Operational Risk Stress Testing:
An Empirical Comparison of Machine Learning Algorithms and Time Series Forecasting Methods

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Motivation

- The European Banking Authority launched 2016 EU-wide stress test with a focus on Operational Risks and Conduct Risks.

- Models to measure the response of the Operational Risk profile of systemic financial institutions to macroeconomic shocks are needed.
We look for a way to accurately predict $Y$ given some values of $X$.

1. Summarize $X$ using PCA. Collect $\tilde{X}$ (principal components) and $\Gamma$(PCA weights).
2. Estimate a model $Y = f(\tilde{X}) + \varepsilon$, which maps $\tilde{X}$ into $Y$.
3. Construct the stressed principal components $\tilde{X}^s = \Gamma X^s$.
4. Compute $\mathbb{E}[Y|\tilde{X}^s] = f(\tilde{X}^s) = \hat{Y}^s$. 

Definitions

$Y = \text{Historical Op.Loss. Series (e.g. frequency of operational loss events)}$

$X = \text{Historical Macroeconomic Variables (e.g. GDP growth, interest rates)}$

$X^s = \text{Macro Stress Scenarios}$
Modelling Approaches

- **MARS Model**: non-parametric regression that automatically models non-linearities and interactions among variables

- **Artificial Neural Network**: regression algorithms able to approximate highly complex functions, to learn and generalize to unknown data

- **Error Correction Model**: time series approach to simultaneously model long and short run dynamics of the variables
Multivariate Adaptive Regression Splines (MARS)

Standard MARS (Friedman 1991):

\[ Y = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(\tilde{X}) + \varepsilon, \]

Hinge functions \( h_m(\tilde{X}) \) are defined using a two-step algorithm that selects knots and relevant regressors for \( Y \).

Bagged MARS (Breiman 1996)

Let \( \hat{\theta}^*_M(x) \) be a bootstrap predictor; the bagged MARS estimate is defined as:

\[ \hat{\theta}_{M;\text{bag}}(x) \approx J^{-1} \sum_{j=1}^{J} \hat{\theta}^*_{M,j}(x). \]
Artificial Neural Networks (ANN)

Model components:

\[ Z_m = \sigma(\alpha_{0m} + \alpha^T_m \tilde{X}), \quad m = 1, \ldots, M, \]
\[ T = \beta_0 + \beta^T Z, \]
\[ Y = g(T) + \varepsilon. \]

The model is estimated using the back-propagation algorithm.
Error Correction Models (ECM)

Model Structure:

\[ \Delta y_t = \psi_0 + \gamma_1 \hat{z}_{t-1} + \sum_{s=1}^{k_{\text{diff}}} \sum_{i=0}^{p} \psi_{1,s,i} \Delta \tilde{x}_{s,t-i} + \]
\[ + \sum_{j=1}^{p} \psi_{2,i} \Delta y_{t-i} + \sum_{s=1}^{k} \sum_{i=0}^{p} \psi_{3,s,i} \tilde{x}_{s,t-i} + \nu_t. \]

\( \hat{z}_t \) stands for the error correction term estimated via the Engle-Granger approach.

Stationarity has been tested using ADF test, KPSS test and PP test.
Operational loss data gathered from the Operational and Reputational Risk Department of a European systemic financial institution.

Macroeconomic data span various regions and different classes. Data are summarized using PCA. Ten principal components are used in all the models.

Figure: Deseasonalized Operational Loss Frequency Series: Monthly Observations
Empirical Applications: MARS Outcomes (1/2)

Eight versions of MARS have been estimated based on:

1. Linear predictors - Nonlinear predictors
2. Degrees of interaction (one or two degrees)
3. Standard MARS - Bagged Mars

Example Predictors: hinge functions
Cross validation has been used to detect the best performing model in terms of out of sample forecast error.
Empirical Applications: ANN Outcomes

Twenty different networks have been fitted according to various combinations of the following features:

1. Starting values of the network weights
2. Number of hidden units and layers
3. Linear and non-linear networks

All variables have been scaled (to ease convergence of the backprop. algorithm) according to:

\[ X_t^* = \frac{\tilde{X}_t - \tilde{X}_{\min}}{(\tilde{X}_{\max} - \tilde{X}_{\min})} \]
Empirical Applications: ANN Outcomes

Figure: Neural Network Outcomes

MSE = 3328.77
Beta = 1.044
R^2 = 0.940
Empirical Applications: ECM Outcomes

The graph shows in-sample fitting performances of the ECM model.

- ECM: Scatter plot actual and fitted values
- ECM: Ts-plot actual and fitted values
- ECM: Residuals q-q plot
- ECM: Residuals autocorrelation function

Significant at the 0.99 level
Once the models are fitted, they can be used to forecast the Operational loss dynamics, conditional to some macroeconomic scenarios.

Stress scenarios are passed through the models as stressed principal components:

\[ PC_{1,T+s} = \alpha_{11}x_{1,T+s} + \alpha_{12}x_{2,T+s} + \ldots + \alpha_{1k}x_{k,T+s} \quad \text{for } s = 1, \ldots, S \]

Stress on OpLoss frequency has been studied using the following models:

- Non-linear bagged MARS
- Linear and non-linear ANNs
- ECM
- Forecast combination (average of forecasts from previous models)
Widespread Scenario - response of loss series

**Figure:** Scenario Widespread Contagion - Forecasts
China Hard-Landing Scenario - response of loss series

**Figure:** Scenario China Hard Landing - Forecasts
Conclusions

- The macro economy and its effects on Operational losses are complex processes: sophisticated methods are needed.

- Empirical testing indicates that ANN, MARS and ECM provide very similar predictions to the same scenarios. Results appear to be robust.

- In terms of forecasting performances, bagged MARS models seem to be the best choice to approach EBA stress tests on Operational Risks.

- Operational losses tend to increase as a consequence of negative shocks from the macro economy.

Future enhancements

1. Estimate time-lag between macro shocks and losses response
2. Estimate non-linear ECM using MARS algorithm
3. Test performance of ANN allowing for adaptive learning rates
Thank you for your attention.

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