IFRS9 Forward-Looking Modeling

Dynamic Regression Models and Estimation Uncertainty

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IFRS9 Forward-Looking Modeling

- IFRS9 requires the inclusion of reasonable and supportable information, available without undue cost or effort, when estimating expected credit losses.
- In practice, this often translates into quantifying the macroeconomic environment's effect on risk parameters, typically at the segment level (e.g., regressing default rates on macro indicators).
- Most 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.
- Another design often discussed among practitioners - but rarely implemented in practice for IFRS9 modeling - is the use of dynamic regression models. Unlike models that simply include a lagged dependent variable, dynamic regression models assume that residuals follow a specific autoregressive structure. Although rarely applied in practice, some practitioners consider this approach suitable for IFRS9 purposes.
- One known challenge in estimating the autoregressive structure in IFRS9 models is the limited length of available time series. This presentation simulates the uncertainty associated with sample size and the estimation of the autoregressive term within a dynamic regression model. While this is only one possible approach, it offers a solid foundation that practitioners can adapt to their specific model design.

Dynamic Regression Models

The dynamic regression model is represented by the following equation:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \eta_t$$

where the residuals η_t follow an ARIMA(p,d,q) process.
More formally, the ARIMA(p, 0, q) process for the regression residuals can be written as:

$$\eta_t = \phi_1 \eta_{t-1} + \cdots + \phi_p \eta_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

where:

- ϕ_1 to ϕ_p are the autoregressive terms;
- θ_1 to θ_p are the moving average terms;
- ε_t represents white noise innovations.

As the following simulation study uses an ARIMA(1, 0, 0) process, the error term structure simplifies to:

$$\eta_t = \phi_1 \eta_{t-1} + \varepsilon_t$$

More details on dynamic regression models can be found in Hyndman, R.J. and Athanasopoulos, G. (2021), Forecasting: Principles and Practice (3rd edition).

Simulation Study Design

The following steps outline the simulation design used to derive the distribution of the predictor coefficient and the autoregressive term of the error in dynamic regression models across different sample sizes. For simplicity, the setup includes only one predictor and a first-order autoregressive process for the error term.

1. Select sample size n (10, 20, 30, 40, 50, 60, 100).
2. For each sample size, simulate predictor values (x_t) from a normal distribution with a mean of 15 and a standard deviation of 1.
3. Simulate error terms (η_t) following an ARIMA(1, 0, 0) process with an autoregressive coefficient (ϕ) of 0.50 and innovations (ε_t) drawn from a standard normal distribution.
4. Using the simulated predictor values (x_t), errors (η_t), an intercept (β_0) of –2.95, and a predictor coefficient (β) of –0.65, generate the target variable as:

$$y_t = \beta_0 + \beta x_t + \eta_t$$

5. Estimate the parameters of the dynamic regression model with an ARIMA(1, 0, 0) error structure by minimizing the sum of squared innovations (ε_t).
6. Repeat steps 2 to 5 a total of 10,000 times for each sample size, and store the estimated coefficients (β and ϕ).
7. Calculate the estimation bias as the difference between the average estimated coefficient and the true value used in the simulation.
8. Graphically present the distribution of the estimated coefficients to illustrate the estimation uncertainty associated with different sample sizes.

Simulation Results

```
##     n Beta_Mean Beta_Bias AR_Error_Mean AR_Error_Bias
##    10    -0.647     0.003         0.204        -0.296
##    20    -0.653    -0.003         0.378        -0.122
##    30    -0.650     0.000         0.421        -0.079
##    40    -0.655    -0.005         0.442        -0.058
##    50    -0.650     0.000         0.455        -0.045
##    60    -0.651    -0.001         0.461        -0.039
##   100    -0.648     0.002         0.476        -0.024
```

Simulation Results cont.