IFRS9 Forward-Looking Modeling

Supervised Macroeconomic Index

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IFRS9 Forward-Looking Modeling in Practice

- IFRS9 requires the inclusion of future reasonable and supportable information, available without undue cost or effort, when estimating expected credit losses.
- In practice, this often involves assessing how the macroeconomic environment affects risk parameters, typically at the segment level - for instance, by regressing default rates on macroeconomic indicators. Such analyses are generally known as forward-looking (FLI) exercises.
- Most FLI implementations rely on OLS regression, with common model types including:
  - OLS regression in the form of the target variable against macroeconomic indicators (with or without time lags);
  - OLS regression, including macroeconomic indicators and an autoregressive term of the target;
  - Two-step error correction models;
  - Principal Component Analysis (PCA) combined with OLS regression;
  - OLS regression with various transformations of the target variable, such as logit or probit.
- Although the above list is not exhaustive, it highlights an important question: even when combining several of these methods and design approaches, can practitioners effectively capture all critical business inputs?

IFRS9 Forward-Looking Modeling Challenges

The main constraint in the FLI exercise that creates most of the challenges for practitioners is the limited number of observations typically available.

Some of the most common challenges caused by the limited number of observations include:

1. Low ratio between the number of observations and available predictors: put simply, practitioners often face a situation where there are too many potential predictors for too few observations. As a result, it is usually not statistically sound to include more than three predictors in a single model. Although this can vary in practice, typically no more than three predictors are used.

2. Incorporation of business-guided macroeconomic indicators in the FLI model: one of the key inputs from the macroeconomic department and business experts is often a list of potentially important predictors for the target variable. In addition to suggesting specific macroeconomic indicators, they typically provide further guidance - such as the expected relationship with the target variable, the impact of an indicator at a specific time lag, or recommendations to group certain indicators that should not appear in the same model. However, the limited number of observations, combined with other statistical constraints, presents a significant challenge for practitioners trying to incorporate these business inputs effectively.

3. Asymmetric or opposing impacts of macroeconomic indicators under different economic conditions or when specific thresholds are reached: in practice, practitioners often discuss this challenge alongside the previous two. When certain macroeconomic indicators are selected for this type of testing, additional analysis is typically required to determine the optimal thresholds for defining economic regimes, as well as to create new derived indicators and incorporate them into the model design. Consequently, this challenge can also be seen as stemming from the limited number of available observations, as practitioners - even without deriving new predictors - often face a relatively low ratio between the number of observations and predictors.

IFRS9 Forward-Looking Modeling Challenges

4. Balancing the impact of macroeconomic indicators and other predictors: often, the development of the target variable cannot be fully explained by macroeconomic indicators alone. However, the typical first step in FLI modeling is to explain as much of the target variable's variability as possible through the macroeconomic environment, then incorporate other important events usually not captured by these indicators. The limited number of observations poses a significant challenge in combining these inputs while controlling for the expected signs of the estimated coefficients.

5. Ensuring model stability and reliable forecasts: when practitioners choose an FLI model that relies on only one or two macroeconomic indicators, such models are often viewed by validators and regulators as overly sensitive to those specific indicators and therefore not well-suited for the FLI exercise. This limited specification is also seen as insufficient to capture the broader and more complex influence of the macroeconomic environment. As with the previous challenge, this issue often stems from the limited number of available observations. Incorporating a larger set of macroeconomic predictors typically introduces difficulties in meeting both business expectations and fundamental statistical requirements for model robustness.

6. Meeting statistical criteria for model selection: in balancing business expectations with statistical rigor, practitioners typically rely on a set of statistical metrics/tests to guide the selection of the FLI model. These criteria are often sensitive to sample size and, in particular, to the ratio between the number of observations and the number of predictors. When sample sizes are small, including too many predictors can undermine model reliability. Consequently, satisfying statistical requirements is generally more feasible when the model is built on a higher observation-to-predictor ratio.

Supervised Macroeconomic Index

In response to the major challenges practitioners face - many of which stem from a limited number of observations - Andrija Djurovic proposes the Supervised Macroeconomic Index (SMI) approach.

The SMI enables practitioners to incorporate critical inputs into the FLI modeling process, such as the overall impact of the macroeconomic environment through model averaging, while maintaining control over the expected relationship between macroeconomic indicators and the modeled target. Additionally, it allows for straightforward control of the contribution of specific macroeconomic indicators to the model predictor in response to correlations among predictors. The greater flexibility of the SMI helps practitioners address key limitations of another method commonly considered in FLI modeling - Principal Component Analysis (PCA).

The following steps provide a general framework for constructing and using the SMI for the purpose of the FLI exercise.

1. Define the set of candidate macroeconomic indicators that can be used as predictors for the FLI model.
2. For each individual macroeconomic indicator, define the maximum time lag to be considered in the modeling process.
3. For each individual macroeconomic indicator, define the expected relationship with the modeled target variable.
4. Based on steps 1 to 3, define groups of predictors to be combined for the model estimation process.
5. Define the maximum number of predictors to be included in the model.
6. Combine the groups of predictors from step 4, up to the maximum number defined in step 5, to generate potential regression models.
7. For each combination of predictors from step 6, estimate a constrained OLS regression of the target variable on the combined predictors. The constraints should, at a minimum, reflect the expected sign of coefficients based on the assumed relationship between macroeconomic indicators and the target variable.
8. Exclude all regression models in which at least one estimated coefficient for a macroeconomic indicator equals zero.

Supervised Macroeconomic Index cont.

9. From the remaining regression candidates, construct the Supervised Macroeconomic Index (SMI) as a model average.
10. Use the SMI from step 9, either alone or in combination with additional predictors that capture significant developments affecting the target but not reflected in the macroeconomic environment, to run an integrated OLS regression of the target variable on the SMI and other predictors.
11. Evaluate model performance, address any violations of OLS assumptions, and fine-tune the model accordingly.

The above steps provide a general framework for constructing and using the SMI, but practitioners can adjust certain parts of the process. For instance, instead of running constrained OLS on all possible combinations from one to the maximum number of predictors, practitioners may choose to begin with bivariate analysis, selecting one or a few macroeconomic indicators per group. This approach can significantly reduce execution time, especially when there are many predictor candidates. Additionally, to account for correlations between macroeconomic indicators, practitioners can go beyond constraining only the expected signs by also controlling the range of coefficient values based on the results of the bivariate regressions. Furthermore, once the SMI is constructed, practitioners can test and implement various regression designs, including modeling in first differences, dynamic regressions, or the inclusion of lagged dependent variables.

Overall, the SMI offers a simple and straightforward way to address some of the key challenges practitioners currently face in the FLI exercise, while maintaining a fully explainable model design - comparable to the standard use of OLS regression for the same purpose.

The following slides demonstrate this process, providing concrete steps for one possible design of the SMI and its use in the FLI exercise.

Simulation Study Design

Assume the FLI exercise is conducted using the following inputs:

1. The FLI exercise is performed under the assumption that the bank risk indicator used is the observed default rate (`ODR`), while the macroeconomic indicators considered as potential predictors are: unemployment (`UNEMP`), year-over-year GDP growth (`GDP`), year-over-year wages growth (`WAGE`), and the 6-month Euribor (`EURIBOR`). Additionally, the bank has defined a dummy variable (`DUMMY`) to account for a significant change in the bank's internal credit risk process that began in `Q1 2021`.
2. The above data are reported as quarterly snapshots, ranging from `Q1 2011` to `Q2 2025`.
3. The data used for this simulation are available at the following link.

With the above input data defined, the following steps demonstrate the construction and use of the SMI for the FLI exercise.

1. Assume that each macroeconomic indicator can have a potential impact on `ODR` with a delay of up to four quarters. In other words, the maximum time lag for each macroeconomic indicator is considered to be four quarters.
2. To create macroeconomic indicator groups, assume that each group consists of a single macroeconomic predictor with the time lag defined in Step 1. This means that in subsequent steps of combining predictors, it is not allowed to include the same macroeconomic indicator with two different time lags in the same predictor combination. The variable `DUMMY` is not considered in this step for the creation of macroeconomic indicator groups, but it will be included in later steps and in the integration regression.
3. Define the expected relationship between the macroeconomic indicators and the target as follows: `GDP` and `WAGE` are negative, while `UNEMP` and `EURIBOR` are positive.

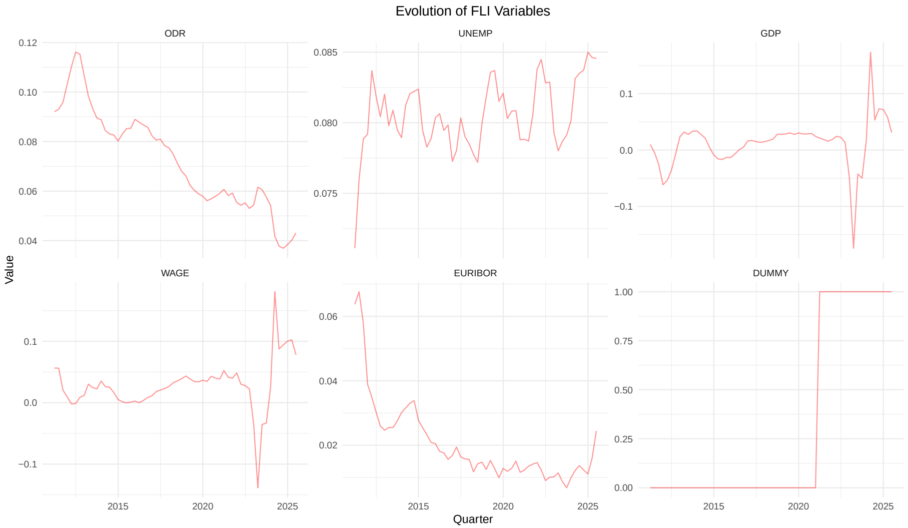
Simulation Study Design cont.

4. Assume that no more than three macroeconomic indicators can be combined.
5. Given the inputs from the above steps, run all possible OLS combinations constrained by the expected sign of each macroeconomic indicator.
6. For all estimated constrained OLS models, discard any regressions where at least one coefficient for a macroeconomic indicator is equal to zero.
7. Calculate the Supervised Macroeconomic Index (SMI) as the simple average of the remaining models from Step 6.
8. Use the SMI to run an integrated OLS regression of the form `ODR ~ SMI + DUMMY` as a candidate FLI model.
9. Perform model validation, including any fine-tuning or adjustment of the estimated coefficients or their standard errors. Use the model to validate the potential forecast and determine the final model.

Note:

The presented steps are intended for demonstration purposes only but provide a solid foundation for further adjustments in the creation of the SMI. Therefore, practitioners are encouraged to adapt the process to better suit specific needs or inputs.

Simulation Results



Simulation Results cont.

SMI Structure Overview

```
##      coefficient estimate
## 1    (Intercept)   0.0356
## 2        EURIBOR   0.2380
## 3   EURIBOR_lag1   0.2852
## 4   EURIBOR_lag2   0.3051
## 5   EURIBOR_lag3   0.2503
## 6   EURIBOR_lag4   0.1819
## 7            GDP  -0.0107
## 8       GDP_lag1  -0.0162
## 9       GDP_lag2  -0.0153
## 10      GDP_lag3  -0.0115
## 11      GDP_lag4  -0.0072
## 12    UNEMP_lag1   0.0061
## 13    UNEMP_lag2   0.0249
## 14    UNEMP_lag3   0.0482
## 15    UNEMP_lag4   0.0943
## 16          WAGE  -0.0179
## 17     WAGE_lag1  -0.0221
## 18     WAGE_lag2  -0.0213
## 19     WAGE_lag3  -0.0142
## 20     WAGE_lag4  -0.0076
```

FLI Model

```
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.0034     0.0061 -0.5535   0.5823
## smi           1.1126     0.0790 14.0773   0.0000
## DUMMY        -0.0131     0.0022 -5.9376   0.0000
```

Simulation Results cont.