Bank i Kredyt 49(6), 2018, 639-670

BANK I KREDYT
BANK & CREDIT

IFRS 9 in credit risk modelling

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Submitted: 1 August 2017. Accepted: 12 July 2018.

Abstract

Analysing model documentation for 17 AIRB and FIRB credit risk models, this paper delivers IFRS 9 gap analysis of the existing models used for capital adequacy requirements. Based on the review of the IFRS 9 regulatory framework, the paper assumes that the use of the existing models may cause IFRS 9-related compliance gaps that render the existing models inadequate for the provisioning of expected losses. Recognising the potential IFRS 9 gaps, the paper addresses the question whether there is synergy between the AIRB and FIRB modelling approaches and the IFRS 9 rules. To this end, the paper confirms that the existing credit risk models cannot be re-used for IFRS 9 in their current forms.

Keywords: IFRS 9, credit risk, modelling, validation, compliance

JEL: C18, C51, C52, G21, M49

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1 Introduction

The International Financial Reporting Standards (IFRS 9) are created to replace the International Accounting Standards (IAS 39) in 2018. Under IAS 39, a bank could add the credit loss to its financial assets based on the evidence that the impartment took place (Borio 2001). According to Bellotti and Crook (2012), this method of calculating incurred credit losses underestimated the build-up of credit risk. Furthermore, Barth and Landsman (2010) argued that IAS 39 was one of the factors contributing to the global financial crisis of 2007–2010 (the credit crunch). Therefore, the new provisioning rules for credit losses were laid out in IFRS 9 in order to facilitate a forward--looking credit loss recognition.

Given the fact that IFRS 9 changes the way the credit provisioning is calculated, the new accounting standards are believed by the banking practitioners to have a significant impact on the credit risk modelling and analytics (Onali, Ginesti 2014; Chawla, Forest, Aguais 2016). Currently, both the practitioners and academics are debating the credit risk modelling changes caused by the IFRS 9 rules. With the new provisioning rules, banks are required to develop expected loss models or redevelop the existing credit risk models in order to estimate the expected credit loss (ECL). As noted by Beatty and Liao (2011), under the IFRS 9 framework, the expected credit loss is taken as a value of all losses that result from a default of an obligor at any time during the exposure.

According to Bushman and Williams (2015), the new accounting rules significantly impact the measurement and recognition of a credit loss. In contrast to the existing rules under the IAS 39, the IFRS 9 framework introduces a single logical model for the classification and measurement of the financial assets and liabilities (Chawla, Forest, Aguais 2016). This is causing an overlap with the probability of default (PD) and the loss given default (LGD), as well as the exposure at default (EAD) models. There are also differences in the concepts of the PD and LGD models under IFRS 9, as highlighted by Novotny-Farkas (2016).

Recognising the aforementioned overlap with the PD and LGD models, the purpose of this paper is to discuss potential IFRS 9 gaps that are present in the existing credit risk models for regulatory capital. These gaps emerge as the currently used credit risk models stay in contrast with the IFRS 9 rules and require connecting model inputs to macroeconomic forecasts, as well as developing more sophisticated model concepts (Yang 2017). For example, as noted by Miu and Ozdemir (2016), calculating the downturn LGD or applying any regulatory floor results in biased LGD estimates that cannot be used for IFRS 9 purposes.

As noted by Reitgruber (2015), applying the same models for the calculation of regulatory capital and the estimation of accounting provisions results in the benefit of retaining the consistency of the models used throughout a bank. Moreover, having one model that addresses both the IFRS 9 and capital adequacy requirements minimises operational costs and complexity (Prorokowski 2016a). However, given the specific requirements under IFRS 9, the use of the existing models may cause IFRS 9-related compliance gaps that render the existing models inadequate for the provisioning of expected losses.

This paper investigates a possible chance of synergy in using the same credit risk models for the regulatory capital and the IFRS 9 provisions. In doing so, the paper analyses the existing credit risk models utilised by selected European banks for the IFRS 9 gaps. A wide range of different models was encompassed by the study in order to deliver an objective picture.

The paper looks into the advanced internal ratings-based (AIRB) and the foundation internal ratings-based (FIRB) banks only. Compared to the banks using the standardised approach in credit risk, the AIRB and FIRB banks have already developed sophisticated, validated, documented and regulatory-approved models for the calculation of the PD, LGD and EAD estimates. In theory, these models can be also used for the IFRS 9 purposes. Thus, the paper attempts to address the question whether the synergy between the AIRB/FIRB modelling approaches and the IFRS 9 rules exists. Investigating a broad range of credit risk models from different European banks and analysing the regulatory frameworks, this paper checks if the current models can be re-used for IFRS 9 purposes.

In total, 17 models from five European banks were identified for the IFRS 9 gap analysis. The paper summarises the results of the IFRS 9 gap analysis of the selected models in Section 5. Based on the findings reported in Section 5, the paper attempts to provide practical implications for banks and regulators with respect to the capability of ensuring compliance synergy between the AIRB/FIRB credit risk models (Basel models) and the IFRS 9 provisions.

2 Regulatory background

This section discusses the key characteristics of the International Financial Reporting Standards (IFRS 9) that impact the use of the current credit risk models. The IFRS 9 provisions are set against the Basel Committee for Banking Supervision's (BCBS) guidelines for the accounting for the expected credit loss (ECL). In doing so, this section provides a study background for the analysis of the IFRS 9 gaps in the existing credit risk models.

Published in July 2014, the IFRS 9 framework introduces important changes to accounting and modelling. Firstly, IFRS 9 proposes a new model for classification and measurement of financial assets and liabilities (Bischof, Daske 2016). Secondly, IFRS 9 highlights the need for a forward-looking expected loss impairment model (Edwards 2014; Pool, De Haan, Jacobs 2015). Finally, IFRS 9 changes the ways of conducting hedge accounting – Ramirez (2015). These changes, being enforced from January 2018, impact on credit risk models that will serve to calculate the ECL. Table 1 presents the IFRS 9 articles that particularly affect credit risk modelling.

Analysing Table 1, one can see that IFRS 9 is based on principles. This is regarded by Ball (2006) as an important step towards simplifying the complex rules of IAS 39. Furthermore, classifying expected losses on the basis of business models allows for a better alignment to the banks' business profiles. As far as the ECL measurement is concerned, all financial assets and liabilities should be measured on either the amortised cost or fair value basis.

Calculating credit losses under the IAS 39 framework entails the use of an incurred loss model, where a credit loss is recognised after the 90-days overdue period. According to Camfferman (2015), the non-timely recognition of a credit loss under IAS 39 results in the under-/overestimation of financial assets. Additionally, Barth and Landsman (2010) argues that this delayed process provides incentives to postpone loss recognition. IFRS 9 addresses this modelling flaw by eliminating the 90-day overdue trigger event. Under the IFRS 9 framework, the ECL is calculated at the origination of the financial instrument and later intervals using forward-looking information.

As indicated in Table 1, the ECL estimation considers the following aspects:

– probability weighted amount – the ECL cannot be based on either the worst or best case scenarios, but should reflect the probability of a loss occurring during the lifetime of the financial instruments;

– time value of money – the ECL should be discounted to the reporting date;

– required forward-looking information – the ECL should use reasonable and supportable information that is accessible without undue cost.

In addition to this, it should be noted that IFRS 9 does not define the significant increase in credit risk, but provides some guidance in this respect by referring to the 30-days past due rebuttable presumption. Therefore, the present paper argues that banks should consult the BCBS guidance on the implementation of IFRS 9 in the context of the principles for sound credit risk practices (BCBS 2015). The BCBS guidance ensures that the internal risk infrastructure provides the essential basis for a high-quality and consistent implementation of the ECL that satisfies both the accounting and capital adequacy requirements. At this point, the current paper expects that the existing credit risk models will require amendments due to the differences between the objectives of the regulatory capital models (Basel models) and IFRS 9. The regulatory capital models are defined by Stolz and Wedow (2011) as tools that use own estimated risk parameters for the purpose of calculating regulatory capital.

The analysis of the regulatory background reveals that the major differences between the Basel models and the IFRS 9 concept relate to the PD/LGD framework. The Basel models are measured on the through-the-cycle (TTC) basis that reflects the cyclical nature of economic conditions. The IFRS 9 models should be point-in-time (PIT). Nonetheless, as highlighted by Carlehed and Petrov (2012), many models developed by European banks already calculate both the TTC and PIT estimates.

The BCBS guidance on the implementation of IFRS 9 stipulates that credit risk models, policy frameworks, procedures and methodologies should incorporate the ECL features, namely, the maximum contractual period, the reflection of the unbiased and probability-weighted amount of credit loss, and the time-value of money (Mukherjee, Maji 2017). With this in mind, this paper points to the need for considering forward-looking information and macroeconomic factors as key specifics of the ECL. Under the IFRS 9 framework, banks are required to demonstrate the understanding of how the ECL estimates fluctuate under different macroeconomic conditions. This process involves the input from a broad range of subject matter experts (e.g. risk managers, economists, business analysts and senior managers). According to Gebhardt and Novotny-Farkas (2011), incorporating forward-looking information poses challenges to banks with the macroeconomic scenarios being subject to a large degree of subjectivity. In addition to this, the BCBS guidance provides recommendations for the use of the forward-looking information that remains in contrast with IFRS 9:

– IFRS 9: the forward-looking information can be used if it is available without undue cost or effort;

– BCBS: banks should not avoid costs associated with obtaining the forward-looking information under any circumstances.

The BCBS guidance addresses the absence of the default definition in IFRS 9. Thus, the default definition adopted by banks falling under IFRS 9 should consider a qualitative criterion to identify credit deterioration before the exposure becomes delinquent and an objective indicator based on material delinquency status. Furthermore, as indicated in Table 1 and already mentioned in the paper, IFRS 9 does not define the significant increase in credit risk. At this point, the BCBS guidance suggests that the measurement of the ‘significance’ should extend beyond the quantitative analysis to include expert judgement. However, the presence of the judgmental analysis in the ECL may result in a bias preventing compliance with IFRS 9 (Reitgruber 2016).

3 Academic background

Academic studies discussing issues centred on IFRS 9 in credit risk are scarce. The first string of studies focused on potential problems associated with classifying financial instruments under IFRS 9 (Nobes 2013). At this point, IFRS 9 divides financial instruments into three groups based on the expected credit loss:

– performing assets – with the 12-month ECL allowance set aside for low credit risk;

– significantly deteriorated assets – with the lifetime ECL allowance set aside for significantly deteriorated credit quality;

– impaired.

The problems arising with the financial asset classification under IFRS 9 for credit risk modelling are related to the measurement of the significant deterioration of credit risk (Leventis, Dimitropoulos, Anandarajan 2011). This implies that credit risk professionals should reconsider the risk of default (measured by PD models). In doing so, banks are required to consider reasonable and supportable information, which, according to Beerbaum (2015), place the burden of reviewing a wide range of credit risk data on the modelling team of a bank.

Another strand of academic literature focused on transforming TTC PD models into the PIT PD models in order to deliver estimates that are compliant with the IFRS 9 standards. Within this strand of scholarly literature, the study of Allison (2010), Carlehed and Petrov (2012), as well as Forest, Chawla and Aguais (2013) focused on the methodologies and techniques of deriving PIT PD estimates for IFRS 9 purposes. For the conversion of the PD estimates into the PIT outputs, Chawla, Forest and Aguais (2016) recommend the use of industry or region credit cycle indicators with the argument that a broad macroeconomic indicator fails to differentiate between various industry sectors. The current paper extends the study of Chawla, Forest and Aguais (2016) by investigating how the analysed credit risk models operate within the PIT framework due to the use of the credit cycle indicators.

The third strand of the relevant academic literature deals with the issues revolving around modelling the PD term structure. As stated by Edwards (2016), the ECL components should reflect the term structure of the underlying instruments. Skoglund (2017) as well as McPhail and McPhail (2014) analyse several modelling approaches for the estimation of the term structure. The study of Wooldridge (2010) illustrates how to construct a model of a discrete-time term structure for the estimation of the lifetime ECL. The current paper departs from delivering methodological solutions for the term structure and focuses on investigating the progress made by the selected banks in estimating the term structure over a life of a specific transaction for the IFRS 9 purposes.

The academic discussion of similarities between the Basel credit risk models and the models utilised in IFRS 9 is limited to the studies indicating the conceptual differences between the current credit risk models and the IFRS 9 requirements. As noted by Novotny-Farkas (2016) and Miu and Ozdemir (2016), these differences relate to methodological assumptions that incorporate regulatory-prescribed floors and caps applied to the PD and LGD estimates. However, there are also studies that argue that the existing models can be re-used for the IFRS 9 purposes despite the compliance gaps. Reitgruber (2015) notes that having the same suit of models satisfying both the Basel and IFRS 9 requirements allows for the consistency in the use of risk models to be retained. At this point, Marlin (2017) observes that banks are continuously adapting their Basel models for the IFRS 9 standards. However, as highlighted by Temim (2016), this process remains challenging due to the need of making significant adjustment to the data underpinning the PD and LGD models. Gea-Carrasco (2015) argues that the adoption of the IFRS 9 rules offers opportunities and challenges for which banks need to be prepared. Therefore, the question whether a synergy exists between the existing credit risk models (under the AIRB/FIRB approach) and the IFRS 9 requirements remains open. The current paper attempts to address this question.

4 Methodology

4.1 Research methods

The main purpose of the current paper is to discuss potential IFRS 9 gaps that stem from the use of the existing AIRB/FIRB credit risk models. This paper formulates the following research question: Based on the identified IFRS 9 gaps, is there a synergy from using the Basel models for the IFRS 9 provisions?

Addressing the above research question, the study reviews bank documentation that contains information about the credit risk models used by the participating banks. The following documents were reviewed in order to find IFRS 9 gaps stemming from the modelling assumptions:

- Model development documentation – the documents containing information about the model history and governance, model scope of application, modelling approach, model estimation, model inputs and variables, model formulation, impact analysis, and sensitivity analysis.
- Model validation documentation – the documents containing information from the independent internal review of the models. For a specific mode, model validation documents analyse data quality standards, the data collection process, data collection criteria, methodological choices, model estimation and calibration, the model development process, model performance, model understanding, and the underlying model documentation.

The aforementioned documentation was reviewed for information about the potential IFRS 9 gaps that are described in the next sub-section. In particular, the documentation was analysed to obtain information regarding measurement standards (e.g. does the existing model's estimate reflect the life of the underlying financial instrument?), measurement framework (e.g. are the estimate based on the PIT framework?), variables and model inputs (e.g. does the model reflect the impact of macroeconomic scenarios?), model estimation (e.g. does the model include regulatory-prescribed floors, caps or add-ons?).

In an attempt to gain insights into the existing models and to identify potential IFRS 9 gaps, the documentation is analysed using the content analysis technique. According to Atteslander (2003), content analysis remains an optimal research tool for documentation review. Gibbs (2002) and Bryman (2004) argue that only content analysis makes it possible for valid inferences to be made from the analysed documentation. In order to retain the consistency of content analysis, the potential IFRS 9 are pre-identified in the next sub-section. As noted by Mayring (2000), the consistency of content analysis ensures the reliability of the findings and the validity of inferences from the analysed text.

The content analysis of the credit risk models documentation facilitates a seamless processing of a substantial amount of written material. Thus, as highlighted by Ritsert (1972), this research method makes it possible to deal with distinct models in a similar fashion. In addition to the established benefits of content analysis, the most recent studies of Neuendorf (2016) and Prorokowski (2016b) point to the fact that this research method enables the researcher to focus on processes, namely the ways the existing credit risk models are developed and applied.

4.2 Potential IFRS 9 gaps

This section presents potential IFRS 9 gaps that can be found in the existing credit risk models. The potential IFRS 9 gaps were identified based on the detailed review of the IFRS 9 requirements and the current regulatory framework for capital adequacy. The review of the IFRS 9 framework revealed four main requirements for the measurement of the ECL:

– unbiased (Article 5.5.17(a) of the IFRS 9);
– point-in-time (PIT) (Article 5.5.8 and Article 5.5.9 of the IFRS 9);
– forward-looking (Article 5.5.11 of the IFRS 9);
– reflecting term structure (Article 5.5.19 of the IFRS 9).

The sample of the existing regulatory capital credit risk models (Basel models) is analysed against each of the above requirements in order to test for IFRS 9 compliance gaps that prevent the use of the existing Basel models to calculate the ECL. The requirements for the measurement of the ECL that constitute potential IFRS 9 compliance gaps in the Basel models are discussed in Table 2.

Summarising Table 2 it should be noted that the Basel models are developed on the principle of ensuring the prudence of their estimates. On the contrary, the ECL model should be accurate (unbiased). The bias towards the regulatory conservatism of model estimates creates IFRS 9 gaps. From the Basel capital requirements perspective, the credit risk models should reflect cyclical current and future credit conditions, as such the model estimates are TTC. However, IFRS 9 requires the ECL to be measured on the PIT basis. Furthermore, under IFRS 9 the ECL should incorporate multi-year forward-looking macroeconomic forecasts. The ECL should also consider the term structure over the lifetime of an exposure, which is in contrast to the 12-month perspective under the capital adequacy requirements.

Having identified the main IFRS 9 requirements for the calculation of the ECL, this paper proposes the following classification of the IFRS 9 gaps:

Gap – the assessed model is not compliant with IFRS 9 and model redevelopment is required to address the identified gap.

Discrepancy – the assessed model is not fully aligned with IFRS 9 requirements, but no significant compliance gap was identified. The discrepancy is expected to be eliminated.

Compliance – the assessed model is compliant with IFRS 9. Continuous monitoring of the IFRS 9 alignment is recommended to prevent the occurrence of IFRS 9 gaps.

The existing Basel models were reviewed for four IFRS 9 gaps. No other IFRS 9 gaps were found upon the review of the new reporting standards. Furthermore, the study of Temim (2016), investigating the IFRS 9 impairment model and its embeddedness within the Basel framework also refers to similar discrepancies between IFRS 9 requirements and the currently used Basel models. According to Temim (2016) and Gea-Carrasco (2015), these discrepancies pose key challenges for credit risk modellers willing to amend their Basel models for IFRS 9 requirements. Table 3 shows the main IFRS 9 gaps found in the existing credit risk models by Temim (2016).

It should be noted that extending the list of potential IFRS 9 gaps beyond the four identified in this study would negatively impact content analysis. Having additional IFRS 9 gaps related to the data, discount rates, the treatment of the cost related to recoveries or the period of observations would yield inconsistent results, as this information is not usually disclosed in the reviewed documentation. In contrast, the credit risk model development documentation includes information that easily lends itself to making inferences about the PIT/TTC estimates, regulatory add-ons/floors/caps, the forward--looking character of model inputs, the incorporation of macroeconomic factors and the reflection of a term-structure. All potential gaps are identified by the researcher upon the review of the modelling documentation.

Finally, one should understand that the paper adopts a broader approach towards defining the unbiased requirement for IFRS 9. In the existing literature, a biased estimate stands for a model's expected value (prediction) that is different from the true values of the estimated parameters (Efron 1986). Therefore, for the IFRS 9 gap assessment, a biased estimate is a model's predicted value with modifications that make it different from the core estimate. For example, any regulatory add-on to the core estimate would cause bias, as the estimate becomes affected by the regulatory prescribed measures or the built-in modelling solutions that aim to maintain/ensure the conservatism of the credit risk models. As noted by Peduzzi et al. (1995) and Forest, Chawla and Aguais (2015), the overly conservative biased estimates are the not accurate reflection of reality, as often shown during the backtesting exercise.

4.3 Data sample

This section describes the credit risk models that are assessed for the IFRS 9 gaps. This section also provides insights into the banks that agreed to participate in the study by submitting the requested model documentation for the IFRS 9 gap analysis.

Initially, 16 European banks were invited to participate in the study by sharing the documentation underlying their FIRB and AIRB models. Table 4 provides details of the documentation that was requested from the banks for the purposes of IFRS 9 gap analysis.

Every model is usually documented by a bank with the underlying documentation stored in the model inventory. The level of comprehensiveness, granularity and accuracy of the underpinning documentation varies across banks with some banks producing detailed reports of the annual review of their models and other banks limiting themselves to PowerPoint presentations of validation checks. Nonetheless, all banks are assumed to have some documents underpinning their credit risk models. Table 3 shows the types of model documents requested from the banks participating in the study.

The invitations to participate in the study were sent to the targeted banks in November 2016 with the deadline to provide the requested documentation set to the 31 January 2017. Five banks agreed to collaborate on this research project by sharing the necessary documentation. Due to the sensitivity of the information contained in the shared documents, the banks were guaranteed anonymity. Table 5 provides insights into the models submitted for the IFRS 9 gap analysis.

17 models from five European banks were submitted for the IFRS 9 gap assessment. Review of Table 5 reveals that the IFRS 9 gap analysis encompasses a wide range of different models (PD and LGD). This makes it possible to generalise the findings and eliminates the bias towards specific models.

Model notations are explained as follows:

$$B_n M_i$$

where $n \in \{1, 2, 3, 4, 5\}$, and $i \in (1, 2, \ldots, k_n)$; B_n denotes a bank participating in the study M_i and denotes the model of that bank, where k_n stands for the number of models submitted for the IFRS 9 gap analysis. For example, if a Bank 1 (B1) submitted the documentation of five different credit risk models, these models would be coded as: B1M1, B1M2, B1M3, B1M4, B1M5.

5 IFRS 9 gap analysis – probability of default (PD) models

This section presents the findings from the review of the targeted models. The section starts with the review of the PD models that are categorised into the following segments:

- public segment – covering sovereigns and public supported entities that benefit from strong government support:
  - sovereign PD (B2M1, B3M2, B4M2),
  - sub-sovereign PD (B4M1),
  - local authority PD (B2M2);
- financial segment – covering banks and non-bank financial institutions (e.g. insurance companies or broker dealers):
  - bank PD (B2M3, B3M1),
  - non-bank financial institution PD (B4M3);
- corporate segment – covering non-financial corporates with specific annual turnover thresholds that distinguish between large, medium and small entities:
  - large corporate PD (B2M4),
  - mid corporate PD (B3M3);
- specialised lending segment – covering highly customised individual projects (e.g. ship financing or property finance):
  - project finance PD (B2M5).

Due to the differences in information disclosed in the model development documentation, some of the analysed credit risk models are described in more detail and others suffer from poor information disclosure. Therefore, the paper provides only the details that are strongly related to identifying the key IFRS 9 gaps.

5.1 Public segment

B2M1, B3M2 and B4M2 define sovereigns as entities established by the central government, central banks included. B4M1 and B2M2 deal with quasi-government entities that have implicit guarantees in place. For all the assessed models, a historical default experience does not exist with no default observations being reported.

B2M1 is calibrated to the PD curve that represents the smoothed long-term average default experience of external agency ratings assigned to financial and non-financial firms. According to the validation documentation of B2M1, this ensures obtaining conservative estimates by B2M1. It should be noted that external agency ratings are derived from macro-economic analysis and include financial, economic and political factors in combination with expert judgment scores/variables. The review of the model development documentation reveals that the underlying data indicate no relationship between defaults and fluctuations in the credit cycle.

B3M2 utilises a range of quantitative inputs such as GDP per capita or FX reserves. The model also uses qualitative/judgmental variables such as monetary policy assessment or private sector soundness analysis. Interestingly, B3M2 receives a high number of overrides to its estimates made by credit officers. It emerges from the model validation documentation that the overrides are usually applied to the Middle-East region (e.g. Qatar, Saudi Arabia) and reflect the PIT variation of the estimates.

B4M2 is built with a conservative bias, because historical default observations are not available to Bank 4. Several alternatives to B4M2 had been tested, but no proposal was accepted due to the inability to produce superior results. The annual review of B4M2 confirms that due to insufficient data, it is prudentially assumed that the model delivers the best possible estimates for sovereign entities. The lack of sovereign default data impacts on the ability to make a clear distinction between the TTC and PIT estimates.

B2M1, B3M2 and B4M2 are estimated over a 12-month horizon that impacts the compliance with the IFRS 9 requirement to provide estimates aligned to a term structure over the life of a specific transaction.

B2M2 is a newly redeveloped model at Bank 2 and has not been implemented. The model is applicable to local authorities that are regarded as regional governments. B2M2 is based on an internal grade replication approach and is anchored to sovereign ratings. Thus, it is ensured that the model does not produce PD estimates that are less conservative than the PD estimates for the sovereigns. In other words, it is assumed that the exposure to a local authority cannot be less risky than the exposure to a sovereign. There is only one default case within the model portfolio, which makes it impossible to assess whether the model delivers accurate estimates. As shown in model documentation, B2M2 is set within both the TTC and PIT frameworks, with the latter producing more conservative estimates.

B4M1 is applicable to the UK housing associations only. The model recognises state support to eligible social housing providers. The analysis of a benchmarking exercise (conducted by Bank 4's validation team) comparing model outputs to the portfolio co-rated by external rating agencies (model validation documentation) indicates that B4M1 is conservatively calibrated. Producing overly conservative estimates results in high override rates for the model's estimates. The override rates are the ratios of changes to the model's estimates made by the end users (e.g. credit analysts) who disagree with the model's output. B4M1 applies a range of macroeconomic and financial factors and also factors assessing management quality and housing demand in order to deliver forward-looking estimates. The review of the model documentation reveals that there is also a penalty factor for small housing associations with gross rental income below GBP 5 mn. Applying the penalty factor may cause the cliff effect for housing associations with the rental income fluctuating around the specified threshold. However, the 2016 annual review of the model confirmed that no entity is subject to the cliff effect. B4M1 is specified under the PIT framework. At this point, the model input factors accompanied by the judgmental assessments from subject matter experts can be considered sufficient to reflect the point-in-time variation. Table 6 presents the details of the IFRS 9 gap analysis for the public segment PD models.

5.2 Financial segment

B2M3 and B3M1 are applicable to any financial services firm that holds a banking license and to its subsidiaries (e.g. investment banks, retail banks, credit unions). B2M3 also includes multilateral development banks.

B2M3 produces PD estimates based on the CAMELS methodology and the changing nature of state support. The CAMELS methodology is a supervisory rating system designed to assess a bank's condition. It emerges from the model documentation that the local regulator demanded that B2M3 be recalibrated to the static S&P benchmarking curve for financial institutions. However, the 2016 validation confirms that the regulatory-induced change has no material impact on the model estimates. B2M3 operates fully within the PIT and TTC frameworks using vendor credit cycle indicators (provided by Kamakura).

B3M1 analyses a bank's risk profile using a wide range of financial factors. The benchmarking and backtesting exercises confirm that the estimates produced by the model are accurate. Overall, upon investigating the model validation documentation, it appears that the model is considered by the validation team to produce unbiased estimates that are suitable for IFRS 9. B3M1 provides both the TTC and PIT estimates based on the Moody's KMV expected default frequency indicators. The Moody's KMV expected default frequency indicators measure the probability of default over a specific period of time based on the current market value of the analysed entity, the amount of debt amassed by the entity and market vulnerability.

B4M3 applies to the financial institutions globally that execute securities transactions for the account of others (brokers) or for their own account (dealers). Despite a limited default history, the analysis of the backtesting results contained in the model validation documentation confirms that the model estimates are aligned closely to the portfolio predictions and external default observations. This is due to the fact that the model is calibrated to a mix of internal and external data using two different PD models that are integrated at a later stage. Upon reviewing the model documentation, it appears that B4M3 is reset within the PIT framework with the 2014 annual review confirming an improved accuracy of the PIT estimates as compared to the previously used TTC estimates. The model development documentation reveals that B4M3 uses a comprehensive set of macroeconomic factors. There are also factors relating to liquidity, asset quality and alternative funding. Table 7 presents the details of the IFRS 9 gap analysis for the financial segment PD models.

5.3 Corporate segment

B2M4 and B3M3 assess large and mid-large non-financial corporate entities respectively. Both models are subjects to regulatory requirements that add a floor of 3 basis points to PD estimates. However, this regulatory add-on is applied at the RWA calculations, and hence does not impact model output. According to model development documentation, B2M4 and B3M3 are also affected by the technical adjustments that serve to smooth the PD distribution within a given range.

The local regulator expects B2M4 to produce TTC estimates that are aligned to their long--run averages per alphabet grade. As evidenced in the results of the backtesting exercise (model validation documentation), this is causing the model's tendency to consistently over-predict estimates. The analysis of the backtesting results contained in the model validation documentation confirms that 50%

of estimates are over-predicted and conservatively biased. B2M4 encompasses a comprehensive range of forward-looking macroeconomic factors accompanied by financial ratios and qualitative judgments.

According to the model redevelopment documentation, B3M3 was recently redeveloped with new model inputs for which no historical specifications exist. No rigorous process was applied to the selection of quantitative and qualitative factors. B3M3 provides both the TTC and PIT estimates. The analysis of the backtesting results contained in the model validation documentation confirms that the PIT estimates are above the actual default rate. The PIT estimates have a one-year horizon and incorporate credit cycle index values at discreet points in time. Table 8 presents the details of the IFRS 9 gap analysis for the corporate segment PD models.

5.4 Specialised lending segment

It should be noted that specialised lending models are highly customised to specific projects. With this in mind, B2M5 applies to institutions whose primary source of income is related to the revenues generated by specific projects that are financed by Bank 2. Interestingly, B2M5 is not used for regulatory capital adequacy purposes. However, Bank 2 expects to receive a relevant waiver in the future from the local regulator.

A benchmarking exercise on B2M5 indicates that the internal default observations follow a similar pattern to the relevant consortium data provided by a third party vendor (Moody's). The model development documentation reveals that B2M5 uses a combination of macroeconomic and financial indicators as well as measures of the volatility of revenues. The backtesting exercise confirms that model estimates are in line with actual observations. The model operates fully within the TTC and PIT frameworks. The PIT estimates are based on the Moody's KMV expected default frequency indices. Upon the review of model documentation, it appears that the model does not fully reflect the term structure of a transaction. Table 9 presents the details of the IFRS 9 gap analysis for the specialised lending segment PD models.

6 IFRS 9 gap analysis – loss given default (LGD) models

LGD models measure the extent of a potential loss exposure. LGD is expressed as a percentage of the total exposure of a bank. This section presents the findings from the review of the targeted LGD models. The section starts with the review of the LGD models that are categorised into the following segments:

- public segment – covering sovereigns, institutions with strong government support or institutions with implicit guarantees in place:
  - sovereign LGD (B2M6, B3M4);
- financial segment – covering banks and non-bank financial institutions (e.g. funds):
  - bank LGD (B1M1. B5M1);
- corporate segment – covering large and mid-large corporates:
  - corporate LGD (B2M7);
- specialised lending segment – partially covering the corporate segment with the focus on specific projects:
  - shipping LGD (B3M5).

Due to the differences in information disclosed in model development documentation, some of the analysed credit risk models are described in more detail and others suffer from poor information disclosure. Furthermore, some of the LGD models are not validated on a frequent basis and lack model validation documentation. Therefore, the paper is limited to providing only the details that are strongly related to identifying the key IFRS 9 gaps across the reviewed LGD models.

6.1 Public segment

B2M6 is a newly developed model. At Bank 2, LGD values used to be derived from the models using the secured and unsecured recovery rates. However, in practice, the collateral is rarely realised at Bank 2. Therefore, a model change was implemented to shift the recovery calculation from the incorporation of collateral valuation to the outcome of debt restructuring with B2M6 being focused on seniority rather than collateral. As evident in the model development documentation, B2M6 is built as a core LGD model with certain outer layers added to the baseline LGD calculations.

Pursuant to the Capital Requirements Directive (CRD IV), the local regulator introduced a 9% floor for discount rates in the LGD estimation. For the IFRS 9 purpose, the 9% floor for discount rates causes a compliance gap. This is due to the fact that IFRS 9 requires the use of the original contractual rate as the discount rate. Therefore, B2M6 does not provide LGD estimates that satisfy IFRS 9 requirements.

B3M4 is applicable to a wide range of sovereigns including their branches and guaranteed entities. In particular, the model encompasses government departments and central banks. Currently, B3M4 is being redeveloped to include local authorities (e.g. municipalities). According to the validation documentation, the model's accuracy and predictive power suffer from the lack of default data for sovereigns. B3M4 estimates are met with a high rate of overrides by country risk analysts.

As shown in the model development documentation, B3M4 uses standard country factors. Additionally, the model recognises the dependency between oil prices and the economic performance of oil producing countries. However, there is no observable relationship between the estimated LGDs and fluctuations in the economic cycles. As a result, there is no difference between the TTC and PIT estimates returned by the model and disclosed in the backtesting exercise reports. As shown in the model development documentation, B3M4 is also subject to regulatory adjustments (e.g. cost of recovery add-on, adjustment for central bank reserves) that are made after the core LGD estimates are calculated, and hence have minimal impact on the model's accuracy. Table 10 presents the details of the IFRS 9 gap analysis for the sovereign segment LGD models.

6.2 Financial segment

For B1M1, as evidenced in the validation documentation, there are no realised LGDs and the backtesting is not performed on the out-of-sample data. B1M1 produces only TTC estimates and downturn LGD estimates. Upon reviewing the model documentation, it appears that the specification of B1M1 does not reflect the systemic credit risk and there are no periodic tests that serve to compare predictions to actual results. B1M1 relies on historical LGD values delivered by third party vendors (Moody's and Bloomberg).

Initially used as a basic loss calculator, B5M1 was gradually improved with the recent addition of trade finance facilities. The model is applicable to all financial services firms that hold a banking license or an equivalent regulatory permit. The scope encompasses retail banks, commercial banks and certain qualifying investment banks, as well as bank holding companies. Ultimately, B5M1 is a decision tree model that applies different LGD benchmarks based on the obligor's and the facility's characteristics. The LGD benchmarks are predefined levels of LGD that individual banks set for different types of credit facilities and obligors. It should be noted that Bank 5 is in the process of gaining the regulatory approval for the AIRB license for B5M1.

As indicated in the model development documentation, B5M1 implements two main drivers for the LGD estimates:

– contractual seniority of debt; and

– country of incorporation of the obligor.

Introducing the country of incorporation as a main driver serves to assess the likelihood that a government would step in with direct support to a troubled obligor. It has been confirmed by Bank 5 independent analysis underpinning the model redevelopment documentation that the availability of government support is a key driver of recovery. Analysing past observations, Bank 5 notes that government intervention results in senior debt holders to incur little or no losses in the event of a bank default.

The model validation documentation reveals that B5M1 consistently over-predicts LGD estimates due to its prudent assumption in order to gain the AIRB approval. B5M1 operates under both the TTC and PIT frameworks. B5M1 does not model the relationship between macroeconomic conditions and loss rates. Table 11 presents the details of the IFRS 9 gap analysis for the financial segment LGD models.

6.3 Corporate segment

B2M7 covers both the large and mid-large corporate entities with the turnover above GBP 50 mn. Although the model has a tendency to over-predict estimates, the distribution of the average PIT LGD estimates shows great accuracy within the 97.5% confidence interval (according to the validation documentation). Bank 2 expects the model's estimate to be more closely aligned to the actual LGDs due to the strategic change that implements updated credit cycle indices. This, however, is to be confirmed in the 2018 backtesting exercise.

Although the regulatory add-ons do not impact the produced LGD estimates, the model has a significantly biased specification that relates to several layers affecting the core LGD. Since the model validation documentation confirms that the UK loss data is not available for the corporate LGD model developed by Bank 2, B2M7 is developed and calibrated based on the US loss data. However, the overwhelming majority of the facilities covered by B2M7 are domiciled in the UK. B2M7 provides both the PIT and TTC estimates for LGD using Moody's KMV expected default frequencies credit cycle indicators. The cross-temporal LGD analysis is currently not conducted on a regular basis. The backtesting analysis relies on an incomplete dataset. Table 12 presents the details of the IFRS 9 gap analysis for a corporate segment LGD model.

6.4 Specialised lending segment

The specialised lending LGD models cover shipping portfolios, project finance, property finance and real estate portfolios. At Bank 3, B3M5 applies to the financing of cargo ships of clients that are representing the sea freight sector. B3M5 also applies to corporates that do not belong to the specialised lending segment, but have cargo ships as collateral. B3M5 is a simple LGD model based on a decision tree that is used to derive baseline LGD estimates.

According to the model documentation, under normal circumstances, the model returns a 35% LGD that is not statistically different from the realised LGDs. A higher LGD value is given in certain cases following the decision tree. For instance, old ships or cargo ships of non-standard size would attract a 45% LGD. All in all, the accuracy of the model was confirmed by the backtesting exercise.

Given the fact that the internal loss data includes 35 default cases concentrated only around the downturn period, B3M5 produces downturn LGD estimates by implication. B3M5 does not operate under the PIT framework. There is not enough data to determine the relationship between economic conditions and loss rates. Furthermore, there are no conceptual reasons to introduce any forward-looking indicators or credit cycle estimations. Table 13 presents the details of the IFRS 9 gap analysis for the specialised lending segment LGD models.

7 Summary of findings and recommendations

This section summarises the review of the PD and LGD models. Practical recommendations are made to address the identified IFRS 9 compliance gaps. It emerges from the gap analysis that the PD models are more aligned with the IFRS 9 requirements than the LGD models. However, none of the reviewed models satisfies the term structure criteria under IFRS 9. Contrary to the solutions addressing the unbiased and PIT requirements, there were no attempts at the participating banks to ensure that the reviewed models estimate a term structure over the life of a specific transaction.

Since the ECL is a function of the PD, LGD and EAD, this paper recommends changes to the time horizon from the regulatory prescribed 12-month period to the maximum residual contractual maturity. At this point, the paper argues that banks can simplify the calculation of the term structure by setting fixed intervals of 5, 10 or 15 years. This should eliminate the computationally demanding use of actual values. The paper suggests that banks determine individually the fixed intervals based on their portfolios.

It should be noted that the estimation of the term structure falls outside of the current capital adequacy requirements. As a result, none of the reviewed models captures the changes in the estimates over the lifetime of a transaction. At this point, the paper argues that capturing the changes in PDs and LGDs should be based on the forecast of systemic credit conditions. In doing so, some banks can benefit from the already utilised credit cycle indicators. Alternatively, banks can employ an industry or region credit cycle indicators.

For the PD models, the probability that the default risk of an obligor remains stable over the lifetime of a transaction is very low due to the expected changes in the idiosyncratic factors as well as macroeconomic conditions. Therefore, this paper suggests the utilisation of the PD transition matrices that show possible future PDs on a year-on-year basis. The PD transition matrices are a set of transition probabilities that fulfil the Markov requirement for the probability of an object being dependent on the current state. The PD transition matrices are offered by many data vendors. However, this approach has three significant limitations (based on the analysis of the CreditMetrics PD transition matrix – an analytical tool for assessing and managing portfolio risk):

– consistent over-prediction of the future PDs for obligors with poor ratings;

– lack of discriminatory powers for the consideration of leverage and volatility characteristics; a highly leveraged obligor with low volatility is assigned to the same migration path as a highly volatile entity with no leverage;

– no transition matrices available for the public segment models (sovereign and sub-sovereign PD models).

For the LGD models, the term structure needs to be transaction specific. This requires the LGD term structure to reflect any changes to the contracts that occur over the life of a transaction. Unfortunately, there are no uniform contractual changes. With the optionality in place, the contractual changes differ across transactions. With this in mind, the paper finds it difficult and computationally burdensome to provide LGD estimates beyond the 1-year horizon.

8 Conclusion

This paper has conducted the IFRS 9 gap analysis on a suit of PD and LGD models from five European banks. Upon the review of the models, the present paper reports that none of the reviewed models is fully compliant with IFRS 9 requirements:

Unbiased. Some of the reviewed models are developed with a built-in bias towards conservatism. The backtesting confirms that the majority of the models consistently over-predict their estimates. For the FIRB models, there are specific regulatory add-ons that affect the accuracy of the estimates.

Point-in-time. Some of the reviewed models do not produce PIT estimates. There are also models that produce both the PIT and TTC estimates, but these cannot be distinguished due to the fact that the affected models suffer from poor data quality that prevent the determination of the relationship between economic conditions and the estimates.

Forward-looking. The majority of the models do not include appropriate macroeconomic indicators that have forward-looking powers.

Term structure. None of the reviewed models estimates a term structure over the life of a specific transaction. The models are limited to a 12-month horizons for their estimates.

For the PD models, the probability that the default risk of an obligor changes over the lifetime of a transaction is high due to the expected changes in the idiosyncratic factors as well as macroeconomic conditions. Therefore, in order to model the term structure under the IFRS 9 requirements, this paper suggests the use of PD transition matrices that show possible future paths of PDs on a year-on-year basis. However, given the reported flaws of the available transition matrices, the decision whether or not a credit risk model can be amended for the IFRS 9 purposes or a new model will need to be developed, requires further analysis that looks into data sources and data completeness. Thus, based on the identified IFRS 9 gaps in the reviewed models, the paper suggests building separate IFRS 9 compliant PD models.

In the case of LGD models, incorporating the term structure becomes computationally burdensome for banks. For example, it would require a bank to generate thousands of statistical scenarios involving the use of time-series models. Such an approach incorporates the value-at-risk (VaR) applications. Therefore, the paper finds out that there is no synergy between the current LGD models and the IFRS 9 requirements, as credit risk modellers are usually not familiar with market risk concepts such as VaR. The IFRS 9 gap analysis leads to the conclusion that the nature of the reviewed LGD models makes the scope of implementing the term structure limited. However, the LGD models are capable of incorporating forward looking indicators that are not currently used for capital adequacy regulations.

Summing up, the paper could not find the synergy of using the same credit risk models for the regulatory capital and the IFRS 9 provisions. Although, theoretically, the regulatory capital models (Basel models) can be used for IFRS 9 purposes, there is no synergy between the reviewed AIRB/FIRB models and IFRS 9 requirements. In particular, the LGD models cannot be used in the calculation of the ECL due to significant IFRS 9 gaps identified in the paper.

The paper is focused on PD and LGD models only. A new study is recommended to extend the scope of the IFRS 9 gap analysis to cover wholesale exposure at default (EAD) models. With this in mind, the paper advocates a cross-temporal analysis of various EAD models in order to test whether the realised credit conversion factors (CCFs) follow the economic cycles. The CCF serves to convert any off-balance sheet exposure to the RWA credit exposure equivalent (Mohan et al. 2012). The paper notes a potential IFRS 9 gap related to the regulatory requirements stating that any EAD estimate cannot be below the current EAD. Furthermore, some local regulators require the use of predefined CFF levels for certain facilities, which leads to obtaining biased estimates.

Finally, the IFRS 9 gap analysis of the submitted models means that banks should start reviewing their existing credit risk models for potential IFRS 9 gaps in a similar fashion in order to ensure compliance with the forthcoming standards. The regulators should understand that the implementation of IFRS 9 to credit risk models requires a transformation of the existing models. This transformation forced banks to invest heavily in new credit risk models as well as IFRS 9 adaptation solutions. The focus on IFRS 9 directs all available resources (credit risk modelling, validation, audit) to focus on reviewing the existing models and improving contemporary credit risk monitoring systems. In some cases, it might have negative implications for the standard duties of bank's credit risk departments, such as annual reviews of the credit risk models, frequent backtesting or maintenance of model risk rating frameworks. For this reason, the paper advocates that regulators and policymakers should show a degree of understanding that banks operate with constrained resources, and hence placing all available resources on the IFRS 9 compliance efforts would result in a temporary decrease in regular credit risk model validation duties.

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Appendix

Table 1
IFRS 9 articles impacting credit risk modelling

Article	Article description	Practical application
5.5.9	Upon reporting, the bank should check if the credit risk on a financial instrument increased significantly from the point of recognition. Instead of assessing the change in the severity of the expected credit losses, the bank should assess the change in the default probability occurring during the lifetime of the financial instrument	The ECL should be compared at specific points in time with the previous results. Thus, the model utilised provide the estimates that are point-in-time (PIT)
5.5.10	Under the exception rule, the bank can assume that the credit risk on a financial instrument has not increased significantly. This exception rule can be applied only if the financial instrument has low credit risk on the reporting date	In practice, this exception can apply to the highly rated sovereign exposures. However, the BCBS guidance stresses that this exception should be used only in rare, exceptional circumstances
5.5.11	The bank cannot rely only on the past information when determining if the credit risk of a financial instrument has increased. The forward-looking information should be used for assessment purposes	The forward-looking information can be used if it is readily available without undue cost. There is an assumption that the significant increase in credit risk appears if the contractual payments are more than 30 days due. This enables the bank to recognise the credit risk increase in advance of the exposure becoming delinquent
5.5.17	The ECL should reflect the following: – the unbiased and probability-weighted amount that stems from assessing a range of possible outcome scenarios; – the time value of money; – information about the past events, current conditions and forecasts of future economic conditions	The ECL calculation process should be unbiased (free of regulatory add-ons) and forward-looking
5.5.18	Upon deriving the ECL, the bank does not need to consider all possible scenarios. However, the scenario for the occurrence of credit loss should be considered	Only the scenarios that are likely to occur should be considered. Furthermore, the bank should note that stress testing requirements include highly unlikely scenarios, which ultimately stand in contrast to IFRS 9
5.5.19	The maximum period for the ECL is the maximum contractual period over which the bank is exposed to credit risk	The maximum period for the ECL should not be longer than the time of exposure to credit risk. Thus, the ECL calculations need to incorporate the term structure

Table 2
Potential IFRS 9 gaps

IFRS 9 gap	**Description**	**Gap assessment**
Unbiased	The ECL model must reflect an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes. The models should provide the most accurate and unbiased estimates of default probability (PD models), loss rates (LGD models) and exposure amounts (EAD)	Backtesting reveals that the model produces estimates that are significantly above or below the predictions for the whole portfolio Model is designed with a built-in bias There is no alignment of model estimates with actual observations Model contains built-in floors and adjustments Model has specification bias
PIT	The ECL model must be a relative model to include the assessment of a significant increase in credit risk	The model specifications do not reflect systemic credit risk The model specifications do not explain why the fundamental obligor factors are suitable to capture the absolute default risk The model is not subject to periodical empirical tests comparing predictions to actual results
Forward looking	The ECL model should use the forward-looking information for assessment purposes. Especially macroeconomic factors should be incorporated to the extent that these factors are material drivers of the model estimates	The model relies only on past information to determine the estimates Macroeconomic factors are not incorporated into the model
Term structure	The maximum period for the ECL is the maximum contractual period over which the bank is exposed to credit risk	The model does not estimate a term structure over the life of a specific transaction The model estimate is limited to a 12-month horizon

Table 3
Key differences between IFRS 9 and Basel models in risk parameters

Risk parameter	Basel model	IFRS 9 model
Measurement timespan	12 months average PD	12 months PD or the remaining life of the underlying exposure
Look-back period	Long-run average-based PD	PIT PD
Reflection of stressed conditions	Downturn LGD Reflection of a significant stress period	Current LGD Forward-looking PD/LGD Reflection of economic conditions
Recovery cost	Direct and indirect costs	Only direct costs
EAD historical data	5 years for retail exposures 7 years for sovereign, corporate and bank exposures	No specific requirements

Table 4
Model documentation

IFRS 9 gap	Requested documentation	Rationale
Unbiased	Annual review of the model Validation of the model	The annual review of the model contains backtesting that provides information about the model's tendency to consistently over-/under-predict estimates. The validation document assesses any built-in biases of the model as well as the model calibration
PIT	Model development Model redevelopment	The model development document (in some cases: model redevelopment document) provides information about the PIT or TTC specification
Forward looking	Model development Model redevelopment Validation of the model	The model development document (in some cases: model redevelopment document) provides information about the input factors with a macroeconomic rationale for the selection of specific input variables. The validation reviews model inputs for their economic justification and reliability
Term structure	Model development Model redevelopment	The model development document (in some cases: model redevelopment document) provides information about the estimation horizon

Table 5
Credit risk models

Bank				Model		
bank code	**country**	**bank type**	**tier***	**regulatory approval**	**model type**	**model code**
Bank 1	Luxembourg	Retail	D-SIB	AIRB	bank LGD	B1M1
Bank 2	UK	Universal	G-SIB	FIRB	sovereign PD	B2M1
				FIRB	local authority PD	B2M2
				FIRB	Bank PD	B2M3
				FIRB	large corporate PD	B2M4
				FIRB	project finance PD	B2M5
				FIRB	sovereign LGD	B2M6
				FIRB	corporate LGD	B2M7
Bank 3	Netherlands	Universal	D-SIB	FIRB	bank PD	B3M1
				FIRB	sovereign PD	B3M2
				FIRB	mid corporate PD	B3M3
				FIRB	sovereign LGD	B3M4
				FIRB	shipping LGD	B3M5
Bank 4	UK	Universal	G-SIB	AIRB	sub--sovereign PD	B4M1
				AIRB	sovereign PD	B4M2
				AIRB	non-bank financial institution PD	B4M3
Bank 5	Austria	Commercial	D-SIB	FIRB/AIRB	bank LGD	B5M1

* As per the FSB list of global systemically important banks (G-SIBs).

Table 6
IFRS 9 gap analysis for the public segment PD models

Model	IFRS 9 gap	Decision	Comments
B2M1	Unbiased	Discrepancy	No built-in biases. However judgmental inputs are present. The calibration is made to the non-sovereign idealised PD curve. The model does not over-/under--estimate predictions
	PIT	Discrepancy	Both the PIT and TTC estimates are calculated by the model. However there is no evident relationship between the default trends and the credit cycle. This makes distinguishing between PIT and TTC impossible
	Forward looking	Compliance	Macroeconomic factors are incorporated into the model. The model uses reliable factors
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction
B3M2	Unbiased	Gap	The model continuously overestimates the predictions for the sovereigns domiciled in the Middle-Eastern region
	PIT	Gap	The model is specified under the TTC framework and does not produce PIT estimates
	Forward looking	Discrepancy	The quantitative inputs are not sufficient to impart forward-looking powers to the model. The GDP per capita and the FX reserves variables cause the estimates to be too high for certain counties
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction
B4M2	Unbiased	Gap	The model is built with a bias towards the conservatism of estimates. However the model output is believed to constitute the best estimates of sovereign entities
	PIT	Discrepancy	Both the PIT and TTC estimates are calculated by the model. However, there is no clear distinction between the PIT and TTC estimates
	Forward looking	Discrepancy	There is not enough information to identify any IFRS 9 gaps with respect to the forward-looking ability of the model
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 6, cont'd

Model	IFRS 9 gap	Decision	Comments
B2M2	Unbiased	Discrepancy	The model has no built-in bias. However, there are methodological assumptions that downgrade the estimates to the sovereign levels. The model is subject to the low default portfolio (LDP) regulatory adjustment
	PIT	Compliance	The model is specified under the TTC and PIT frameworks.
	Forward looking	Compliance	Macroeconomic factors in combination with the assessments from credit officers are incorporated into the model. The model uses reliable factors
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction
B4M1	Unbiased	Discrepancy	The model is considered to produce the best possible estimates. However, a high override rate exists for the model output
	PIT	Compliance	The model is specified under the PIT framework. The model input factors are considered sufficient to reflect point-in-time variation. The model incorporates external credit cycle indicators (M-KMV expected default frequency)
	Forward looking	Compliance	Macroeconomic factors in combination with the assessments from credit officers are incorporated into the model. The model uses reliable factors
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 7

IFRS 9 gap analysis for the financial segment PD models

Model	IFRS 9 gap	Decision	Comments
B2M3	Unbiased	Discrepancy	The regulatory-induced recalibration should be assessed for potential impact on IFRS 9 provisions
	PIT	Compliance	The model operates fully within the PIT and TTC frameworks. The model uses Kamakura credit cycle indicators in order to account for the PIT variation
	Forward looking	Compliance	The model is based on the CAMELS methodology that is regarded as appropriate
	Term structure	Discrepancy	The model is undergoing a redevelopment change to account for the term structure and become compliant with IFRS 9
B3M1	Unbiased	Compliance	The model has no built-in bias. The backtesting exercise confirms that the estimates are accurate
	PIT	Compliance	The model provides both the TTC and PIT estimates based on the Moody's KMV Expected Default Frequency indicators (M-KMV expected default frequency)
	Forward looking	Discrepancy	The model includes a wide range of financial and qualitative factors. However, the macroeconomic indicators are sparsely used in the modelling phase
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction
B4M3	Unbiased	Compliance	The model has no built-in bias. The backtesting confirms that the model estimates are aligned closely to portfolio predictions and external default observations
	PIT	Compliance	The model is specified under the PIT framework. The model incorporates industry and regional credit cycle indices (FIRE – financial institutions and real estate)
	Forward looking	Compliance	The model uses a comprehensive set of macroeconomic factors supported by firm-specific factors
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 8
IFRS 9 gap analysis for the corporate segment PD models

Model	IFRS 9 gap	Decision	Comments
B2M4	Unbiased	Gap	The model is subject to regulatory floors and adjustments. The model consistently over-predict estimates (50% of the estimates are over-predicted)
	PIT	Gap	The model produces TTC estimates as requested by the local regulator
	Forward looking	Discrepancy	The model includes a comprehensive range of forward--looking macroeconomic factors accompanied by financial ratios and qualitative judgments. However the estimates are aligned to long-term averages
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction
B3M3	Unbiased	Gap	The model is subject to regulatory floors and adjustments causing a conservative bias
	PIT	Compliance	The model provides both TTC and PIT estimates. The PIT estimates have a one-year horizon and incorporate credit cycle indices
	Forward looking	Discrepancy	The model does not include appropriate macroeconomic indicators that have forward-looking powers. No rigorous process was applied to the selection of quantitative and qualitative factors
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 9
IFRS 9 gap analysis for the specialised lending segment PD models

Model	IFRS 9 gap	Decision	Comments
B2M5	Unbiased	Compliance	The model is considered to produce the best possible estimates. The backtesting exercise confirms that the estimates are accurate
	PIT	Compliance	The model operates fully within the TTC and PIT frameworks. The PIT estimates are based on the Moody's KMV – expected default frequency
	Forward looking	Compliance	The model uses a combination of macroeconomic and financial indicators as well as measures of the volatility of revenues
	Term structure	Discrepancy	The model does not fully reflect the term structure of a transaction

Table 10
IFRS 9 gap analysis for the sovereign segment LGD models

Model	IFRS 9 gap	Decision	Comments
B2M6	Unbiased	Gap	The 9% floor for discount rates in LGD estimation stands in contrast with the IFRS 9 expectations of use being made of the original contractual rate
	PIT	Gap	The model provides TTC estimates only. The default data for the credit portfolio are limited. The non-existent default data prevent the derivation of PIT estimates
	Forward looking	Gap	Model inputs need to be updated. For instance, the static World GDP per capita value remains constant for the entire historical observations
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 10, cont'd

Model	IFRS 9 gap	Decision	Comments
B3M4	Unbiased	Gap	The model consistently over-predicts LGD estimates that are above the realised LGDs. The model estimates are met with a high rate of overrides
	PIT	Gap	The model produces both the TTC and PIT estimates. However, there is no difference between the TTC and PIT estimates since the cyclical behaviour is not accounted for
	Forward looking	Discrepancy	The model uses standard country factors that do not have forward-looking powers
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 11

IFRS 9 gap analysis for the financial segment LGD models

Model	IFRS 9 gap	Decision	Comments
B1M1	Unbiased	Gap	The model produces conservative estimates due to the built--in bias. No backtesting is performed
	PIT	Gap	The model produces only TTC estimates and downturn LGD estimates. The model specification does not reflect the systemic credit risk cycle
	Forward looking	Gap	Vendor's model estimates are used. The model uses bonds, loan, jurisdiction and seniority inputs. There are no macroeconomic factors
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 11, cont'd

Model	IFRS 9 gap	Decision	Comments
B5M1	Unbiased	Discrepancy	The model consistently over-predicts LGD estimates due to its prudent assumptions. However, the model takes future uncertainty into consideration. The over-prediction is being addressed by the bank
	PIT	Gap	The model operates under both the TTC and PIT frameworks. However, the model does not distinguish between TTC and PIT estimates
	Forward looking	Gap	There is no relationship between macroeconomic conditions and loss rates. LGD estimates are based on the obligor's and facility's characteristics only
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 12
IFRS 9 gap analysis for the corporate segment LGD models

Model	IFRS 9 gap	Decision	Comments
B2M7	Unbiased	Discrepancy	The model is developed on US-specific data, but applied to the UK facilities. The LGD estimates are conservative, but show great accuracy
	PIT	Compliance	The model produces both TTC and PIT estimates. The model uses the Moody's KMV – expected default frequencies credit cycle indicators
	Forward looking	Gap	There is no underlying data for several input factors. The model does not incorporate forward-looking indicators
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction

Table 13
IFRS 9 gap analysis for the specialised lending segment LGD models

Model	IFRS 9 gap	Decision	Comments
B3M5	Unbiased	Compliance	The model produces LGD estimates that are confirmed to be accurate. There is no built-in bias
	PIT	Gap	The model does not produce PIT estimates. There is not enough data to determine the relationship between economic conditions and the loss rates
	Forward looking	Gap	The model does not incorporate forward-looking indicators due to conceptual reasons
	Term structure	Gap	The model estimate is limited to a 12-month horizon. The model does not estimate a term structure over the life of a specific transaction