. 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 will need to demonstrate conservatism that the estimated aggregate EAD amount for a facility type is higher than the realised aggregate EAD amount for that facility type (see subsection 9.4).

9.3.2 For off-balance sheet items, EAD of foreign exchange, interest rate, equity, credit, and commodity-related derivatives will be calculated according to the rules for the calculation of credit equivalent amounts, i.e. based on the replacement cost plus potential future exposure add-ons across the different product types and maturity bands (see "Weighting Framework for Credit Risk (Standardised Approach)").

9.3.3 For the estimation of EAD for non-derivative off-balance sheet items, such as lines of credit, loan commitments, letters of credit and credit guarantees, AIs should use one of the following expressions:

- EAD = current drawn amount + CCF × (current limit – current drawn amount); or
- EAD = UR × current limit

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 9.2.3 and 9.2.5. CCF or UR then becomes the subject variable that requires estimation. Under either expression, the estimated EAD amount cannot be less than the current drawn amount.

9.3.4 AIs are permitted to take 100% of current limit as the EAD estimate. If AIs use this method, they will need to demonstrate conservatism that the estimated aggregate EAD amount for a facility type is higher than the realised aggregate EAD amount for that facility type (see subsection 9.4).

Possible risk factors for EAD estimation

9.3.5 The HKMA will expect AIs 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 AI's willingness to supply funding/facilities;
- the attitude of third parties (e.g. other AIs, 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).

Some possible risk factors that AIs may consider in the estimation of EAD are given in Annex C[17].

[17] The list of risk factors in Annex C is not intended to be exhaustive. The HKMA will expect AIs to take into account the predictive power of additional factors that may influence EAD.

Estimation process

9.3.6 The estimation process of EAD for non-defaulted 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 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, AIs 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, AIs 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 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 AIs manage credits[18]. The HKMA will expect AIs to have a process in place for ensuring that estimates of

[18] 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.

EAD take into account these developments. In particular, the process should ensure that AIs 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, AIs 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 The HKMA will expect AIs 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.

9.4 Validation of EAD estimates

9.4.1 The HKMA will expect AIs to be able to demonstrate that they have conducted the same types of analyses and tests for assessing LGD estimates (see paragraph 8.5.1) in their assessment of the accuracy of EAD in terms of UR or CCF. AIs should develop statistical tests[19] to back-test their internal EAD estimates against the realised EAD of the new defaulted facilities, establish internal tolerance limits for the differences between the estimates and the realised EAD, and have a policy that requires remedial actions to be taken when policy tolerances are exceeded[20]. The general requirements for AIs 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, AIs should compare their internal estimates with external benchmarks. Where external benchmarks are not available, the HKMA will expect the

[19] AIs are permitted to develop their own statistical tests, provided that they are theoretically sound, well-documented and consistently applied.

[20] For example, AIs can assume a parametric distribution on the CCF or UR estimate for a certain type of product. Based on this distribution, AIs 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 realised default-weighted average CCF or UR of the new defaulted facilities may fall.

AIs to develop internal benchmarks for this purpose. The HKMA may also require AIs to provide the relevant data for comparison amongst AIs' internal EAD estimates for similar facilities in order to identify potential outlying predictions.

9.4.3 Where AIs use 100% UR or CCF for some non-derivative off-balance sheet items (see paragraph 9.3.4) and current outstanding balance for the on-balance sheet items (see paragraph 9.3.1), the HKMA will not normally expect them to conduct the analyses and assessments described in paragraph 9.4.1 for validating the accuracy of EAD estimates. However, the HKMA will expect AIs to be able to demonstrate, no less than once every 12 months, that these EAD estimates are sufficiently conservative[21]. In particular, the HKMA expects AIs to:

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

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

If the estimated aggregate EAD amount is below the realised 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.

[21] There can be situations where the realised 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 realised EAD is larger than the current outstanding balance for the on-balance sheet items (e.g. accumulation of accrued but unpaid interest and fees).

10. Issues on LDPs[22]

10.1 Types of LDPs

10.1.1 LDPs' main characteristic is that they lack sufficient default data, which presents challenges for risk quantification and validation. In practice, there are several types of portfolios that may have relatively low numbers of defaults:

(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);

(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 The types of portfolios mentioned in paragraph 10.1.1 should be considered as examples of portfolios that may have relatively low number of defaults. They are neither definitive (e.g. an AI may record many defaults even if it is a recent market entrant) nor exhaustive. Therefore, the HKMA considers that it is unnecessary to develop a separate definition and an additional set of rules or principles specifically for LDPs. An AI should consider whether any of its portfolios have characteristics of the LDPs and design the 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, the

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

HKMA will expect AIs to demonstrate that they have taken into account the considerations in paragraphs 10.2.3 to 10.2.6, which extend the validation principles of the Validation Subgroup of the AIG of the Basel Committee.

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 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 the module. In all cases, AIs will need to justify their chosen techniques, understand the limitations and apply conservatism to the results where necessary.

Forward-looking and predictive risk component estimates

10.2.3 While estimates of 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 LGD and EAD, where applicable) estimates. Where, for example, there is a lack of recent loss data, but historical experience or other analysis suggests that the potential risk of loss in a portfolio is not negligible (type (iv) in paragraph 10.1.1), AIs should base the 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 will expect 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 will expect AIs to demonstrate the use of some or all of the following techniques to enhance data richness[23]:

- AIs can combine internal portfolio segments with similar risk characteristics for estimating and validating the 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 risk components for the calculation of regulatory capital requirements.
- AIs can combine different rating grades, and estimate or validate the risk components for the combined grade. This technique is especially useful for AIs 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), AIs can use the lowest non-default rating as a proxy for default.

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

- AIs can analyse intra-year rating migrations as separate rating movements to infer the annualised PD.

Effective use of benchmarking tools

10.2.6 When AIs do not have sufficient loss data (even if data-enhancing techniques are used) to back-test their internal estimates of the risk components, the HKMA will expect 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 Definition of and HKMA requirement on benchmarking

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

11.1.2 Generally, the HKMA will expect 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 will expect AIs to provide valid justifications and demonstrate that they have other compensating measures (e.g. comprehensive back-testing at a frequency higher 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 will 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 risk components are credible, this requirement may, subject to the HKMA's prior approval, be waived. In this case, however, the HKMA will encourage the AI to develop suitable internal benchmarks to supplement its back-testing analyses.

11.1.4 In addition, while the HKMA will not actively promote data sharing 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 requirement on benchmarking for validation purpose is depicted in Annex D.

11.2 HKMA expectations regarding the 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 risk components. The HKMA expects an AI to integrate benchmarking into its validation process and conduct benchmarking at least annually on a representative sample of its current portfolio.

11.2.2 There are different types of benchmarking (see subsection 11.3). AIs should choose the types that are suitable for their portfolio characteristics and justify their choices. AIs should document and consistently apply the policies and methodologies adopted. Nonetheless, AIs should reassess the appropriateness of the types of benchmarking and methodologies chosen before conducting the regular benchmarking exercise, in light of changes in the AIs' portfolio characteristics and the external environment.

11.2.3 AIs 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, AIs 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 requirements for AIs 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.

11.2.4 An AI should report the benchmarking results and analysis to senior management and relevant business line managers. The AI should also provide the Board with a summary report on the benchmarking results and actions taken, if any.

11.2.5 An AI will need 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 AI's portfolio;
- quality of the benchmarks in terms of accuracy of the benchmarks 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 exercise;
- adequacy of the use of the benchmarking results in relation to the AI's risk management policies;
- 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.

11.2.6 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 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 it 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 will normally expect 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 borrowers/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;
- 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 borrowers/facilities.

11.3.3 The above list of benchmarking techniques is not intended to be exhaustive. The HKMA will expect 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 systems for the same portfolio, for example one for the purpose of the regulatory capital calculation and another for benchmarking. In such cases, the HKMA will expect 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 The HKMA expects an AI 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, the HKMA will expect it to 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.

11.4.3 The HKMA will recognise a benchmark for validation purposes subject to the following conditions:

- the AI can 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 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.

11.5 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.

11.5.3 When designing a consistent mapping to a master scale, AIs 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 HKMA approach to stress-testing

12.1.1 Stress-testing involves the use of various techniques to assess an AI's potential vulnerability to "stressed" business conditions. It should identify possible events or changes in economic conditions that could have unfavourable effects on the credit exposures of an AI, and hence assess the AI's ability and capital adequacy to withstand such events or changes.

12.1.2 The HKMA will consider the results of stress tests conducted by an AI and how these results relate to its capital planning according to the principles set out under the supervisory review process. The use of stress tests for risk management purposes and the HKMA's approach to evaluating the appropriateness and effectiveness of stress tests conducted by AIs are set out in IC-5 "Stress-testing" as well as the "Minimum

Requirements for Internal Rating Systems under IRB Approach".

12.1.3 The HKMA will expect stress tests conducted by an AI to take into account the following factors:

- the complexity and level of risks of the AI's activities;
- the adequacy of stress tests (e.g. stress scenarios and parameters chosen) employed by the AI in relation to its activities;
- the appropriateness of the assumptions used in the stress tests;
- the adequacy of the AI's risk management policies and stress-testing procedures;
- the level of oversight exercised by the Board and senior management on the stress-testing programme and results generated; and
- the adequacy of the AI's internal review and audit of its stress-testing programme.

12.1.4 The HKMA expects AIs to:

- conduct a regular (no less than once every three months) credit risk stress test to assess the effect of specific conditions on their total regulatory capital requirements for credit risk. The test would 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 the AI's own data as well as external ratings for estimation of the migration; and
- take remedial action to reduce risks and/or to hold additional capital/provisions when the results of an AI's stress test indicate a deficiency of capital calculated based on the IRB Approach.

12.2 Development and application of stress-testing

12.2.1 In taking into account the results of an AI's stress tests for the purposes of validation, the HKMA will consider the following factors:

- data quality;
- consideration of portfolio composition and general conditions;
- completeness of risk factors included in the stress tests;
- extraordinary changes in risk factors;
- acceptance by management;
- reporting;
- definition of remedial actions;
- regular updating; and
- documentation and approval.

Data quality

12.2.2 AIs should ensure that their internal ratings are up to date and valid. Other important data relevant to credit risk exposures of an AI include the outstanding volume of each credit facility, the interest rate, as well as any available collateral values.

Risk factors

12.2.3 A list of risk factors that the HKMA expects AIs to take into account can be found in the "Minimum Requirements for Internal Rating Systems under IRB Approach". AIs should also identify their own risk factors having regard to circumstances specific to their institutions, the specific nature of the credit portfolio and an analysis of the correlation between relevant risk factors.

12.2.4 When identifying risk factors, AIs should involve experts from various areas and organisational levels in order to ensure that the stress tests attain the necessary level of acceptance. Senior management should also be consulted while developing stress tests.

12.2.5 AIs should analyse the prevailing social, economic, and political conditions in identifying all the relevant risk factors, stressing these factors and hence formulating the stress scenarios that are relevant to their own circumstances.

12.2.6 If the AI uses risk models such as credit portfolio models or credit pricing models, it is necessary to ensure that the assumptions underlying the risk models will also be valid in stress situations, especially regarding default rate volatility, rating migrations, and correlation between individual credit facilities or borrowers.

Stress scenarios

12.2.7 AIs should determine the appropriate assumptions for stress-testing risk factors included in a particular stress scenario, and formulate the stressed conditions based on their own specific circumstances. In designing stress scenarios, AIs should take into account both past episodes of market stress as well as constructing hypothetical scenarios to reflect the risks arising from latest market developments.

12.2.8 Comprehensive and realistic stress scenarios should include simultaneous changes in all essential risk factors wherever possible. One-factor stress tests should only act as complementary analyses of a portfolio's sensitivity to individual factors.

12.2.9 Stress tests conducted by an AI should cover a wide range of external conditions and scenarios that are relevant to its own circumstances. At a minimum, a mildly stressed scenario chosen by the AI should resemble the economic recession in Hong Kong in the second half of 2001 and the first quarter of 2002, as set out in the "Minimum Requirements for Internal Rating Systems under IRB Approach". Other examples of stress scenarios relating to credit risk are outlined in IC-5 "Stress-testing".

12.2.10 The HKMA expects AIs to develop potential remedial actions for stress scenarios. For this purpose, it is necessary to design sufficiently differentiated stress tests in order to enable targeted causal analyses for potential losses in stress situations.

Regular updating and reporting

12.2.11 AIs are expected to review and update the methodology and effectiveness of the stress-testing programme on a regular basis, taking into account any changes in portfolio composition as well as social, economic and political conditions, and assessing whether the underlying assumptions are still valid. Such review and updating should be conducted at least once a year, and more frequently if the portfolio or the environment changes significantly.

12.2.12 AIs should keep their senior management and relevant business line managers closely informed of the results of routine stress tests as well as those of new tests based specifically on the prevailing economic situation. Such reports should draw attention to potential risks and vulnerabilities identified and make recommendations for possible courses of remedial action.

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.

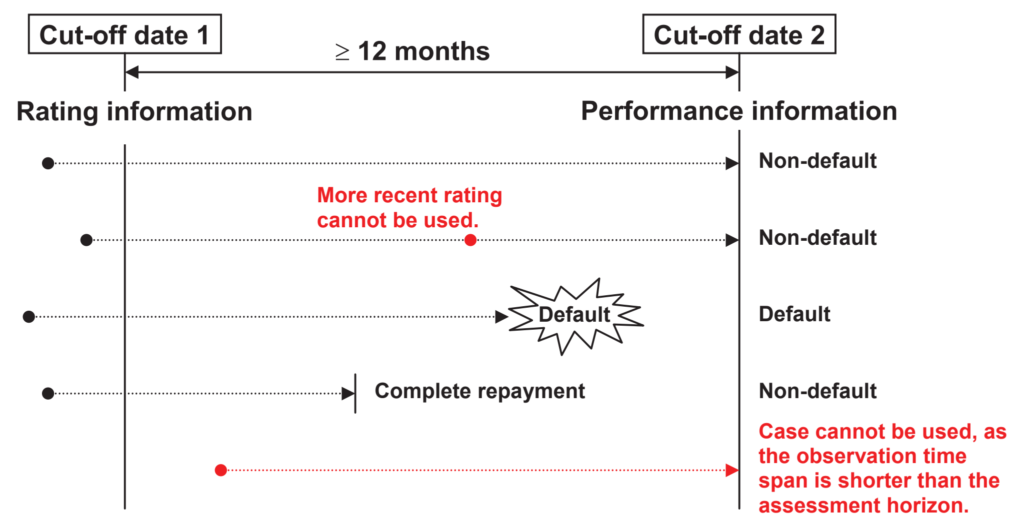
A1.3 Information on obligors that have defaulted before the first cut-off date cannot be used. Cases for which the loans were properly repaid during the assessment horizon should be included and are classified as "non-default". Cases for which no rating information as of the first cut-off date is available (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 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")

<u>CAP</u>

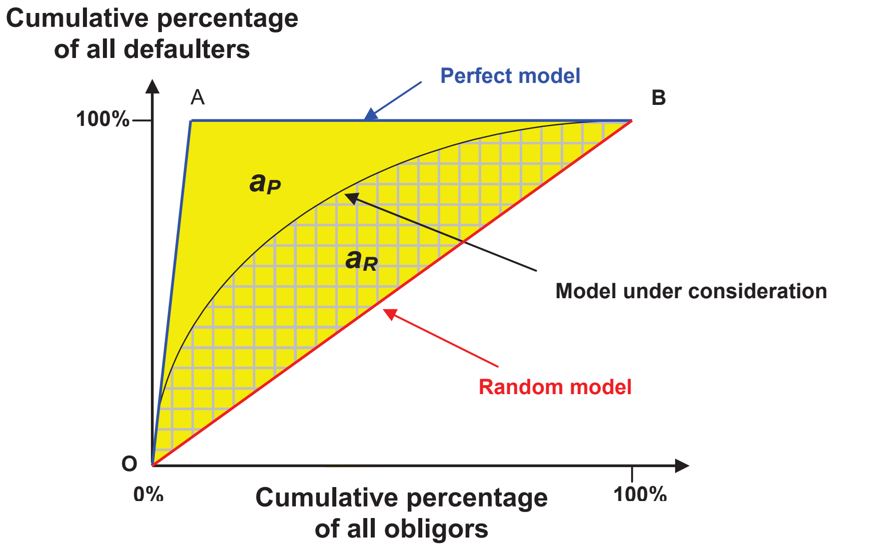
A2.1 **CAP** is also known as the **Gini curve**, **Power curve** or **Lorenz curve**. It is a visual tool whose graph can be drawn if two samples of obligor grades (or scores) for defaulters and non-defaulters are available.

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 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.:

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

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.

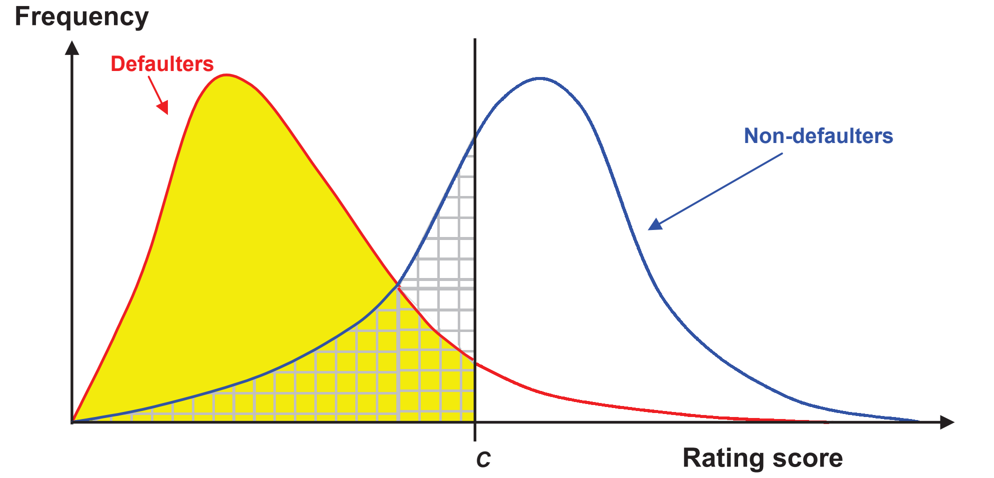
A2.7 AR is always between 0% and 100% for any rating system better than random assignment of ratings. The better the rating system, the closer is AR to 100%.

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.

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:

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

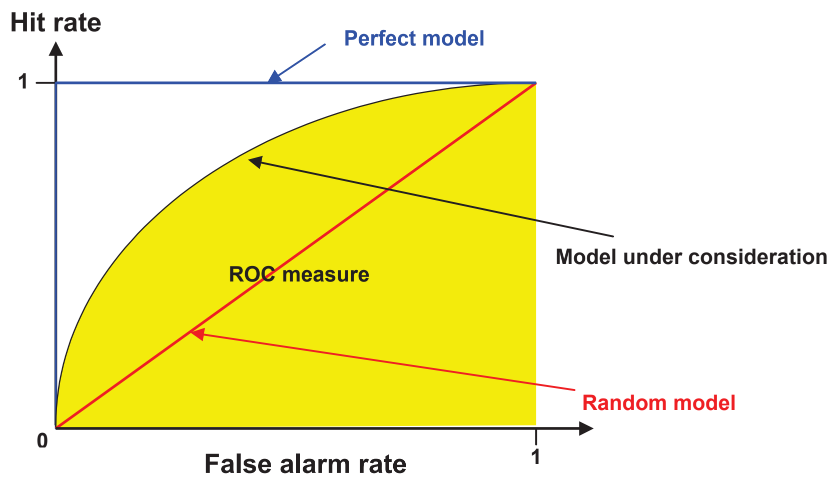
where *H(C)* is the number of defaulters predicted correctly with the cut-off value *C,* and N_D is the total number of defaulters in the sample. This means that the hit rate is the fraction of defaulters that was classified correctly for a given cut-off value *C*. The false alarm rate *FAR(C)* is defined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

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 **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 ROC measure equal to 50%, and 100% for a perfect model[24].

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.

Pietra Index

A3.9 Geometrically, **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:

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

A3.10 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 ROC measure has statistical properties coincided with the Mann-Whitney statistic. Therefore, AIs can construct confidence intervals for the ROC measure of a rating system and test the difference between

[24] The AR and ROC measure have a linear relationship:

AR = 2 (ROC measure) - 1.

the ROC measures of two rating systems which are validated on the same data set[25, 26].

A3.12 The term *HR(C) - FAR(C)* in the calculation of the Pietra Index is the Kolmogorov-Smirnov test statistic of the distribution functions *HR(C)* and *FAR(C)*. Therefore, as with the ROC measure, testing for the dissimilarity in discriminatory powers between two rating systems can be conducted.

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.

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25 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.

26 With the linear relationship between AR and ROC measure (see footnote 24), AIs using the former in assessing rating systems' discriminatory powers can calculate the confidence intervals and conduct statistical tests as with the ROC measure.

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

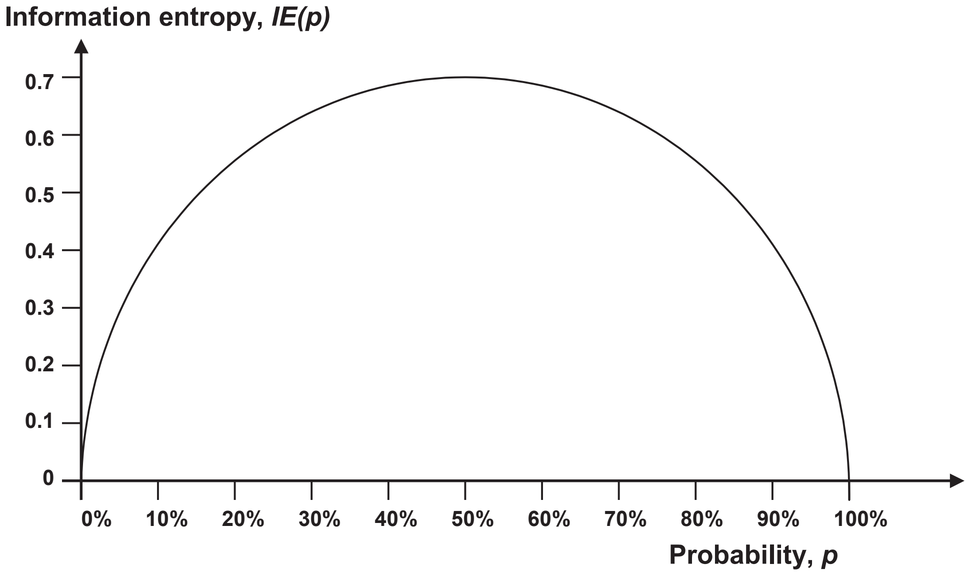
A5.1 Entropy is a concept from information theory that is related to the extent of uncertainty eliminated by an experiment. In application to validating a rating system's discriminatory power, entropy measures assess the information gained (or uncertainty reduced) by using the rating system in predicting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

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) $K = \{K_1, K_2, \ldots, K_k\}$, 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 $p(D \mid K_i)$ 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, $p(D \mid K_i)$ can be defined as:

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

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.:

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

$CE(K)$ 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 of which 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:

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

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

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:**

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

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.

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:

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

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

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.:

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

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 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 calculated[27]. 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 ratings[28].

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 obligor defaults and zero otherwise.

A8.2 BS is always between zero and one. The closer is BS 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:

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

[27] 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.

[28] 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.

A9. Divergence

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

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

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.

Annex B: Statistical methodologies in validating calibration[29]

B1. Binomial test with assumption of independent default events

B1.1 Consider a rating model assigning obligors to a set of k obligor grades $K = \{K_1, K_2, \ldots, K_k\}$. 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:

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

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:

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

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:

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

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

[29] 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.

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:

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

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

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

B2.3 AIs have the 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 (see "Weighting Framework for Credit Risk (IRB Approach)").

B2.4 For example, for retail residential mortgage loan exposures, 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, the upper bound of ρ depends on the PD forecast (i.e. $\hat{PD}_i$) of a particular obligor grade (pool):

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

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, AIs can apply the **chi-square** (or **Hosmer-Lemeshow**) test.

B3.2 Let $\hat{PD}_1$, $\hat{PD}_2$, … , $\hat{PD}_m$ denote the forecasts of default probabilities of obligor grades K_1, K_2, … , 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.

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 corporate 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 fewer accesses 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 to 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.

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.

Annex D: Flowchart depicting HKMA requirement on benchmarking