Model Risk - In the Context of the Regulatory Climate Change

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Abstract

Model risk management plays a significant role in today's financial marketplace. Apart from other types of risk such as market risk and credit risk, model risk is the risk within a model indicating whether the model is incorrect or misused. The outcomes and reports based on the used model significantly influence the decision making process of any financial institutions or organizations regarding future events.

This article addresses model risk in financial domains involving risk management in the context of new regulations and requirements. We first review the major quantitative methods involved in risk forecasting and the two distinct approaches towards defining model risk: the value approach and the price approach. Then, we discuss model risk from regulatory and accounting perspectives, in light of the decisive roles of BCBS 239 and IFRS 9 and their associated challenges. We further discuss the recent regulatory developments on model risk management.

Keywords: model risk management, quantitative methods, regulatory and accounting perspectives

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1 Introduction

Model risk is a very live topic in the financial market. It is largely important for banking organizations and financial institutions, in particular, to understand how to measure and manage the risk arising from the models they chose to use. However, due to its sophisticated nature, model risk measurement can become an important but challenging task.

Just as the weather forecast is used as a predictor of the weather for the upcoming days, financial forecasting is used and relied upon by banking institutions to predict future financial events. In particular, a risk forecast is used to predict the risk of future losses arising from using an incorrect or misused decision making model in the context of financial instruments valuation. In other words, a poor performance of predictions from a chosen model causes a poor financial performance for decision makers and the risk of future losses.

Principally, modeling requires two important issues to be considered: the uncertainty stemming from the model and the valuation to support future decision making. These issues begin first and foremost with the model risk, as the model is used to build the future predictions and decisions the institutions rely on. Therefore, it is particularly important for a bank to consider the model risk of its financial instruments.

Following the 2007 global financial crisis and earlier reported cases in the 90's, risk forecasting of the chosen pricing models captured the interest of mathematicians, especially in quantifying model risk. We follow this area in section 2 and review the two major quantitative approaches to measuring model risk with their associated challenges. We then share insights from several studies and specify some common and fundamental errors regarding quantitative models. In section 3, we discuss value approach and price approach and their different concepts in describing model risk.

In practice, banks are concerned with the amount of regulations and requirements concerning their function and risk management. Changes in regulations, developed by the Basel Committee on Banking Supervision (BCBS), have included regulatory capital requirements not only on market risk and credit risk but also on model risk management. Therefore, the establishment of a framework for risk management that includes standards for model development, implementation and validation is crucial. Ultimately, this framework must be covered by suitable policies through including governance and maintaining controls over the risk management activities. Thus, we continue in sections 4 and 5 by investigating model risk management from regulatory and accounting perspectives with the decisive roles of BCBS 239 and IFRS 9. In section 6, we review the recent regulatory developments approaching towards an effective framework for model risk management. We conclude in section 7 with our findings from this work and discuss some remarks on the future research on the topic.

2 A Sample of Quantitative Approaches

Accurate forecasting of future events has a challenging role for financial modelers and risk managers. One way to handle the problem is to estimate information data and use an estimated model to forecast the future events. Consequently, a risk management consultant may try to find a specific model and a related suitable forecast among a wide range of different parametric models and forecasts. However, there is not much accuracy in such an approach, since the rest of the forecasts which could include useful information are simply ignored.

In order to bring more accuracy, one should follow an approach to combine the forecasts of different models instead of considering individual ones. The advantage of forecast combination is that it considers the dependency of future predictions on time, strategy type and any other relevant variables.

In theory, this combination is considered by combining different models that forecast in different ways. One important approach to such model aggregation is Bayesian model averaging [1]. Another important approach is called worst case scenario [2], which includes the risk of maximum loss hedging under the worst possible case.

Conceptually, these two quantitative approaches[1] combine individual forecasts in different ways. Bayesian model averaging deals with model uncertainty through assessing future probabilities, while the worst case approach considers weight estimation through minimizing loss functions.

One common example of using these approaches is on stochastic modeling for a stock price. Distribution of parameters, sampled from financial market data, e.g. option pricing, can be framed in Bayesian methodology. However, in the case of model uncertainty and insufficiency of the information on option prices, one may use the worst case approach, where the stress testing and scenario analysis should be implied. Below we further describe each approach in more detail.

[1] By the term quantitative approach, we refer to a method that processes input data into quantitative estimates and can be applied for measuring risks.

2.1 Bayesian Model Averaging

Bayesian model averaging proposes a powerful way of using multiple models to forecast variables of interest, but places the burden of mathematical sophistication on the end-user, especially probabilistic sophistication. Users are assigned the challenging task of assigning prior probabilities to the parameters of interest and to each model being considered, before facing the expensive task of computing the joint model. Recently, the approach has gained traction, though, as a result of developments in posterior computation technology.

Essentially, the method takes a weighted average of models, creating a joint probability distribution that can be used to forecast desired parameters [3]. Below we discuss some of the mathematical steps and requirements to averaging models in such manner.

X = set of data being considered,
K = total amount of models being considered,
$k = 1, ..., K$ = index for the k^{th} individual model within a group of K models,
M_k = the k^{th} model,
w_k = weights for each model k,
$\hat{\beta}_k$ = estimate of the parameter of interest in model k,

$$Model\ Average = \sum_{k=1}^{K} w_k * \hat{\beta}_k. \tag{1}$$

The weights can then be more formally viewed as the respective posterior probabilities for each model and the estimates being averaged can be viewed as the posterior probability distributions for the parameters being forecasted. Further, denoting $p(M_k|X)$ as the posterior probability for each model and $f(\hat{\beta}_k|X, M_k)$ as the probability distribution function for the parameters of interest, we have

$$Model\ Average = \sum_{k=1}^{K} p(M_k|X) * f(\hat{\beta}_k|X, M_k). \tag{2}$$

Estimating the posterior distributions of the parameters is then a standard application of Bayes' rule: a likelihood function for the data being considered is multiplied by a prior distribution for the parameters of interest,

$$f(\hat{\beta}_k|X, M_k) = \frac{f(X|\hat{\beta}_k, M_k) * f(\hat{\beta}_k|M_k)}{f(X|M_k)}. \tag{3}$$

The posterior probabilities require the posterior distribution of each model, which in turn require the marginal likelihood of the model ($p(X|M_k)$) and a prior belief on the model ($p(M_k)$),

$$p(M_k|X) = \frac{p(X|M_k) * p(M_k)}{f(X)}. \tag{4}$$

The collective weighted average provides much better predicting ability, in theory, than any single model. Principally, because using one single model can mismanage the variability of the data being used, mismanage the uncertainty in the entire mode space, and lead to over-confident inferences.

The method has not proved practically ideal though, because as is evident in the mathematical overview above, the weighted average requires several probabilistic estimations and specifications that are theoretically challenging for the end-user and computationally expensive to calculate [1]. Moreover, the weighted sum of all relevant models requires computational power that is expensive and often infeasible, specifically because of the integrals involved.

That being said, the following methods have been developed as solutions to some of these difficulties. For instance, instead of averaging over all competing models M_k, one can average over a subset that is supported by the data, reaping the benefits of model averaging and avoiding the computational difficulties of such a large sum and joint distribution [1]. This approach was developed by Madigan and Raftery in 1994 and is appropriately called Occam's Window Method. The method/approach excludes models that are considerably weaker than the most predictive single model and excludes complex models when the data supports simpler models. In other words, only a subgroup of models is kept in the window of interest to be considered for the averaging process.

Furthermore, several algorithms have been developed to search for models to include in such "window". Madigan and Raftery developed a two-part algorithm that compares models in pairs, excluding the less favorable model and its relevant sub-models based on complexity and support from data. Another popular algorithm used to determine models that fit in the window is the "leaps and bound" algorithm developed by Volinsky, Madigan, Raftery and Kronmal [4]. Finally, in addition to the Occam's window method, a computational approximating method called Markov Chain Monte Carlo model composition (MC3) has been developed that leverages computer simulation ability and Markov Chain construction to directly approximate the average over all relevant models [5].

In closing, Bayesian model averaging provides much stronger predictive power than any single model because of better management of data variability. However, the approach tends to only improve predictive ability and does not facilitate or improve risk measurement, so it is not the standard practice or most relevant practice. Moreover, this approach treats all sources of risk (model risk, market risk, credit risk, etc.) as the same and thus makes it difficult to manage model risk in particular.

2.2 Worst Case Scenario

The worst case scenario approach can be much more favorable in design because it can require much less sophistication from the end-user with regard to its inputs, and model risk can be more relevantly distinguished from other risks [6].

One of the more conventional uses of the worst case scenario approach is in stress testing of risk models. In such application, stress scenarios are created separately from the base risk model and then integrated into the model to produce a more comprehensive risk measurement. This is valuable because popular base risk models, such as the value at risk model (VaR) or the expected tail loss model, fit to historical data and losses, but do not consider different situations that have not been historically observed. Furthermore, stress testing and stress scenarios allow unseen but plausible scenarios that can affect the performance of the bank or entity to be considered.

There are multiple ways to produce these scenarios and incorporate the information into the base models. Scenarios can be produced with scenario loss distributions and loss probabilities that are then mixed with the historical loss distributions [7] into one stress risk model. This method, however, requires assumptions to be made concerning the distributions and can begin to present challenges for the user. In addition, stress scenarios can be produced using Monte Carlo Simulation of the underlying risk factors [8]. However, this approach ignores extreme scenarios that can be relevant and creates a challenge when looking to incorporate the scenarios into the base model.

Scenarios, however, can also be produced in simpler fashion and still be well integrated into the base model, specifically using the worst case scenario approach. Scenarios can be produced and defined by a lower bound on loss amount and a frequency [6]. The loss amounts can be derived from different types of risk (portfolio market risk, credit risk, interest rate risk, operational risk, etc.) and the frequency of occurrence is commonly defined in terms of relevant time periods (days, months, years, etc.). The worst case scenario for a period is then defined as the scenario that has the highest lower bound of loss and the highest frequency among all other scenarios with a minimum frequency of 1 over the given period length.

Mathematically, worst case scenarios must be able to be compared with values from the base model. Further, worst case scenarios losses are understood as risk measures and linked to quantiles in the base loss distribution through their implied cumulative probabilities, which then allows a comparison to be made between a stressed risk measure and a base model risk measure. A combined loss distribution is then formed, usually using a process called stochastic dominance [6]. The method combines information into one distribution as shown below:

v_i^s = risk measure for worst case stress scenario i, for a given frequency period,

q_i = quantile in base model distribution corresponding to worst case stress scenario i,

F_b = cumulative distribution function of the base model,

$F_b^{-1}(q_i)$ = base model risk measure that corresponds to worst case stress scenario i,

$\Delta_i = v_i^s - F_b^{-1}(q_i)$ = difference in risk measure between stress scenario and corresponding risk measure in base model.

(1) All the scenarios that do not follow the constraint below are removed,

$$\Delta_i = v_i^s - F_b^{-1}(q_i) \geq 0. \tag{5}$$

In other words, the stress measure of risk cannot be lower than the corresponding risk measured by base model.

(2) Once all irrelevant worst case scenarios are removed, a combined distribution is made by augmenting the base model by the chosen worst case scenarios.

Δ_t = total difference in risk measure between base model and stress scenarios, for all worst case scenarios that satisfy constraint above, $F_b^{-1}(n)$ = base model measure of risk at a given n,

Stress(n) = combined measure of risk between base model and stress scenarios at a given n,

$$\mathrm{Stress(n) = F_b^{-1}(n) + \Delta_t}. \tag{6}$$

In closing, the worst case scenario approach allows one to combine scenarios that add relevant and valuable information to a base risk model. Further, a combined distribution is formed that integrates multiple sources of information allowing an appropriate and more precise model risk measure to be taken, unlike the Bayesian averaging approach that cannot distinguish model risk from other types of risk. Thus, the approach is more widely used towards and recommended for managing and measuring model risk. The approach in economics has been further developed by Cont [9].

2.3 Common and Fundamental Errors in Quantitative Models and Regarding Quantitative Models

There are several common and fundamental errors regarding quantitative models such as internal errors, wrong or inadequate assumptions, the inclusion of wrong input information, a misapplication of the model itself or a misinterpretation of their results [10, 11]. The following examples illustrate common errors:

- **Lack of calibration regarding Subject Matter Experts (SMEs):** If input by SMEs for Monte Carlo models is used, their subjective inputs may appear systematically over-confident. This issue may cause understating risks.

- **The risk paradox:** This may occur, when organizations apply a sophisticated risk analysis method to low-level operational risks, whereas the bigger risks use softer methods or none at all.

- **The measurement inversion:** This is the case where the focus of organizations is on the least valuable measurements. Consequently, this might be at the expense of the most valuable measurements [12].

- **Distribution assumptions:** The normal distribution is commonly used, even though it is often an inappropriate approach. For instance, if the distribution is heavily skewed such as credit risk and operational risk distributions [13].

- **Inadequate testing regarding goodness of fit:** The Kolmogorov-Smirnov-test is often used to determine the goodness of fit for a normal distribution. However, the test is not sensitive to how fat the tails are. Therefore, since the main concern for risk analysts is on the tails of the distributions, the K-S-test is often inappropriate [12].

- **Ignoring the psychological dimension of managing risk:** A significant aspect of the risk to be managed is psychological. However, institutions often do not consider empirical findings from the field of psychology such as SP-A theory, prospect theory, the link between biases and risk and the link between personality and risk. Examples of biases relevant to risk modeling are group-think, confirmation bias, over-confidence, illusion of control and Bayesian avoidance [14].

- **Lack of proper guidelines and metrics regarding the inadequate assessment of model risk:** Model risk often lacks practical implementation and thus the recommendations and guidelines remain usually qualitative. This complicates representing risks in the model and assessing changes concerning the model risk and further consequences like speed and performance of the model [15].

- **Inadequate model data:** When the input data have major flaws, even the best model can generate misleading results. Data flaws can not only occur due to the data quality but also from a partial selection of the data history. Housing prices displayed upward trending for many years and then banks used this part of the historical data in the housing price models and the credit default risk models. Consequently, it was impossible to obtain tail risk levels anywhere close to the losses during the 2007 financial crisis [16].

3 Model Validation

In line with designing a model based on a quantitative approach, one should basically notice how the model is validated overall. Model validation is a set of processes verifying that the model is performing as expected. This is a fundamental issue as it brings the importance of validation check within the definition of model risk.

The two leading approaches to measuring model risk and consequently executing model validation are the value approach developed by Derman [17] and the price approach developed by Rebonato [18].

The value approach essentially claims that real losses arise only because of discrepancies between model values and the fundamental value of the object being forecasted. Such approach recognizes that an exhaustively realistic model is practically infeasible, but claims that a model has a risk of not being realistic when it fails to consider factors that affect the object's fundamental value.

On the other hand, the price approach understands model risk exclusively as the difference between the model value of the object being forecasted and the market price. Further, even if the market is unreasonable or counterintuitive, losses are not considerable as long as the value of the model agrees with the market price [19]. Practically speaking, this is sound because model losses occur in practice when the model value and market value diverge [19]. The divergence usually occurs because the model differs from the market sentiment, the model's implementation is impaired, or the model is consistent with a market sentiment that then changes. Respectively, these three issues can be addressed in the following ways: market due diligence and intelligence, price verification (software verification, execution verification) and consideration of future changes [20].

Model losses with regard to the price approach are of particular interest because they highlight key similarities between the two approaches and the importance in considering both when validating models. A worthwhile example is the modeling of mortgage backed securities and models losses that occurred during the recent market crash. Models had gone wrong because historical data supported low default probabilities an increasing trend in housing prices that resulted from liberal cash lending by banks and value guarantee. Moreover, models were founded on assumptions that housing prices would continue to grow at a historically supported rate with low default probabilities. However, in the subprime crisis, the models experienced severe losses, as the price approach would account. Because of impairment in model fundamentals, these losses were principally highlighting a key similarity between the price approach and the value approach. The mortgage backed security models were not realistic and disregarded factors that affected the object's value (default probabilities, correlations, etc.) causing the model value to deviate from the market price. As such, the reason the model failed under the price approach was because of a failure to consider factors that affect object value [20].

In closing, there are two guiding approaches to model validation that contain differences in their understanding of model risk, but also contain important underlying similarities. Losses under the price approach can result from failure to consider factors that affect object value and losses under the value approach can arise from failing to consider market sentiment as a real factor. Furthermore, we believe both approaches should be considered by risk managers when executing model validation. We believe that the validation check must be in consistency with reality and market consensus.

4 The Context of BCBS 239 and Model Risk

One of the significant issues which came into view during the global financial crisis was the inadequacy of banks' information technology (IT) and data architectures to support the board management. Therefore, the need for a set of guidelines developed to help institutions understand the issue and respond to a better evaluation and analysis was recognized.

4.1 Overview of BCBS 239

The Basel Committee on Banking Supervision released BCBS 239 as principles for effective risk data aggregation and risk reporting in 2013 [21]. This document demands high validation standards of risk data aggregation, as well as accuracy and reliability of data to guarantee normal and stress phases.

Data Aggregation

The use of data processing and quantitative tools by banking organizations has been increased during the past decades. In this context, validation standards are required from the banks to enable them to measure their performance against the risk appetite. BCBS 239 defines risk data aggregations as the process of determining, gathering and processing risk data according to the banks' risk reporting requirements.

The aim of the principles from the risk data perspective is that data must be stored and aggregated in a way that any question related to the data is a fast response exercise. This helps the organizations to realize the risk of possible losses before they occurred and thus ascertain their risk strategies at a higher level. This can be also applied to stress testing phase by accuracy and reliability of data.

Reporting

However, although there is a lot of focus on the data side, risk reporting is equally important as risk data. To improve reporting in accordance with the BCBS 239 principles, organizations must focus on supplying information to the end-user and delivering the effective data that they need. This is one of the significant improvements to past procedures, where reporting had weak interaction with the end-user and relied upon delivering a lot of data to decision makers.

Scope of Application

The 14 Principles listed in [21] cover the following sections:

(I) overall governance and infrastructure (through principles 1 and 2),

(II) risk data aggregation capabilities (through principles 3-6),

(III) risk reporting practices (through principles 7-11),

(IV) supervisory review, tools and cooperation (through principles 12-14).

Only after fulfilling these requirements will the implementation process be possible.

The scope of the application of BCBS 239 includes three major areas of risk management data, risk management models and risk management processes. According to the principles, all necessary data must be monitored and tracked for risk control and guarantee sufficient quality.

Furthermore, accuracy, completeness and consistency of the models are explicitly required. Risk management models consist of models for pillar I capital requirements such as internal ratings-based approach (IRB) and advanced measurement approach (AMA), models for pillar II as well as value at risk models.[2] Finally, data must be aggregated based on an automated data process. However, despite providing well-founded regulations and principles in BCBS 239, it is challenging to find optimal best practice solutions in this area.

4.2 Impact on Model Risk

The risk of a model strongly depends on the quality of data which is applied in specific cases. Thus, the highest level of the board is directly responsible for providing the improvement of data quality. As part of their responsibilities, they assure that suitable processes with the purpose of monitoring and escalation are established. In general, the risk management board of financial institution is responsible for applying the principles throughout the data collection, control process, aggregation and reporting.

Effective implementation of the principles enhances risk management and decision making processes at banks. BCBS 239 also concerns institutions with data quality and times of stress phase. Effective data aggregation reduces the time of recognizing the risk and increases the capability to react in a timely manner. On the other hand, the new reporting requirements ensure that institutions have their current risk data available for internal control. Likewise, the effective reporting gives the chance to supervisions to get a better overview of intervention.

Another important issue is that the models must be as accurate as the data used in the calculation. The impact of the principles applies to all significant internal models such as AMA, foundation and advanced internal ratings-based approaches (F-IRB and A-IRB) as well as VaR.

After all, making improvements in risk data aggregation and risk reporting practices to comply with BCBS 239 continues to be a big challenge for

[2]Several attempts in the literature to analyze the model risk on VaR can be found in [22, 23, 24].

many banking organizations. This is, on one hand, due to the usage of poor data quality and data aggregation technology at the banks and on the other hand, due to the principle-based nature of BCBS 239. As a result, the role of model risk in running the organization entails challenges such as governance issues, operating models, data quality and technology issues.

To address these challenges, investing in data aggregation technology and the so-called single source of truth (SSOT) is extremely relevant to meeting the new requirements and regulations.[3]

5 The Context of IFRS 9 and Model Risk

The need for considering model risk in accounting has emerged as a big challenge in practice. Following the accounting consequences of the global financial crisis, there were critical voices concerning the approaches of existing risk management models and lack of available credit lines. This clearly emphasized that the model of "incurred losses" is not adequately included in accounting risk management. Consequently, it was decided to take the "expected losses" into account in the future in international accounting.

The conversion from the incurred loss model (ILM) to expected credit loss model (ECL) resulted historically from the G-20 summit in 2008 in Washington. However, bringing this content to the practice creates some functional and technical challenges.

The new guidelines of IFRS 9 increase the focus on model risk management and model risk valuation in terms of capital requirements. For complex risk valuations, model risk should also be considered by statistical analysis of historical losses through forward-looking stress tests and market-based analysis of expected future cash flows.

5.1 Overview of IFRS 9

The new requirements regarding IFRS 9 at all its levels concern every financial institution extensively. Moreover, these new requirements are not only relevant to accounting, but also affect the entire data delivery path, from the source systems to the identification of individual transactions and regulatory reporting.

[3]SSOT refers to the practice of structuring models and information systems such that each data is stored only once. This helps to have single representations of data rather than multiple databases. Thus, it ensures that reports can be quickly provided at a higher level.

Although the evolution of cutting edge technology such as big data has lead financial institutions to increase revenues and reduce costs, it also represents security threats to the underlying information systems as well as inaccuracy in evaluation due to the large amount of data. In this sense, the systematic risk assessment has a great impact on the financial situation of any institution or organization. To address these new challenges, the regulations are evolving by recognizing the relevance of information management, data governance and controls. These evolving elements based on the new regulations undoubtedly pose challenges of handling the new impairment standards.

Expected Credit Losses (ECL)

The International Accounting Standards Board (IASB) released an exposure draft entitled "Financial Instruments: Expected Credit Losses" in 2013 [25]. This document considers the recognition and measurement of a credit loss impairment based on a forward-looking procedure referred to as expected credit losses approach. In contrast to the previous incurred loss accounting approach where loan losses were recognized only when they occurred, the current exposure draft states that institutions must develop approaches to track and measure credit risk.

The principles are structured into two classifications: 12-month expected losses and lifetime expected losses. At the initial recognition of 12-month expected losses in stage 1, no significant deterioration in credit quality has occurred. Deterioration of credit quality is recognized in stage 2, where a significant increase in credit risk has happened and subsequently in stage 3 where objective evidence of credit losses is available. The challenging questions here are: how to measure credit risk impairments and how to recognize significant increase in credit risk. The 12-month ECL is a portion of the lifetime ECL, which is associated with the probability of default occurring over the 12-month period. The lifetime ECL, however, is estimated based on the present value of all contractual and expected cash flows (shortfalls) over the remaining lifetime of the financial instrument. In the case that the credit risk recovers, the allowance can be again limited to the credit losses over the next 12 months. Financial institutions have to update the ECL amounts at each reporting date to reflect changes in the credit risk of financial instruments. This significantly increases the amount of information to be collected and the frequency of impairment calculations.

Subsequently, the updated IFRS 9 standards issued in 2014 replaced IAS 39 "Financial Instruments: Recognition and Measurement" from the IAS board [26].

Scope of Application

The standards of IFRS 9 contains three main phases:[4]

1. classification and measurement of financial assets and liabilities,
2. impairment methodology,
3. hedge accounting.

According to IFRS 9, financial assets or financial liabilities initially have to be accounted for at their fair value.[5] After initial recognition, the subsequent measurement of financial assets shall be executed in accordance with the classification of financial assets in paragraphs 4.1.1-4.1.5 at:

- amortised cost,
- fair value through other comprehensive income (FVOCI), or
- fair value through profit or loss (FVTPL).[6]

Analogously, the subsequent measurement of financial liabilities shall be done in accordance with the classification of financial liabilities in paragraphs 4.2.1-4.2.2.[7]

Further, IFRS 9 requires the implementation of the impairment model based on the expected credit losses. The impairment requirements shall be applied to assets that are not measured at FVTPL.[8] In this phase, institutions should consider the recognition of expected credit losses on:

- lease receivables,
- contract assets,
- loan commitments,
- financial guarantees,
- financial assets measured according to paragraphs 4.1.2-4.1.2A.[9]

[4]IFRS 9.IN6.
[5]IFRS 9.5.1.1.
[6]IFRS 9.5.2.1.
[7]IFRS 9.5.3.1.
[8]IFRS 9.5.2.2.
[9]IFRS 9.5.5.1.

In addition to the measurement of the loss allowance at an amount equal to 12-month expected credit losses, institutions must always measure the loss allowance at an amount equal to lifetime expected credit losses for:

- trade receivables or contract assets resulting from transactions within the scope of IFRS 15,

- lease receivables resulting from transactions within the scope of IFRS 16,[10] if the institution chooses to measure the loss allowance at an amount equal to lifetime expected credit losses.[11]

The third phase of the standards aligns hedge accounting with risk management activities with the aim of reflecting the arising risks that may affect profit or loss or other comprehensive income.[12]

5.2 Impact on Model Risk

The conversion of the incurred loss to the expected loss model requires forward-looking estimates. However, changing from a backward-looking accounting towards a future-oriented method has a significant impact on the determination of risk.

The consequences not only increases inaccuracy and systematic errors, but it also causes more complexity in the model due to portfolio-specific estimates. Therefore, designing new policies with forward-looking estimates and assumptions is essential.

The above challenges drive a focus on revising the existing models and evaluating forward-looking adjustments. In other words, the loss estimates need to comply with the requirements placed on the capital levels. Moreover, the ECL approach gives defaults in the evaluation standards through the whole lifetime. Therefore, new validation and consistent calibration of the models are essential to minimize the resulting model risk through recognition of the losses. Although no ideal solution is found in this regard in practice,

[10]IFRS 16 will replace IAS 17 Leases and will be effective from 01.01.2019.

[11]IFRS 9.5.5.15.

[12]For hedge accounting purposes, IFRS 9 allows to designate hedging instruments including derivatives or non derivatives financial assets and liabilities measured at FVTPL. Additionally, it allows assets, liabilities, firm commitments or highly probable forecast transactions to be designated as hedged items. Therefore, a hedging relationship between a hedging instrument and a hedged item can be designated according to paragraphs 6.2.1-6.3.7. However, institutions may only apply hedge accounting to hedging relationships that meet the criteria in paragraph 6.4.1 (ref. IFRS 9.6.2.1, 9.6.2.2, 9.6.3.5, 9.6.1.2 and 9.6.5.1).

the authors believe that optimal solutions through revising the current methods are crucial for the perspective of risk management. The optimal models must support the large amounts of data and ECL calculations. Furthermore, it is important that financial institutions generate accurate impairment calculations to meet regulatory reporting requirements.

6 Regulatory Developments on Model Risk Management

As mentioned in previous sections, regulatory requirements have increased for different segments. Yet in European regulations, there exist no standardized guidelines specifying model risk management. This is due to the fact that the risk models and their valuation adjustments are measured and managed differently from one another and differently across different institutions and organizations. Therefore, model risk is generally recognized and modeled in different ways.

However, there are certain important statements that must be considered in all methods of model risk assessment to measure model risk in Europe (particularly in Germany). These statements include the capital requirements for model risks from internal models in Pillar I and the Internal Adequacy Process (ICAAP) in Pillar II. Further, they are expressed as guidelines from the following references: German Minimum Requirements for Risk Management (MaRisk), Capital Requirements Regulation and Directive (CRR/CRD), and the European Banking Authority (EBA), on Supervisory Review and Evaluation Process (SREP) and on prudent valuation.

- MaRisk:
  - Guidelines on examining the adequacy of methodologies used in market risk activities.
  - Guidelines on taking into account the restrictions of these methodologies [27].
- CRR/CRD:
  - Guidelines on measuring the model risk arising from using internal models, i.e. as part of the assessment of operational risk [28].

- EBA on SREP:
  - Guidelines on assessing the model risk of internal models in the main business areas and operations.
  - Guidelines on holding risk capital, since there exists a direct link between model deficiencies and capital requirements (ICAAP). [29].
- EBA on prudent valuation:
  - Guidelines on measuring model risk through valuation adjustments associated with existence of a range of different valuation models or model calibrations [30].

Compared to European regulation and guidelines, American guidelines are more standardized and defined under a framework for model risk management. Further, the Office of the Controller of the Currency (OCC) specified such framework to the Federal Banking Reserve System [31], and its major guidelines are included below:

- OCC/FED:
  - Guidelines for proper model development and implementation. The model development process and its proper documentation are explained. In addition, guidelines are provided for data quality assurance, model testing, and the establishing of model requirements.
  - Guidelines for model use, model testing, and the application of appropriate conservatism in model development and use.
  - Guidelines for the processes of model validation and the key elements involved, including the evaluation of conceptual soundness, ongoing- monitoring, and qualitative and quantitative techniques for outcome analysis such as back-testing.
  - Guidelines and steps for the validating of models built by third party vendors, including model selection processes, systematic procedures for validation, and contingency plans.
  - Guidelines for developing and maintaining appropriate governance, policies and controls over the model risk management framework. Governance guidelines are set for both the board of directors and senior management of the organization, and the responsibilities for the different roles in the model risk management framework are expressed and explained, including reporting lines and incentives.

- Guidelines are set for the internal audit process of the risk management system, the proper use of external resources, and managing the model inventory.
- Guidelines are set for the proper documentation required throughout the model risk management framework, especially during the development and the validation phases.

Impacted by these set of guidelines, known as SR 11-7, a model risk management framework is formed as a global standard. In response to these supervisory guidelines and establishing the mentioned framework, banking organizations need to adopt the regulations and improve their systems through assessment of all the relevant factors. This is possible through considering requirements for governance and policies, risk controlling, quantitative methods, implementations, model validation activities and documentations by banks. Available recommendations proceed with incorporating model risk management requirements into the model development process. In this regard, integrating model risk management into the best practice needs identifying issues in models, quantify the possible risks, assessing the impacts, implementing risk controls and finally managing them upon an effective framework.

7 Conclusion

It is fundamental to evaluate predictions through financial risk forecasting. One of the main lessons learned from the global financial crisis was concerning the result of neglecting model risk related to either model deficiencies or model misuses. Today, model risk is clearly not an area that can be ignored without consequences, since its ultimate impact is on decision making for risk managers. Quantitative economists on one hand and regulators on the other hand have provided improved mathematical methods and regulations to manage the model risk in a more efficient manner.

As discussed in section 2, we agree that among the quantitative approaches to model risk, the worst case scenario is a suitable approach. While the model averaging does not allow for desired risk measure, the worst case approach can be practically associated with quantifying model risk in favor of risk managers. In line with these approaches, we also reviewed several other studies regarding some common and fundamental errors in quantitative models. We further believe that both descriptions of value approach and price approach, discussed in section 3, are equally relevant and should be highly considered in model risk management in practice.

As discussed in sections 4 and 5, the compelling need for risk management with regard to accounting and regulatory requirements is a crucial topic to be further improved. The BCBS 239 principles lead the way for enterprising data management and supporting analysis of data and ultimately a better visibility of risk. If the data information is generated and distributed quickly, the risk control function can become more efficient for the people taking on those risks. Moreover, the new regulations based on IFRS 9 is not only relevant to accounting, but also affects the entire data delivery path and reporting systems. Many financial institutions are conscious of this issue and thus the new ECL model has been developed to tackle it systematically. In [32], the authors showed the selected requirements of the ECL model and the resulting impact on regulatory aspects under "Capital Requirements Directive IV" and "Capital Requirements Regulation" in the context of user practice. Case studies remain to be done in the future in order to clarify the impact of these requirements in practical examples.

In summary, the issues of BCBS 239 and IFRS 9 give the opportunity to put data risk management as one of the core priorities and functions of banking organizations and financial institutions.

Further, in section 6 we summarized recent regulatory developments in Europe and the US concerning guidelines for this important area. Regulatory developments for model risk management are formed by the US and EU standards through the US Office of the Comptroller of the Currency (OCC) and European Banking Authority (EBA). Through SR 11-7, the US regulatory guidelines have emerged to be more comprehensive and perspective than those adopted by European countries. This set of guidelines requires banks to control and manage their model risk periodically by using more rigorous design, implementation, validation and adequate documentation. In this regard, an effective model risk management framework emphasizes on the need for a more rigorous process of governance policies over the entire model. Therefore, despite of differences between US and European banks, SR 11-7, as a global standard of model risk management, being adjusted by banks and regulators in Europe.

Moreover, while the main concern of the US regulations on model risk management addresses the governance, the greater emphasis of European regulations is on the technical aspects of model risk. However, overcoming the lack of resources and practice for aggregating model risk remain as challenges toward the future steps on European regulations.

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