OESTERREICHISCHE NATIONALBANK
EUROSYSTEM

Assessing Credit Risk of the Companies Sector

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Agenda

- Introduction
  - Purposes of the Assessment of Credit Risk of the Companies Sector by Central Banks
  - Tools for the Assessment of Credit Risk of the Companies by Central Banks – A Short Overview of OeNB’s Analytical Framework

- Example I: OeNB’s Inhouse Credit Assessment System (ICAS)
  - Overview and Main Features of OeNB’s ICAS
  - Data and Method
  - Results and Performance

- Example II: The Importance of OeNB’s Central Credit Register (CCR) for the Analysis of Credit Risk of the Companies Sector
  - Main Features and Uses of the Austrian CCR
  - An Illustrative Application: OeNB’s Benchmarking Methodology

- Conclusion

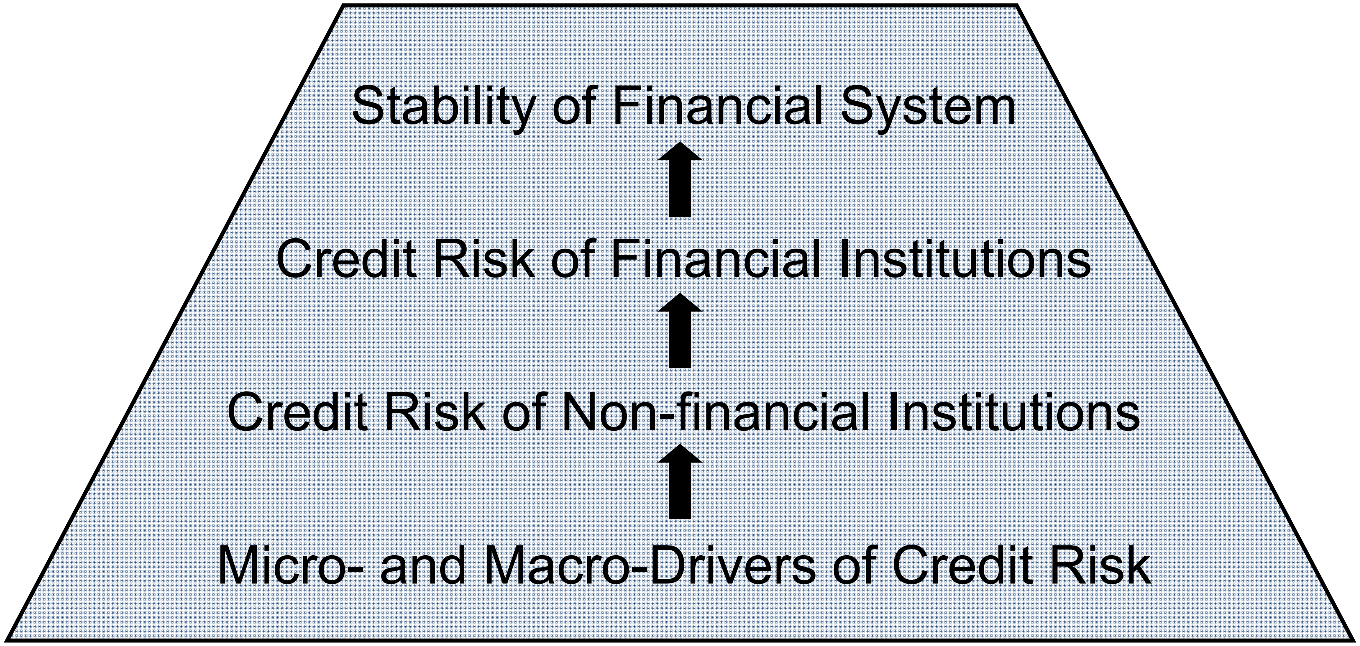
Motivation for the Assessment of Credit Risk

- Assessment of Credit Risk, and especially ensuring accuracy and reliability of credit ratings by means of validation is of critical importance to many different market participants motivated by their specific objectives.
- BIS, 2003: “Exposure to credit risk continues to be one of the leading sources for problems in banks worldwide”.
- Definition “Credit Risk”:
  - Traditional: Risk of loss due to a debtor’s non-payment of a loan (default).
  - Mark-to-market definition: Risk of losses due to a rating-downgrade (i.e. an increased probability of default) or the default of a debtor.

Key Purposes for the Assessment of Credit Risk of Companies by Central Banks

- Keeping track of the (credit risk of the) economy from a macro-economic perspective
- Assessing credit quality of collateral in the context of monetary policy operations
- Assessing and ensuring financial market stability from a macro-prudential perspective

The Importance of Credit Risk of Companies for Financial Stability



A Short Overview of OeNB’s Analytical Framework

- OeNB places great emphasis on developing and implementing sophisticated, up-to-date off-site analysis models
- OeNB possesses an In-House Credit Assessment System for the assessment of credit risk of Corporates (ICAS)
- The ABBA (Austrian Banking Business Analysis) analytical framework consists of the following tools:
  - Statistical Models (LOGIT- and Cox-type)
  - Structural Model (Credit, Market, and Operational VaR)
  - Systemic Risk Monitor
  - CAMEL
  - Peer Group Analysis/Filtering System
  - Interest Rate Risk Outliers
  - Austrian Banking Act (ABA) Violations
  - Problem Loan Coverage
  - Overall Analysis of Major Loans Register
  - Consistency of Rating Systems

Reliable Parameter Estimates as a Precondition for Meaningful Assessment of Credit Risk

- Main “Ingredients” of Credit Risk
  - Probability of Default (PD):
    - The probability that the obligor will default (will not meet the agreed payments) over the next year
  - Exposure at Default (EAD):
    - The amount outstanding in the case of default. This amount may exceed the current amount outstanding if the obligor is granted a credit line and they increase the amount borrowed prior to the default
  - Loss Given Default (LGD):
    - The proportion that will be lost if default occurs. The LGD may be reduced by collaterals.
  - Default Correlation:
    - From a portfolio perspective, dependencies in defaults probabilities have to be accounted for

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Example I: OeNB’s Inhouse Credit Assessment System (ICAS)

- Purpose:
  - Prediction of probabilities of default for Austrian corporates
- Advantages of ICASs:
  - models are exactly described
  - models can be recalibrated easily
  - knowledge and expertise is built up / stays within the central bank
  - lower costs than external tools
  - no dependence on external providers

Overview of OeNB’s ICAS and its components

OeNB's ICAS

Quantitative Assessment by means of statistical methods:

4 LOGIT-Models (1 base-model plus 3 industry-specific sub-models)

Qualitative Assessment by means of expert system:

Analysis of additional, mostly qualitative information, such as: management quality, newspaper entries, …

Main features of OeNB's ICAS

- *Parameter Selection:* „Rating systems are intended to „… quantify the expected likelihood of future borrower default…"
  ➔ PD (i.e. probability of default) is predicted.
  (Krahnen et al. 2001)

- *Time Horizon:* The time horizon was set to three years.
  The models predict a 3-year probability of default.

- *Explanatory Variables:* accounting ratios combined with general firm specific information

Main features of OeNB's ICAS

- *Default Definition: Basel II (§§452, 453):*
  - A default is defined by two events:
    - obligor is unlikely to pay its credit obligations to the banking group in full
    - obligor is past due more than 90 days
  - The elements to be taken as indications of unlikeliness to pay include:
    - The bank puts the credit obligation on non-accrued status.
    - The bank makes a charge-off or provision due to decline in credit quality
    - The bank sells the credit obligation at a material economic loss.
    - The bank consents to a distressed restructuring of the credit obligation
    - bankruptcy or insolvency (➔ failure) of the firm

private and ambiguous

public and unambiguous

Main features of OeNB's ICAS

- *Our statistical models: LOGIT Models*
  - LOGIT analysis has found considerable applications in default predictions
  - allow to measure the goodness of fit of the model
  - are (more) robust against deviations from normality
  - allow to test for omitted variable bias and heteroskedasticity (*Davidson/MacKinnon (1984)*)
  - LOGIT-Models allow to check easily whether the empirical dependence between the potential input variables and default risk is economically meaningful. *(Hayden (2002))*
  - ESCB requires ICAS to estimate PDs which are direct output of models

Data used in OeNB's ICAS

- *Data Sources:*
  - Financial statement data (~5000 analyzed each year) with a bias to
    - large firms,
    - firms with good credit quality,
    - corporations, and
    - manufacturing and commerce (wholesale/retailing)
  - Additional, general firm specific and industry specific data
    - obtained from commercial register, and other external data providers
      such as Statistik Austria

Methodology

- *Steps in Model Building and (Re-)Calibration:*
  - Selection of Candidate Variables
  - Test of Linearity Assumption
  - Univariate LOGIT Models
  - Derivation of the Default Prediction Models

Methodology – Selection of Candidate Variables

- Our database of potential exogenous variables consists of 392 ratios

- These candidate ratios were identified in an extensive literature survey – we studied:
  - Models of external rating agencies
  - Models of other central banks / regulatory authorities
  - Models of commercial banks
  - Models presented in scientific papers or books

Methodology – Selection of Candidate Variables

- *Classification of Accounting Ratios*
  - Analysis of expense structure (e.g. interest expenses / assets),
  - Profitability analysis (e.g. (EBIT + interest income) / assets),
  - Analysis of leverage (e.g. liabilities / assets),
  - Investment analysis (e.g. Deprecition / fixed assets),
  - Turnover analysis (e.g. net sales / assets),
  - Liquidity Analysis (e.g. current assets / current liabilities),
  - Analysis of macro developements (e.g. GDP growth),
  - Analysis of management quality (e.g. admin. Expenses / num. of employees)
  - Analysis of firm growth (e.g. net sales / last net sales),
  - Productivity analysis (e.g. personell costs / net sales),
  - Analysis of market value (e.g. price-earnings-ratio)

Methodology – Selection of Candidate Variables

- Calculation of the ratios
- Descriptive analysis of the ratios and their evolvement over time
  - Comparision of the distribution of the ratios
- Identification and exclusion of „problematic“ ratios, e.g.
  - Based on theoretical reasons: e.g. hypothesis about relationship of between value of ratio and probability of default unclear/ambiguous
  - Based on practical reasons: e.g. nominator can take on negative values, or ratio not computable for large number of companies due to data restrictions

Methodology – Test of Linearity and Monotonity Assumptions

- Having selected the candidate accounting ratios, the next step is to check whether the underlying assumptions of the LOGIT model apply to the data.
- The LOGIT model can be written as:

$$\mathrm{Prob}\left(Default\right)=\frac{e^{\alpha_0+\beta_1 x_1+\ldots+\beta_k x_k}}{1+e^{\alpha_0+\beta_1 x_1+\ldots+\beta_k x_k}}$$

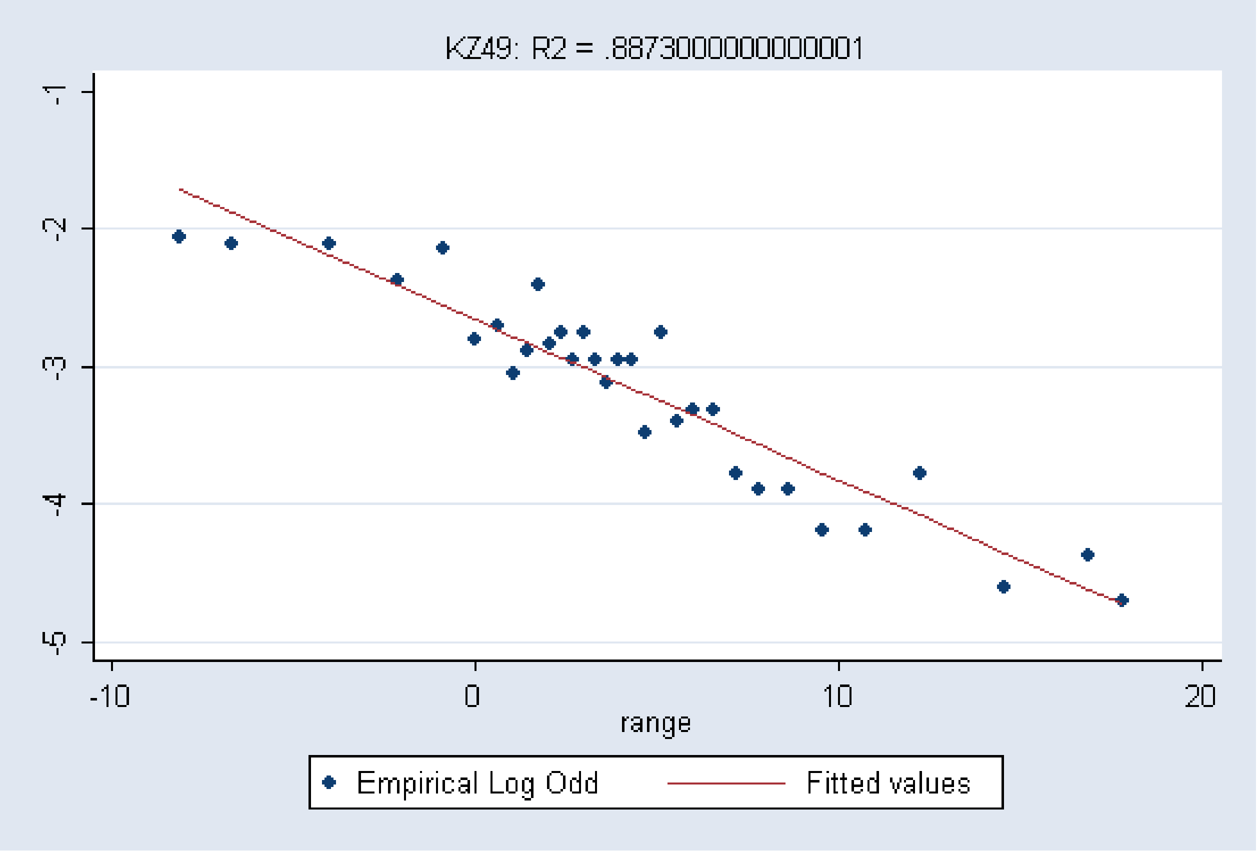
- This implies a linear, monotone relationship between the Log Odd and the input accounting ratios:

$$LogOdd = \alpha_0 + \beta_1 x_1 + \ldots + \beta_k x_k$$

- To test for this assumption, the sample is divided in several subsamples that all contain the same number of observations. Within each group the historical default rate (respectively the empirical Log Odd) is calculated. Finally a linear regression of the Log Odd on the mean values of the variable is estimated.

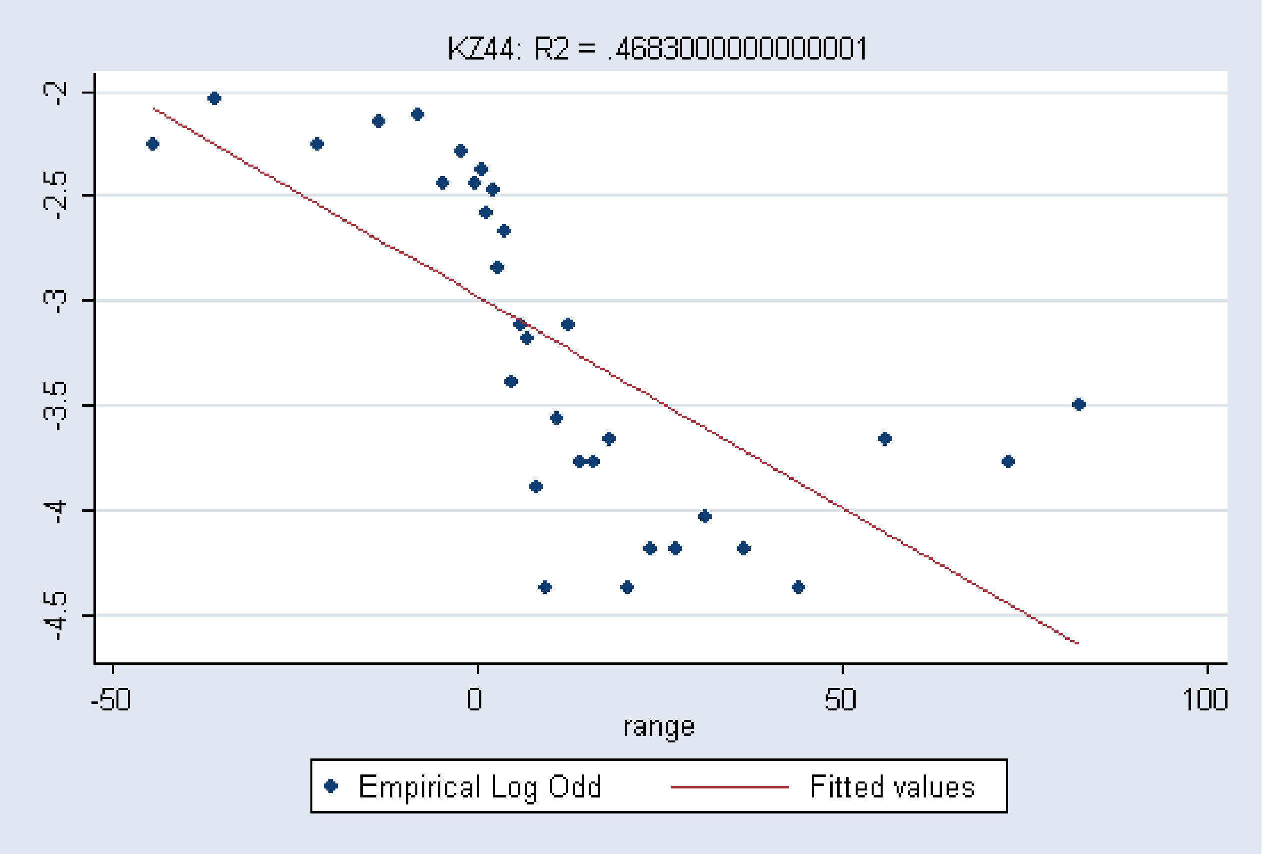
Methodology – Test of Linearity and Monotonity Assumptions

- For more than half of the available accounting ratios we find that the assumptions are valid:



Methodology – Test of Linearity and Monotonity Assumptions

- A violation of one of the assumptions leads to the exclusion of the corresponding variable:



Methodology – Univariate LOGIT Models

- Next step is to estimate univariate LOGIT models with the remaining candidate ratios to find the most powerful variables
  per risk factor group

- Univariate discriminatory power of accounting ratios is evaluated based on Accuracy Ratios.

- Ratios with an univariate AR of less than 5% are dropped

Methodology – Test for Multicollinearity

- Next step is to check for multicollinearity:
- Correlation matrices for all the selected variables are calculated.
- Only the best variables (highest Accuracy Ratio) of each correlation subgroup are selected.
  - Ratios are sorted by their Accuracy Ratio
  - Correlations are studied and variables are dropped if correlation coefficient is higher than 0,7

Methodology – Test for Multicollinearity

- Example: Correlation Matrix for remaining Turnover Ratios

	k125	k126	k127	k130	k131	k132	k133	k138	k146	k159	k161	k162	k163
Rank	2		3	1					4				
k125	1,00	0,99	0,49	0,46	0,49	0,50	0,90	0,86	0,33	-0,41	0,86	0,77	0,76
k126	0,99	1,00	0,50	0,45	0,48	0,48	0,90	0,86	0,33	-0,40	0,86	0,77	0,76
k127	0,49	0,50	1,00	0,25	0,35	0,35	0,44	0,43	0,16	-0,39	0,43	0,39	0,40
k130	0,46	0,45	0,25	1,00	0,78	0,79	0,40	0,47	0,38	-0,75	0,47	0,42	0,40
k131	0,49	0,48	0,35	0,78	1,00	0,99	0,44	0,49	0,38	-0,85	0,49	0,44	0,41
k132	0,50	0,48	0,35	0,79	0,99	1,00	0,45	0,48	0,38	-0,85	0,48	0,44	0,41
k133	0,90	0,90	0,44	0,40	0,44	0,45	1,00	0,77	0,29	-0,35	0,77	0,85	0,83
k138	0,86	0,86	0,43	0,47	0,49	0,48	0,77	1,00	0,29	-0,40	1,00	0,91	0,91
k146	0,33	0,33	0,16	0,38	0,38	0,38	0,29	0,29	1,00	-0,18	0,29	0,25	0,25
k159	-0,41	-0,40	-0,39	-0,75	-0,85	-0,85	-0,35	-0,40	-0,18	1,00	-0,40	-0,34	-0,32
k161	0,86	0,86	0,43	0,47	0,49	0,48	0,77	1,00	0,29	-0,40	1,00	0,91	0,91
k162	0,77	0,77	0,39	0,42	0,44	0,44	0,85	0,91	0,25	-0,34	0,91	1,00	0,99
k163	0,76	0,76	0,40	0,40	0,41	0,41	0,83	0,91	0,25	-0,32	0,91	0,99	1,00

Methodology – Derivation of the Final Default Prediction Model

- Out of the ratios which passed all:
  - What is the optimal combination of ratios?
  - Which ratios should the final multivariate model contain?

- One way: backward (or alternatively forward) selection
  - Estimation of full model
  - Elimination of “worst’’ covariates one by one based on their significance (calculated with a likelihood ratio test)

- However, the “optimal’’ model composition obtained and its discriminatory power will dependent on:
  - Relation of defaulted to non-defaulted companies
  - Sectoral composition of companies

Methodology – Derivation of the Final Default Prediction Model

- Our solution:
  - We apply a bootstrapping methodology and conduct 5,000 runs
    - In each run we set the proportion of non-defaulted to defaulted companies 50 : 50
    - For this purpose we use all the defaulted firms and draw a (stratified) random sample out of the non-defaulted firms
    - In a first step the portfolio is held „sector neutral" – i.e. the default rate is uniform (50%) in each sector
    - Using the respective sample data we then apply our backward selection method
    - Finally, we
      - count how often a certain model specification is obtained,
      - count how often each and every ratio is observed in a model specification

Results

- The model that is observed most often consists of 5 ratios:
  - K15: interest expenses / balance sheet total
    - Class: Analysis of expense structure
    - Relative frequency of occurrence: 61%
  - K31: EBIT / balance sheet total
    - Class: Profitability analysis
    - Relative frequency of occurrence: 79%
  - K79: liabilities to banks / total outstanding debt
    - Class: Analysis of leverage
    - Relative frequency of occurrence: 67%
  - K119: fixed assets / balance sheet total
    - Class: Investment analysis
    - Relative frequency of occurrence: 71%
  - K127: short term debt / total revenues
    - Class: Turnover analysis
    - Relative frequency of occurrence: 35%

Results

- Estimation results in first bootstrapping exercise:

Coefficient estimates obtained in first bootstrapping exercise							
variables		K15	K31	K79	K119	K127	constant
average		0,301	-0,065	0,018	-0,015	0,019	-1,181
standard dev.		0,063	0,009	0,003	0,003	0,003	0,163
95% confidence interval	lower	0,182	-0,085	0,012	-0,020	0,013	-1,488
	upper	0,426	-0,049	0,025	-0,010	0,026	-0,841

Results

- For calibration a second bootstrapping exercise (sensitivity analysis) in conducted (again 5000 runs):
  - This time the composition of OeNB's true portfolio regarding number of companies and their sectoral affiliation is accounted for
  - For each of the companies one financial account is chosen randomly in each run
  - On this data the 5 ratios are computed and the coefficients for the five ratios are estimated

Coefficient estimates obtained in second bootstrapping exercise

variables		K15	K31	K79	K119	K127	constant
average		0,289	-0,063	0,017	-0,012	0,019	-3,995
standard dev.		0,0075	0,0014	0,0003	0,0002	0,0003	0,0175
95% confidence	lower	0,274	-0,065	0,016	-0,012	0,018	-4,030
interval	upper	0,304	-0,060	0,018	-0,011	0,020	-3,962

Performance – Model Validation

- To validate the model different techniques are applied:
  - Check for discriminatory power based on
    - ARs,
    - ROCs,
    - Hit Rates,…
  - Check for calibration quality based on
    - ECAF Traffic Light Approach,
    - Brier Score and Spiegelhalter Test,…

Performance – Model Validation

- Discriminatory Power
  - Results obtained in 5000 runs:

AR-results obtained in second bootstrapping exercise				
		AR accounting for all defaults	ROC accounting for all defaults	Hit Rate
average		58,42	79,21	70,25
standard dev.		0,23	0,11	0,24
95% confidence interval	lower	57,98	78,99	69,79
	upper	58,87	79,43	70,72

  - It is very interesting to note that the model seems to be equally / even more powerful in the prediction of failures:

AR-results on failures		
		AR accounting for failures only
average		61,36
standard dev.		0,34
95% confidence interval	lower	60,69
	upper	62,04

Performance – Model Validation

- Calibration Quality:
  - ECAF Traffic Light Approach:

benchmark pd of ECAF	0,10%
Size of eligible set	**Performance Checking Thresholds**
up to 500	Monitoring Level 0,20%
	Trigger Level 1,00%
up to 1000	Monitoring Level 0,20%
	Trigger Level 0,60%
up to 5000	Monitoring Level 0,18%
	Trigger Level 0,34%
more than 5000	Monitoring Level 0,16%
	Trigger Level 0,28%

If the decision had been based solely on the model, no default would have been recorded amongst the set of eligible debtors
➔ always green zone!!!

Performance – Model Validation

- Calibration Quality:
  - Brier Score:
    - The Brier Score (also known as Mean Square Error (MSE)) is defined as follows (Brier 1950) :

$$MSE = \frac{1}{N}\sum_{i}^{N}(y_i - p_i)^2$$

    - where there are 1, …, N obligors with individual probability of default estimates p_i . y_i denotes the default indicator (y=1, default) and (y=0, no default) respectively
    - The Brier Score gets small if the forecast PD assigned to defaults is high and the forecast PD assigned to non defaults is low. In general, a low Brier Score indicates a good rating system.
    - The Brier Score for our model is 0.0514. Is this low enough?

Performance – Model Validation

- Calibration Quality:
  - Spiegelhalter Test:
    - Using the Brier Score we can conduct a hypothesis test with H0:
    - "All probability of default forecasts, p_i, match exactly the true (but unknown) probability of default for all i.''
    - Under the assumption of independence of default events, the MSE has an expected value of

$$E[MSE] = \frac{1}{N}\sum_{i=1}^{N} p_i(1-p_i)$$

    - and a variance of

$$\mathrm{var}[MSE] = \frac{1}{N^2}\sum_{i=1}^{N} p_i(1-p_i)(1-2p_i)^2$$

    - it can be shown that under the null hypothesis the test statistic

$$z = \frac{MSE - E[MSE]}{\sqrt{\mathrm{var}[MSE]}}$$

    - follows approximately a standard normal distribution which allows a standard test decision
    - For our model z = 0.2203 . Thus H0 cannot be rejected!

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Example II: The Importance of Credit Registers

- The information stored in Credit Registers may also be used to track credit risk in the companies sector
- In particular, Credit Registers may also be used to address many of the issues which supervision entails, a.o.
- Credit Registers may be used to
  - Estimate credit risk parameters for central banks own risk models
  - Study the validity and reliability of risk parameters reported by banks
  - Analyse the evolution of risk parameters in the course of time

Main Features of the Austrian CCR

- The Austrian CCR contains information on all direct lending activities of all types of Austrian financial institutions (banks, financial and insurance companies) above a threshold of EUR 350,000, in particular
  - Exposures to be reported in the balance sheet
  - Exposures arising from off-balance sheet transactions pursuant to Annex 1 to Annex 22 of the Federal Banking Act
  - Derivatives pursuant to Annex 2 to Annex 22 of the Federal Banking Act
- In addition to the amounts, the Austrian Credit Register on Major Loans also contains risk-related information, such as:
  - Past-Due Claims
  - Rating Information (i.e., Rating System, Rating Grade, and Probability of Default)
  - Collateral
  - Risk-weighted assets
  - Expected Loss
- Reporting frequency: monthly

An Illustrative Application: OeNB's Benchmarking Methodology

- Purpose of Benchmarking
  - Measure similarity/dissimilarity, i.e. proximity of ratings from different sources.
  - There are three aspects of proximity:
    - Association, agreement and bias
  - Each aspect can be measured (TauX, Cohen's Kappa, and Bias)
- Goal of Benchmarking = Study Proximity in order to
  - Detect Outlier Raters
  - Detect Outlier Segments/Subgroups of Companies
  - Derive "Consensus"-Ratings for Companies

Benchmarking

- Benchmarking techniques overcome two of the major disadvantages of backtesting procedures:
  - They do not rely on historical default data.
  - They use contemporaneous information only.

- Requirement: Multi-rater panel
  - Contemporaneous ratings of an overlapping set of obligors stemming from different sources:
    - Rating agencies, banks, central banks’ inhouse assessment systems, credit bureaus, ...

- Multi-rater information treated as partial weak orderings.
  - Not all obligors are rated by all raters.
  - There are (many) ties.

Multi-Rater Panel

- Example of a general multi-rater panel:

	Rater						
Obligor	1	2	3	4	5	6	7
1	$AA+$	$Aa2$	AAA	$1+$		2	0.0001
2	$BB-$	$Ba1$		$4+$		$4c$	0.03
3		$Ba2$	BB	$4-$	4	$5a$	0.04
4	C	Ca	CCC	$8+$		$6b$	
5	$A-$	$A2$	AA	$4+$	1	2	0.0003
6		$Baa1$	BB	$2-$		$4a$	
7		$B+$	B	$7-$		$6b$	0.08
8	BB		CCC	$7+$		$6b$	

- Rating systems have different numbers of classes and ratings have different meaning.

Measuring Association I

- Distance metric is needed to construct association measures.
- Any suitable metric has to obey the Kemeny-Snell axioms.
  - E.g., Spearman's ρ and Kendall's τ do not meet this requirement.
  - Triangle inequality is violated due to treatment of ties (the distance from A to B should be less or equal to the sum of the distances from A to C and C to B).
- TauX is a suitable association measure
  - Relates to the Kemeny-Snell metric (Emond and Mason, 2002)
  - Based on the number of half-flips needed to achieve a zero distance.
  - No common scale is needed.

Measuring Association II

- The association measure TauX between rater A and rater B is defined as:

$$\tau_x(A,B) = 1 - \frac{\sum_{u=1}^{N_{A,B}} \sum_{v=1}^{N_{A,B}} |a_{uv} - b_{uv}|}{N_{A,B}(N_{A,B}-1)}$$

where for rater A

$$a_{uv} = \begin{cases} 1 & \text{if obligor } u \text{ is ranked ahead of obligor } v, \\ 0 & \text{otherwise,} \end{cases}$$

similarly $b_{u,v}$ for rater B

and $N_{A,B}$ is the number of obligors rated by both banks.

Measuring Agreement I

- In some cases rating outcomes are on a common scale.
  - Rating systems aim at estimating PDs (Basel IRB).
  - PDs can be mapped into a “master scale”.
- In general, if PDs can be related to each rating class, a mapping to a master scale is possible.
- Weighted version of Cohen’s is a suitable measure
  - Observed agreement is compared to agreement in the case of independence.
  - Weights suggested by Fleiss and Cohen (1973)
  - Disagreement is quadratic in the difference in rating classes.
  - Possible extensions may use different weights.

Measuring Agreement II

- Cohen's Kappa measures agreement between rater A and rater B as

$$\kappa_w(A,B) = \frac{P_{o(w)} - P_{e(w)}}{1 - P_{e(w)}}$$

and compares the observed agreement $P_{o(w)} = \sum_{j=1}^{R} \sum_{i=1}^{R} w_{ij} p_{ij}$ to that expected if the ratings were independent (and hence $p_{ij} = p_{i\cdot} p_{\cdot j}$), given by $P_{e(w)} = \sum_{j=1}^{R} \sum_{i=1}^{R} w_{ij} p_{i\cdot} p_{\cdot j}$, where the weights proposed by Fleiss and Cohen are:

$$w_{ij} = 1 - \left(\frac{i-j}{R-1} \right)^2$$

where R is the common number of rating classes.

Measuring Bias

- Near-at-hand extension of Cohen's κ.
- Average deviation among all co-ratings is measured.
- Bias related to the direction of disagreement.
- Bias is computed as

$$\theta(A,B) = \sum_{i=1}^{R} \sum_{j=1}^{R} \frac{i-j}{R-1} p_{ij}.$$

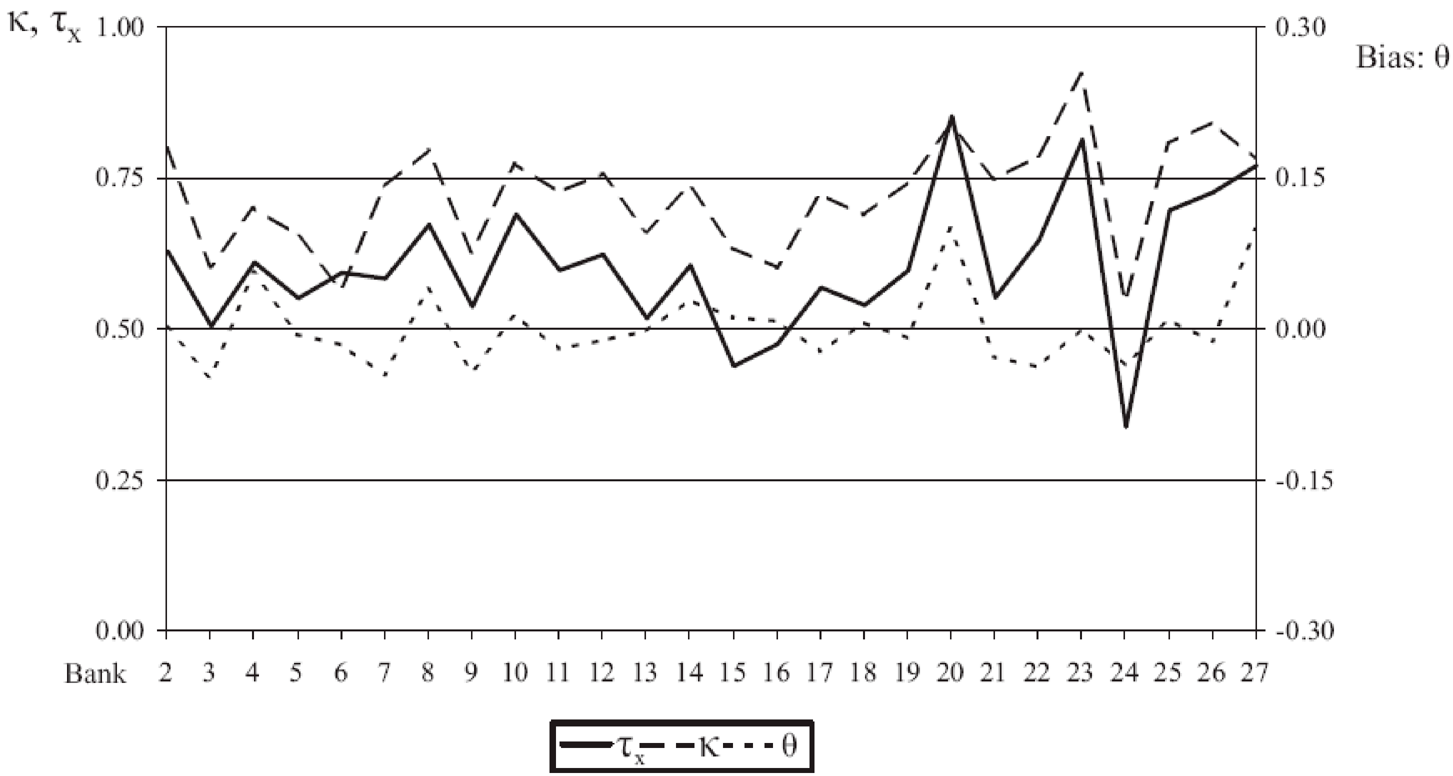
Data

- Data from the Austrian Credit Register
- Multi-rater panel containing:
  - obligor specific information (country, industry, ...)
  - rating information (original rating, master scale rating).
- Methodology is applied to detect outliers both, on a
  - Rater- (i.e., Bank),
  - Ratee- (i.e., Company / Company Sector)

  Level.

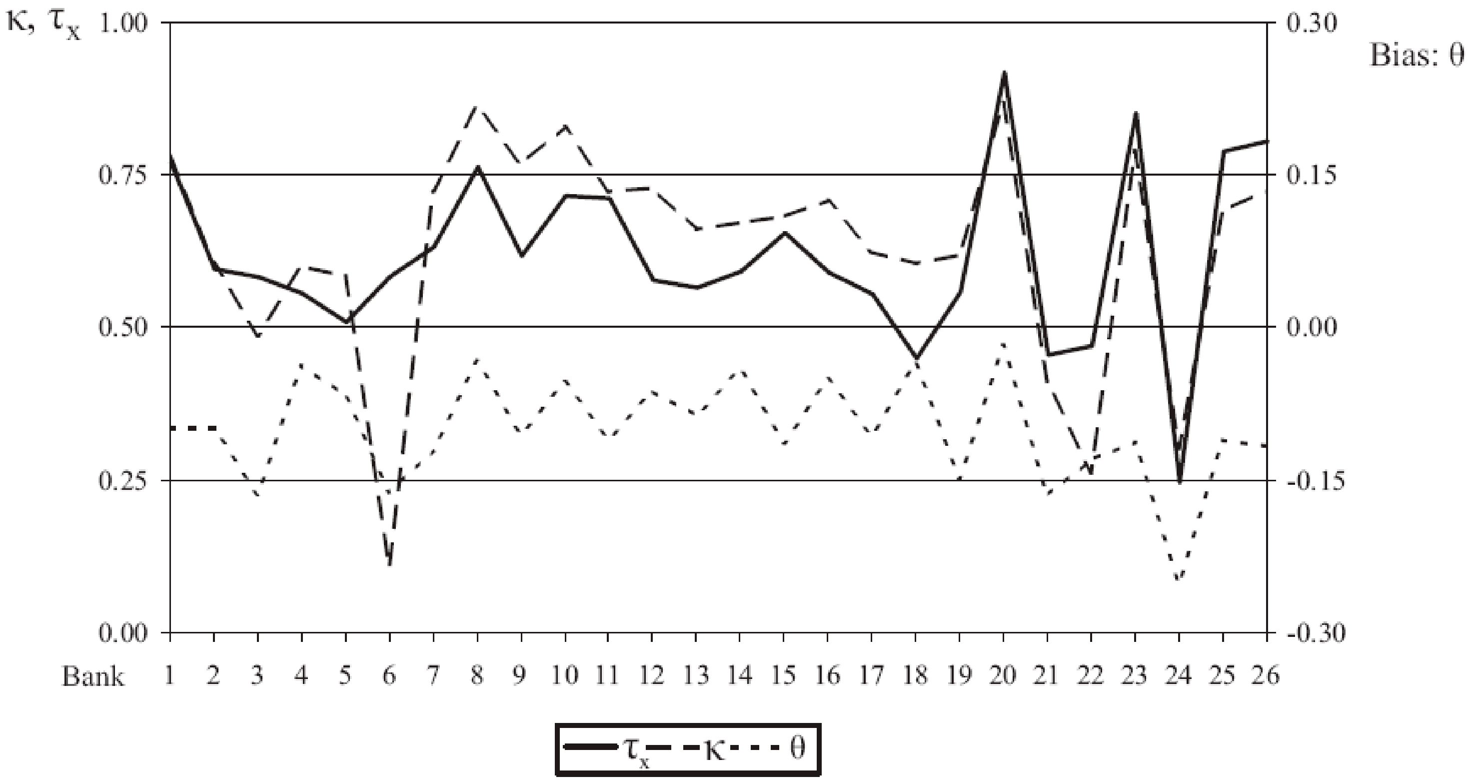
Example: Outlier Detection on a Rater Level I

- Bank specific: Bivariate comparison of bank 1 to all other banks



Example: Outlier Detection on a Rater Level II

- Bank specific: Bivariate comparison of bank 27 to all other banks



Example: Outlier Detection on a Rater Level III

	Measure of Proximity				Measure of Proximity				Measure of Proximity		
Bank	τ_x	κ	θ	Bank	τ_x	κ	θ	Bank	τ_x	κ	θ
1	0.602	0.723	0.001	10	0.696	0.696	0.010	19	**0.500**	**0.517**	0.025
2	0.550	0.586	**0.040**	11	0.637	0.682	0.025	20	0.647	0.625	-**0.063**
3	**0.539**	**0.495**	**0.082**	12	0.610	0.710	0.004	21	**0.469**	**0.485**	-**0.033**
4	0.666	0.680	0.011	13	0.611	0.732	-0.005	22	0.625	0.623	0.006
5	0.621	0.721	-0.007	14	0.672	0.741	-0.020	23	0.669	0.727	0.019
6	0.573	**0.467**	0.010	15	0.681	0.663	0.026	24	**0.449**	**0.478**	0.014
7	0.588	0.713	0.032	16	0.638	0.709	-0.025	25	0.610	0.635	-0.014
8	0.611	0.689	-0.027	17	**0.544**	0.628	0.012	26	0.646	0.686	-0.006
9	0.647	0.674	0.010	18	0.563	0.657	-0.026	27	0.617	0.631	-**0.100**

Example: Outlier Detection on a Ratee Level I

- Determinants of rating heterogeneity in European credit ratings.
- Three hypotheses:
  - We expect more similar ratings outcomes on obligors in the domestic market than in the foreign markets.
  - We expect that the overall similarity of ratings outcomes is lower in transition economies than in non-transition economies.
  - We expect that heterogeneity decreases with the degree of involvement of Austrian banks in the respective market.

Example: Outlier Detection on a Ratee Level II

- Marginal frequencies of rating deviations for all obligors in terms of rating classes
  - In a comparable study Carey (2001) finds:

	Rating deviation				
	0	1	2	3	4 or more
All obligors	44.0	39.0	12.1	3.3	1.6

  - Results for Austria:

	Rating deviation				
	0	1	2	3	4 or more
All obligors	41.6	41.9	12.0	3.7	0.8

- Overall proximity in AT thus comparable to US

Example: Outlier Detection on a Ratee Level III

Customer Group	Comparison Based on τ_x: Average 1st group	Average 2nd group	p-value	Comparison Based on κ: Average 1st group	Average 2nd group	p-value
Domestic vs. Foreign	0.5116	0.4300	**0.0050**	0.6069	0.5122	**0.0144**
Non-Transition vs. Transition	0.4456	0.3550	**0.0305**	0.5112	0.3331	**0.0028**
High Involv. vs. Low Involv.	0.4612	0.3841	**0.1349**	0.5808	0.4144	**0.0010**
Non-Transition & High Involv. vs. Transition & High Involv.	0.4537	0.3753	**0.6021**	0.6005	0.3997	**0.0324**
Non-Transition & Low Involv. vs. Transition. & Low Involv.	0.4144	0.2893	**0.0361**	0.4146	0.2389	**0.0098**
Non-Transition & High Involv. vs. Non-Transition & Low Involv.	0.4537	0.4144	**0.4091**	0.6005	0.4146	**0.0102**
Transition & High Involv. vs. Transition & Low Involv.	0.3753	0.2893	**0.0609**	0.3997	0.2389	**0.0142**
Non-Transition & High Involv. vs. Transition & Low Involv.	0.4537	0.2893	**0.0018**	0.6005	0.2389	**0.0001**
Transition & High Involv. vs. Non-Transition & Low Involv.	0.3753	0.4144	**0.9707**	0.3997	0.4146	**0.8256**

Conclusions

- Assessment of Credit Risk of Companies by Central Banks important for many reasons, a.o. for:
  - Banking Supervision and Evaluation of Financial Stability,
  - Assessment of Credit Quality of Collateral
- Inhouse Credit Assessment Systems and Credit Registers allow Central Banks to address many issues in the above mentioned areas of responsibility

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