Looking forward with the IFRS 9 expected loss model: An illustrative example

Certainly one of the key-aspects of the new IFRS 9 requirements is the new expected loss framework, which should lead to earlier recognition of potential credit losses. During the crisis, the current IAS 39 framework was criticized for too late recognition of losses and therefore underestimation of provisions. The new standards prescribe the usage of forward-looking information for estimating future losses in credit portfolios.

In this white paper, we discuss one of the main challenges for IFRS 9 model developers: the inclusion of forward-looking information such as macro-economic forecasts into the expected loss model. Using a relatively simple example and basic statistics, we illustrate how a model, which seems promising at first sight, can be sub-optimal and is subject to model risk. Moreover, we propose an alternative, more direct approach for the use of macro-economic forecasts in the expected loss framework.

Although from a statistical perspective this alternative approach could lead to models that are more accurate, it is worth noting that there are more aspects to consider, such as alignment of other internal processes within banks. Since such an assessment is institution specific, the aim of this paper is to provoke a critical view on the use of macro-economic forecasts in the risk framework.

This paper presents a message for modellers in the field of credit risk. Namely, we introduce the idea that perhaps forecasts should play a fundamental role in IFRS 9 models, rather than being treated as an ex-post input. For readers less familiar with IFRS 9 and financial models, this paper can serve as an introduction to some modelling aspects and illustrates why the forward-looking nature of IFRS 9 is challenging.

Main takeaways
- The use of economic forecasts is recommended for IFRS 9 expected loss estimation.
- Relating a credit portfolio to economic forecast data is challenging.
- The way forecasts are treated in an IFRS 9 model could affect both the accuracy of the expected losses and the volatility of the required provisions over time.
- RiskQuest believes forecasts should play a key role in the IFRS 9 models, instead of being an ex-post input.
Introduction

At the moment of writing, financial institutions are preparing for new accounting standards as issued by the International Accounting Standards Board (IASB) and referred to as IFRS 9. These standards will become effective in 2018 and consist of three elements: classification and measurement of financial instruments, hedge accounting and impairment of financial instruments. From a modelling point of view, the latter poses a challenge due to the changes compared to the current IAS 39 standards.

A key-aspect introduced by the IFRS 9 impairments framework is an expected loss model, which results in earlier recognition of credit-losses. Within IFRS 9, credit risk models must: “recognise lifetime expected credit losses (...) considering all reasonable and supportable information, including that which is forward-looking” 1. For credit risk modellers, this forward-looking aspect introduces an extra dimension, which is often captured by relating expected losses to the macroeconomic variables (e.g. GDP, unemployment rates). This will pose new challenges due to the underexposed use of macro-economic information within credit risk modelling. Moreover, macro-economic modelling is an entirely separate area, with the need for the build-up of much new expertise. Yet the quantitative modelling of the macro-economy has proven to be difficult.

The new accounting standards will have a significant impact on the provisions of financial institutions, which serve as a back-up for expected credit losses, hence, credit portfolios will typically be valued lower in the accounting book. In addition, the provisions will tend to be more volatile as it will depend heavily on economic cycles. For that reason, expected credit loss models will have a more profound impact on the balance sheet and profit and loss statement of financial institutions.

In this article, we illustrate how economic forecasts can be used to estimate future credit losses. Hereby we focus on the forecast of default rates through the Probability of Default (PD) estimation. Although this is only one component of a credit loss model, it might be most easily interpretable for a wide audience. Financial institutions use diverse approaches to build IFRS 9 compliant models, and often PD has an important role2 due to its heavy use in most credit-risk systems. Furthermore, the discussion in the paper can be placed in a broader perspective, as all IFRS 9 models have in common that certain components must be dependent on economic forecasts.

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1 Refer to IFRS 9 5.5.4.
2 Note that a possible approach can be not to model the PD as a separate parameter of expected loss.
As it is widely accepted that default rates are correlated with the state of the economy, economic figures are often used to model default rates. However, which macro-economy information is most suitable depends on multiple factors, such as the type of loan portfolio and financial institution.

In Figure 1, developments of the mortgage default rates and the unemployment rates are drawn. For this paper, a fictive dataset is constructed, which is partially based on public data. The above graph confirms the idea that the two statistics are correlated. Indeed, the correlation of the two time series constructed for this paper equals 84%.

In the remainder of this paper, a simplified regression model is built describing the relation between default rates and the macro-economic variable. Afterwards, we discuss a weakness of the model, namely that it does not take into account additional uncertainty and possible biases of the macro-economic forecasts that will be used to predict the default rate. We show that a model built directly on forecasts is considerably different and demonstrate that this might be a viable alternative to a model built on the observed macro-economic quantities.

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3 The default rates used for this paper are based on the S&P/Experian First Mortgage Default Index. The unemployment rates are taken from IMF’s World Outlook Databases. As the IMF database only contains end-of-year data and a limited amount of predictions, cubic splines are used to obtain a bi-yearly time sequence. Please note that, therefore, the dataset used for this paper is fictive. Although the numbers presented in this paper seem representative, no direct conclusions can be drawn from the data.
Building a model

In this section, a simplistic model is constructed based on the realised observations of semi-annually default and unemployment rates. From a theoretical perspective, 23 observations might seem low; however, in practice longer default rate data is often not available. The resulting observations are plotted in Figure 2.

From this point, performing a regression seems the first choice. The model used to relate the unemployment rates to the default rates\(^4\) is:

\[
r_{\text{default}} = \exp(a + b \cdot r_{\text{unemployment}})
\]

Here \(r_{\text{default}}\) represents the estimated default rate, which is the variable we would like to estimate. The variable \(r_{\text{unemployment}}\) is the explanatory variable, which is the unemployment rate in this example. The parameters \(a\) and \(b\) are chosen such that the estimated default rates \(r_{\text{default}}\) are as close as possible to the observed default rates. More precisely, the squared errors are minimized. In Figure 2 the resulting curve is plotted. The figure supports the hypothesis that there is a relation between unemployment and mortgage defaults in this sample. Furthermore, the root mean squared error (RMSE) is relatively small, namely 0.443%. Hence, with not much effort, it seems that a relatively strong model is constructed.

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\(^4\) Note that in the limit of low default rates the above model is similar to logistic regression (logit model), a model commonly used for PD.
From a modeller’s point of view, the above results seem satisfying. The challenge however, lies in the model’s application. Suppose, for example, that the model is used for forecasting default rates one year in advance. Along with the unemployment rates, International Monetary Fund (IMF) publishes forecasts as well, which can be used to test the model. We test the model by replacing the observed unemployment rates by their forecasts one year in advance and at the same time fixing the parameters $a$ and $b$. The resulting RMSE is 0.924%. The model performance decreases significantly when including forecasts.

The use of forecasts thus introduces an additional error to the prediction of default rates and hence expected losses for IFRS 9. When focusing on relating default rates to the macro-economy, potential pitfalls stem from ignoring that forecasts are needed for model application. Besides additional uncertainty, it can also be the case that the model used for unemployment predictions is biased, hence incorporating such biases into the expected loss prediction. Such biases cannot be excluded, since macro-economic forecasts often contain some form of expert knowledge.

In the following section, it is illustrated how model performance can be improved when taking into account explicitly its predictive application in the model design.

**Model on forecasts**

We now present an alternative to the discussed approach. We will not make any changes in the model itself, but only adjust the way forecasts are included in the model. Instead of regressing on the observed unemployment rates, the regression is performed on the unemployment rates as forecasted one year in advance. In other words, the explanatory variable $r_{\text{unemployment}}$ is replaced by its forecasts. In Figure 3 the regression is drawn next to the fit of our original method. The relation between the unemployment and default rate has become slightly weaker. This is understandable, since the default rates include the effect of the realised macro economy in contrast to a forecast, which can contain inaccuracies. For that reason, the fit is worse than in the original approach. The RMSE of the new fit is 0.885%, which is significantly larger than the 0.443% of the original fit. However, in the first method the RMSE increased to 0.924% when including the forecast. For the second approach this step is already included in the fitting process. The second method, therefore, has slightly smaller errors on the forecasts.

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5 A more comprehensive test would involve a backtest, which calibrates and estimates on different data sets. This is not conducted in this paper to preserve simplicity, and because data is scarce.
Now that two methods of building a forecast model for the default rates are introduced, we can compare results for both models. One can see that, by construction, the RMSE is always smaller for the second method. In Table 4 the errors are compared for various forecast horizons. We see that the difference in errors is relatively small when forecasting for semi-annual or annual horizons, but increases significantly when increasing the forecasting horizon. Note that from an IFRS 9 perspective, this increases the uncertainty of multi-year forward expected loss estimates.

Besides the increase in accuracy, the alternative model exposes two additional results. Firstly, an IFRS 9 model, which takes into account uncertainty of the macro-economy (with the use of forecasts), is likely to show more realistic errors in EL estimation. Secondly, in a model with forecasts, the relation between the losses and the economy is generally weaker. Note that the latter results in a less volatile expected loss model.

<table>
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<tr>
<th>Forecast horizon</th>
<th>Method 1</th>
<th>Method 2</th>
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<tr>
<td>0.5</td>
<td>0.770</td>
<td>0.743</td>
</tr>
<tr>
<td>1.0</td>
<td>0.924</td>
<td>0.885</td>
</tr>
<tr>
<td>1.5</td>
<td>1.396</td>
<td>1.215</td>
</tr>
<tr>
<td>2.0</td>
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<tr>
<td>2.5</td>
<td>1.936</td>
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</tr>
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</table>

*Table 4: RMSE (%) for both methods.*
Discussion
In this paper, two simplified default rate forecast models are compared, making use of unemployment rate data. Initially, the first model seemed promising, as relatively small regression errors were observed. However, these errors turned out to be misleading, as they did not take into account the accuracy of the forecast of the macro-economic variable needed when the model is used. More realistic errors were estimated in the second model. The second model turned out to be more accurate when considering forecast data.

In practice, IFRS 9 models will be far more sophisticated than the models presented in this white paper. Nevertheless, the simplistic models in this paper serve as an illustrative message for IFRS 9 modellers. Namely, that the inaccuracy in forecasts is one of the main drivers of model errors. Furthermore, it can very well be beneficial to have forecasts in the core of the model, instead of treating them as an add-on. Although the inclusion of macro-economic forecast as an add-on can serve as a means of adding expert information into provisions, this should not hamper the direct use of macro-economic forecast during calibration. For example, forecasts could be included in the model’s calibration process to take into account for the bias in the forecasts. This makes the model less sensitive for (false) forecasts, makes the expected losses less volatile, and above all, can result in a more accurate model.

However, from a governance perspective this could imply a radical change in the use of macro-economic forecasts. It is often that such forecasts are determined internally within banks and used for multiple purposes e.g. portfolio strategy, budgeting, stress testing. Alignment between the various processes is important, hence potential changes to this framework should first be carefully assessed.

Conclusion
The IFRS 9 forward-looking property of expected loss models introduces a new challenge for credit risk modellers. The challenge does not limit to relating the losses to the economy, but lies for a significant portion in the application of the model to scarce and unreliable forecast data. Using an illustrative example, this paper shows how an expected loss models’ accuracy could easily be overestimated. The example indicates that expected loss models could be more accurate and less volatile over time when including forecasts directly in the estimation process, instead of treating them as ex-post input.
Appendix: Some additional considerations

Why data is so scarce

A statistician might argue that the data used for this paper is too restricting in order to perform reliable analyses. Only annual unemployment rates are used for a period of less than 12 years. One might even argue that there is only one observation, as the study considers only one economic cycle.

Indeed, in practice default and economic data is scarce. Each credit portfolio has its own characteristics, so it is challenging to make assumptions about a portfolio’s future behavior, especially when data is available for only a short time period. A consistent data source for economic forecasts is, almost by definition, scarce as well. Furthermore, the economy’s behavior changes over time and there are no laws that will hold endlessly.

Thus, the best a modeler can do is using as much information as possible, without relying too much on the statistical power of the model. Moreover, it is important to use common sense as a modeler and not solely rely on statistics.

Advanced models

For this paper, a relatively basic model is used to be able to address a wide audience and not to distract the reader from the relevant points made. In practice, however, models tend to be more advanced. A better model can be achieved when varying the regression model. In addition, more economic data can be used to achieve a higher correlation and more accurate forecasts. For example, default rates are known to be strongly correlated to the gross domestic product.

Another improvement can be achieved by modeling on relative values. For example, a model on the change of default rates can be more accurate than a model on the absolute value.

Finally, we would like to address a less straightforward way of improving the model’s predictive power. One could apply time shifts to both the realizations and forecasts. Combining different realizations and forecasts of different time instants might improve the model’s predictive power.

Besides predictive power, data availability and complexity, there are various aspects that can determine a choice for a model. Therefore, it is not feasible to construct a generic IFRS 9 model that is optimal for every credit portfolio.
RiskQuest is an Amsterdam based consultancy firm specialised in risk models for the financial sector. The importance of these models in measuring risk has strongly increased, supported by external regulations such as Basel II/III and Solvency II.

Advanced risk models form the basis of our service offer. These models may be employed in a frontoffice environment (acceptance, valuation & pricing) or in a mid-office context (risk management and measurement).

The business areas that we cover are lending, financial markets and insurance. In relation to the models, we provide advice on: Strategic issues; Model development; Model validation; Model use.