Supervisory Policy Manual

CA-G-3	Use of Internal Models Approach to Calculate Market Risk	V.2 - 31.01.07

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 explain the criteria that the MA will use in assessing an AI's eligibility for adopting the internal models approach ("IMM approach") to calculate its market risk for capital adequacy purposes

Classification

A technical note issued by the HKMA

Previous guidelines superseded

Technical paper "Use of Internal Models to Measure Market Risk" dated October 1997

Application

To locally incorporated AIs which apply to use the IMM approach to calculate their market risk for capital adequacy purposes

Structure

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1. Introduction

1.1 Terminology

1.1.1 Unless otherwise specified, the terms used in this module have the same meaning as those used in the Banking (Capital) Rules ("the Rules").

1.1.2 For the purposes of this module, the interpretation of certain terms set out in the Rules is recast or elaborated upon as follows:

- "default risk" means the risk of loss in the value of an AI's market risk exposures resulting from failure of the obligors to make timely repayments in respect of those exposures;
- "event risk" means the risk of loss (other than default risk) in the value of an AI's market risk exposures arising from any event (other than market-wide shocks) which results in large changes in market prices of the exposures;
- "general market risk" means the risk of loss in the value of an AI's market risk exposures arising from changes in interest rates, exchange rates, equity prices or commodity prices;
- "internal capital", in relation to an AI's market risk, means the amount of capital which the AI holds and allocates internally as a result of the AI's assessment of the market risk faced by the AI;
- "market risk" means the risk of loss arising from fluctuations in the value of an AI's market risk exposures. It encompasses both specific risk and general market risk;
- "market risk capital charge" means the amount of an AI's capital required to cover specific risk and general market risk of its market risk exposures;
- "market risk exposures", in relation to an AI, means -
  - (a) the AI's trading book positions held in -
    - (i) debt securities;
    - (ii) debt-related derivative contracts;
    - (iii) interest rate derivative contracts;
    - (iv) equities; and
    - (v) equity-related derivative contracts; and
  - (b) the AI's positions held in -
    - (i) foreign exchange (including gold);
    - (ii) exchange rate-related derivative contracts;

(iii) commodities; and

(iv) commodity-related derivative contracts;

- "market risk management system" means the methods, models, processes, controls and data collection and information technology systems used by an AI which enable the identification, measurement and control of market risk by the AI;
- "risk category", in relation to the calculation of an AI's market risk, means the class of the AI's market risk exposures which are at risk from -

  (a) changes in debt security prices or interest rates;

  (b) changes in exchange rates;

  (c) changes in equity prices; or

  (d) changes in commodity prices;
- "specific risk" means the risk of loss in the value of an AI's market risk exposures arising from -

  (a) changes in the price of debt securities owing to factors relating to the issuers of the debt securities;

  (b) changes in the price of equities owing to factors relating to the issuers of the equities;

  (c) changes in the price of debt-related derivative contracts owing to factors relating to the issuers of the underlying debt securities; and

  (d) changes in the price of equity-related derivative contracts owing to factors relating to the issuers of the underlying equities; and
- "value-at-risk" ("VaR"), in relation to a portfolio of market risk exposures, means a measure of the worst expected loss on the portfolio resulting from market movements over a period of time within a given confidence interval.

1.2 Overview

1.2.1 The capital adequacy framework for calculating an AI's market risk capital charge is set out in Part 8 of the Rules. AIs are advised to read this module in conjunction with the Rules. In case of any discrepancy between this module and the Rules, the Rules shall prevail.

1.2.2 The IMM approach, which is set out in Divisions 11 and 12 of Part 8 of the Rules, is one of the prescribed approaches to calculation of an AI's market risk. An AI may use this approach only if it has the MA's approval to do so under §18(2)(a) of the Rules.

1.2.3 Generally, the MA shall grant approval to an AI to use the IMM approach if the AI demonstrates to the satisfaction of the MA that the requirements specified in Schedule 3 to the Rules applicable to or in relation to the AI are met. The relevant criteria are described in sections 2, 3 and 4 below.

1.2.4 The MA may grant approval to an AI to use the IMM approach on a partial basis under §18(5) of the Rules if the MA is satisfied that it is not practicable or not yet ready for the AI to use the IMM approach to calculate both specific risk and general market risk, or use this approach across all of its risk categories or business.

1.2.5 Where necessary, the MA may request for a period of initial monitoring and live testing of an AI's internal models before the models are allowed to be used by the AI for capital adequacy purposes. Any AI which intends to use internal models to calculate its market risk should be prepared to participate in any such testing exercise to facilitate the MA's assessment of the accuracy and reliability of such models (see also section 5 below).

2. Qualitative criteria

2.1 Board and senior management oversight

2.1.1 The board of directors (or a committee designated by the board) and the senior management of an AI are expected to be actively involved in the market risk management process and to regard market risk management as an essential aspect of the business to which significant resources need to be devoted. In particular, they should:

- approve all the key elements of, and any material changes to, the AI's market risk management system;
- possess an understanding of the design and operation of, and the management reports generated by, the AI's market risk management system adequate for them to perform their functions specified in this subsection;
- exercise oversight of the AI's market risk management system sufficient to ensure that the system complies with subsection 2.2 below; and
- ensure that there is a reporting system within the AI to provide sufficient information (including that relating to any material changes to, or deviations from, established policies and procedures or any material findings identified in independent reviews or audits conducted in accordance with subsection 2.9 below) to them regularly as will enable them to exercise sufficient oversight as required above and make informed decisions relating to the AI's market risk exposures (e.g. in terms of formulating trading strategies or setting trading limits).

2.2 Market risk management system

2.2.1 An AI's market risk management system should be:

- suitable for the purposes of identifying, measuring and controlling the AI's market risk, taking into account the characteristics and extent of the AI's market risk exposures; and
- operated in a prudent and consistently effective manner.

2.2.2 An AI should have policies and procedures to ensure that the valuation of the AI's market risk exposures is prudently made whenever there are uncertainties affecting the accuracy of valuation estimates.

2.3 Market risk control unit

2.3.1 An AI should have a market risk control unit which is functionally independent of the AI's staff and management responsible for originating and trading market risk exposures (i.e. trading units) and reports

directly to the AI's senior management. This unit should generally be responsible for:

- the design or selection of the AI's market risk management system;
- the testing and implementation of the AI's market risk management system;
- the oversight of the effectiveness of the AI's market risk management system;
- the production and analysis of daily management reports based on the output of the AI's internal models (including an evaluation of the relationship between measures of market risk exposures and trading limits);
- the ongoing review of, and changes to, the AI's market risk management system; and
- the conduct of a regular (at least quarterly) back-testing programme to verify the accuracy and reliability of the AI's internal models. This refers to an ex-post comparison of the VaR measures generated by the internal models against the actual daily changes in portfolio value over time as well as the hypothetical changes in portfolio value based on static positions[1].

2.4 Market risk factors

2.4.1 An AI's internal models should capture and accurately reflect, on a continuing basis, all material factors affecting market risk inherent in the AI's market risk exposures (see Annex A for specification of these market risk factors).

2.5 Use of internal models

2.5.1 An AI's internal models should play an essential role in the AI's daily risk management process. The model outputs should accordingly be used in the process of planning, monitoring and controlling the AI's market risk.

2.5.2 The VaR measures generated from an AI's internal models should, in particular, be used in determining the

[1] This assumes that end-of-day positions remain unchanged during the holding period (say one day).

AI's trading limits. The relationship between the AI's internal models and those limits should be maintained consistently over time and understood by the AI's senior management and staff engaged in trading activity.

2.5.3 An AI should have a sufficient number of staff who are qualified and trained to use the AI's internal models in the AI's business, risk control, audit and back-office functions as will enable these functions to work effectively in identifying, measuring and controlling the AI's market risk.

2.6 Compliance and documentation

2.6.1 An AI should clearly document its internal models and the internal policies, controls and procedures relating to the operation of the models and have a system for monitoring and ensuring compliance with those internal policies, controls and procedures.

2.6.2 There should, for example, be a manual that describes the basic principles of an AI's market risk management system and provides an explanation of the empirical techniques used to calculate the AI's market risk.

2.7 Internal validation

2.7.1 An AI's internal models should have a proven track record of acceptable accuracy in calculating market risk (see Annex B for the use of back-testing).

2.7.2 An AI should have a reliable system for validating the accuracy and consistency of the AI's internal models by parties:

- who are qualified and trained to do so (i.e. with relevant and sufficient expertise and experience); and
- who are independent of the trading functions and the development of the internal models,

with the aim of ascertaining whether the internal models are conceptually sound and able to capture all material factors affecting market risk (see subsection 2.4 above).

2.7.3 Such model validation should be conducted by an AI when an internal model is initially developed or when any significant changes are made to the internal model.

2.7.4 Such model validation should be conducted regularly or when there have been significant structural changes in the market or changes to the composition of the AI's portfolio of exposures which might lead to the internal model concerned no longer being adequate to capture all material factors affecting market risk (see subsection 2.4 above).

2.7.5 An AI should have appropriate methods and procedures for assessing the validity and performance of, and the results generated by, its internal models. The AI should also have procedures to ensure that both the assumptions and approximations underlying its internal models are prudent and appropriate for the calculation of its market risk.

2.7.6 For the purposes of para. 2.7.5 above, model validation should not be limited to back-testing. An AI should use other model validation techniques appropriate for assessing the validity of its internal models, including:

- tests to demonstrate that any assumptions made within the AI's internal models are appropriate and do not underestimate risk. These assumptions may include the use of normal distribution, the use of square root of time to scale from a one-day holding period to a 10-day holding period and those associated with the use of extrapolation or interpolation techniques or pricing models;
- other than those required under the regulatory back-testing framework adopted by the MA (see Annex B for more details), any additional model validation tests which may include -
  - testing carried out for periods (e.g. three years) longer than normally required for an AI's regular back-testing programme. The longer time period generally improves the power of back-testing, except when the AI's internal models or market conditions have changed to the extent that historical data are no longer relevant;
  - testing carried out using confidence intervals other than the 99% confidence interval required under para. 3.2.2 below; and

– testing of sub-portfolios[2]; and

- the use of hypothetical portfolios to ensure that an AI's internal models are able to account for particular structural features that may arise, for example -

  – where the data history for a particular instrument does not meet the quantitative criteria set in section 3 below and where the AI needs to map these positions to proxies, it should ensure that the proxies produce prudent results under relevant market scenarios;

  – the AI should ensure that material basis risks are adequately captured. These may include mismatches between long and short positions by maturity or by issuer; and

  – the AI should ensure that its internal models capture concentration risk that may arise in a portfolio that is not diversified.

2.7.7 Where specific risk is also modelled by an AI, it is important for the AI to conduct more extensive model validation and demonstrate that it satisfies the criteria for specific risk modelling set out in subsection 4.2 below.

2.8 Stress-testing

2.8.1 An AI should have a comprehensive stress-testing programme conducted regularly to supplement the AI's risk analysis based on the daily output of its internal models (see Annex C for more details).

2.8.2 The results generated by an AI's stress-testing programme should be reported routinely to the AI's senior management and periodically to the AI's board of directors (or a committee designated by the board).

2.8.3 The stress-testing results should also be taken into account in:

[2] Testing of sub-portfolios may be applicable to an AI which classifies its market risk exposures into sub-portfolios in accordance with the risk categories (e.g. interest rate risk and foreign exchange risk) or characteristics of these exposures.

- setting the AI's market risk management policies (including trading and market risk exposure limits); and
- performing an assessment of the adequacy of the AI's regulatory capital and internal capital for market risk and the AI's ability to withstand any future events, or changes in market conditions, that could have adverse effects on the AI's market risk exposures (see C5 of Annex C for more details).

2.8.4 Where stress tests reveal to an AI any particular vulnerability to a given set of circumstances, the AI should take prompt measures (e.g. by means of hedging or downsizing its market risk exposures or increasing its capital level) to manage those risks appropriately.

2.9 Independent review or audit

2.9.1 An independent review or audit of an AI's compliance with the requirements specified in Schedule 3 to the Rules should be conducted regularly by the AI's internal auditors or by independent external parties which are qualified to do so.

2.9.2 Such review or audit should include the activities of an AI's trading and market risk control units. A review of the AI's market risk management system should take place regularly (ideally not less than once a year) and should specifically address, at a minimum, the following areas:

- the adequacy of documentation of the AI's market risk management system (including its internal models);
- the organisation of the AI's market risk control unit;
- the integration of the AI's market risk measures into daily risk management;
- the AI's approval process for pricing models and valuation methods used by its front- and back-office units;
- the validation of any significant change in the AI's market risk management system;
- the scope of market risk captured by the AI's internal models;

- the integrity of the AI's management information system;
- the accuracy and completeness of position data;
- the verification of the consistency, timeliness and reliability of data sources used to run the AI's internal models, including the independence of data sources;
- the accuracy and appropriateness of volatility and correlation assumptions;
- the accuracy of valuation and risk transformation calculations; and
- the verification of accuracy of the AI's internal models by reviewing -
  - the results of internal validation as required in subsection 2.7 above; and
  - the quarterly back-testing results as described in Annex B.

3. Quantitative criteria

3.1 General

3.1.1 The quantitative criteria set out in this section apply mainly to AIs which use VaR techniques in their internal models to calculate market risk.

3.1.2 As no particular type of internal models is prescribed by the MA, an AI has flexibility to devise its internal models based on, for example, variance-covariance matrices, historical simulations or Monte Carlo simulations as long as the models can capture all material factors affecting market risk of the AI (see subsection 2.4 above).

3.2 Minimum criteria

3.2.1 VaR should be computed by an AI on a daily basis.

3.2.2 A one-tailed 99% confidence interval should be used by an AI in calculating VaR.

3.2.3 The minimum holding period used by, or assumed by, an AI's internal models for its portfolio of exposures should be 10 trading days. The AI may use VaR calculated by its internal models according to a shorter holding period

scaled up to 10 days by the square root of time (see para. 3.2.8 below for the treatment of option positions).

3.2.4 The historical observation period for calculating VaR should not be less than one year (i.e. 250 trading days). If an AI applies a weighting scheme to the historical observations for the calculation of VaR, a higher weighting should be assigned to recent observations such that the effective observation period would be at least one year (i.e. the weighted average time lag of the individual historical observations cannot be less than six months).

3.2.5 An AI should be able to use a shorter historical observation period for the calculation of VaR if the MA requests the AI to do so on the ground that, in the opinion of the MA, this is justified due to a significant increase in volatility in the price of the AI's portfolio of exposures (e.g. collapse in stock market).

3.2.6 An AI should update the data used at least once every three months and reassess them whenever market prices are subject to material changes.

3.2.7 An AI's internal models should only recognise empirical correlations of factors affecting market risk within and across its risk categories, provided that the AI's system for identifying and measuring correlations is effective and implemented in a prudent manner.

3.2.8 An AI's internal models should accurately capture the unique risks associated with option positions within each of the risk categories and, in particular -

- the AI's internal models should be able to capture the non-linear price characteristics of the option positions (e.g. gamma risk);
- the AI is expected to apply a full 10-day movement in price to its option positions or positions that display option-like characteristics. However, if the AI is unable to do so, it should be able to use other methods (e.g. periodic simulation or stress-testing) to adjust its market risk capital charge for such positions;
- the AI's internal models should have a set of risk factors that capture the volatilities of the rates and

prices of the AI's option positions, i.e. vega risk; and

- if an AI's portfolio of options is relatively large or complex, the AI should have detailed specifications of the relevant volatilities. This means that the AI should measure the volatilities of its option positions at different maturities.

3.3 Daily market risk capital charge

3.3.1 Pursuant to §317(2) of the Rules, an AI's internal models should enable the AI to calculate, on a daily basis, its market risk capital charge expressed as:

- the higher of -
  - the AI's VaR for the risk categories applicable to its internal models as at the last trading day; and
  - the average VaR for the last 60 trading days multiplied by a multiplication factor as determined by the MA under §319 of the Rules (see para. 3.4.1 below); and
- where applicable [3] (see section 4 below), an additional capital charge for default risk calculated in accordance with §318 of the Rules (see paras. 4.2.5 to 4.2.7 below).

3.4 Multiplication factor

3.4.1 The multiplication factor to be used by an AI is the sum of:

- the value of three;
- a plus factor, ranging from zero to one, assigned to the AI in accordance with the number of back-testing exceptions during the last 250 trading days as set out in the table under B3.2 of Annex B; and
- any additional plus factor which may be assigned to the AI on the basis of its compliance with Schedule 3 of the Rules. For example, the MA

[3] An AI may calculate its additional capital charge for default risk less frequently (e.g. monthly) if it is impractical for the AI to do so on a daily basis and there is no cause for the AI to believe that there will be a significant increase in such additional capital charge during the period concerned.

may assign such a factor if he is satisfied that the AI has ceased to comply fully with the qualitative criteria set out in section 2 above after being granted approval to use the IMM approach to calculate its market risk.

3.4.2 In other words, an AI may have a multiplication factor of three only if the AI complies fully with Schedule 3 of the Rules and its back-testing results are satisfactory (i.e. the number of back-testing exceptions during the last 250 trading days is fewer than five).

4. Specific risk

4.1 General

4.1.1 An AI using internal models may calculate its market risk capital charge for specific risk based on modelled estimates, provided that:

- the AI has a VaR measure that incorporates specific risk and meets all the qualitative and quantitative criteria set out in sections 2 and 3 above respectively; and
- the AI's internal models for specific risk meet the additional criteria set out in subsection 4.2 below.

4.1.2 Where an AI's internal models for specific risk are unable to meet the above-mentioned criteria, the AI should use the standardized (market risk) approach, which is set out in Divisions 2 to 10 of Part 8 of the Rules, to calculate its market risk capital charge for specific risk.

4.2 Minimum criteria

4.2.1 The criteria for the MA's recognition of an AI's modelling of specific risk require that the AI's internal models should capture all material components of market risk and be responsive to changes in market conditions and the composition of the AI's portfolios of exposures. In particular, the AI's internal models should:

- be capable of providing a justification for the historical price variation in the AI's portfolios[4];
- be sensitive to changes in portfolio construction and result in higher market risk capital charge for portfolios which have increased concentrations in particular issuers, entities or sectors of exposures;
- be able to signal rising market risk in an adverse environment[5];
- be sensitive to name-related basis risk, that is, the material idiosyncratic differences between similar but not identical positions (e.g. debt securities with different levels of subordination and maturity mismatches, and credit derivative contracts with different credit events);
- be able to capture event risk[6]; and
- be validated through back-testing aimed at assessing whether specific risk is being captured adequately (see subsection 4.3 below).

4.2.2 Where an AI is subject to event risk that is not reflected in the AI's VaR measures because it is outside the 10-day holding period used or assumed by the AI's internal models and the 99% confidence interval used in calculating VaR, the AI should ensure that the impact of event risk is factored into its internal capital adequacy assessment process through stress-testing as described in subsection 2.8 above.

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[4] The key ex-ante measures of model quality are "goodness-of-fit" measures which address the question of how much of the historical variation in price value is explained by the risk factors included within the AI's internal model. One measure of this type which can often be used is an R-squared measure from regression methodology. If this measure is to be used, the risk factors included in the AI's internal model would be expected to be able to explain a high percentage, such as 90%, of the historical price variation or the AI's internal model should explicitly include estimates of the residual variability not captured in the factors included in this regression. For some types of internal models, it may not be feasible for the AI to calculate a goodness-of-fit measure. In such cases, the AI is expected to work with the MA to define an acceptable alternative measure which would meet this regulatory objective.

[5] This could be achieved by incorporating in the historical estimation period of the AI's internal model at least one full credit cycle and ensuring that the AI's internal model would not have been inaccurate in the downward portion of the cycle. Another approach for demonstrating this is through simulation of historical or plausible worst-case environments.

[6] For debt securities, this should include migration risk. For equities, events that are reflected in large changes or jumps in prices should be captured, e.g. merger break-ups or takeovers. In particular, the AI should consider issues related to survivorship bias.

4.2.3 An AI's internal models should prudently assess the market risk arising from less liquid positions and positions with limited price transparency under realistic market scenarios. Proxies may be used only if:

- available data are insufficient or are not reflective of the true volatility of an exposure or a portfolio of exposures; and
- such proxies are prudent.

4.2.4 As modelling techniques and best practices evolve, an AI should avail itself of these advances.

4.2.5 An AI should have an approach for calculating the market risk capital charge for specific risk which captures separately the default risk of its trading book positions if it cannot capture, or adequately capture, such risk in its internal models. To avoid double counting, the AI may, when calculating the market risk capital charge for the default risk of its trading book positions, take into account the extent to which default risk has already been incorporated into its internal models, especially for positions that would be closed within 10 trading days in the event of adverse market conditions or other indications of deterioration in the credit environment.

4.2.6 No specific approach for capturing the default risk of an AI's trading book positions is prescribed; it may be embedded in the AI's internal models or take the form of an additional capital charge separately calculated by the AI. Where an AI captures its default risk through an additional capital charge, this capital charge will not be subject to a multiplication factor or regulatory back-testing but the AI should be able to demonstrate that the capital charge provides sufficient capital to cover the default risk in respect of its trading book positions.

4.2.7 Whichever approach is used, an AI should satisfy the minimum requirements[7] comparable to those for the use of the internal ratings-based approach ("IRB approach") for the calculation of credit risk (see Schedule 2 to the

[7] In particular, the AI is expected to use a one-tailed 99.9% confidence interval over a one-year time horizon, under the assumption of a constant level of risk, to calculate the default risk of its trading book positions. The assumption of a constant level of risk implies that the AI will rebalance its trading book positions over time to maintain the same level of target risk, such as VaR.

Rules), with any necessary adjustments to reflect the impact of liquidity[8], concentrations[9] and hedging[10] on, and the option characteristics[11] of, its market risk exposures.

4.3 Back-testing requirements

4.3.1 An AI which applies modelled estimates of specific risk is required to conduct back-testing aimed at assessing whether specific risk is being adequately captured.

4.3.2 The methodology an AI should use for validating its specific risk estimates is to perform separate back tests on sub-portfolios using daily data on sub-portfolios subject to specific risk. The key sub-portfolios for this purpose are generally trading book positions in debt securities and equities. If, however, the AI classifies its trading book positions into finer categories (e.g. emerging markets), it is appropriate for the AI to use such categorisation for sub-portfolio back-testing purposes. The AI should also maintain and use such sub-portfolio structure consistently unless it can demonstrate that there are valid grounds to change the structure.

4.3.3 An AI is required to have a process to analyse exceptions identified through the back-testing of specific risk. This process is intended to serve as the fundamental way in which the AI corrects its internal models of specific risk in the event they become inaccurate. There will be a presumption that the AI's internal models which incorporate specific risk are

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[8] One possible way to adjust for the impact of liquidity is to measure default risk on an appropriate liquidity horizon. The liquidity horizon of an exposure or a portfolio of exposures is the amount of time the AI will take to sell the exposure or the portfolio of exposures or hedge all of the material risks of the exposure or the portfolio of exposures. The AI should set the liquidity horizon in a prudent manner reflecting stressed market conditions.

[9] The AI should consider all types of concentrations, including name concentration and market concentration.

[10] The adjustment for hedging impact should reflect the offsetting of long and short positions in a single instrument, adjusted for basis risk and maturity gaps of such positions when these positions are expected to be maintained at least over the liquidity horizon.

[11] The AI may adjust for the impact of option characteristics of its market risk exposures by reflecting the non-linearity of option contracts or other non-linear positions if the impact has a material effect on default risk.

"unacceptable" if the results at the sub-portfolio level produce a number of exceptions commensurate with the "red zone" as defined in B3 of Annex B.

4.3.4 An AI with "unacceptable" specific risk models is expected to take prompt actions to fix the problem in the models and ensure that there is a sufficient capital buffer to absorb the risk that the AI's internal models could not adequately capture.

5. Model review

5.1 Acceptance criteria

5.1.1 In reviewing an AI's internal models, the MA will require assurance that:

- the internal validation (see subsection 2.7 above) and independent review or audit (see subsection 2.9 above) are conducted by the AI in a satisfactory manner;
- the formulae used in the AI's calculation process as well as for the pricing of the AI's option positions and other complex instruments are validated by qualified parties which are independent of the AI's trading functions (see para. 2.7.2 above);
- the complexity and structure of the AI's internal models are appropriate with regard to the AI's portfolio of exposures;
- the AI's internal models provide a reliable measure of potential losses over time by reviewing the results of the AI's back-testing, i.e. comparing the daily VaR measures with actual profits and losses of the AI's portfolio of exposures; and
- data flows and processes associated with the AI's internal models are transparent and accessible. In particular, it is essential that the MA should have easy access, whenever considered necessary, to the model's specifications and parameters.

5.2 Portfolio testing

5.2.1 From time to time, the MA may require an AI using internal models to participate in a portfolio testing exercise. The test portfolios are generally determined by the MA.

5.2.2 The portfolio testing exercise will serve as a peer group comparison among AIs using internal models and the results of such exercise will form part of the MA's continuing assessment of the accuracy and reliability of individual AIs' internal models.

5.3 Recognition of internal models

5.3.1 Where an AI makes an application under §18(1) of the Rules, the model review process conducted by the MA will entail at least one on-site visit before any internal model, which is the subject of the AI's application, is recognised by the MA for the purposes of calculating the AI's market risk capital charge.

5.3.2 Under §18(4) of the Rules, any significant change to an AI's internal model, which has been recognised by the MA and is the subject of his approval under §18(2)(a) of the Rules, requires the MA's prior consent.

5.3.3 An AI should regularly inform the MA of the results of its internal validation (e.g. back-testing results). The MA will base on such information to determine whether a higher multiplication factor should be assigned to the AI concerned or whether the AI's internal models remain acceptable to calculate market risk for capital adequacy purposes.

5.3.4 In the case of an application made by an AI which has already been using internal models to calculate its market risk for capital adequacy purposes prior to **1 January 2007** and seeks to continue using such models to calculate its market risk under the IMM approach, the MA may not carry out a full-scale model review.

5.3.5 The scope and extent of the MA's model review in such cases will vary depending on, but not limited to, the following factors:

- whether the AI's internal models are used to calculate general market risk, specific risk or both;
- when the AI's internal models were last validated by the MA;
- whether there have been any significant changes to the AI's internal models since the last validation;
- the number of back-testing exceptions arising from the AI's internal models during the last 250 trading days; and
- any major findings relating to the AI's market risk management system identified by the MA or by the AI's external or internal auditors.

Annex A: Specification of market risk factors

A1. General

A1.1 It is important for an AI's internal models to contain an appropriate set of market risk factors, i.e. the market rates and prices that affect the value of the AI's market risk exposures, which are sufficient to capture the risks inherent in these market risk exposures. Although the AI may have some discretion in specifying the risk factors for its internal models, the guidelines set out in this Annex should be observed.

A2. For interest rates

A2.1 An AI's internal models should incorporate risk factors corresponding to interest rates in each currency in which the AI holds significant trading book positions[12] which are interest rate sensitive.

A2.2 An AI's internal models should model a yield curve using one of the generally accepted approaches, e.g. by estimating the forward rates of zero coupon yields. The yield curve should be divided into various maturity segments in order to capture variations in the volatility of interest rates along the yield curve. There will typically be one risk factor corresponding to each maturity segment (e.g. one month, three months, six months and one year).

A2.3 For material exposures to interest rate movements in the major currencies and markets, an AI should model the yield curve using a minimum of six risk factors. The number of risk factors used, however, should ultimately be driven by the nature of the AI's trading strategies. For instance, if an AI engages in complex arbitrage strategies or if an AI's portfolio of exposures comprises various types of securities across many points of the yield curve, the AI's internal models should have a greater number of risk factors in order to capture its interest rate risk more accurately.

[12] The AI should have a set of risk factors for each currency accounting for 5% or more of its trading book positions.

A2.4 An AI's internal models should incorporate separate risk factors to capture spread risk (e.g. between bonds and swaps). A variety of approaches may be used to capture the spread risk arising from less than perfectly correlated movements between the interest rates of sovereigns and other fixed-income instruments, such as specifying a completely separate yield curve for non-sovereign fixed-income instruments (e.g. swaps or municipal securities) or estimating the spread over sovereign interest rates at various points along the yield curve.

A3. For equity prices

A3.1 An AI's internal models should incorporate risk factors corresponding to each of the equity markets in which the AI holds significant positions.

A3.2 At a minimum, there should be a risk factor that is designed to capture market-wide movements in equity prices (e.g. a market index). Positions in individual equities or in sector indices can be expressed in "beta equivalents"[13] relative to this market-wide index.

A3.3 A more detailed approach is to have risk factors corresponding to various sectors of the overall equity market (e.g. industry sectors or cyclical and non-cyclical sectors). As mentioned above, positions in individual equities within each sector can be expressed in beta equivalents relative to the sector index.

A3.4 The most extensive approach is to have risk factors corresponding to the volatility of individual equities.

A3.5 The sophistication and nature of the modelling technique for a given equity market should correspond to the AI's overall exposures to the market as well as its concentration on individual equities in that market.

A4. For exchange rates (including gold)

A4.1 An AI's internal models should incorporate risk factors corresponding to individual foreign currencies in which the AI's positions are denominated. Since the VaR measures generated by the AI's internal models are

[13] A "beta equivalent" position can be calculated from a market model of equity price returns (such as the CAPM model) by regressing the return on the individual equity or sector index on the risk-free rate of return and the return on the market index.

expressed in the AI's domestic currency, any net position denominated in a foreign currency will give rise to foreign exchange risk. Thus, the AI's internal models should incorporate risk factors corresponding to the exchange rate between the AI's domestic currency and each foreign currency in which the AI has a significant position.

A5. For commodity prices

A5.1 An AI's internal models should incorporate risk factors corresponding to each of the commodities in which the AI holds significant positions.

A5.2 It is acceptable for AIs with relatively limited positions in commodities to have a straightforward specification of risk factors. Such a specification would likely entail one risk factor for each commodity price to which the AI is exposed. In cases where the AI's aggregate positions are small, it may be acceptable for the AI to use a single risk factor for a relatively broad sub-category of commodities (e.g. a single risk factor for all types of oil).

A5.3 The internal models of an AI with more active trading in commodities should encompass:

- directional risk to capture the exposure from changes in spot prices arising from net open positions;
- forward gap and interest rate risk to capture the exposure to changes in forward prices arising from maturity mismatches; and
- basis risk to capture the exposure to changes in the price relationships between two similar but not identical commodities.

In addition, the models should take account of variation in the "convenience yield"[14] between derivative positions (such as forward contracts and swaps) and cash positions in the commodity.

[14] The convenience yield reflects the benefits from direct ownership of the physical commodity (e.g. the ability to profit from temporary market shortages) and is affected both by market conditions and by factors such as physical storage costs.

Annex B: Use and interpretation of back-testing results

B1. General

B1.1 This Annex describes the framework for incorporating back-testing into the IMM approach to the calculation of an AI's market risk and elaborates the supervisory approach to interpreting the AI's back-testing results.

B1.2 The process whereby an AI routinely compares its daily profits and losses with model-generated risk measures to gauge the accuracy and reliability of its internal models is known as back-testing.

B1.3 The essence of back-testing, as set out in this Annex, is the daily comparison of an AI's actual trading results with the VaR measures generated by the AI's internal models. If this comparison reveals limited differences, the back-testing raises no concern regarding the quality of the internal models. In some cases, however, the comparison may uncover significant differences, indicating likely problems with the internal models or the assumptions of the back tests. In between these two situations is a grey area where the back-testing results are, on their own, inconclusive.

B1.4 In considering how to incorporate the back-testing results more realistically into the IMM approach, the MA acknowledges that AIs may perform different types of back-testing comparisons and use different standards to interpret the comparison results and the concerns over the imperfect nature of the signals generated by back-testing.

B2. Description of back-testing framework

B2.1 Back-testing programmes comprise a periodic comparison of an AI's daily VaR measures with the subsequent daily profits or losses ("trading outcomes"). The VaR measures are intended to be larger than all but a certain fraction of the trading outcomes, where that fraction is determined by the confidence interval of the VaR measures. Comparing the VaR measures with the trading outcomes means that the AI counts the number of times the VaR measures were larger than the trading outcomes. The fraction covered can then be compared

with the intended level of coverage to gauge the performance of the AI's internal models.

B2.2 The back tests applied by an AI compare whether the observed percentage of trading outcomes covered by the VaR measures is consistent with the assumption of a 99% confidence interval. That is, these tests attempt to determine if the AI's 99% VaR measures truly cover 99% of its trading outcomes.

B2.3 The regulatory back-testing framework adopted by the MA requires the comparison of an AI's daily trading outcomes with its VaR measures calibrated on a one-day holding period. This one-day requirement differs from the quantitative criterion stated in para. 3.2.3 above (i.e. a 10-day holding period). This is aimed at reducing any possible contamination arising from changes in an AI's portfolio composition during the holding period which will be reflected in its actual trading outcomes but not in its VaR measures which assume a static portfolio.

B2.4 The concern about contamination of the trading outcomes is relevant, however, even for one-day trading outcomes[15]. A more sophisticated approach to deal with this may involve a detailed attribution of trading outcomes by source, including fees, spreads, market movements and intra-day trading results. In such a case the VaR measures can then be compared with the outcomes arising from market movements alone.

B2.5 To the extent that the back-testing programme is viewed purely as a statistical test of the integrity of the calculation of VaR measures, it is essential to employ a definition of daily trading outcome that allows for an uncontaminated test. To achieve this, an AI should develop the capability to perform back tests based on the hypothetical changes in portfolio value that would occur were end-of-day positions to remain unchanged during the holding period (say one day).

B2.6 Back-testing using actual daily trading outcomes is also a useful exercise because it can uncover cases where

[15] There is a concern that the overall one-day trading outcome is not a suitable point of comparison because it includes the effects of intra-day trading, possibly including fee income. In addition, intra-day trading will tend to increase the volatility of trading outcomes and may result in cases where the overall trading outcome exceeds the VaR measures.

the VaR measures do not accurately capture trading volatility in spite of such measures being calculated with integrity.

B2.7 For these reasons, the MA encourages every AI to develop the capability to perform back tests using both hypothetical (i.e. using changes in portfolio value that would occur were end-of-day positions to remain unchanged) and actual trading (i.e. excluding fees, commissions and net interest income) outcomes. Each approach has its own value. In combination, the two approaches are likely to provide a strong understanding of the relation between VaR measures and trading outcomes.

B2.8 The regulatory back-testing framework entails formal testing and counting the number of exceptions (i.e. the instances in which daily trading losses in a portfolio of exposures are above the daily VaR measures generated by an internal model) on a quarterly basis using the most recent 12 months of data. For example, over 200 trading days, a 99% daily VaR measure should cover, on average, 198 of the 200 trading outcomes, leaving two exceptions.

B2.9 Using the most recent 12 months of data yields approximately 250 daily observations for back-testing purposes. The MA will use the number of exceptions (i.e. out of 250) identified by an AI's internal model as the basis for a supervisory response which, in serious cases, means that the MA may require the AI to hold additional capital by means of the supervisory review process (see CA-G-5 "Supervisory Review Process") or disallow the AI from continuing using the IMM approach to calculate its market risk for capital adequacy purposes.

B2.10 The formal implementation of an AI's back-testing programme should begin on the date that the AI's internal model for calculating its market risk capital charge became effective. This implies that the first formal counting of exceptions under the AI's back-testing programme will occur 12 months later. This, however, does not preclude the MA from requesting the AI to provide its back-testing results prior to that date and using such results as part of the MA's initial assessment.

B2.11 Once an AI's internal model is recognised by the MA for the purposes of the IMM approach, the MA will monitor the AI's back-testing results on a quarterly basis through data collected in Part IV of the "Return of Capital Adequacy Ratio of an Authorized Institution Incorporated in Hong Kong - MA(BS)3(IV)".

B3. Three zone approach

B3.1 With the statistical limitations of back-testing in mind, the MA has established a framework for the interpretation of back-testing results that encompasses a range of possible supervisory responses, depending on the strength of the signal generated from the back tests. These responses are classified into three zones:

- the green zone corresponds to the back-testing results that do not suggest a problem with the quality of an AI's internal model;
- the yellow zone encompasses results that raise questions on the quality of an AI's internal model but where such a conclusion is not definitive; and
- the red zone indicates a back-testing result that almost certainly indicates a problem with an AI's internal model.

B3.2 The table below sets out the boundaries of these three zones and the presumptive supervisory response for each back-testing outcome, based on a sample of 250 observations. Where the back-testing results indicate weaknesses in an AI's internal model, the minimum multiplication factor of three will be increased by adding a plus factor (see subsection 3.4 above) as shown below.

Zone	Number of exceptions out of 250 observations	Plus factor
Green zone	Less than 5	0.00
Yellow zone	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red zone	10 or more	1.00

Green zone

B3.3 The green zone comprises the range of zero to four exceptions.

B3.4 Since an AI's internal model that truly provides 99% coverage is quite likely to produce as many as four exceptions in a sample of 250 observations, there is little reason for concern raised by a back-testing result that falls within this range. In such a case, the minimum multiplication factor of three will be applied to the VaR measures generated by the AI's internal model, provided that the AI complies fully with all the qualitative criteria set out in section 2 above.

Yellow zone

B3.5 The yellow zone comprises the range of five to nine exceptions.

B3.6 Outcomes in this range are plausible for both accurate and inaccurate models, although they are generally more likely for inaccurate models than for accurate models. Moreover, the presumption that an internal model is inaccurate should grow as the number of exceptions increases in the range from five to nine. As such, it is justifiable for the MA to apply a higher plus factor to an AI in accordance with the table in B3.2 above if the AI's back-testing results have a higher number of exceptions in the yellow zone.

B3.7 It should be stressed, however, that such increases in the plus factor are not meant to be purely automatic. The results in the yellow zone do not always imply an inaccurate model and it is not the MA's intent to penalise any AI solely for bad luck. Nevertheless, back-testing results falling within the yellow zone will generally cause an AI attracting a higher plus factor unless the AI can prove to the satisfaction of the MA that the model in use is fundamentally sound and the exceptions are temporary.

B3.8 There are many different types of information an AI may provide to the MA to prove that a higher multiplication factor may not be warranted. For example, an AI engaging in regular back-testing programmes may disaggregate its back-testing results by breaking up its overall trading portfolio into trading units organised by risk factors or product categories. Disaggregating in this fashion could allow the tracking of a problem that surfaced at the aggregate level back to its source at the level of a specific trading unit or model. The AI may also implement back-testing for confidence intervals other than 99% or perform other statistical tests as mentioned in para. 2.7.6 above to prove the accuracy and reliability of its internal models.

B3.9 Further, an AI should document all of the exceptions generated from its ongoing back-testing programme (including explanation for the exceptions) and categorise them according to the types of explanation (see B4 below). This process is useful for the MA to determine an appropriate supervisory response (see B5 below).

Red zone

B3.10 The red zone comprises ten or more exceptions.

B3.11 In contrast to the yellow zone, where the MA may exercise judgement in interpreting the back-testing results, outcomes in the red zone should automatically lead to a presumption that a problem exists with an AI's internal model. It is extremely unlikely that an accurate model would independently generate ten or more exceptions from a sample of 250 observations. In general, therefore, if the AI's internal model falls within the red zone, the MA will generally increase the

multiplication factor by adding a plus factor of one (i.e. increasing the multiplication factor from three to four).

B3.12 The MA will also perform on-site examinations to investigate the reasons why the AI's internal model produced such a large number of exceptions and require the AI to take immediate actions to fix the modelling problems. In the case of a severe problem with the basic integrity of an AI's internal model, the MA may disallow the AI to continue using the IMM approach to calculate its market risk for capital adequacy purposes.

B3.13 Although ten exceptions are a very high number for a sample of 250 observations, there will on very rare occasions be a valid reason for an accurate model to produce so many exceptions (see B4.4 below). In particular, when financial markets are subject to a major regime shift, many volatilities and correlations are expected to shift substantially as well. Any AI using an internal model is expected to update the volatility and correlation estimates underlying the model very promptly in this situation; otherwise such a regime shift could generate a number of exceptions in a short period of time. In essence, however, these exceptions would all be occurring for the same reason and therefore the appropriate supervisory response might not be the same as when there were ten exceptions but each from a separate incident. One possible supervisory response in this instance is simply to require the AI to take account of the regime shift in its internal model as quickly as it can while maintaining the integrity of its procedures for updating the model.

B3.14 It should be stressed, however, that this supervisory response will only be given under extraordinary circumstances. In most cases, the MA will automatically increase an AI's multiplication factor to the value of four.

B4. Reasons for exceptions

B4.1 Exceptions will generally fall into the following four categories:

- the flaws in the basic integrity of a model (see B4.2 below);
- the model's accuracy requiring improvements (see B4.3 below);

- markets moved in a fashion unanticipated by the model (see B4.4 below); and
- intra-day trading (see B4.5 below).

B4.2 Samples of exceptions arising from flaws in the basic integrity of a model include:

- the AI's market risk management system is not able to capture the risk of the positions, e.g. the positions are being reported incorrectly; or
- model volatilities or correlations are calculated incorrectly, e.g. the computer erroneously calculates daily model volatilities on a 280-day basis when it should be on a 250-day basis.

B4.3 An example of an inaccuracy in a model that may cause exceptions is that the model is not able to assess the risk of some instruments with sufficient precision, e.g. too few maturity buckets or a spread omitted.

B4.4 Reasons for exceptions resulting from unanticipated market movements include:

- random chance (i.e. a very low probability event);
- markets moved by more than the model predicted was likely, i.e. volatility was significantly higher than expected; or
- markets did not move together as expected, i.e. correlations were significantly different than what was assumed by the model.

B4.5 Intra-day trading can cause exceptions, e.g. there was a large change in an AI's positions causing losses or income-earning events between the end of the first day (when the risk estimate was calculated) and the end of the second day (when trading results were tabulated).

B5. Consideration of explanations and factors by the MA

B5.1 In general, problems relating to the basic integrity of an AI's internal model are potentially the most serious. If exceptions are attributable to this category for a particular trading unit in the AI, the plus factor should apply. In addition, the AI's internal model may be in need of substantial review or adjustment. For serious cases, the MA may disallow the AI to continue using the IMM approach to calculate its market risk for capital

adequacy purposes until appropriate corrections are undertaken by the AI.

B5.2 The second category of problem, i.e. the model's accuracy requiring improvements, is one that can be expected to occur at least part of the time with most risk measurement models. No model can hope to achieve infinite precision as all models involve a certain degree of approximation. If, however, a particular model used by an AI appears more prone to this type of problem than others, the MA will impose a plus factor or take other appropriate supervisory responses to encourage the AI to improve its model's accuracy.

B5.3 The third category of problem, i.e. unanticipated market movements, is also expected to occur at least some of the time with an AI's internal model. Even an accurate model cannot be expected to cover 100% of trading outcomes. Some exceptions will be the random of 1% that the model can be expected not to cover. In other cases, the behaviour of the markets may shift so that previous estimates of volatility and correlation are no longer appropriate. No VaR model will be immune from this type of problem; it is inherent in the reliance on past market behaviour as a means of gauging the risk of future market movements. Exceptions due to such reasons do not suggest a problem. If, however, the shifts in volatilities and correlations are considered to be permanent, the MA may require the AI to re-calculate its VaR measures using volatilities and correlations based on a shorter observation period.

B5.4 Depending on the definition of trading outcomes employed for back-testing purposes, exceptions could also be generated by intra-day trading results or an unusual event in trading income other than from the trading outcomes arising from an AI's portfolio. Although exceptions arising from these reasons may not necessarily suggest a problem with the AI's internal model, they could still be causes for concern. The imposition of the plus factor will be considered by the MA.

B5.5 Another consideration is the extent to which a trading outcome exceeds the VaR measure. With all other things being equal, exceptions generated by trading outcomes far in excess of the VaR measures are of

greater concern than those outcomes which are only slightly larger than the VaR measures.

B5.6 In deciding an appropriate supervisory response to an AI, the MA will weigh the above factors, together with the assessment of the AI's extent of compliance with the qualitative criteria set out in section 2 above and any additional information provided by the AI in respect of the quality of its internal model. In general, the imposition of a plus factor on an AI for outcomes in the yellow zone is an appropriate supervisory response if the MA believes the reason for being in the yellow zone is a problem in the AI's internal model that can be corrected. This is contrasted with the case of an unexpected bout of high market volatility (i.e. temporary), which nearly all models may fail to predict.

Annex C: Stress-testing

C1. General

C1.1 An AI which uses the IMM approach for calculating its market risk capital charge should have a rigorous and comprehensive stress-testing programme. Stress-testing is to identify events or influences that could greatly impact the AI's financial soundness and forms a key component of the AI's internal assessment of capital adequacy. This Annex should be read in conjunction with IC-5 "Stress-testing" that provides general guidance on the use of stress tests for risk management purposes.

C1.2 An AI's stress scenarios need to cover a range of factors that can create extraordinary losses or gains in its trading portfolios or make the control of risk in those portfolios very difficult. These factors include low probability events in all major types of risk, including the various components of market, credit and operational risks. Stress scenarios need to shed light on the impact of such events on positions that display both linear and non-linear price characteristics (i.e. option positions and any other positions that have option-like characteristics).

C1.3 An AI's stress tests should be of a quantitative and qualitative nature. Quantitative criteria should identify plausible stress scenarios to which the AI could be exposed. Qualitative criteria should emphasise that two major goals of stress-testing are to evaluate the capacity of the AI's capital to absorb potential large losses and to identify steps the AI can take to reduce its risk and conserve capital.

C1.4 An AI's stress tests should also incorporate both market risk and liquidity aspects of market disturbances. For example, an AI may not be able to unwind some trading positions quickly during a crisis situation and the values of these positions may be very volatile. Such considerations are particularly important for positions in emerging markets.

C1.5 An AI should combine the use of supervisory stress scenarios with its own stress tests to reflect its specific risk characteristics. In particular, the MA may require the AI to provide information relating to its stress-testing

results in three broad areas as discussed in C2 to C4 below.

C2. Supervisory scenarios requiring no simulation by the AI

C2.1 An AI should provide the MA with information on its five largest daily losses experienced during each calendar quarter. Such losses should be reported in Part IV of the "Return of Capital Adequacy Ratio of an Authorized Institution Incorporated In Hong Kong - MA(BS)3(IV)".

C2.2 This loss information can be compared to the level of an AI's capital and the corresponding VaR measures that are generated from the AI's internal models. This comparison will help provide the MA with a picture of how many days of peak daily losses incurred by the AI would have been covered by its corresponding VaR measures.

C3. Supervisory scenarios requiring simulation by the AI

C3.1 An AI should subject its portfolios to a series of simulated stress scenarios and provide the MA with the results quarterly. These scenarios may include testing the AI's current portfolio against past periods of significant disturbance, for example, the 1987 equity crash, the ERM crises of 1992 and 1993, the fall in bond markets in the first quarter of 1994, the Mexican crisis at the end of 1994, or the Asian crisis of 1997 and 1998, incorporating both the large price movements and the sharp reduction in liquidity associated with these events.

C3.2 A second type of scenario is to evaluate the sensitivity of an AI's market risk exposures to changes in the assumptions about volatilities and correlations. Applying this test requires an evaluation of the historical range of variation for volatilities and correlations and evaluation of the AI's current positions against the extreme values of the historical range. Due consideration should be given to the sharp variation that at times has occurred in a matter of days in periods of significant market disturbance. The 1987 equity crash, the suspension of the ERM or the fall in bond markets in the first quarter of 1994, for example, all involved correlations within risk factors approaching the extreme values of 1 or -1 for several days at the height of the disturbance.

C4. Scenarios developed by the AI

C4.1 An AI should also develop its own stress tests which it identifies as severe but plausible events based on the characteristics of its portfolio (e.g. problems in a key region of the world combined with a sharp move in oil prices). The AI should provide the MA with a description of the methodology used to determine the scenarios as well as a summary of the results derived from these scenarios.

C5. AI's internal capital adequacy assessment

C5.1 An AI's assessment of the adequacy of internal capital for market risk, at a minimum, should be based on both VaR modelling and stress-testing appropriate to its trading activity, including an assessment of concentration risk and of illiquidity under stressed market conditions.

C5.2 An AI should supplement its VaR models with stress tests (i.e. factor shocks or integrated scenarios whether historical or hypothetical) and other appropriate risk management techniques. In the AI's internal capital adequacy assessment, the AI should demonstrate that it has enough capital to not only meet the minimum regulatory capital requirements but also to withstand a range of severe but plausible market shocks. In particular, it should factor in, where appropriate -

- illiquidity / gapping of prices;
- concentrated positions (in relation to market turnover);
- one-way markets[16];
- non-linear products / deep out-of-the-money positions;
- event risk and jump-to-default risk;
- significant shifts in correlations; and
- other risks that may not be captured appropriately in VaR (e.g. recovery rate uncertainty, implied correlations or skew risk).

[16] "One-way market" refers to a market in which only the offer or bid price of an instrument exists (i.e. an illiquid market).

C5.3 The stress tests applied by an AI and, in particular, the calibration of those tests (e.g. the parameters of the shocks or types of events considered) should be reconciled back to a clear statement setting out the premise upon which the AI's internal capital adequacy assessment is based (e.g. ensuring there is adequate capital to manage the trading book portfolios within stated limits through what may be a prolonged period of market stress and illiquidity, or that there is adequate capital to ensure that, over a given time horizon to a specified confidence interval, all positions can be liquidated or the risk hedged in an orderly fashion). The market shocks applied in the tests should reflect the nature of the AI's portfolios and the time the AI could take to hedge out or manage risks under severe market conditions.

C5.4 An AI should demonstrate how it combines the VaR measures generated from its internal models and the results of its stress tests to arrive at the overall internal capital for market risk.

C5.5 If the MA considers that an AI does not have sufficient internal capital to cover the results of the AI's stress tests, the MA may require the AI to reduce its market risk exposures or hold additional capital through the supervisory review process (see CA-G-5 "Supervisory Review Process").