A new approach to
Early Warning
Systems for smaller
European banks

Developed by Division Analysis and
Methodological Support
DG Micro-prudential Supervision III
European Central Bank

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Agenda

1. Introduction
2. Approach
3. Results
4. Conclusion and next steps
5. Discussion

Disclaimer
This presentation should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.
Background: General approach to indirect supervision

ECB / DG-MS 3
Supervisory oversight

Regular reporting of quantitative and qualitative information

Guidelines and general instructions

NCAs
Banking supervision

Approx. 3,000 LSIs
High priority

ECB is responsible for the effective and consistent functioning of the SSM and is entrusted with an oversight responsibility to ensure that the supervisory activities are of the highest quality

High priority

Crisis

Banking supervision

Regulatory reporting

LSIs
(Less Significant Institutions)

A new approach to Early Warning Systems
Motivation

• In order to fulfil its mandate DGMS3 has developed an early warning system tailored for indirect supervision in the context of less significant institutions = LSI-EWS

• Existing EWS are usually based on conventional modeling techniques, e.g. logit, calibrated using only a very small number of distress events

• In contrast, we propose a different approach:
  – Application of **machine learning** techniques to derive a decision tree based model
  – **Broadened definition of distress** based on triggering of Bank Recovery and Resolution Directive’s (BRRD) early interventions measures in addition to conventional definition
    • Banks which breach or are close to breaching the minimum capital requirements
    • Complemented by qualitative indicators, e.g. notifications by National Competent Authorities

• Explanatory variables consider three different sets
  – **bank-specific**,  
  – **banking-sector** variables and 
  – country-level **macro-financial** indicators
Underlying data

- The quality of the resulting tool is determined by the underlying data → most important step in the project
- The study builds on a unique dataset comprising
  - more than 3,000 small banks including approx. 350 distress events
  - period from 2014Q4 – 2016Q1

- Several challenges identified!

Data availability
Financial reporting data collection was only available once a year
Time gaps between reference date and submission of data

Data quality
Reporting is often not complete (missing values)
Reported data points might contain errors

Data comparability
Majority of LSIs (approx. 75%) report financial figures according to national GAAP which are not in line with IFRS
Resulting comparability issues might distort prediction results

→ In-depth data preparation to mitigate issues and follow-up actions
Data pre-processing

- Required to ensure that unreliable, noisy data and irrelevant/redundant information is eliminated, i.e.

**Data cleaning**: Removal of certain banks and variables
- Banks where the majority of relevant data is missing
- Variables where the majority of values is missing or variance is nearly zero
- Variables which are highly correlated with each other

**Data transformation**: Create consistency and comparability across banks
- Adjust data to consider nGAAP specifics, i.e. profitability adjusted for non IFRS compliant reserves
- Normalization of variables through creation of ratios, e.g. RoA, RoE or NPL ratio

- Final set of indicators is selected based on their ability to predict distress:
  **Variables are ranked** according to their importance, captured by the AUC for each indicator; outcome presents the top 100 variables as input for the modelling
Modelling – Why to apply ML for distress prediction

- LSI-EWS as a complement to the LSI Risk Assessment System within the SREP and other projects which are mainly based on expert knowledge
  - In respective cases “ground truth” considered to be known
  - Follow a different approach and learn from data/past observations a model
  - In addition, recent literature suggests the application of Machine Learning (ML) approaches for default prediction

- Supervised learning setting using a decision tree classifier considering
  - Predictive performance, transparency and usability of the model
  - Robustness of the model and results
  - Capability to handle missing values

- Quinlan’s C5.0 classifier to build the classification tree model comprising boosting, which constructs an ensemble of classifiers
Modelling

• Prediction horizon is 3-months

• Conservative approach to avoid missing distresses:
  We assume during modelling that the cost of misclassifying a distress event is twice as large as the cost of misclassifying a non-distress event

• To increase the robustness of the variables to be included in the final model we follow a similar approach to Alessi and Detken (2014):
  – Instead of using a single tree, n separate decision trees (trials) are grown and combined to make more accurate predictions. = Boosting
  – Then, rank variables by occurrence within the trials and select the top 20 variables to go into the final model complemented by expert judgement
  – Ensures robustness of the model
The resulting model

• The identified tree consists of 19 nodes and covers 12 distinct explanatory variables (see also annex)
• The indicator in the parent node is profitability, adjusted for different accounting standards across SSM jurisdictions.
• The tree nicely illustrates interactions between different variables, e.g.:

For profitable banks, one can notice that if the non-performing loans ratio is high, the coverage ratio is considered. → Coverage ratio can compensate if sufficient allowances on non-performing loans are created…
Validation

• The in-sample predictive performance of the LSI-EWS is very high which is confirmed by an out-of-sample validation (based on a 75% vs. 25% split of initial data)

• Results assessed in terms of
  ▪ Area Under the receiver operating characteristic Curve and
  ▪ Cohen’s kappa statistic

  Both are standard measures of accuracy in the early warning system literature and are robust to imbalances in the class distribution

• Application of a logit model also showed very good results, but the logit model missed more distress events than the decision tree

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<thead>
<tr>
<th></th>
<th>In-sample (Training)</th>
<th>Out-of-Sample (Test)</th>
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<tbody>
<tr>
<td>AUC</td>
<td>0.95</td>
<td>0.92</td>
</tr>
<tr>
<td>Cohen’s Kappa</td>
<td>0.886</td>
<td>0.803</td>
</tr>
<tr>
<td>Type I error rate</td>
<td>0.010</td>
<td>0.033</td>
</tr>
<tr>
<td>Type II error rate</td>
<td>0.109</td>
<td>0.099</td>
</tr>
</tbody>
</table>
Conclusion

- The LSI-EWS provides a new approach for identifying bank distress in the European banking system:
  - Distress is based on a broadened definition, e.g. considering the BRRD, to overcome the problem of limited actual distress events and to ensure a forward looking approach
  - The tool follows a machine learning approach based on a decision tree model to provide more transparency and good performance → confirmed by promising first results and additional backtesting
- Several items identified to further improve the current approach:
  - Enrichment of the data (FINREP and additional variables) and extension of the prediction horizon to up to six months
  - Differentiate between severeness of distress events
- Finally, deploy the LSI-EWS in the supervisory process
Questions?

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Regulation
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European Banking Authority
The Cross Industry Standard Process for Data Mining (CRISP-DM) is a process model that describes commonly used approaches that data mining experts use to tackle problems.
Target Variable

A bank is considered in distress when:

• It is facing a conventional bank distress event (following prior literature), e.g. bankruptcy or liquidation

• It meets the condition for early intervention (art.27 BRRD), e.g. breach of thresholds for capital adequacy indicators

• It is placed under special administration (art.29 BRRD) triggered by notification;

• It is deemed to be failing or likely to fail (art.32 BRRD) e.g. rely on emergency liquidity assistance;

• There is a rapid and significant deterioration of its financial situation (art.96 Framework Regulation) triggered by notification.
## Data Sources - Overview

### Bank Specific Variables
- Financial Reporting Data
- Capital Requirements
- Euro-system Liquidity and Collateral
- Qualitative Information

### Macro-Economic and Banking Structure Variables
- Macro-Economic Information
- Banking Sector Structure
A new approach to Early Warning Systems

Annex

Prediction horizon

Prediction data as of 2015Q1 to account for publication lag

Predict distress within the next quarter

2015Q1 2015Q2 2015Q3

Stars denote distress events

• Short prediction horizon counterbalanced by the definition of distress, which is based on early signs of financial difficulties, allowing supervisors to react
What is Machine Learning (ML)?

Problem → Algorithm → Solution

Transform input to output

Problem → Solution

Unclear how to transform input to output

But: What we lack in knowledge, we make up for in data!

A new approach to Early Warning Systems
What is Machine Learning?

- Assumption that there is a **process** that explains the data we observe
  - Details of the process regarding underlying data generation unknown
  - **But**: Process not completely random, there are **certain patterns**!
  - → construct a good and **useful approximation of the process**

- “Machine learning is programming computers to **optimize** a performance criterion using example data or **past experience**.”
  (Ethem Alpaydın)
Annex – Validation terminology

<table>
<thead>
<tr>
<th>Outcome of the diagnostic test</th>
<th>Condition (e.g. Disease) As determined by the Standard of Truth</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
</tr>
<tr>
<td>Positive</td>
<td>TP</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>FN</td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Column total</strong></td>
<td><strong>TP+FN</strong></td>
</tr>
<tr>
<td></td>
<td>(Total number of subjects with given condition)</td>
</tr>
</tbody>
</table>

Table 1. Terms used to define sensitivity, specificity and accuracy

Sensitivity, specificity and accuracy are described in terms of TP, TN, FN and FP.

Sensitivity = \( \frac{TP}{TP+FN} \) = (Number of true positive assessment)/(Number of all positive assessment)

Specificity = \( \frac{TN}{TN+FP} \) = (Number of true negative assessment)/(Number of all negative assessment)

Accuracy = \( \frac{TN+TP}{TN+TP+FN+FP} \) = (Number of correct assessments)/(Number of all assessments)
Annex – Validation terminology

Figure 1: ROC Space: shadow area represents better diagnostic classification

As we can see from the above equations, TPR is equivalent to sensitivity and FPR is equivalent to (1 – specificity). All possible combinations of TPR and FPR compose a ROC space. One TPR and one FPR together determine a single point in the ROC space, and the position of a point in the ROC space shows the tradeoff between sensitivity and specificity, i.e. the increase in sensitivity is accompanied by a decrease in specificity. Thus the location of the point in...