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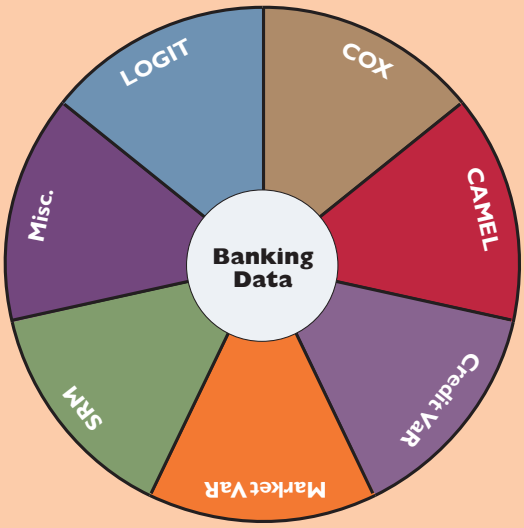
ONB

Off-Site Analysis Framework of Austrian Banking Supervision

Austrian Banking Business Analysis



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Preface

A reliable and financially sound banking sector is an essential prerequisite for a country's stability and economic growth. For this reason, monitoring and examining the financial situation of banks is of great interest to regulatory authorities throughout the world. The fact that regulators – even within the EU – use a variety of approaches to attain this goal can be explained by the different structures not only of the authorities themselves but even more so of the relevant financial centers (in particular the number of banks). As on-site audits require substantial amounts of time and resources and thus cannot be carried out very frequently (especially in view of the large number of legally independent banks in Austria), off-site analyses play a major role in the supervision process. Therefore, the Oesterreichische Nationalbank (OeNB) and the Austrian Financial Market Authority (FMA) place great emphasis on developing and implementing sophisticated, up-to-date off-site analysis models to make full use of the resources of both institutions.

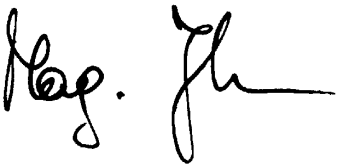
Aside from deploying analysis tools which have proven their value in practice over a number of years and regularly undergo recalibration and upgrades, Austria's regulators also use new tools which are developed on a well-grounded theoretical basis and represent the state of the art by international standards.

In order to provide all market participants as well as people interested in the Austrian financial market with insight into the analysis tools employed, the OeNB has decided to publish a general overview of the ABBA (**A**ustrian **B**anking **B**usiness **A**nalysis) analytical framework.

In closing, we hope you will find this publication on ABBA and the analytical tools used in Austrian banking supervision interesting and useful.

Vienna, February 2005

Michael Hysek
Head of Department
Banking Supervision, FMA



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The Analytical Framework in Austrian Banking Supervision

1 Introduction

The analytical framework of Austrian banking supervision is characteristically defined by the main *objective* of *risk-based supervisory analysis*. The individual analysis tools used in this context either serve to pursue this objective or they are combined with other results to yield an overall risk-based assessment.

This risk orientation is accompanied by a second objective in supervision analysis, namely that of *systematization*. This means that the various types of tools used yield a periodic, standardized report as the basis for further measures.

The objectives mentioned above are attained by the following means:

– *risk orientation:*
  risk type identification
  risk source identification
  scenario analyses (analyzing effects of changes in the environment)
  RORAC/RAROC (approximated risk-adjusted return metrics)
– *systematization:*
  combination of a broad range of analysis modules
  reorganization of the reporting system
  integration of Austria-specific characteristics (sector-specific solutions, etc.)

In line with the OeNB's and FMA's jointly defined roles, process design for overall bank risk assessment is among the duties of the FMA and is communicated back to the OeNB so that it can be integrated into the upstream analytical framework. These activities incorporate quantitative information (bank reports, ratings, models) as well as qualitative information (on-site reports, bank reports, assessments) from all recordable risk categories in the microanalysis process.

The tools described here cover the purely quantitative aspects of analysis; all tool results (such as the calculated value at risk (VaR) from the structural model) are used for the purpose of assessing a bank's risk components and are then combined in an overall Technical Analysis Report (ABBA Overall Report).

For the purpose of risk-based supervision, it is necessary to categorize banks in order to ensure optimum resource allocation in the supervisory process. This categorization is not meant to be performed by conventional means analogous to sector or peer group definitions (see below); instead, it should be based on a risk/relevance classification. The risk category is determined on the basis of the results from the analysis process, while the relevance is identified pragmatically by considering different factors like the size of the banks or their interbank network. This categorization lies at the heart of the supervisory process and is to be performed at regular intervals on the basis of quantitative criteria. However, ultimately this iterative process also involves ad hoc and individual qualitative feedback (on-site inspections, media reports, etc.), meaning that it is also subject to immediate and direct changes.

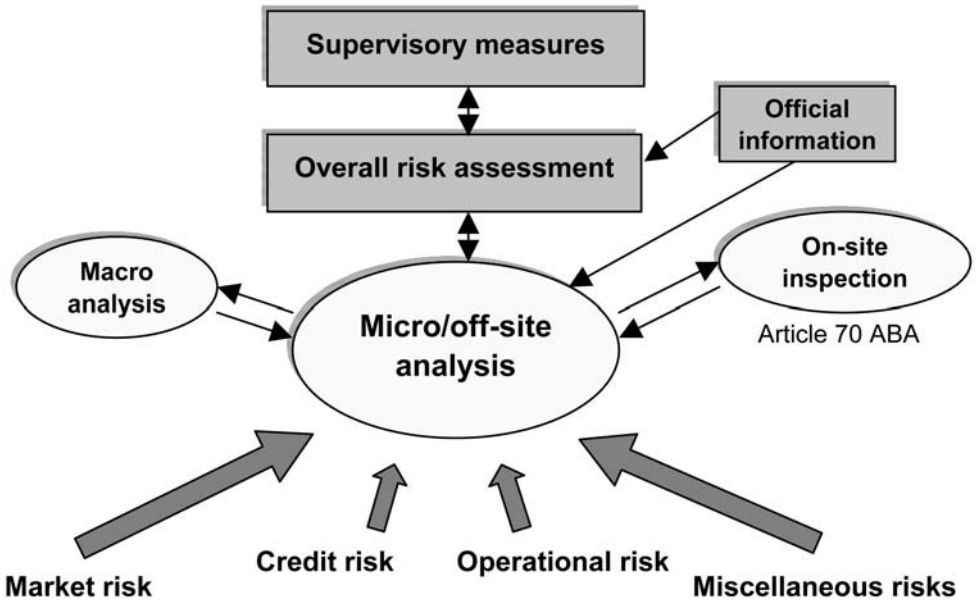

Figure 1: Risk Assessment Process

Effects on individual banks are derived from macro analysis on the basis of additional *scenario and stress test analyses* so that this information can also be used for micro analysis.

Scenario calculations refer to altering environmental variables or shifting market factors (changes in interest rates, stock prices or foreign exchange rates, declines in industry revenues, macroeconomic variables, etc.). They measure the effects of changes in position values on a bank's profitability performance and equity (reserves) based on the bank's current overall risk positions. As the approximate value at risk (VaR) calculated in the structural model already comprises the volatility and/or sensitivity of the risk factors (which may vary depending on the method chosen), some of the scenario calculations described are already included in the analysis process implicitly or can be recreated with relative ease.

In any case, individual sensitivity analyses/scenario calculations and stress tests are carried out regularly and their results are utilized accordingly.

2 General Process Description/Overview of Analytical Framework

An integrated *analysis process* which is coordinated between the OeNB and FMA ensures that all of the relevant information is combined in a uniform categorization scheme and that inaccurate assessments resulting from missing analysis data are avoided in order to ensure a high level of quality.

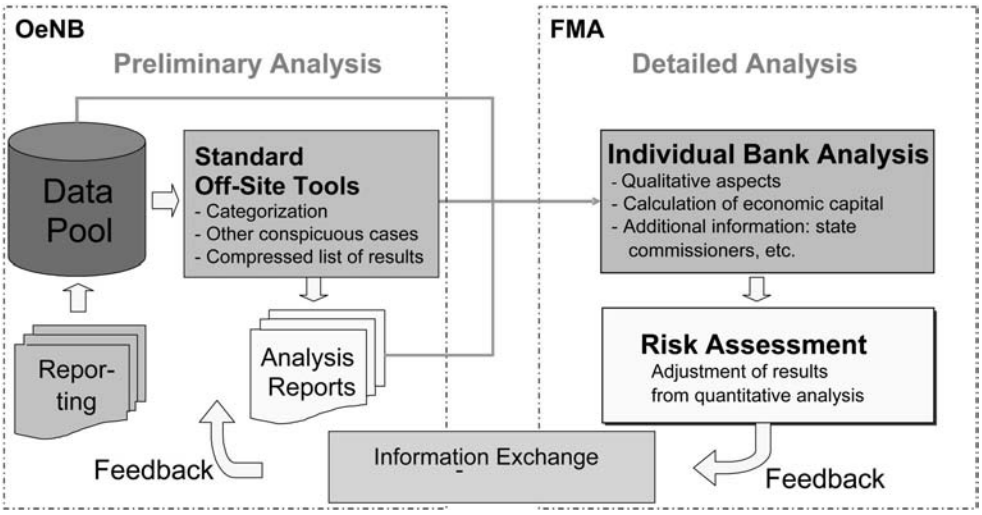

Figure 2: Process Description

In accordance with the OeNB's and the FMA's jointly defined roles and their statutory mandate to ensure the stability of the Austrian financial market, the OeNB handles most of the *preliminary analysis stage*, which involves the largely standardized and automated evaluation of data from all Austrian credit institutions, while the FMA essentially deals with the *detailed analysis stage* by means of qualitative individual bank analysis.

The two institutions communicate the results of these processes to each other via established channels, thus enabling the standardized optimization of the tools deployed.

2.1 Preliminary Analysis Stage using Standard Analyses (OeNB)

The *OeNB* handles the technically oriented part of this analysis work, which comprises the entire reporting system (collection and aggregation of data, links to the data pool) and the preliminary analysis stage. All Austrian banks are analyzed using off-site tools, most of them on a quarterly basis.

The next (IT-assisted) step involves the preliminary aggregation of results and a rough categorization based on computational decisions (the *final product* of technical analysis; see below for further information). In this context, the selection process will certainly be subjected to further refinements and recalibrations over time. At present, each tool flags banks which are conspicuous according to the tool's parameters. This helps identify deviating results from the various analysis tools (which may well cover a wide variety of areas and pursue very different objectives). The individual flags are then merged in an overall report.

All results, which have been based on purely *quantitative* (or quantifiable qualitative) input factors up to now, are stored along with historical results in the existing systems in such a way that the information can be *distributed* and *queried* using established internal supervisory *analysis systems* as well as all other drill options.

The preliminary analysis stage only yields a rough risk categorization; like all other qualitative criteria, qualitative criteria which reduce exposure are not yet taken into account at this point.

Overview of individual tasks and results:

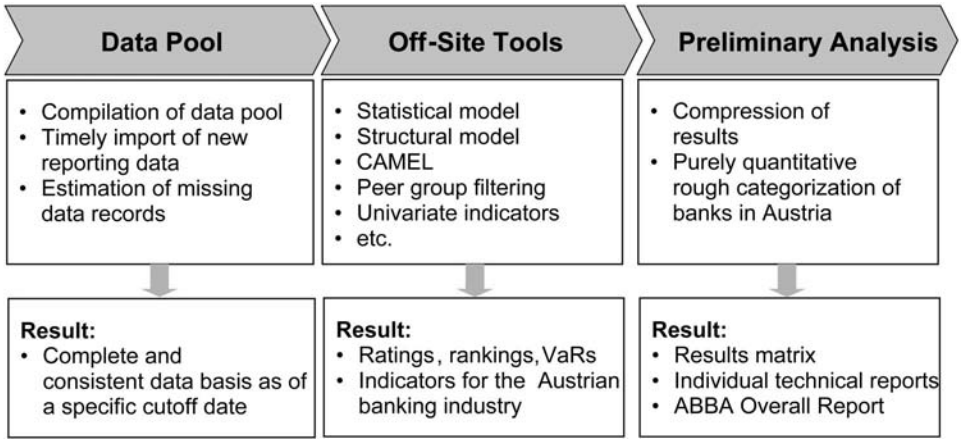

Figure 3: Quantitativ Analysis

2.2 Detailed Analysis Stage (FMA)

In order to take specific measures on the basis of off-site analysis results, the categorizations determined by means of calculation have to be subjected to qualitative reviews.

At this point, the FMA carries out its qualitative individual bank analysis. In addition to the results from standard tools, important parameters such as additional information from official sources and qualitative research are also included in this analysis.

After automated categorization and preparation of the data by the OeNB, the *FMA is able to recategorize risks* by inputting additional qualitative criteria.

The final risk categorization and *any required official measures* constitute a new phase in the supervisory process and are handled by the FMA.

The FMA's evaluation of results is again incorporated into the tool approaches via clearly structured channels, thus ensuring the consistency and significance of the models' output.

The results of the preliminary analysis stage are reported to the responsible decision-making bodies so that their discussions not only cover individual results but also the synthesized output of all analysis tools.

The FMA's qualitative assessments and overall risk assessment as well as any official measures taken are communicated back to the OeNB on a regular basis. This distribution of tasks has proven to be highly effective in practice and is documented accordingly in the joint position paper published by the OeNB and the FMA.

2.3 Details on Technical Analysis – Development Process

In order to ensure that the objectives described above are attained, it is also necessary to implement technical processes for the maintenance and further development of tools within the relevant organizations.

In addition to ongoing expert evaluation, it is also important to ensure that the results do not become skewed or outdated due to changes in the economic environment. For this reason, it is indispensable to establish a process for ensuring the suitability and accuracy of the tools employed.

The main tasks involved in this process are as follows:

- maintenance and ongoing analysis of models employed
- annual review of approaches used (in joint OeNB and FMA workshops)
- analysis and back-testing of risk assessments
- maintenance of the list of troubled banks
- maintenance and review of the input data used

3 Analysis Models in Austrian Banking Supervision

This section presents the models which have already been implemented in Austrian banking supervision and focuses on describing their methods, results and data input as well as their respective advantages and drawbacks.

In addition, the FMA and OeNB employees responsible for each model, the frequency of analyses and the date of the last update are all indicated at the beginning of each section. For more detailed studies on these tools, please refer to the relevant publications indicated.

3.1 Statistical Models

The category of statistical models comprises the logit and the Cox model. Both of these model types employ a historical data set in order to estimate the empirical relationship between explanatory variables and the problem event in the banks under examination. In this way, both models optimize the weights with which indicators contribute to the output. More detailed descriptions on each model are presented below.

3.1.1 Logit Model

Contacts:
OeNB: Evelyn Hayden
FMA: Jürgen Bauer

Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: June 1, 2004
Latest adaptation/model revision: June 1, 2004

Further information:
FMA/OeNB. 2004. New Quantitative Models of Banking Supervision. Vienna.

3.1.1.1 General Model Description

At present, one of the central instruments used in off-site analysis is a logit model. In both academic literature and in practice, logit models are regarded as the state of the art in credit assessment modeling, and their results can be interpreted directly as probabilities or ratings.

In order to develop this specific logit model, the project team used a database of 280 indicators from 10 risk categories (bank characteristics, credit risk, capital structure, profitability, market risk, liquidity risk, operational risk, reputational risk, management quality and macroeconomic factors).

The model currently in use contains the 12 most significant indicators identified in numerous univariate and multivariate tests; these indicators are listed in the table below together with their respective risk categories and effects.

Category	Indicator	Effect	Transformation
Bank characteristics	Sector assignment (dummy variable)	+	No
Credit risk	One-year relative change in claims on customers	–	No
Credit risk	Troubled loans / Total loans	+	No
Credit risk	One-year relative change in loan loss provisions	+	Yes
Credit risk (Major Loans Register)	Total volume in excess of limit / Total loan volume	+	No
Capital structure	Assessment base / Total loans	+	No
Capital structure	Relative change in capital since previous year	+	Yes
Profitability	Profit on ordinary activities / Balance sheet total	+	Yes
Profitability	Annual result after risk costs / Balance sheet total	–	No
Profitability	Hidden reserves / Balance sheet total	–	No
Profitability	Percentage deviation in profit on ordinary activities (quarterly report 3 vs. quarterly report 5 of previous year)	+	No
Macroeconomics	Change in consumer price index	–	No

Figure 4: Logit-Model-Ratios

The effect column shows how a change in the indicator will influence the output of the logit model, with "+" signifying an increase in the probability of problems as the indicator value rises (regardless of the permitted range of the indicator) and "–" signifying a reduction.

The logit model calculates the 12 indicators mentioned above, weights them, adds them up and transforms them into a problem probability on a quarterly basis. If an indicator cannot be calculated for a bank (e.g. if the previous year's figures are not available from a newly established bank), the missing indicator is substituted by the corresponding median for all banks (i.e. a practically "neutral" value) in order to create as undistorted an assessment as possible using the remaining indicators. Likewise, extreme indicator values (e.g. resulting from dividing by values close to zero) are set to predefined limit values in order to avoid implausible results, such as problem probabilities of up to 99.9%.

Moreover, it is important to note that three indicators are transformed before being fed into the logit model because they actually do not fulfill the assumption of linearity underlying the model. This transformation was based on the data set and served to translate the indicator values into univariate problem probabilities, which are then input to the multivariate model in lieu of the original indicator values. In the table above, the effect of these indicators is thus always labeled with a "+", as an increase in the univariate probabilities will also bring about a rise in the multivariate probabilities.[1]

The output of the logit model is then smoothed over the previous four quarters (with heavier weights assigned to the more current periods) in order to eliminate excessively large short-term changes in estimated problem probabilities resulting from one-time outliers in the banks' reported data. In order to provide a better overview, these smoothed probabilities are also mapped to the OeNB master scale, which is structured in such a way that it makes the banks' risk estimates easily comparable with the rating classes of international rating agencies.

[1] *Due to their nonlinearity, the effect of the original indicators changes in various value ranges.*

3.1.1.2 Input Data and Assumptions

The input to the model consists of the indicators mentioned above, which are generated from the existing supervisory reporting system (balance sheet data, earnings data, etc.).

Among other reasons, a logit model was chosen because this type of model requires relatively few assumptions. The most important assumption used in the logit model is that there is a linear relationship between the explanatory indicators and the log odd (the transformed probability) of the logit model. If this assumption is not fulfilled, indicators in the model which are actually influential might not be returned as significant, thus reducing the model's goodness of fit. In order to prevent this from happening, all indicators in the logit model described were checked for this characteristic and transformed (i.e. linearized) if necessary.

The predictive power of the logit model (as in all statistical models) is also based on the assumption that the historical relationship between the model's indicators and its log odd (the transformed probability) will remain unchanged in the future. Given the wide range of possible events such as changes in banks' accounting policies or structural disruptions in the banking industry, this assumption is not guaranteed over longer periods of time. Hence, it is necessary to recalibrate the model regularly (e.g. every three to four years) in order to ensure that its predictive power does not diminish.

3.1.1.3 Description of Model Output

The "problem probability" calculated each quarter refers to the probability with which a bank will encounter defined problem situations in the upcoming 12 months. In order to facilitate the assessment of these probability levels, they are mapped to the OeNB master scale, which is structured in such a way that it makes the banks' risk estimates easyly comparable with the rating classes of international rating agencies.

3.1.1.4 Strengths, Weaknesses and Limitations

The table below provides a brief summary of the strengths ("+") and weaknesses ("–") of the logit model:

Strength/ Weakness	Description
+	This type of model requires very few assumptions.
+	The most important assumption – that of linearity – can be ensured by transforming the indicators.
+	The weights with which individual indicators are fed into the model are optimized statistically and account for correlations between the indicators.
+	The quality of the model's output is statistically ensured.
–	The model is based on the empirically measured historical relationship between the explanatory indicators and the occurrence of problem situations at banks; this relationship will not necessarily remain the same in the (long-term) future.
–	The model information is derived from highly aggregated indicators which ultimately cannot provide precise information about the actual causes of problems.
–	Sensitivity analyses are not possible.

3.1.1.5 Possible Future Extensions

A number of theoretically promising candidate indicators for the logit model could not be included in its current version because the required data history was not available. In several years' time, once the necessary time series are available, it will be possible to examine the suitability of these indicators for the logit model.

3.1.2 COX Model

Contacts:
OeNB: Evelyn Hayden
FMA: Jürgen Bauer
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: June 1, 2004
Latest adaptation/model revision: June 1, 2004
Further information:
FMA/OeNB. 2004. New Quantitative Models of Banking Supervision. Vienna.

3.1.2.1 General Model Description

In addition to the logit model, a Cox model was developed recently in order to enable a closer examination of the time structure of problem probabilities. In contrast to the logit model, the Cox model does not determine the problem probability for a specific period (e.g. one year) but makes it possible to estimate the expected duration until the occurrence of the event in question.

First, a traditional and relatively simple Cox Proportional Hazard Rate Model was developed in which banks' indicators were captured only at the starting time. The data set and indicators examined are the same as those used in the logit model. The table below lists the six indicators incorporated in the final Cox Proportional Hazard Rate Model along with their respective risk categories and effects.

Category	Indicator	Effect	Transformation
Credit risk	Troubled loans / Total loans	+	No
Capital structure	Assessment basis / Total loans	+	No
Profitability	Profit on ordinary activities / Balance sheet total	+	Yes
Profitability	Annual result after risk costs / Balance sheet total	–	No
Profitability	Hidden reserves / Balance sheet total	–	No
Profitability	Percentage deviation in profit on ordinary activities (quarterly report 3 vs. quarterly report 5 of previous year)	+	No

Figure 5: Cox-Model-Ratios

The effect column shows how a change in the indicator will influence the output of the logit model, with "+" signifying an increase in the probability of problems as the indicator value rises (regardless of the permitted range of the indicator) and "–" signifying a reduction.

When the Cox model is applied, the six indicators are calculated, weighted, added up and transformed into a Distance to Defined Problem (DtD, i.e. the expected duration until the event occurs) on a quarterly basis. If an indicator cannot be calculated for a bank (e.g. if the previous year's figures are not available from a newly established bank), the missing indicator is substituted by the corresponding median for all banks (i.e. a practically "neutral" value, as in the logit model) in order to create as undistorted an assessment as possible using the remaining indicators. Likewise, extreme indicator values (e.g. resulting from dividing by values close to zero) are set to predefined limit values in order to avoid implausible results.

Moreover, it is necessary to note that one indicator is transformed before being fed into the Cox model, as it actually does not fulfill the assumption of linearity underlying the model. This indicator is transformed in the same way as the ones in the logit model, as the linearity assumptions in both models are asymptotically identical for low probabilities.

Thus the output of the Cox model is a DtD (Distance to Defined Problem), i.e. the expected duration until defined problems arise in the bank (expressed in quarters). The higher this value is, the better the rating assigned to the bank.

3.1.2.2 Input Data and Assumptions

The input consists of the indicators mentioned above, which are generated from the existing supervisory reporting system (balance sheet data, earnings data, etc.).

The advantage of the Cox model compared to the logit model is that the logit model only allows estimates of problem probabilities for a specific period, while the Cox model determines a survival function and thus makes it possible to calculate the expected duration until the event in question occurs. The drawback of this model is that Cox models (which are rather easy to estimate) are based on rather simplifying assumptions, while more realistic models are much more difficult to implement.

For example, the Cox Proportional Hazard Rate Model is based on the assumption that the explanatory indicators do not change over time. In addition, the model is constructed in such a way that the observation periods for all banks begin at the same point in time, regardless of each bank's specific risk status. We can assume that these simplifying assumptions compromise the predictive power of the model, but it is difficult to estimate the extent to which this is the case compared to more complex models.

Moreover, all Cox models – as in the case of the logit model described in section 3.1 – assume that there is a log-linear relationship between the explanatory indicators and the event in question. If this assumption is not fulfilled, indicators in the model which are actually influential might not be returned as significant, thus reducing the model's goodness of fit. In order to prevent this from happening, all indicators in the Cox model described were checked for this characteristic and transformed (i.e. linearized) if necessary.

In addition, as in all statistical models the predictive power of the Cox model is based on the assumption that the historical relationship between the model's indicators and the event in question will remain unchanged in the future. Given the wide range of possible events such as changes in banks' accounting policies or structural disruptions in the banking industry, this assumption is not guaranteed over longer periods of time. Hence, it is necessary to recalibrate the model regularly (e.g. every three to four years) in order to ensure that the model's predictive power does not diminish.

3.1.2.3 Description of Model Output

The Cox model calculates the six indicators described above, weights them, adds them up and transforms them into a Distance to Defined Problem (DtD, i.e. the expected time until the event occurs) for all Austrian banks on a quarterly basis. The higher this value (which indicates the number of quar-

ters), the better the rating assigned to the bank. The maximum possible DtD which can be calculated is 22 quarters (5.5 years), as this is the longest observation period in the data set. In cases where the estimated DtD for a bank amounts to more than 22 quarters, the default value of 24 is used.

3.1.2.4 Strengths, Weaknesses and Limitations

The table below provides a brief summary of the strengths ("+") and weaknesses ("–") of the Cox model:

Strength/ Weakness	Description
+	The model makes it possible to calculate a survival function and thus also the expected duration until defined problems arise.
+	The weights with which individual indicators are fed into the model are optimized statistically and account for correlations between the indicators.
+	The quality of the model's output is statistically ensured.
+	The linearity assumption can be ensured by transforming the indicators.
–	Simplifying assumptions.
–	The model is based on the empirically measured historical relationship between the explanatory indicators and the occurrence of problem situations at banks; this relationship will not necessarily remain the same in the (long-term) future.
–	The model information is derived from highly aggregated indicators which ultimately cannot provide precise information about the actual causes of problems.
–	Sensitivity analyses are not possible.

3.1.2.5 Possible Future Extensions

At the moment, work is underway to develop a more complex Cox model which does not rely on the simplifying assumptions of the Cox Proportional Hazard Rate Model. This advanced approach accounts for the fact that the values of explanatory indicators change over time, and it is designed to determine dynamically the point in time from which a bank's observation period begins on the basis of the logit model's output.

As in the case of the logit model, several promising indicators could not be included in the current version of the Cox model because the required data history was not available. In several years' time, once the necessary time series are available, it will be possible to examine the suitability of these indicators for Cox models as well.

3.2 Structural Model

Contacts:
OeNB: Evgenia Glogova, Gerhard Coosmann, Andreas Höger, Christian Doppler
FMA: Jürgen Bauer
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: March 31, 2005
Latest adaptation/model revision: March 31, 2005
Further information:
FMA/OeNB. 2004. New Quantitative Models of Banking Supervision. Vienna.

3.2.1 General Model Description

In addition to developing the statistical models described above, the OeNB and FMA decided to develop a structural model intended to show the clear causal relationships between banks' risks and problem probabilities. For this purpose, a system of value at risk (VaR) models was constructed for the most important risk factors to which banks are exposed (credit risk, market risk, and operational risk) and then placed in relation to banks' predefined capacities to cover losses. The individual components of this model are summarized below.

3.2.1.1 Credit VaR Model

This model is used to calculate credit risk (expected loss, overall credit VaR distribution and expected shortfall, or ES) in a bank's portfolio. The estimated credit VaR measures a loan portfolio's maximum possible loss in value at a given probability level over the next year as a result of an increase in the probabilities of default (PDs) of the loans in the portfolio. The ES is also calculated for each confidence level and gives the expected loss above the given quantile value.

The approach chosen for calculating credit risk is based on the CreditRisk+ portfolio model developed by Credit Suisse Financial Products in 1997. This method was chosen for two main reasons:

1) The approach is well suited for application to the data set available at the OeNB; and
2) Credit VaR can be calculated using a stable recursive numerical algorithm, which reduces computational effort and thereby makes quarterly calculations for all credit institutions in Austria possible.

The input fed into the model is a combination of various supervisory reporting data and external data on risk developments in specific industries, making it possible to estimate the probable loss for the following year based on a bank's credit exposure.

Standardized calculations are performed for all banks in Austria on a quarterly basis. The parameters of the model can be changed by the user, using a special user interface developed in the Bank.

The model is sufficiently flexible to cater for a wide range of sensitivity analyses.

Model assumptions:
In this model there is only one risk factor – the risk related to the economy as a whole. This affects all borrowers systematically and to the same extent, causing joint fluctuations in their probabilities of default (PDs), i.e. a correlation of PDs.

Contingent on a certain realization of the risk factor, i.e. given a specific economic situation, the default probabilities of individual borrowers are independently Poisson distributed. The risk factor itself is assumed to follow a gamma distribution. The distribution of the total number of defaults in the portfolio for the next period is generated on the basis of the distributions mentioned above. Once the distribution of the total number of defaults has been determined, it is related to the bank's loan given default volume in order to calculate the distribution of possible future losses. To reduce the quantity of input data required, bank-specific exposure bands are defined, and each exposure is approximated by a multiple of the band width.

Exposure:
The amounts for the individual borrower exposures reported to the Major Loans Register are calculated as the maximum value of the credit line and utilization. Exposures which fall below the Major Loans Register's reporting threshold of EUR 350,000 are accounted for in aggregated form on the basis of other reports. The approximated total volume of a bank's small-scale loans is assigned to the lowest exposure band.

Loss given default (LGD):
In accordance with the Basel II framework, an LGD factor of 45% for the unsecured portion and 35% for the secured portion (given a minimum collateralization level of 30%) is applied to each individual exposure. In the case of small-scale loans, an LGD of 40% is assumed.

Probabilities of default (PDs):
On the basis of data from the Austrian rating agency Kreditschutzverband von 1870 (KSV), an average probability of default and its volatility are calculated for each industry group.

The default probabilities for individual borrowers are modeled as random variables (with a certain assumed distribution), and the mean and volatility of their distribution are estimated as follows:

The PDs of individual exposures (mean of the distribution) are calculated as the weighted average of

1) the PDs reported to the Major Loans Register by the credit institution (and mapped to a master scale by the OeNB); and
2) the PD of the borrower's industry group (calculated on the basis of KSV data, as mentioned above).Borrowers which are not assigned to an industry group are assigned the average default probability of all industries.

The individual borrower PDs calculated in this way are then adjusted so that

– the industry group PDs (across all banks) calculated after the adjustment are equal to the average industry PD determined on the basis of KSV data; and

– the average PD for all individual borrowers (for all banks) matches the PD on the Major Loans Register master scale.

Exposures which have already defaulted are not processed by this algorithm; instead, their LGD exposures are totaled and added to the loss calculated by the model.

Risk factor volatility:
The volatility of the risk factor is estimated as the sum of the individual PDs' volatilities. Currently, a value equaling ½*PD is assumed for the volatility of individual PDs, as this appears to be the best approximation based on empirical studies.

3.2.1.2 Market VaR Model

This VaR module determines the total interest rate risk, foreign exchange risk and equity position risk for each bank. The approach chosen for calculating market risk is based on the RiskMetrics approach.

In general, calculating value at risk is encumbered by the fact that individual financial instruments and positions cannot be considered in isolation but have to be evaluated according to their respective risk contributions within the context of the portfolio. This problem is taken into account by including covariances as a measure of the interdependencies between various financial instruments.

However, due to the large number of financial instruments and the resulting high levels of numerical effort and storage capacity requirements, it is impossible to incorporate all covariances directly in the VaR calculation (for 5,000 individual instruments or positions alone, the number of covariance values would be 25 million). In order to account for the diversification effects in a portfolio, an attempt is made to explain changes in market value for all instruments using only a few risk factors. As only the covariances of the changes in risk factors have to be taken into account, this procedure drastically reduces the dimensions of the covariance matrix. The correlations are therefore included in the VaR calculations indirectly by way of the correlations between risk factors and the factor sensitivities of the positions.

The point of departure in VaR calculation is the "portfolio" defined in the mapping process. It consists of the risk factors P_R and is equivalent to the asset portfolio P_A only in terms of risk:

$$P_A = \sum_{k=1}^{m} w_k \, A_k \overset{Mapping}{\Rightarrow} P_R = \sum_{k=1}^{m} \sum_{i=1}^{n} w_k \, a_{k,i} \, R_i = \sum_{i=1}^{n} f_i \, R_i$$

where w_k denotes the share of asset k in the portfolio and f_i refers to the weight of the risk factor i (i.e. the factor load). The volatility of portfolio P_R (and thus also the volatility of portfolio P_A) can therefore be calculated by multiplying the factor covariances with their respective risk weights:

$$\sigma(P_R) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} f_i \, f_i \, \sigma(R_i, R_j)}$$

The value at risk is then calculated by multiplying this volatility with the market value of the portfolio and the selected confidence level α:

$$VaR_P = \alpha \cdot MV \cdot \sigma(P_R)$$

The procedure used to calculate VaR makes it clear that value at risk is not additive, neither in terms of risk factors nor in terms of assets.

This characteristic of the VaR indicator prompted the definition of incremental value at risk. The incremental VaR of a securities position or a risk factor is the contribution to VaR this position makes within the context of the portfolio. In formal terms, this VaR is expressed by deriving the VaR for the risk weight f_i (incremental VaR of a risk factor) or the asset weight w_k (incremental VaR of an asset) multiplied by the respective weight value.

Incremental VaR of risk factor R_I

$$incVaR_{R_i} = \frac{\delta VaR_P}{\delta f_i} f_i = VaR_P \frac{\sigma(R_i, P_R)}{\sigma^2(P_R)}$$

Market VaR consists of three components:

Interest rate risk:
The input used to calculate interest rate risk comprises the net positions reported in interest rate risk statistics (OeNB monthly balance sheet report, part B2). In these tables, the total of assets and liabilities (with due attention to +/– signs) in each currency (EUR, USD, JPY etc.) is provided for predefined time intervals.

In the first step, these positions are mapped to the corresponding risk factors. Thirteen risk factors are defined per currency; for the euro, e.g., these risk factors are:

EUR – 1-month money market interest rate
EUR – 3-month money market interest rate
EUR – 6-month money market interest rate
EUR – 12-month money market interest rate
EUR – 2-year zero coupon bond yield
EUR – 3-year zero coupon bond yield
EUR – 4-year zero coupon bond yield
EUR – 5-year zero coupon bond yield
EUR – 7-year zero coupon bond yield
EUR – 10-year zero coupon bond yield
EUR – 15-year zero coupon bond yield
EUR – 20-year zero coupon bond yield
EUR – 30-year zero coupon bond yield

When the values from interest rate risk statistics are mapped to these risk factors, the following requirements have to be fulfilled:[2]

- the present value of the split payments must match the present value of the original payment;
- the risk (volatility) of the split payments must match the risk of the original payment; and

[2] *See RiskMetrics, Technical Document for further details, 1996.*

– the split payments must have the same sign (+/–) as the original payment.

In this way, for example, data from interest rate risk statistics with a notional residual maturity of 6 years are calibrated to the closest risk factors – in this case to the 5-year and the 7-year zero coupon bond yields.

Equity position risk:
The balance sheet data from the monthly balance sheet reports (Part A) banks submit to the OeNB are used to measure equity position risk. At the time of publication, however, Austrian regulators only had data on the total of domestic and foreign equities at their disposal.

Foreign exchange risk:
For the purpose of measuring foreign exchange risk, the best approximation available can be found in the reports required under Article 26 of the Austrian Banking Act. At present, the problem in this context is that these reports are based on the respective highs per currency and month, not on certain cutoff dates or monthly averages.

3.2.1.3 Operational VaR Model

Although banks in Austria have already begun to collect the required data on operational losses in order to quantify this risk properly, these data are not yet available to the regulators. According to international studies, operational risk constitutes a significant risk factor. In fact, the relevant calculations indicate that up to 30% of the economic capital held by banks is intended to cover operational risk. On the basis of this assumption, the following workaround has been developed using the Basic Indicator Approach (Basel II) in order to enable at least a rough approximation of this risk factor to be integrated into the first version of the structural model.

If we assume that the frequency of operational loss events is geometrically distributed and approximate the loss per event using exponential distribution, then the total loss attributable to operational risk will likewise be exponentially distributed, meaning that it can be described completely by identifying a single parameter. As a result, once this parameter is known, the operational VaR can be calculated for any confidence level. This calculation is based on the fact that advanced measurement approaches under Basel II require a confidence level of 99.9% in order to calculate minimum capital requirements and on the assumption that the easy-to-implement Basic Indicator Approach has been calibrated to that confidence level.

3.2.1.4 Aggregation of VaRs

Once the individual VaR distributions have been calculated, they are aggregated in order to calculate a total VaR for each bank. First, the individual VaRs are adjusted to represent risk measures for equal time periods, as the credit VaR and operational VaR are based on an annual time horizon, while the market VaR uses a daily horizon. As rating agencies generally quote annual default probabilities and the Basel II framework also favors this time horizon, the market VaR was adjusted accordingly by scaling up the daily market VaR by the square

root of 250. This is the best and most consistent method, although it must be noted that this approach certainly overestimates market risk, given the fact that it is far easier for banks to restructure their portfolios over a much shorter time period.

With regard to the actual aggregation of the individual VaR components, two approaches were evaluated – aggregation using a variance/covariance matrix and the application of copulas. However, neither method was able to deliver entirely convincing results. On the one hand, the use of a variance/covariance matrix is an impure solution from the theoretical perspective, as risk factors have to be normally distributed, which seems especially questionable in the case of credit risk and operational risk. Moreover, it seems unclear how the covariances are to be estimated. On the other hand, using copulas is rather cumbersome, and it remains to be seen whether this degree of precision is even necessary for aggregation given the approximations required to calculate the individual VaRs. Based on these considerations and the view that it is preferable to overestimate a bank's risks in cases of doubt, the more conservative approach in which the total VaR is defined as the sum of the individual VaRs was chosen. This corresponds to a variance/covariance approach with perfect correlations.

$$VaR_{Total} = \sqrt{\begin{pmatrix} VaR_{Credit} \\ VaR_{Market} \\ VaR_{Op} \end{pmatrix}^T \begin{pmatrix} 1 & \rho_{K,M} & \rho_{K,O} \\ \rho_{K,M} & 1 & \rho_{M,O} \\ \rho_{K,O} & \rho_{M,O} & 1 \end{pmatrix} \begin{pmatrix} VaR_{Credit} \\ VaR_{Market} \\ VaR_{Op} \end{pmatrix}}$$

where ρ_{ij} represents the correlations between market and credit risk, between market and operational risk, and between credit and operational risk; at present, these correlations are always equal to 1.

3.2.1.5 Banks' Capacity to Cover Losses

The final step in the structural model is to relate banks' total VaR with their capacity to cover losses. Using the total VaR distribution, it is possible to identify the significance level for which a bank's covering funds are precisely equal to its total VaR.

In general, equity serves to cover potential risks. Depending on the perspective taken, one can look at the book value or the net asset value of equity, or use the regulatory definition of capital. The latter definition, however, recognizes hidden reserves only to a limited extent, although they may well be used as potential cover in internal calculations. As there are other assets besides equity that can be used as coverage capital, it seems appropriate to classify risk coverage capital into different categories.

Classification of coverage capital:[3]

Classifying reserves (i.e. the capacity to cover losses) makes it possible to account for the fact that risks have different probabilities on the one hand and that the availability of financial funds varies widely on the other. In this way, a bank's total VaR can be calculated for different confidence levels and subsequently compared to various risk coverage assets.

[3] *Cf. Schierenbeck, H. 2003. Ertragsorientiertes Bankmanagement.*

- *Level 1 reserves* consist of loan loss provisions plus the risk costs budgeted during the year, excess profits/annual losses and the profit/loss carried forward from previous years. The bank has relatively free access to these funds. In this context, it is assumed that one can divide expected annual profit into two components:
  - Minimum profit: An expected minimum return on paid-in capital and a distribution to shareholders are assumed and allocated to level 3 reserves.
  - Excess profits: This is equal to the total loss for the year or the amount of (expected) profits above the minimum profit level.
- *Level 2 reserves* are calculated by adding hidden reserves to level 1 reserves and accounting for changes in intangible assets. However, as hidden losses are currently not reported in a useful form and therefore cannot be included in the calculation, level 2 reserves are considered equal to level 1 reserves.
- *Level 3 reserves* consist of level 2 reserves plus excess equity (solvency level over 8%), minimum profits and the fund for general bank risks. When a bank resorts to these funds, it means that reserves have already been tapped to a severe extent.
- *Level 4 reserves* are calculated by adding a bank's core (tier 1) capital to level 3 reserves. In order to avoid recording excess equity twice, it is deducted from level 4 and level 5 reserves according to the ratio of available tier 1 and tier 2 capital. If level 4 reserves are exhausted, insolvency is certainly an issue, but the question of damage to customer interests is not yet raised.
- *Level 5 reserves* consist of a bank's level 4 reserves plus its tier 2 and tier 3 capital. If losses exceed level 5 reserves, the bank will default and cause damage to customer interests (even before level 5 reserves are tapped, exhausting tier 2 funds may have also caused such damage).

3.2.1.6 Summary

The structural model has already been used in a number of calculations. In each case, the model has yielded results of plausible magnitude, thus confirming the model specifications selected.

Although the structural model is currently based on a number of simplifying assumptions, the general foundations have been laid for a comprehensive model which, by using very clear causal relationships, can explain and predict the risks faced by banks. The modular structure of this model will facilitate further improvements, as specific components can be updated immediately whenever new data or insights are available without requiring an adaptation of the entire system.

3.2.2 Input Data

The input data used in these model calculations include Major Loans Register data, KSV industry default data, market data from RiskMetrics, interest rate risk statistics as well as equity and earnings data from banking statistics reports.

3.2.3 Description of Model Output

The calculations yield the following results in the individual risk categories:

3.2.3.1 Credit Risk

The results of the periodic standard calculation are the 1-year VaR and the 1-year expected shortfall (ES) due to credit risk at all confidence levels. These values can be aggregated with the corresponding risk values from the other categories to determine a bank's overall risk. It is also interesting to observe changes in credit risk over time.

Additional analyses of individual banks can also be performed, for example to determine how sensitive the bank's portfolio is to macroeconomic developments or how severe the effects of an increase in industry or rating class exposures or in the default rate would be.

For some credit institutions, especially those which report collateral incompletely, the current approach to calculating LGD may be too conservative.

Sufficiently detailed data on small-scale loans are not available. The volume of these loans can only be estimated in aggregate form, and the corresponding default data are not available. For this reason, it is only possible to obtain a rough approximation of the credit risk borne by banks with a very large proportion of small-scale loans.

The expected shortfall is always higher than the credit VaR calculated for the same confidence level. For the measurement of credit risk alone, the ES is assumed to be more suitable for estimating unexpected losses (according to proven management practices and academic studies), as this indicator accounts for all possible losses in the upcoming period (and not only those up to the given confidence level).

Many of the input values can be controlled as adjustable parameters. The results of various special analyses can be compared in order to ensure the plausibility of the standard analysis' results and to identify the causes underlying the specific risk situation.

3.2.3.2 Market Risk

The result of the periodic standard calculation is the 1-year VaR at all confidence levels. These values can be aggregated with the corresponding risk values from the other categories to determine a bank's overall risk.

Naturally, the *absolute VaR* is heavily influenced by the size of the portfolio and is therefore not suitable for generating comparisons between individual banks.

However, the *relative VaR* (calculated at a standard confidence level of 95%) is more meaningful, as it is defined by the ratio of absolute VaR to the value of the portfolio or to eligible capital. As a ratio, it is also independent of the size of the bank.

As discussed above, the *incremental VaR* also provides an important source of information for analysis. In this model, the incremental VaR is output as a percentage for the sake of easy interpretation. This value directly indicates the percentage of overall risk which can be attributed to individual risk factors (e.g. the EUR 1-year interest rate or EUR/USD exchange rate). In contrast to absolute VaRs, incremental VaRs have the advantage of being additive. This issue is most easily explained using the following example:

Assume a portfolio with two stocks, A and B, where the investor holds EUR 100 worth of Stock A and EUR 50 in Stock B. The result of a VaR calculation will be as follows:

Value of portfolio (A+B)	=	EUR 150
Absolute VaR of Stock A	=	EUR 11
Absolute VaR of Stock B	=	EUR 5
Absolute VaR of the portfolio	=	EUR 15 (not additive, as 11 + 5 = 16)
Relative VaR of the portfolio	=	15/150 = 10%
Incremental VaR of the portfolio	=	100%
Portion attributable to Stock A	=	65%
Portion attributable to Stock B	=	35%

The *undiversified VaR* is calculated using a fictitious covariance matrix. In this context, all correlations are assumed to be perfectly positive (= +1). This makes it possible to estimate the extent to which portfolio diversification has reduced the risk. This estimate is intended for portfolios containing long positions only. If the portfolio contains long and short positions, it becomes more difficult to interpret the results.

3.2.3.3 Operational Risk

As specified in the model description, the result of the periodic standard calculation is the 1-year VaR at all confidence levels. In addition, the distribution function can be used to calculate the expected loss per bank.

3.2.3.4 Overall Risk

Aggregating the values for all three risk types yields the overall bank risk. The result of the periodic standard calculation is the *absolute 1-year VaR* at all confidence levels. Another important element is the *relative VaR* (at a confidence level of 95%), which is defined as the ratio of absolute VaR to eligible capital, the balance sheet total or the individual levels of reserves.

The sum of individual expected losses (which is always 0 in the case of market risk) shows the *expected overall loss for the bank* and the accompanying confidence level.

Another interesting aspect is the *composition of overall bank risk* and the values for individual risk types (see chart below).

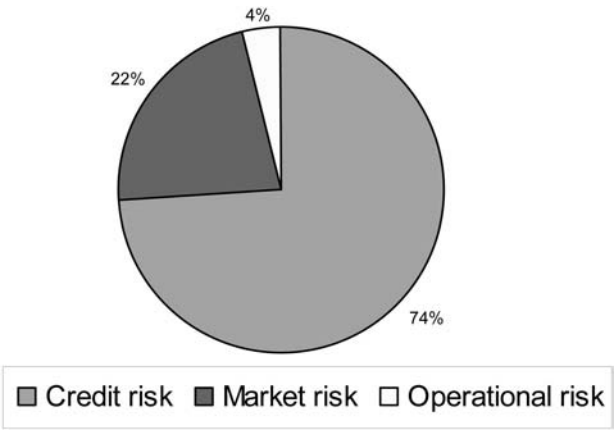

Figure 6: Overall Bank-Risk-Composition

3.2.3.5 Comparison of Results

When the individual results are compared, it is possible to make initial statements on a bank's current risk level. First, it is possible to compare the results with historical risk developments in order to ascertain whether the bank's risk levels have increased or decreased over time.

Especially in this context, particular attention is paid to the interaction between relative VaR (in relation to eligible capital or reserves) and absolute VaR (in monetary units):

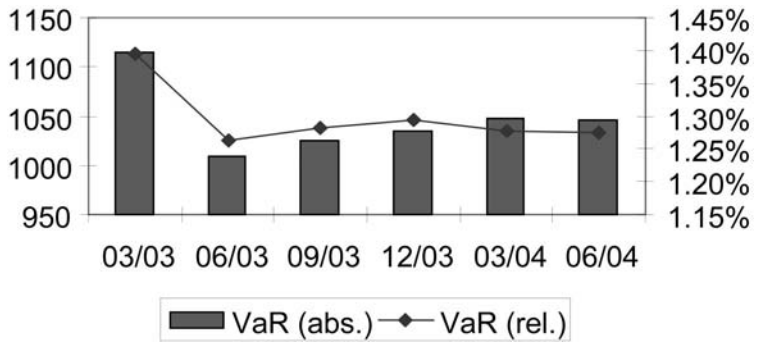

Figure 7: Time-Series of VaR

The model developed allows the regulators to draw comparisons between banks in order to detect whether the risk level of an individual bank has changed or whether the entire sector/country has undergone structural changes.

Some indicators are better suited for this purpose than others. Naturally, absolute indicators such as VaR depend heavily on the size of the bank and hardly provide information on a bank's risk level, while relative indicators such as relative VaR and the composition of a bank's overall risk allow us to draw clear conclusions.

Comparisons of individual banks are performed on three different levels:

- sector level: segmentation of the Austrian banking industry by legal form of business organization and membership in specific trade associations;
- peer group level: for a definition, please refer to Section 3.5.1.1., Peer Groups; and
- global level: comparison with the overall banking industry in Austria.

3.2.3.6 Analysis of Risk-Bearing Capacity

The aggregation of individual risks yields a total value at risk. This value indicates that (with a probability of α) the sum of expected losses from the three risk categories – market, credit, and operational risk – will not exceed this level within one year. In addition to the information on absolute VaR, the changes in values observed over time (i.e. the extent to which VaR has changed upward or downward) and the relationship between economic capital calculated using VaR and coverage capital are especially significant from the regulators' perspective.

Classifying reserves (i.e. the capacity to cover losses) makes it possible to account for the fact that risks have different probabilities on the one hand, while the availability of financial funds varies widely on the other.

The first meaningful analysis can be performed once certain confidence levels and their accompanying probabilities of occurrence are assigned to specific loss events:

- Expected loss: the appropriate confidence level can be determined by iteration.
- Risk potential in negative cases: corresponds to the overall bank VaR at a confidence level of 95%.
- Risk potential in worst-case scenarios: corresponds to the overall bank VaR at a confidence level of 99%.

The next question is whether the banks have set aside sufficient risk provisions for these potential loss events. From the regulators' standpoint, banks should always maintain the following standards:

- level 1 reserves > expected loss
- level 3 reserves > risk potential in negative cases
- level 5 reserves > risk potential in worst-case scenarios

Adherence to these equilibrium requirements can be illustrated clearly using a "traffic light" model:

Equilibrium Conditions	Bank x	Bank y	Bank z
Expected loss < Level 1 reserves	Over limit	Just under limit	Under limit
Risk potential in negative cases **(95%)** < Level 1 to 3 reserves	Over limit	Under limit	Under limit
Risk potential in worst-case scenario **(99%)** < Level 1 to 5 reserves	Under limit	Under limit	Under limit

Figure 8: "Traffic-Light-Approach" of the Structural Model

Calculation of implicit problem probabilities:
According to the definitions given above, every bank has five classes of coverage capital (reserves), each in the amount of D_j , at its disposal. The total VaR can now be used to solve the following equation. The objective is to find the significance level α for which the following is true:

$$VaR^{Total}(\alpha) - D_j = 0$$

The significance level at which the total value at risk equals the available coverage capital D_j is the bank's probability of default as determined by the model.

Therefore, it is possible to compare the loss distribution with the various levels of reserves with due attention to the quality of the capital employed to cover losses. As a rule, the first step consists in reversing the reserves allocated for potential losses or using up any excess profits. Subsequently, hidden reserves are used, or the fund for general bank risks may be tapped. Only once these sources have been exhausted will subscribed capital or disclosed reserves be utilized. Subordinated capital components are touched only in extreme cases (for a more detailed description, see the section on banks' capacity to cover losses).

Such a classification would allow a number of intuitive interpretations:

- the probability that losses will exceed the level for which provisions were made in response to expected losses (comparison with level 2 reserves);
- the probability that components of balance sheet capital will have to be used to cover losses but the bank will remain in business (comparison with level 3 reserves);
- the probability that components of balance sheet capital will have to be used to cover losses and that the bank will be unable to remain in business, that is, the bank's probability of default without causing damage to customer interests or requiring the intervention of a deposit insurance organization (comparison with level 4 reserves); and
- the probability that the bank's capital will not be sufficient to cover losses, that is, the bank's probability of default with damage to customer interests and the intervention of a deposit insurance organization (comparison with level 5 reserves).

The results can be presented as problem probabilities (in the first two cases) and probabilities of default in the broader sense of the term (in the latter two cases) as follows:

	Bank X	Bank Y	Bank Z
Probability that losses will exceed the level for which provisions were made in response to expected losses	>30%	25.00%	12.00%
Probability that components of balance sheet capital (excess equity) will have to be used to cover losses	5.80%	1.01%	0.01%
Probability that balance sheet capital will have to be used to cover losses and that, as a result, the bank will be unable to remain in business (i.e. the bank's probability of default)	2.40%	below 0.01%	below 0.01%
Probability that the bank's entire capital (tier 1 + 2) will not be sufficient to cover losses, that is, the bank's probability of default with damage to customer interests and the intervention of a deposit insurance organization	below 0.01%	below 0.01%	below 0.01%

Figure 9: Interpretation of Structural Model Results

The statements above all refer to VaRs on an annual basis without the appropriate countermeasures.

3.2.4 Strengths and Weaknesses of the Structural Model

The table below provides a brief summary of the strengths ("+") and weaknesses ("–") of the structural model:

Strength/ Weakness	Description
+	Highly innovative bank risk analysis system which allows a detailed analysis of a credit institution's individual risk types.
+	Portfolio model which is sensitive to concentration and diversification effects as well as market developments.
+	Implemented with a modular structure. Modules can be analyzed separately; new developments can be added efficiently by replacing modules.
+	Calculations (some of which are approximate) are possible using available data.
+	Stress and scenario analyses are possible.
+	The combination with market data enables the integration of market expectations.
–	Main problem: insufficient data quality and data availability.
–	High interpretation requirements for results concerning specialized institutions.
–	High coordination effort required.
–	Aggregation of risk types is highly conservative.

3.2.5 Possible Future Extensions

Possible extensions to the credit risk model comprise estimating multiple risk factors and including their correlations, implementing stochastic LGD rates and creating ways to calculate the risk contributions of individual borrowers.

Extensions for total VaR aggregation, especially the integration of theoretically grounded, complex approaches, are also under consideration.

3.3 Systemic Risk Monitor (SRM)

Contacts:
OeNB: Martin Summer, Gerald Krenn, Michael Boss
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: January 1, 2006
Latest adaptation/model revision: new implementation
Further information/publications:
Elsinger, H., A. Lehar and M. Summer. 2002. Risk Assessment for Banking Systems. OeNB Working Paper No. 79. Boss, M. 2002. A Macroeconomic Credit Risk Model for Stress Testing the Austrian Credit Portfolio. In: OeNB. Financial Stability Report 4.

3.3.1 General Model Description

The Systemic Risk Monitor (SRM) is a model-based, quantitative, software-assisted application for the regular analysis of systemic stability in the Austrian banking industry. It is also used for stress testing for systemic risk, i.e. the risk of widespread bank failures in Austria. The Systemic Risk Monitor is based both on the OeNB's research findings on the analysis of systemic financial stability and on the experience gained in the course of the FSAP[4] in the field of quantitative stress tests for the Austrian banking system.

The SRM combines various reporting data from banks, market data and macroeconomic data in model-based simulation calculations to achieve quarterly assessments of systemically relevant cases of bank insolvency and of the resulting financial damage in the ensuing quarter. In addition, the model also enables stress tests which consistently simulate shocks in the economic environment of Austrian banks. This simulation produces an estimate of systemically relevant bank insolvencies and the resulting financial damage in the ensuing quarter assuming one or more predefined stress scenarios.

Calculations are controlled via a user interface which allows the user to set the desired values for model parameters.

The model is based on an overall portfolio for all Austrian banks, which is compiled from various data sources. Relationships between individual banks are simulated by means of a bilateral network of financial contracts, which includes both interbank loans as well as equity interests held in individual banks. Financial stakes in nonbanks are depicted in aggregate positions. The portfolio components are functions of changes to risk factors, the multivariate distribution of which is modeled using a copula approach over a quarterly time horizon.

This distribution integrates risk factors for market and credit risk. A variety of valuation modules for market and credit risk make it possible to determine a profit/loss position for each bank on a quarterly time horizon. These simulated profit/loss positions are translated into insolvencies using a network model with due attention to the relationships between banks; this approach makes it possible to distinguish direct insolvencies from insolvencies caused by second round effects. Using this model of risk factors' multivariate distribution, stress tests are performed by setting one or more factors to extreme values and running the simulation with the resulting conditional distribution.

[4] *Financial Sector Assessment Program (IMF).*

3.3.2 Input Data and Assumptions

The input data used for the SRM are monthly reports from individual banks, reports to the Major Loans Register, market data from Bloomberg and insolvency data from a special analysis performed by the Austrian rating agency Kreditschutzverband von 1870 (KSV).

The SRM operates under the assumption that the portfolio of risk positions compiled from reporting data for each credit institution exists at the time of reporting. The value of the portfolio in a given quarter depends on the realization of a risk factor profile which affects both banks' market and credit risk.

On the basis of historical data, the multivariate distribution of these risk factors is estimated using a copula approach which is especially effective for capturing joint shocks in risk factors and their dependencies. The future development of risk factors is simulated on the basis of this distribution, and the profit/loss distribution is determined simultaneously for each individual bank. These distributions are then translated into the resulting insolvency and damage distributions in the system using a network model. The network model assumes that the technical insolvency of each individual bank will be ascertained at the end of an observation period of one quarter after the realization of risk factors. This makes it possible to identify direct insolvency risks as well as any chain reactions.

3.3.3 Model Output and Significance

The model outputs probabilities of default for individual banks as well as banking groups and the overall system. These insolvencies can be divided into first round and second round (contagion) effects. These statistics can be calculated for both the status quo and for stress scenarios. Typical stress scenarios include adverse developments in the structure of interest rates, in important stock prices or in exchange rates for international key currencies, as well as macroeconomic shocks. The model's output also includes financial damage at the system level (i.e. the ES). These results enable two types of statements: In quantitative terms, it is possible to estimate probabilities of default, the probability of chain reactions, the collapse of systemically important banks and the financial dimensions of these defaults under normal and extreme circumstances. In qualitative terms, it may be possible to assess whether the combination of all quantitative results justifies statements as to whether or not the banking system will remain sound in terms of systemic risk in a stress scenario.

3.3.4 Strengths, Weaknesses and Limitations

The strengths of the SRM lie in the networked analysis of all reporting data from various sources, as these data are examined in context. Moreover, the SRM is especially well suited for capturing systemic events because it performs two essential functions which cannot be performed in individual bank analysis:

First, the multivariate risk factor distribution captures the dependencies of banks through joint exposures. Second, the network model also captures network dependencies and chain reactions caused by insolvencies. Therefore, the two decisive sources of systemic risk are modeled effectively. One weakness of the SRM is its mechanical examination of portfolios, which does not allow for endogenous reactions on the part of market participants. This form of

endogenous risk is especially important at the systemic level. At present, no satisfactory solutions for modeling this aspect can be found in the literature. The SRM's limitations lie in the fact that although the data are highly detailed, they only provide a rough picture of the banking system's risk position. In particular, interrelationships with the global economy are depicted only in a very rudimentary manner.

3.3.5 Possible Future Extensions

The SRM has a modular structure, which means that individual parts of the model can be exchanged without compromising the general framework. For this reason, it is especially desirable to continue developing individual modules in the future and to advance the SRM in line with technical progress in risk analysis.

3.4 CAMEL

Contacts:
OeNB: Evelyn Hayden
FMA: Jürgen Bauer
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: January 1, 1995
Latest adaptation/model revision: December 31, 2003
Further information:
Turner, J. 2000. The Austrian Supervisory Risk Assessment System. In: OeNB. Focus on Austria 01/2000.

3.4.1 General Model Description

The CAMEL bank ranking system – which is used by the Federal Reserve in the U.S. – assigns grades to the five areas described below in order to calculate an overall index value for banks. Substantial elements of this system were already implemented in the Austrian banking analysis system years ago and have now been revised to allow quarterly revisions of the rankings.

The model uses supervisory reporting data to calculate indicators in each of these five areas for all banks, which are then sorted and ranked according to these indicators. Next, the respective bank rankings in each area are weighted and added up on the basis of their overall relevance and the distribution of the individual indicators in order to determine an average weighted composite ranking as the final result. If a specific indicator cannot be calculated for a bank (e.g. if the previous year's figures are not available from a newly established bank), the missing indicator is substituted by the corresponding median for all banks (i.e. a practically "neutral" value) in order to create as undistorted an assessment as possible using the remaining indicators.

The five areas as well as their corresponding indicators and weights are shown in the table below.

	Area	Indicator	Weight
C	Capital	Equity ratio (extended solvency coefficient)	0.5
A	Assets	Risk assets/utilization according to Major Loans Register (including small-scale loans)	2.0
M	Management	Ratio of profit on ordinary activities in quarterly report 3 and quarterly report 5	1.0
E	Earnings	Expected annual result before risk costs/core capital	2.0
L	Liquidity	Measure for capital maturity transformation	0.5

Figure 10: CAMEL-Ranking-Ratios

Details on the above indicators:

– The equity ratio is based on data from the supervisory reporting system for banking statistics and calculates a type of solvency coefficient with due attention to market risk. This means that the capital requirements for market risk are covered with low-quality capital (tier 3) as long as eligible capital is available in that category, and that higher-quality capital is not tapped until later. The remaining capital (excluding potential excess capital under tier 3) is then placed in relation to the assessment base (as in the case of solvency).

- In order to depict the quality of assets, loan volumes in the Major Loans Register (adjusted for collateral and loan loss provisions) are multiplied by the default probabilities for the corresponding rating class (reported and mapped to the OeNB master scale) and then added up. The risk assets calculated in this way, which include an approximation of small-scale loans from other reports, are then placed in relation to the total loan volume.
- While all of the other indicators are updated on a quarterly basis, the indicator for approximating the qualitative criterion of management quality can only be calculated annually because it is defined as the percentage deviation of profit from ordinary activities as forecast in quarterly report 3 for the year and the actually realized profit on ordinary activities (in quarterly report 5).
- To capture banks' profitability performance, the annual result before risk costs according to the quarterly report is placed in relation to core capital to yield an indicator which reflects return on equity.
- Finally, liquidity is based on residual maturity statistics and provides a measure for capital maturity transformation.[5]

3.4.2 Input Data and Assumptions

The input consists of indicators generated from the existing supervisory reporting system (balance sheet data, earnings data, etc.).

The clear advantage of the CAMEL system is its simple, easy-to-understand structure. As it was not developed and optimized using an empirical data set but instead constitutes what is referred to as an expert model, it is not based on any major assumptions.

3.4.3 Description of Model Output

The five indicators described above are calculated on a quarterly basis for all banks, which are then sorted and ranked according to the results. In a next step, the respective bank rankings in each area are weighted and added up to determine an average weighted composite ranking as the final result. The lower a bank's final ranking, the lower is the rating assigned to the bank.

[5] *For details, please refer to section 3.5, Peer Group Analysis/Filtering System.*

3.4.4 Strengths, Weaknesses and Limitations

The table below provides a brief summary of the strengths ("+") and weaknesses ("–") of the CAMEL model:

Strength/ Weakness	Description
+	Simple, easy-to-understand structure.
–	The weights with which individual indicators are fed into the model are not optimized statistically and do not include correlations between the indicators.
–	The quality of the model's output is not statistically ensured.
–	Information is lost in the transition from indicator values to rankings, as consecutive rankings are spaced evenly, while indicator values can be very close to one another or show very large differences.

3.4.5 Possible Future Extensions

No changes are planned at the moment.

3.5 Peer Group Analysis/Filtering System

Contacts:
OeNB: Christoph Klamert, Christian Doppler
FMA: Jürgen Bauer
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: January 1, 1995
Latest adaptation/model revision: January 1, 2003
Further information:
Turner, J. 2000. The Austrian Supervisory Risk Assessment System. In: OeNB. Focus on Austria 01/2000.

3.5.1 General Model Description

This analysis tool compares indicators for individual banks within predefined reference groups (i.e. peer groups). These reference groups are not based on the partly inhomogeneous sectors or size classes but are defined across sectors according to specific criteria. In this way, balance sheet and earnings data as well as indicators for banks showing similar structures can be compared and developments can be identified using a reference group.

3.5.1.1 Peer Groups

Credit institutions in Austria were grouped in peer groups according to structural similarity. Defining these peer groups was indispensable for all modules of the analysis system as banks wanted to draw comparisons with competing institutions and there was a general interest in detecting special trends in individual institutions which deviate from the reference group.

One question which arose was that of the criteria by which the credit institutions should be grouped together:

– Analyses based on size differences (comparison of balance sheet totals) can provide interesting general information; however, such size comparisons fail to detect more specific problems. Due to various structural problems, comparisons between large and small credit institutions as well as institutions of approximately equal size involve difficulties in several respects.
– Analyses based on intrasectoral comparisons of credit institutions likewise failed to produce the desired results due to substantial differences in size and structure within the sectors.

For this reason, it was necessary to define a new classification method. In order to avoid distortions in the ensuing classification process, a number of institutions had to be heuristically assigned to separate groups from the outset because they hold special positions:

– All *large banks* with a balance sheet total in excess of EUR 2 billion were classified in Peer Group 1.
– All *foreign banks* (i.e. with foreign assets greater than 30% of the balance sheet total) which did not fall into Peer Group 1 were assigned to Peer Group 2.
– All *specialized banks* (i.e. those previously assigned to the special purpose bank sector, including building and loan associations, the Oesterreichische

Kontrollbank, sectoral investment banks and investment companies) were assigned to Peer Group 3. For internal purposes, this rather heterogeneous group is divided into more homogeneous subgroups (investment companies, banks specializing in automobile financing, loan guarantee cooperatives and housing banks).

The remaining credit institutions were then classified according to their balance sheet structure. The liabilities side of the balance sheet delivered insufficient discriminatory power; especially as savings deposits correlated closely with the balance sheet total, this classification would have been too similar to the balance-sheet-total criterion. For this reason, the developers of the model decided to group the remaining banks using the assets side of the balance sheet which – with the exception of off-balance sheet transactions – provides a fairly true reflection of a bank's risk potential. The relation between domestic interbank claims (DIC) to claims on domestic nonbanks (CDNB) was used as a grouping criterion. This parameter covers approximately 85% of the balance sheet volume.

Initial attempts to create strictly delineated groups using these two criteria (different intervals for each criterion, which were later merged) produced inhomogeneous groups because too many similar credit institutions could fall into different groups (i.e. discriminatory power was too low).

Although they yielded better results, tests using multivariate statistical procedures such as cluster analysis (grouping of objects on the basis of several criteria) did not prove to be practicable or transparent, also with regard to annual recalculations. However, these procedures were instrumental in discovering the current – and nearly optimum – solution. A simple heuristic grouping procedure was inferred from a graphic depiction of the cluster analysis solution: a strata-based model in which the two variables mentioned above could be used as combined (as opposed to consecutive) discriminatory criteria.

Discriminatory power tests by means of variance analyses and other procedures showed that the heuristic approach only deviated slightly from the optimized cluster solution but proved to be far easier to handle in application and provides more stable results over a period of several years.

This new classification generates groups of banks characterized by a trend toward increasing domestic interbank transactions and at the same time decreasing domestic nonbank business. The correlation between the two parameters is approximately 93%. While Peer Group 4 mainly consists of banks with a high proportion of claims on nonbanks, Group 9 is made up of banks with claims arising almost exclusively from interbank transactions.

This new means of grouping banks makes it impossible for similar credit institutions to qualify for two different groups (discriminatory power).

Number	Name	Number of Banks		Definition
		2004	2003	
1	Large banks	28	28	Balance sheet total > EUR 2 billion
2	Foreign banks	41	42	Foreign assets as a percentage of balance sheet total > 30%
3	Specialized banks	99	88	
4		24	33	CDNB – 2*DIC > 60%
5		128	141	CDNB – 2*DIC > 35%
6		158	152	CDNB – 2*DIC > 15%
7		96	126	CDNB – 2*DIC > 0%
8		203	179	CDNB – 2*DIC > –30%
9		117	108	CDNB – 2*DIC <= –30%
TOTAL	Total number of banks	894	897	

DIC: Domestic interbank claims as a percentage of balance sheet total
CDNB: Claims on domestic nonbanks as a percentage of balance sheet total

Figure 11: Peer Group Criterias

The multiplication factor of 2 applied to domestic interbank claims (DIC) in the table above was introduced as a weighting factor in order to offset size-related differences compared to claims on domestic nonbanks (CDNB).

Group membership is recalculated for each upcoming year using the data of the December monthly balance sheet report.

The filtering system then uses the peer groups described above. Above all, this system examines the continuity of a bank's business as it develops over time as well as the conformity of an individual bank's balance sheet structure and earnings development with the peer group data. However, conspicuous deviations must not be misinterpreted as early warning indicators. Instead, they should be seen as triggers for a closer investigation of the structure and development of the specific bank in certain business segments.

Closer investigation involves calculating the extent to which a bank deviates from its respective peer group for 15 different indicators. If a bank's indicator values leave a certain target range, the system flags this development. When a bank persistently deviates from the peer group's general trend but remains within its own target range, this flagging function is automatically overridden, assuming that – despite its atypical development – the bank is developing without problems, or that this particular development is already known.

The following 15 indicators are used in this model:

4 business development indicators:

- increase in balance sheet total (percentage deviation from previous year)
- growth in off-balance sheet transactions (percentage deviation from previous year)
- direct credits to the nonbank private sector (as a percentage of total direct credits)
- off-balance sheet transactions (as a percentage of balance sheet total)

7 earnings development indicators:

- net interest income (as a percentage of balance sheet total)
- euro interest spread
- foreign currency interest rate spread
- operating result (as a percentage of balance sheet total)

- operating result per employee
- annual result after risk provisions (as a percentage of core capital)
- annual result after risk provisions (as a percentage of balance sheet total)

4 risk development indicators:

- loan loss provisions (as a percentage of loans)
- risk costs (as a percentage of expected annual result before risk provisions)
- capital maturity transformation – CMT (liquidity risk):
  Data input: residual maturity statistics.
  CMT is defined within a range of [–8; +8].
  High positive values for CMT point to high liquidity risk, while high negative values indicate low liquidity risk.
  Therefore, banks can be ranked according to CMT.

  $$CMT = \frac{\sum_{i=1}^{5} M_i \cdot A_i}{\sum_{i=1}^{5} Abs(A_i)}$$

  where: M_i = Maturity in maturity band i
  A_i = Net amount (assets minus liabilities) in maturity band i

- Interest maturity transformation (interest rate risk)
  Data input: interest risk statistics.
  Interest maturity transformation is defined within a range of [–25; +25].
  High indicator values indicate high interest rate risk (regardless of the direction of interest rate changes), while low values signify low interest rate risk.
  Therefore, banks can be ranked according to interest maturity transformation as an absolute amount.

  $$IMT = \frac{\sum_{i=1}^{13} M_i \cdot A_i}{\sum_{i=1}^{13} Abs(A_i)}$$

  where: M_i = Maturity in maturity band i
  A_i = Net amount (assets minus liabilities) in maturity band i

3.5.1.2 Deviation Criteria

In order to calculate a bank's deviations from its peer group for each indicator, two types of deviation criteria can be used:

1. static deviation criteria
2. dynamic deviation criteria

While statistical values cause dynamic deviation criteria to automatically adjust to predefined indicators that vary over multiple periods, static criteria remain constant.

Static deviation criteria

When static criteria are used, the following three deviation indicators can be applied:

- Absolute ranges: If a credit institution's indicator value is outside the defined range of values, the credit institution is excluded from the calculation of the mean peer group value for this indicator in order to ensure that the mean is not skewed by such outliers and that calculated statistics are robust.

- Ranges around the peer group mean: All of a bank's indicators are compared to the corresponding peer group mean values. If the bank's indicators remain within the defined ranges, the credit institution is considered "normal" and is not flagged. However, when a value is outside of its defined range, the procedure described below is applied.
- Fluctuation ranges around a bank's individual indicator values: When an indicator lies outside the ranges around the peer group mean value, then the bank's values for this indicator are compared over the previous year. If a value exceeds the individual fluctuation ranges even once, the filtering system flags the institution for further monitoring.

Absolute ranges are given in absolute figures. For the two other ranges, it is possible to predefine either an absolute value (i.e. a certain predefined percentage) or a relative value (deviation from the peer group mean in %).

Dynamic deviation criteria:
When dynamic ranges are used, which is generally the case at present, the formula below is used to calculate (and thus standardize) deviations for each credit institution and indicator.

$$\varepsilon = \frac{x - \mu}{\sigma}$$

ε: Deviation
x: Bank's indicator value
μ: Peer group's indicator value
σ: Standard deviation of indicator values within peer group

In total, this formula is applied to each bank twice. After the first application, those banks whose deviation exceeds a predefined value are excluded from the recalculation. As with the absolute ranges used for static criteria, this step is intended to yield more robust statistics.

After the second run, which is carried out using the new means and standard deviations, banks whose values lie outside predefined limits are reported. These limits define a range of approximately [–1.5; +1.5] and vary slightly depending on the indicator in question. Assuming normal distribution, it is possible to make probabilistic statements regarding filtering efficiency on the basis of these limits.

The effectiveness of the filtering system depends on the homogeneity of the peer groups and on the quality of the defined indicators and ranges, as the number of banks filtered out should not be excessively high or low.

The filtering system makes it possible to boost analytical efficiency drastically by focusing on a few essential elements or positions and thus clearly reducing the number of potential cases for analysis. At present, the banks flagged for further monitoring are displayed in a matrix (bank × indicator) with a simple label as well as the respective indicator value and deviation criterion for the purpose of further processing. Further automation measures (automated activation of quick information functions once a certain number of flags has been exceeded) are currently being implemented in order to allow individual business-based analyses and the separate examination of various deviations (strengths and weaknesses, irregular developments) of the individual banks and indicators.

Naturally, deviations from the peer group can also indicate a "positive" trend. In other words, the filtering system alone cannot clearly determine whether a deviation is to be assessed as positive or negative (e.g. growth in off-balance sheet transactions). For this reason, follow-up analysis – which cannot be automated – is highly significant for evaluating the results of filtering.

3.5.2 Input Data

The input consists of the indicators mentioned above, which are generated from the existing supervisory reporting system (balance sheet data, earnings data, etc.).

3.5.3 Description of the Model Output

The composition of peer groups is calculated each year on December 31 for the upcoming year. The resulting list shows to which peer group each bank belongs.

The filtering system is run each quarter and outputs a table of all banks and indicators along with their respective deviations and the accompanying indicator values. Statistics on the structure of deviations and changes in the previous quarter are also included.

If a bank is considered an outlier, it is not yet clear whether the institution is doing better or worse than its peer group. Large banks and all banks with more than seven deviating indicators are subjected to thorough analysis; their indicator values must always be compared with the peer group values in order to establish whether the institution stands out because it is doing better or worse than the peer group.

3.5.4 Strengths and Weaknesses

The filtering system has the following advantages and drawbacks:

Strength/ Weakness	Description
+	Simple procedure.
+	Peer groups can be used in a variety of ways.
+	Reason for outlier status is clearly visible.
–	Comparing a bank to its peer group only provides a relative indication of the bank's situation, but no absolute results.
–	Forecasts are not supported.
–	Results are not summarized into a single indicator.

3.5.5 Possible Future Extensions

No extensions are planned at the moment.

3.6 Interest Rate Risk Outliers

Contacts:
OeNB: Gerhard Coosmann
FMA: Jürgen Bauer

Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: December 31, 2001
Latest adaptation/model revision: December 31, 2001

Further information:
FMA/OeNB. 2004. New Quantitative Models of Banking Supervision.
OeNB Guidelines for Monthly Balance Sheet Reports (MAUS-Ausweisrichtlinien)
Coosmann, G. and T. Hudetz. 2000. Interest Rate Risk in the Banking Book. In: OeNB Focus on Austria 03/2000.

3.6.1 General Model Description

Since the end of 2001, the OeNB has been using the monthly reports on interest rate risk statistics to monitor the interest rate risk of all banks in Austria. Such a report essentially consists of an interest gap analysis, and its principles follow the Basel Committee document "Principles for the Management and Supervision of Interest Rate Risk". In this context, interest rate risk is defined as the potential change in the value of equity given a parallel interest rate shift of 200 basis points. If this change in value exceeds 20% of current equity, then the bank is considered to be an outlier, that is, an institution with especially high interest rate risk. This instrument enables the regulators to identify credit institutions with significant maturity mismatches and to initiate the appropriate countermeasures.

The report is based on the following principles:

- All interest rate-sensitive assets and liabilities are to be assigned to maturity bands.
- The maturity bands are defined in accordance with the recommendations in the Basel Committee document. These bands are identical to those used in the standard procedure for the trading book:
  - short-term: up to 1 month, 1 to 3 months, 3 to 6 months, 6 months to 1 year
  - medium-term: 1 to 2 years, 2 to 3 years, 3 to 4 years, 4 to 5 years
  - long-term: 5 to 7 years, 7 to 10 years, 10 to 15 years, 15 to 20 years, over 20 years
- The assignment of all instruments to maturity bands must be based on the respective interest commitment (not on residual maturity).
- Off-balance sheet positions are to be broken down into synthetic assets and liabilities, which are then entered using the same method applied to on-balance sheet positions.
- Interest exposures are to be classified by currency, with separate reports for EUR, USD, CHF, JPY, GBP and "Other currencies" (i.e. all other currencies are aggregated in one category).
- The report is not consolidated.
- The report is submitted on a quarterly basis.

In connection with the Basel Committee document, two specific issues were the subject of intense international debate and thus of particular interest during the implementation process:

– How to assign products lacking definite repricing intervals (savings deposits, loans with early repayment provisions, etc.) to the maturity bands?
– How to treat balance sheet positions which are not sensitive to interest rates (equity, etc.)?

The first issue was resolved by avoiding explicit prudential requirements of how such products are to be assigned to maturity bands; instead, institutions are allowed the largest possible degree of freedom in selecting methods for estimating actual interest commitments. Therefore, they are also allowed to use the methods they apply in their internal interest rate management for the purpose of reporting. In this way, the regulators are able to avoid forcing credit institutions to carry out time-consuming redundant calculations and to maintain multiple reporting formats in parallel. However, these methods have to be sufficiently documented in a manner which is satisfactory to the regulators so that the methods can be tested for plausibility during on-site inspections.

The same considerations applied to the second issue: For balance sheet items which are not sensitive to interest rates (e.g. equity), many (but not all) banks apply institution-specific benchmarks in their interest rate management processes, and they are also allowed to use those benchmarks for reporting. Here it is also important that the (notional) interest commitments resulting from the benchmarks are applied uniformly and consistently, as well as being documented for the regulators in an understandable manner.

This documentation is also submitted to the regulators and provides more in-depth information on the nature of each institution's risk management processes.

The indicators *"Change in present value with assumed interest rate change"* and *"as a percentage of eligible capital,"* which form the analytical basis, are calculated in the standard procedure as follows:

1. For each currency to be reported, a positive or negative net position is to be calculated using the "Total assets" and "Total liabilities" values for each maturity band.
2. Each net position must then be weighted with a factor predefined by the OeNB for the respective maturity band. These factors simulate a fictitious interest rate shock of 200 basis points.
3. In the third step, all of the weighted positions in each currency are added up, and the positive and negative (weighted) net positions are offset against each other. This yields the (positive or negative) weighted overall position in the banking book (or in the trading and banking book) for the respective currency.
4. In the fourth step, these weighted overall positions are added up across all currencies without attention to +/– signs. The resulting value represents the weighted overall position in the banking book (or in the trading and banking book).

5. The indicator calculated in step 4 is placed in relation to eligible capital (i.e. defined as a percentage of eligible capital).
6. If this indicator is greater than 20%, the bank is considered an outlier.

This standard calculation procedure for identifying outlier institutions has to be carried out, and the results have to be reported, by all banks. Institutions which employ deviating internal models to calculate risk in addition to the procedure described above are also required to report the results of those calculations.

3.6.2 Input Data

Interest rate statistics are the only input data used in this model. Banks in Austria report these data every quarter in their monthly balance sheet reports (part B2).

3.6.3 Description of Model Output

The figure calculated in this model is a direct indicator of the banks' sensitivity to interest rates (the higher the indicator, the higher the interest rate risk). As the indicator is calculated for every bank, it is possible to rank all credit institutions in Austria by interest rate risk every quarter. Outliers in terms of interest rate risk can also be read directly from this ranking. Interest rate risk is defined as the potential loss given a parallel interest rate shift of 200 basis points. However, this analysis does not enable inferences regarding probabilities.

3.6.4 Strengths and Weaknesses

The interest rate statistics model has the following strengths and weaknesses:

Strength/ Weakness	Description
+	Sound overview of the potential loss in all credit institutions given a standard stress scenario for interest rate risk.
+	Identification of "outlier institutions" in terms of interest rate risk.
–	Does not support probability statements.
–	The quality of reports is not yet optimized; ongoing improvements are made in the course of on-site inspections and through other measures.

3.5.5 Possible Future Extensions

No extensions are planned at the moment.

3.7 Austrian Banking Act (ABA) Violations

Contacts:
OeNB: Jürgen Eckhardt
FMA: Michael Höllerer
Availability:
Frequency of ongoing analyses: monthly
Implementation date of version 1: January 1994
Latest adaptation/model revision: September 2004
Further information:
Austrian Banking Act

3.7.1 General Model Description

Every month, (unconsolidated) supervisory reporting data for individual credit institutions as well as (consolidated) data for groups of credit institutions under Article 30 ABA are reviewed by electronic means in order to ascertain whether all regulatory standards laid down in the Austrian Banking Act (specifically Articles 22, 23, 25, 27 and 29) have been observed. The results are stored in a table of ABA violations.

a) *Review of individual credit institutions and groups of credit institutions: Does capital under Article 23 ABA cover the total capital requirements under Article 22 ABA?*
Total capital requirements under Article 22 ABA:
- Capital requirement *for solvency*: 8% of the assessment base according to Article 22 paragraph 2 ABA, which comprises risk-weighted assets, off-balance sheet transactions and special off-balance sheet financial transactions.
- The capital requirement *for the securities trading book* under Article 22b ABA equals the total capital required for position risks; these calculations have to be available on a daily basis.
- The capital requirement for open *foreign exchange positions and gold* under Article 26 ABA is as follows: If the credit institution's or group's overall currency position calculated pursuant to paragraphs 3 and 4 (sum of the net total amount of foreign exchange positions and of the net gold position) exceeds 2% of eligible capital (immateriality threshold), the capital requirement for foreign exchange risk amounts to 8% of the overall currency position (standard approach).
- Capital requirement under *Article 29 paragraph 4* ABA for qualified nonfinancial equity stakes with a book value exceeding 15% of eligible capital.

Under Article 23 ABA, capital is made up of the following components:
- Core capital *(tier 1 capital)* comprises paid-in capital, open reserves including liability reserves, confirmed interim profits and the fund for general bank risks.
- Supplementary capital *(tier 2 capital)* includes hidden reserves, supplementary capital, subordinated capital, revaluation reserves and the liability sum surcharge (i.e. additional cover by cooperative members).

– Short-term *subordinated capital (tier 3 capital)* comprises short-term subordinated capital and tier 2 capital reallocated to tier 3.

b) *Review of individual credit institutions:*
Does the bank's first- and second-degree liquidity (LI 1 and LI 2) cover its first- and second-degree liabilities under Article 25 ABA?
– According to the Liquidity Regulation, banks are required to hold 2.5% of miscellaneous liabilities in first-degree liquidity (LI 1); this is the *target level of LI 1*. The assessment base for LI 1 comprises average euro liabilities with a notice period or term of less than 6 months, e.g. demand deposits of credit institutions under 30 days, overnight funds and time deposits with notice periods or terms of less than 6 months, etc.
– The available first-degree liquidity includes cash in hand, holdings of freely convertible foreign currency, minted and unminted precious metals, balances with the Oesterreichische Nationalbank or the European Central Bank; this is the *actual level of LI 1*.
– Comparison of *actual LI 1 vs. target LI 1*.
– According to the Liquidity Regulation, banks are required to hold 20% of miscellaneous liabilities in second-degree liquidity (LI 2), including miscellaneous LI 1 requirements; this is the *target level of LI 2*. The assessment base for LI 2 comprises average euro liabilities with a notice period or term of less than 36 months, for example all euro liabilities in the assessment base for LI 1, time deposits with notice periods or terms of 6 to 36 months, etc.
– The available LI 2 includes e.g. checks and maturing bonds, interest coupons, income/dividend rights, etc.; this is the *actual level of LI 2*.
– Comparison of *actual LI 2 vs. target LI 2*.

c) *Review of individual credit institutions under Article 26 ABA:*
– Does the amount of the open position exceed 50% of eligible capital given quarterly maturity?
– Does the amount of the open position exceed 50% of eligible capital given semiannual maturity?

If the credit institution's or group's overall currency position calculated pursuant to Article 26 paragraphs 3 and 4 (sum of the net total amount of foreign exchange positions and of the net gold position) exceeds 2% of eligible capital (immateriality threshold), the capital requirement for foreign exchange risk amounts to 8% of the overall currency position (standard approach).
Banks are required to limit their open term positions under Article 26a. In the case of credit institutions which do not apply Article 22b paragraph 2, this applies to term positions which are not included in the securities trading book.
The sum total of open term positions in individual foreign currencies which become due in each quarter of the calendar year must not exceed 50% of eligible capital at the close of business each day. Exceptions to this are the current and two immediately ensuing quarters of the calendar year.

The sum total of open term positions in individual foreign currencies which become due in each half of the calendar year must not exceed 50% of eligible capital at the close of business each day. Exceptions to this rule are the current and immediately ensuing half of the calendar year.

d) *Review of individual credit institutions and groups of credit institutions (CI groups) under Article 27 ABA:*
   - Does any one large exposure exceed 25% of a credit institution's or CI group's eligible capital, or does a large exposure to an individual group of connected clients exceed 20% of the credit institution's or group's eligible capital (with due attention to the transitional provisions under Article 103 no. 21 ABA)?
   - Is the sum total of all large exposures more than eight times the eligible capital of the credit institution or group?
     According to Article 27 ABA, "Credit institutions and groups of credit institutions shall at all times appropriately limit the particular banking risk inherent in a large exposure. An exposure is considered to be large if the following items, calculated pursuant to Nos 1 through 4, exceed, with an individual client or a group of connected clients, 10% of the credit institution's own funds to be taken into account or of the group of credit institutions' consolidated own funds to be taken into account and amount to at least 500,000 euro."
     The ABA violation table is compiled by means of a standardized analysis procedure.

3.7.2 Input Data

The input for this model consists of indicators generated from the existing supervisory reporting system (balance sheet data, earnings data, etc.).

3.7.3 Strengths and Weaknesses

The ABA violation table has the following strengths and weaknesses:

Strength/ Weakness	Description
+	Transparent presentation of results.
+	Low numerical effort.
+	High data availability.
–	No automatic reporting of causes for ABA violations.

3.7.4 Possible Future Extensions

At present, only minor changes are planned (in response to changes in the ABA).

3.8 Bad Loan Coverage

Contacts:
OeNB: Evgenia Glogova, Doris Datschetzky
FMA: Jürgen Bauer
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: December 2003
Latest adaptation/model revision: June 2004

3.8.1 General Model Description

From the supervisory standpoint (and not only due to Basel II), it is important to be able to assess the level of risk to which a bank or banking sector is exposed and the extent to which this risk can be covered. When reviewing a sector, the regulators need to assess the extent to which this sector can bear risk and whether it would be able to withstand the default of one or more banks.

One initial step in quantifying the risk to which a bank is exposed involves calculating the bank's credit risk. For this purpose, the credit ratings of all borrowers listed in the Major Loans Register report as well as the volume of the underlying loans (the current level of credit utilization) are taken into account. These assets at risk can then be compared to the various reserves available to cover losses. If the assets at risk amount to less than the funds available, the bank has made sufficient provisions and should be able to cover its risks. This calculation method (comparison of assets at risk and capacity to cover losses) is the simplest way of analyzing a bank's risk-bearing capacity.

Since January 2003, banks in Austria have been reporting borrower information as well as the accompanying ratings or rating classes to the Major Loans Register. Each bank has its own rating system or rating scale, but this information is mapped into a master scale developed by the OeNB; thus the reported ratings are standardized.

In addition, the banks also report the volume of collateral attributable to a borrower. The OeNB takes this collateral into account in order to ensure more realistic calculations of assets at risk. In this way, it is possible to calculate and analyze the assets at risk of individual banks, sectors and primary sector levels on a quarterly basis in order to assess the risk-bearing capacity of these three levels.

Data quality and master scale:
The provisions on the Major Loans Register (as set forth in the ABA) were expanded in the Financial Market Supervision Act of 2002 to include new data sets in the reporting requirements. Since the beginning of 2003,[6] Austrian credit institutions have also had to report the value of collateral, the amount of loan loss provisions and the credit rating for each borrower subject to OeNB reporting requirements.[7]

[6] *This reporting requirement was introduced in the business year ending after April 1, 2002. As the business year of most banks ends on December 31, the first reporting date for most banks was January 31, 2003.*

[7] *The reporting requirements apply to borrowers in the Major Loans Register if their credit line or credit utilization with a bank exceeds EUR 350,000.*

In order to enable a comparison of different rating systems among institutions obliged to report to the Major Loans Register, the OeNB developed a master scale into which the institutions' rating systems are mapped. Each risk class on this scale is assigned a specific probability of default.

The OeNB master scale comprises a coarse and a fine scale; the coarse scale has mainly been used in the early stages.

The OeNB master scale includes the following classes:

Coarse scale:

- 7 non-defaulting classes
- 6 defaulting classes
- 1 class for unrated borrowers

Fine scale:

- The 7 non-defaulting classes on the coarse scale are subdivided into 3 classes each, resulting in a total of 21 classes for solvent/non-defaulting borrowers.
- The six defaulting classes on the coarse scale are transposed onto the fine scale with the same names.
- The class of unrated borrowers is also taken from the coarse scale without alterations.

Calculation of assets at risk:

The difference between current utilization and collateral is assumed to be the basis risk. The resulting volume can also be referred to as the uncovered portion of the exposure. These uncovered assets are calculated for all seven rating classes, multiplied by the corresponding default probabilities and then added up to a total. This value equals the total amount at risk for all loans in excess of € 350,000 (the reporting threshold for the Major Loans Register). Loans under this threshold are approximated using other reports. However, as the collateral provided for these loans is not reported, this volume is multiplied by 45%, as is the case in the LGD assumptions of Basel II. The resulting uncovered assets are weighted using a default probability of 1.23% (the result of QIS 3[8]).

Calculation of capacity to cover losses:

The available funds (i.e. the capacity to cover losses) are compared to overall risk assets. In this context, five different types of reserves are differentiated, based on the assumption that banks will resort to different funds to cover losses depending on the size of the credit default.[9] For details, please refer to Section 3.2.1.5, Banks' Capacity to Cover Losses.

3.8.2 Input Data and Assumptions

The input for this model consists of indicators generated from the existing supervisory reporting system (balance sheet data, earnings data, etc.).

[8] *Qualitative Impact Study.*

[9] *Cf. Schierenbeck, H. 2003. Ertragsorientiertes Bankmanagement.*

3.8.3 Description of Model Output

The uncovered assets and the capacities to cover losses are calculated and analyzed on a quarterly basis. The result is a table of all banks, showing their respective uncovered assets and their capacities to cover losses. Subsequently, those banks which could not cover their assets at risk using level 1 to level 4 reserves are listed and analyzed. The table also shows values for both sectors and primary sector levels as well as changes and conspicuous developments since the previous quarter.

In this context, it is important to bear in mind that the analysis of conspicuous institutions/sectors/primary sector levels is only based on the credit risk to which individual banks are exposed.

3.8.4 Strengths, Weaknesses and Limitations

The analysis instrument for bad loan coverage has the following strengths and weaknesses:

Strength/ Weakness	Description
+	Low numerical effort.
+	High data availability.
–	Data quality depends on the reporting discipline of institutions subject to reporting requirements.
–	The calculation of overall risk is based on a highly simplified model and ignores diversification effects.

3.8.5 Possible Future Extensions

No extensions are planned at the moment.

3.9 Overall Analysis of Major Loans Register

Contacts:
OeNB: Gerhard Winkler, Doris Datschetzky, Markus Hameter, Anita Strouhal-Schneider, Sabine Wukovits
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: June 2004 (analysis as of December 2003)
Latest adaptation/model revision: December 2004 (analysis as of September 2004)

3.9.1 General Model Description

In order to ensure the stability of the financial market, it is necessary to continuously monitor and review the numerous risks to which various financial intermediaries are exposed in fulfilling their duties. This is especially true in the case of credit risk, as this type of risk is usually the main cause of problems arising in banks and financial institutions. In this context, of course, it is especially important to monitor large loans which are reported to the Major Loans Register.

Against this backdrop, the stated objective of this analysis model is to provide a current and detailed analytical overview of the Major Loans Register and its development over time. Therefore, the primary source of data for this model is the Major Loans Register itself. These analytical processes systematically prepare the wealth of data contained in the Major Loans Register and make it possible to elucidate the risk inherent in large loans more effectively, especially in light of the new Basel II framework.

This analysis tool consists of three modules: The first module, the "Major Loans Register Overview," provides a global view of the Major Loans Register and also includes analyses of the data set by individual banking sector and country. These processes provide a basis for the identification and detailed analysis of especially risky institutions, to which the second module ("Conspicuous Cases in the Major Loans Register") is devoted. The third module ("Industry Analysis") enables the risk-based observation of large loan exposures among credit and financial institutions to the various industries.

In this model, a multiattribute measurement method is employed in order to identify conspicuous credit institutions (module 2) and industries (module 3). For this purpose, this measurement method uses the following three basic characteristics/classes:

- size
- static risk
- dynamic risk

In this context, an institution or industry is generally considered conspicuous when

- it has a high volume of major loan commitments (→ size);
- and/or it was exposed to high risk as of a specific cutoff date (→ static risk);
- and/or its major loan commitments/risks have changed drastically compared to the previous quarter (→ dynamic risk).

In concrete terms, these three basic characteristics which define whether an institution is considered conspicuous are each based on multiple indicators (→ multiattribute procedure). An institution is thus considered conspicuous when

- its specific characteristic values place it in the 1% quantile among large institutions for at least one of the two indicators/filter criteria in the size class;
- its specific characteristic values place it in the 5% quantile among the worst institutions for at least half of the indicators/filter criteria in the "static risk" class; and/or
- its specific characteristic values place it in the 5% quantile among the worst institutions for at least half of the indicators/filter criteria in the "dynamic risk" class.

An industry is considered conspicuous with regard to a specific characteristic if the 90% quantile value for that characteristic is exceeded, i.e. the indicator value for the respective industry ends up in the top 10% range of the distribution.

Following this methodology, a number of indicators in the three classes described above are calculated for all institutions. These institutions or industries are then subjected to further examination. The results are evaluated and interpreted according to the three basic characteristics/classes mentioned above.

Indicators/filter criteria for identifying conspicuous institutions/industries:

- size
  - exposure
  - utilization
  - number of borrowers
- *static risk* (i.e. risk observed at a point in time)
  - average utilization per borrower (as a measure of the average size of individual exposures);
  - Herfindahl index:
    The Herfindahl index provides a measure for concentration/diversification and is calculated on the basis of utilization as follows:

$$HI = \frac{\sum_{b=1}^{B} \left(\frac{U_{t,b}}{\sum_{b=1}^{B} U_{t,b}} \right)^2 - \frac{1}{B}}{1 - \frac{1}{B}}$$

    where U_t,b … borrower b's level of utilization at time t
    The following applies: 0 ≤ HI ≤ 1 (situation: "equal utilization") ≤ HI ≤ (situation: "one borrower responsible for all utilization");
  - uncovered percentage of exposure (as a measure of collateralization);
  - utilization of loans granted to borrowers outside euro area countries as a percentage of overall utilization;
  - average loan loss provisions (as a measure of the average extent of risk provisions per borrower);

- loan loss provisions as a percentage of uncovered volume:
  A bank's loan loss provisions reflect the cautionary provisions it has made for probable/expected (partly) bad loans. Therefore, these provisions can be interpreted as accounting estimates of expected loss (EL), which is generally calculated as follows:
  EL = PD × EAD × LGD
  where PD … probability of default
  EAD … exposure at default
  LGD … loss given default
  For this reason, the "Loan loss provisions as a percentage of uncovered volume" indicator (see calculation below) can be used as an accounting estimate for bank i at time t.

$$LLPPD_{i,t} = \frac{\sum_{b=1}^{B} LLP_{i,t,b}}{\sum_{b=1}^{B} Max(0, U_{i,t,b} - C_{i,t,b})}$$

  The greater the specific value of this indicator is for a bank or industry, the more attention it deserves.
  $LLP_{i,t,b}$ … loan loss provisions of bank i at time t and for borrower b
  $U_{i,t,b}$ … borrower b's level of utilization with bank i at time t
  $C_{i,t,b}$ … volume of collateral provided by borrower b for bank i at time t
- uncovered portion as a percentage of utilization for rating classes 7 and 8 on the OeNB master scale (as an additional measure for the collateralization of loans in the "watch list" and "default" classes); and
- volume-weighted average PD (as a measure of the average credit rating of borrowers).

- *dynamic risk* (i.e. risk observed over a period of time)
  The dynamic risk indicators in the model reveal the changes in the static risk indicators over a quarter for conspicuous cases and over a year for industry analyses. The following dynamic risk measures are included in this assessment:
  - percentage change in exposure
  - percentage change in utilization
  - percentage change in number of borrowers
  - percentage change in average utilization per borrower
  - absolute change in the Herfindahl index
  - absolute change in the uncovered portion (percentage)
  - absolute change in the utilization of loans granted to borrowers outside euro area countries as a percentage of overall utilization
  - percentage change in loan loss provisions
  - absolute change in loan loss provisions as a percentage of uncovered volume
  - absolute uncovered portion as a percentage of utilization in rating classes 7 and 8 on the OeNB master scale (new)
  - absolute change in volume-weighted average PD

3.9.2 Input Data and Assumptions

The Major Loans Register Overview Report is based on data from the Major Loans Register itself and from SNA[10] data.

3.9.3 Description of Model Output

The objective of this report is to provide a current and detailed analytical overview of the Major Loans Register and its development over time and to identify credit institutions that are conspicuous from the perspective of the Major Loans Register.

3.9.4 Strengths, Weaknesses and Limitations

The model has the following inherent strengths and weaknesses:

Strength/ Weakness	Description
+	Multiattribute procedure.
+	Data availability.
–	Data quality depends on the discipline of institutions reporting to the Major Loans Register.

3.9.5 Possible Future Extensions

No extensions are planned at the moment.

[10] *System of National Accounts.*

3.10 Consistency of Rating Systems for Major Loans Reports

Contacts:
OeNB: Gerhard Winkler
Availability:
Frequency of ongoing analyses: semiannual
Implementation date of version 1: June 2004 (analysis as of December 2003)
Latest adaptation/model revision: December 2004 (analysis as of August 2004)

3.10.1 General Model Description

This analysis tool examines the consistency of results produced by different rating systems. The stated objective of this consistency analysis is to enable a comparison of the results (i.e. credit ratings) generated by system-relevant Austrian credit institutions using their schemes for assessing the creditworthiness of borrowers. This analysis serves to determine the consistency among different bank-specific credit rating systems.

Such analyses provide important insight for off-site analyses as they can later serve as filters for identifying those institutions which systematically rate borrowers differently. Each bank has its own rating system or rating scale, but this information is mapped into a master scale developed by the OeNB, thus ensuring that reported ratings are standardized and comparable. The data set used comprises the credit ratings of system-relevant credit institutions from the Major Loans Register (mapped into the OeNB master scale).

In terms of method, the consistency in these rating systems is defined and measured using the following indicators:

- The first basic measure of consistency used here is the relative frequency of identical ratings arising from pairwise comparisons. This involves comparisons of all possible pairs of institutions, i.e. comparing each individual institution to all other institutions and determining in each process the relative frequency of cases in which two institutions assign the same borrower to the same rating class on the OeNB master scale.
- However, in the case of split ratings (i.e. deviating credit assessments) the results of these comparisons do not allow us to determine whether the two institutions systematically generate different credit ratings (i.e. whether one institution systematically rates borrowers higher or lower). In order to answer this question, Kendall's tau, a (ranking) correlation coefficient based on ordinal data, is used to measure the connection between two variables. (As ratings/rating classes represent ordinally scaled information, a conventional Bravais-Pearson correlation coefficient – which requires interval-scaled input data – cannot be used.) Based on the ranking information, this measure of the connection between variables is calculated as follows:

  $$\text{Kendall's tau} = \frac{n_k - n_d}{n(n-1)/2}$$

  where n_k stands for the number of concordant pairs and nd for the number of discordant pairs. Kendall's tau thus covers all comparison results (i.e. all three types of ties) which can result from the pairwise comparisons. If exclusively concordant pairs are found, the total number of comparisons $n(n-1)/2$ is equal to n_k, and Kendall's tau is equal to 1. In contrast, if

the connection is the complete opposite, n_k would equal 0 and Kendall's tau would thus be –1.

- Finally, the extent of the deviation is also examined. A simple measure is used for this purpose: the average absolute deviation, which is calculated from the ratings v and w (assigned to borrower i by two different banks) as follows:
  average absolute deviation $= \frac{\sum_{i=1}^{n} | v_i - w_i |}{n}$
  The average deviation thus shows the average number of rating classes on the OeNB master scale by which credit ratings for the same borrower differ between two different institutions.

The above-mentioned measures for consistency can only be determined by pairwise comparisons of two banks, but ultimately the overall quality of a bank's rating system is the main topic of interest. Therefore, the results obtained from comparing one institution's rating with those of all other system-relevant institutions have to be aggregated into a single indicator.

- First, a bank-specific mean is calculated using all of the measures proposed above (relative frequency of consistent ratings, Kendall's tau, average deviation per borrower). This mean shows how closely (or poorly) an institution's ratings match the credit assessments of the rest of the credit industry (i.e. all other system-relevant banks) on average. If the market is assessed correctly (that is, bank-specific differences are balanced overall and the majority is accurate), then those institutions which show substantial average deviations from all other institutions are deemed conspicuous in the course of off-site analysis.
- However, this mean does not reveal how heavily the extent of consistency fluctuates in individual pairwise comparisons. Therefore, the above-mentioned measures of consistency are also used to calculate the standard deviation as a measure of bank-specific fluctuations in these values.
- In general, the following applies:
  - The higher the mean of the indicators arising from the pairwise calculations is for
    - the relative frequency of matching ratings
    - and Kendall's tau
  - and the lower the mean of the average absolute deviation per borrower is, the more consistent a bank's rating system is with those of other banks. Likewise, the following holds true:
  - The lower the institution-specific standard deviation is for all bank-specific indicators, the more consistent a bank's ratings are with the rest of the credit industry.

  Therefore, as the last indicator of consistency (k),
  - the quotient of the bank-specific mean and standard deviation for
    - the relative frequency of matching ratings
    - and Kendall's tau

    appears to be suitable, and the following holds true: The higher k is, the better a bank's rating system proves to be in comparison to other institutions.

– the product of the bank-specific mean and standard deviation for the average absolute deviation per borrower appears suitable, which means that the following applies: The higher k is, the more probable it is that a bank's rating system should be considered conspicuous.

3.10.2 Input Data and Assumptions

In line with its purpose, this consistency analysis uses data from monthly reports to the Major Loans Register.

Each institution is compared to all other system-relevant banks. Only if the (single) assumption in this tool – that the market is assessed correctly (that is, bank-specific differences are balanced overall and the majority is accurate) – is true can those institutions which show substantial average deviations from all other institutions be classified as conspicuous in off-site analysis. Therefore, systemic risk (e.g. the majority of institutions rates borrowers inaccurately and only one – the outlier – rates them correctly) cannot be assessed with this model.

3.10.3 Description of Model Output

In this tool, the consistency of the rating systems used by system-relevant credit institutions is evaluated on the basis of their reports to the Major Loans Register.

The measures used for consistency are as follows:

– the relative frequency of matching ratings
– Kendall's tau
– the mean of average absolute deviations per borrower
– an innovative consistency measure k which is calculated for all indicators mentioned.

3.10.4 Strengths, Weaknesses and Limitations

The model has the following inherent strengths and weaknesses:

Strength/ Weakness	Description
+	Outstanding data quality (the problem of low data quality found in many other Major Loans Register data does not arise here).
+	Outstanding data availability.
+	Small number of indicators; a methodically and theoretically grounded procedure which has proven itself in practice.
+	Intuitive comprehensibility of results.
–	System risk (i.e. all institutions rate incorrectly) is not measurable.

3.10.5 Possible Future Extensions

No extensions are planned at the moment.

3.11 Summary

Many analysis systems and tools (including international ones) are readily described as "early warning systems." The analytical tools described here are not presented as an early warning system, rather as a system with the function of a "warning lamp" at best.

The reasons for this careful definition are obvious:

- There is a lag between the time of data delivery and the period the data actually covers: Individual items are sometimes submitted with a delay of up to six months.
- Data quality can be verified using plausibility checks, but only to a limited extent. In some areas it is possible to check positions, but many positions can only be verified over time.
- Although descriptive instructions are provided for report forms, banks may interpret individual positions differently (definition, valuation).
- As banking analysis is not capable of recording and flagging all data on an ongoing basis, gaps in the systems can never be ruled out (too many banks with too many possible problems).
- Certain trends cannot be inferred from the data and can only be identified in on-site inspections; in effect, even external auditors verify banks' adequacy of accounting and compliance with laws and regulations only once per year, and in so doing they depend on information provided by the banks themselves. In many cases, dubious transactions cannot be detected at all or only too late.
- Lack of background information: All too often, the data alone do not allow direct conclusions. One example is loan loss provisions, where high provisions may be made for tax reasons or for problem loans, while low provisions might be attributable to earnings problems or a sound lending portfolio.

As the individual calculations always rely on "historical" data, the banking analysis system described in this document cannot be regarded as a short-term early-warning system. The time lag between data delivery and analysis (some indicators are based on quarterly reports) causes delayed reactions to sudden changes which are not immediately evident in reporting data. However, the system allows regulators to more efficiently monitor irregularities, disruptions in development, structural weaknesses as well as strengths or generally negative developments in individual institutions. In general, this analytical framework, like most other automated analysis tools, effectively supports the identification of problem areas using the available data material and provides a solid basis for more in-depth individual analyses.

4 Reports and Analyses

4.1 Standard Reports

In line with the tasks assigned to the FMA and the OeNB, the regular creation of reports is also part of the joint analysis process. Up to now, reports have been compiled for all of the models used. This wide variety of analyses, which in some cases also overlap in terms of content, will soon be replaced by a risk-based report system which includes an overall banking analysis report.

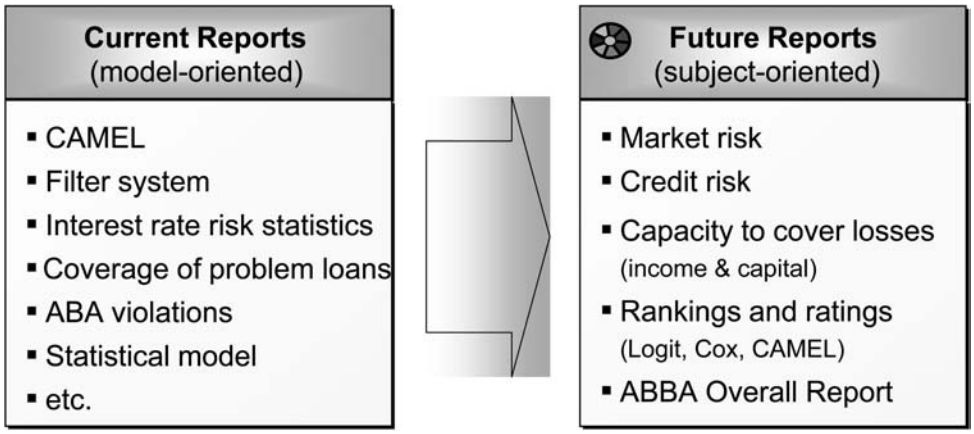

Figure 12: Standard-Reports

4.2 Other ABBA Reports

The following additional reports and analyses are necessary for the ongoing maintenance and development of this new analytical framework:

– update of the problem banks list (once per year): identification of problem banks in accordance with the model definition (including sector allowances, malversation, mergers, etc.); and
– joint evaluation of models (once per year): analysis of the models' predictive power as well as suggestions for improvement and extensions.

4.3 ABBA Overall Report

Contacts:
OeNB: Evelyn Hayden
FMA: Jürgen Bauer, Johann Palkovitsch
Availability:
Frequency of ongoing analyses: quarterly
Implementation date of version 1: March 31, 2005
Latest adaptation/model revision: March 31, 2005

4.3.1 General Model Description

The objective of that Technical Analysis Report is to combine the numerous individual analyses available into an overview of the situation in the Austrian banking system. However, due to the (still insufficient) history of results from individual models, especially in the case of recently developed analysis tools, it is currently not possible to aggregate individual results using statistical procedures. This means that the significance of the individual models as well as their correlations cannot be included in detailed form in the aggregation of results.

Due to these (temporary) problems, the regulators have chosen a pragmatic approach in which all banks are currently assigned to three classes using a "traffic lights" system. The first class (red) describes conspicuous banks for which more detailed analysis and review seem appropriate. The second class (yellow) includes all banks which do not appear to be troubled on the basis of the data currently available, but whose development should be monitored more closely nonetheless. The third class (green) refers to banks which are considered "normal"; this class comprises the majority of banks.

Banks are assigned to these three classes using a two-stage procedure. First, banks are sorted and given rankings based on the results of the most comprehensive models (i.e. the logit model, CAMEL ranking and structural model). These rankings are then weighted and added up in order to determine a composite ranking and thus a weighted average assessment of banks across the various models. In this context, the weight of the logit model is twice as high as the weight assigned to the other models, as the logit model is currently the best validated model in empirical terms. Banks with the lowest (i.e. worst) rankings are assigned to the red class, while banks with higher rankings are assigned to the yellow class.

In the second step, all banks with especially poor ratings in individual models are assigned to either the red or yellow class. It is sufficient for a bank to be labeled as conspicuous by a single model in order to be placed in the red class. Therefore, good rankings from other models cannot offset a single very poor ranking; this ensures that the overall assessment of banks remains conservative in cases of doubt. This procedure also makes sense because the various analysis tools are based on different assumptions and pursue various objectives.

Once again, not all individual analysis tools are used in this second step in the classification of banks. The reason for this is that some tools (such as the filtering system) assess banks in comparison to their peer group, meaning that general statements are not possible without assessing the entire group, while other approaches (such as the "Problem loan coverage" tool) only emphasize specific aspects of the banks' risk situation which are likewise aggregated in

other models (such as the structural model). However, those individual tools which are not used in overall bank assessment still appear as additional information in the Technical Analysis Report, thus making the possible causes of problems easier to identify in the case of conspicuous banks.

The table below gives a brief overview of which analysis models are included in the overall assessment (and why) and shows how the limits for class assignments are defined:

Analysis Model*	Included in Overall Assessment	Red Class	Yellow Class
Logit model	Yes – modern aggregate model	Fine rating class >= 130	Fine rating class 120
Cox model	No – simple model variant, result correlates strongly with logit model	–	–
Structural model	Yes – modern aggregate model	95% VaR / Level 3 reserves > 1	95% VaR / Level 3 reserves > 66%
Systemic Risk Monitor	No – model will not be completed until late 2005, will be included in the future	–	–
CAMEL	Yes – well-known aggregate model	10 worst-ranked banks	Banks ranked 11 to 20
Filtering system	No – only rates banks in relation to their peer groups, not in absolute terms	–	–
Interest Rate Risk Outliers	Yes – outliers are assigned to red class	All violations	–
Austrian Banking Act (ABA) violations	Yes – outliers are assigned to red class	All violations	–
Earnings situation	Yes – also a core criterion in reserves	Operating result / Balance sheet total < –0.05%	Operating result / Balance sheet total < = +0.05%
Problem loan coverage	No – only analyzes part of banks' risk situation	–	–
Overall Analysis of Major Loans Register	No – only analyzes part of banks' risk situation	–	–
Rating consistency	No – only analyzes part of banks' risk situation	–	–

* For further details, please refer to the respective sections in this document.

Figure 13: Models included in the Overall Assessement

4.3.2 Input Data and Assumptions

The input data for the quantitative overall bank assessment are generated using the input data for the individual analysis models.

The current method used for overall bank assessment is a heuristic procedure based on the assumptions that the selected models are most meaningful and that the boundaries for class assignments are optimized. However, neither assumption can be validated statistically at present because of the insufficient history of result data in some cases.

4.3.3 Description of Model Output

The results of the Technical Analysis Report are evaluated and analyzed on a quarterly basis. The model's core output comprises a list of results generated by all individual tools as well as a classification of all banks in Austria into three classes (red, yellow and green). For the time being, banks are only ranked provisionally within those classes (i.e. assigned weighted rankings) on the basis of the model results fed into the overall assessment.

4.3.4 Strengths, Weaknesses and Limitations

The table below provides an overview of the strengths ("+") and weaknesses ("–") of the overall assessment approach:

Strength/ Weakness	Description
+	Simple, easy-to-understand classification procedure.
+	Graphic "traffic lights" approach which is easy to understand.
+	Conservative approach; a single very poor rating is sufficient to classify a bank as conspicuous.
+	Simultaneous identification of banks with generally poor assessments due to the aggregation of individual model results.
–	The analysis models chosen for overall assessment (and their limitations) are not necessarily optimized statistically.
–	Correlations between the models are not taken into account.
–	In the transition from indicator values to rankings, information is lost because consecutive rankings are equidistant.

4.3.5 Possible Future Extensions

In several years' time, once the necessary time series of individual tool results are available, it will be possible to aggregate the results of the analysis models using statistical procedures. Then the appropriate procedures can be employed to identify the optimum aggregation weights with due attention to correlation effects.

5 Concluding Remarks

By grouping individual analysis tools by subject, ABBA has succeeded in implementing the principle of risk orientation in Austrian banking supervision even more efficiently and thus also more economically.

Due to the modular structure of the analytical tools and the extremely wide variety of approaches used, it is possible to react relatively quickly to changes as they arise. In addition, the depth of the analysis modules, which varies widely in terms of content (ranging from comparing indicators to approaching concepts such as economic capital) makes it possible to cover a broad range of analytical questions and to optimize the use of resources at the same time. Semi-automated precategorization enables the regulators to focus their qualitative analytical activities on credit institutions with higher risk levels without completely losing sight of banks which show less conspicuous results based on reporting data and models.

The results generated by standardized analysis tools depend heavily on the quality of their input data. Therefore, in order to optimize the models in use, it is absolutely necessary to question reporting procedures on an ongoing basis and to intensify communication with the supervised credit institutions in this area.

As the preliminary stage before official measures as well as the international representation of Austrian credit institutions, the analysis of all market participants in the banking sector constitutes an essential pillar of banking supervision and should continue as an internal and independent core process handled by the OeNB and the FMA.

In this context, it is necessary to find a reasonable balance between minimizing effort (also in downstream analysis steps) and developing high-quality models and analyses in order to ensure and enhance the stability of the Austrian financial market.

6 Appendix

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