A RATING SYSTEM PROPOSAL FOR SUPERVISORY PURPOSES

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The primary purpose of any rating system is to support investor's decisions. It has been developed for easy navigation across a variety of businesses and other entities, without the need for detailed analyses of their operation. Owing to its straightforward results (entities are graded on a scale) it did not take long to become a widespread tool for managers, investors and, not least, regulators in different fields. In case of banking sector with large number of banks, it tells the regulator which banks to watch more closely.

For if a rating is geared towards assessing the risk profile of bank's core activities (e.g. capital position, assets quality, credit and market risks, liquidity and profitability), rather than producing a single overall rating, it can pinpoint trouble spots for a more in-depth follow-up analysis. Although any rating can't substitute a detailed analysis, if it is a part of an early warning system (EWS), it can draw the attention to the critical areas of a bank's operation in time.

History

The first rating system used for banking supervision at the NBS was a bank rating model based on the CAEL, later CAELS methodology. It scored five key areas of bank operations (capital adequacy – C, asset quality – A, operating efficiency – E, liquidity – L, and sensitivity – S) based on 79 ratios. Each ratio was assigned a rating depending on its value measured against predefined critical thresholds. The final rating was computed in several steps as a weighted average of ratings assigned to ratios belonging to particular area, subject to additional constraints, with manual expert interventions where necessary.

The number of ratios soon turned out to be too high.* Both parametric and nonparametric statistical tests of Pearson and Spearman correlation coefficients have proven significant correlation among several indicators. The nonparametric Spearman method was applied because it does not require the assumption of normal data distribution.

The next step was to determine which of the correlating indicators to discard and which to keep in the rating system. This meant to consider both the economic interpretation of individual variables and their discriminatory power shown in an ad-hoc testing model.

* The tendency observed in models featured in literature is a sharp reduction in the number of parameters, such that remaining parameters describe a bank's operations in an economical and meaningful, yet accurate manner. See Jagtiani et al. 2003, Ong (ed.) 2003.

The result was a set of 18 ratios describing bank's activity in particular areas (C, A, E, L and S), with 3 or 4 ratios per area.

The revision of rating inputs eventually prompted a full review of the rating system.

Current rating system

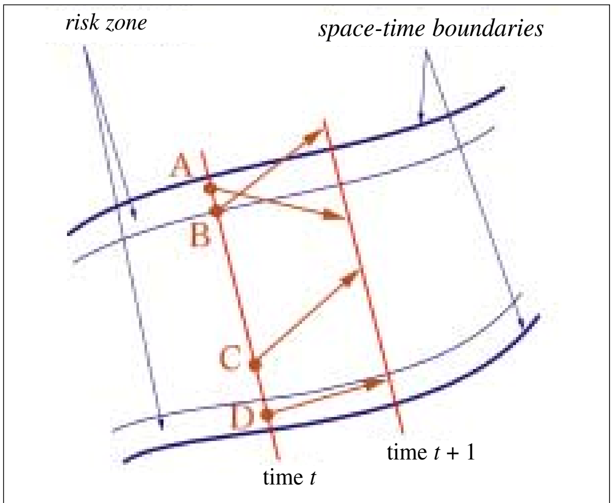
The design of the rating system had to reflect some specifics of the situation in Slovakia:

- a turbulent development of the banking sector in the 1990s; the situation back then is incomparable to today's. Consequently, consistent data is only available from 2000. With only audited year-end data taken into account, the time series is extremely short;
- small size of the banking sector – counting about 20 banks in the period considered;
- frequent changes in the reporting system and required disclosures, calling for high system flexibility.

Apart from that, the system had to be compatible with earlier CAELS ratings and integrate the existing bank rating system based on CAELS methodology and expert assessment available for years 2002 and 2003. This was to ensure that new rating would have essentially the same interpretation as the previous one.

The new rating system is based on an abstraction which could be called a multidimensional banking space-time. A bank moves through the time in a space bounded by the limitations of the market, legislation and regulatory requirements. If the bank comes near a boundary, it becomes a watchcase; if the boundary is crossed, it is a case for regulatory action. In addition to static analysis – a snapshot of the bank in the banking space-time at a given moment – it is essential for the rating system to include information about the direction through time – its development trend. Obviously, we need both types of information to assess correctly the bank's situation, as there is a difference between two banks with the same position at a given time and different directions, or between two banks with the same direction but different starting points.

Figure 1



A scheme showing a banking space-time and movement of banks A – D in time. A 2D version was chosen for better illustration (one indicator plus time), the actual model works in a 19-dimensional space (18 indicators plus time).

For instance, bank A has a worse position at time t than bank B in the picture, because it is closer to the space-time boundary. However, looking at its trend, bank A deserves a higher rating as its trend will bring it out of the risk zone by time $t + 1$, whereas at $t + 1$ bank *B*will find itself outside the boundaries defined by market rules and regulations. Bank *D* stays within the risk zone and its position is clearly worse than bank *C's*.

The rating system is based on a model of a bank. It specifies the indicators to be considered in the rating and allows the definition of their relations and limits to be respected. This makes a dynamic system that simulates movement of a bank – described by financial indicators – in a banking space-time. It is possible to define how indicator values will change over time, how profit will be distributed, etc. Due to the short span of the available time series, evolution trends of individual indicators cannot be determined by a statistical method.

As an approximation of trend estimate, one of the following options may be taken:

• the indicator value remains constant;

• the trend at time t will be equal to the slope of the tangent to a parabola passing through the values of the indicator at times $t – 2$, $t – 1$ and t at time t. Such a trend estimate is based on the assumption that in the near future the bank is not going to stray from the track followed in the last three years, either by its own decision or as a result of external factors. The periods $t – 2$, $t – 1$ and t need not be equidistant, e.g. we may use values reported as at 31 December 2003, 31 December 2004 and 30 June 2005. In this case the system will transform the indicators from profit/loss statement – values of which accrue throughout the year – into projected year-end values by linear extrapolation;

ß the trend will be calculated as in the previous paragraph while adding/subtracting a pro rata portion of profit/loss in case of balance sheet items. The pro rata portion can be determined, for instance, as the share of the relevant item in total assets/liabilities or, for instance, taking into account a strategy to invest 70% of resources into government bonds – depending on the bank model settings;

• the indicator is derived from other indicators using user-supplied formula.

Each indicator can be constrained by limits, which must be satisfied, or alternatively by a set of permitted intervals. Membership in an interval indicates the bank's position in the banking space-time at a given point in time. The interval boundaries were set using quantiles of empirical distribution functions of available values for individual indicators, where specific quantile values were determined by experts' knowledge – based on experience from banking supervision, theory and the legacy CAELS rating system.

The bank model is flexible and lets the end-user modify the rating system without any need for re-programming.

For the moment, financial indicators provided by the banking supervision information system are the only inputs into the rating system, broken down into groups according to the CAELS system. However, other indicators, e.g. macroeconomic ones, can be introduced by a simple change to the bank model.

To assign a rating, the program uses artificial intelligence algorithms – learning systems – fully automatically, without the need for expert action. In learning systems, data is usually processed in two main stages: the learning stage and the gained knowledge application stage. Data entering each stage is time-lagged, so that periods $t – 2$, $t – 1$ and t are processed at the learning stage, and periods $s – 2$, $s – 1$ and s at the rating stage, where $s > t$.

Each stage involves the following calculations:

• data from the banking supervision information system and the user-defined model is used to compute trends for individual indicators and their values in the next period ($t + 1$ and $s + 1$),

• the results are transformed to be usable for the learning system.

The transformation turns the numerical value of an indicator into a series of zeros and ones indicating, for instance, membership in a certain interval or a derivation sign.

The following transformation methods are implemented at present:

1. Interval + tangent: each indicator is recorded by means of 2n parameters taking values 0 or 1, where n is the number of intervals to which the indicator may belong. Each pair represents membership in an interval as follows:

• 0 0 if the indicator does not fall into the interval,

• 1 0 if the indicator falls into the interval and the slope is nonnegative,

• 1 1 if the indicator falls into the interval and the slope is negative.

2. Interval + next interval: each indicator is recorded by means of 3n parameters taking values 0 or 1, where n is the number of intervals to which the indicator may belong. Each triplet represents membership in an interval as follows:

• 0 0 0 if the indicator does not fall into the interval,

• 1 0 0 if the indicator falls into the interval in both the current and the next period,

• 0 1 0 if the indicator falls into the interval, but in the next period its value drops to another interval,

• 0 0 1 if the indicator falls into the interval, but in the next period its value rises to another interval.

This means that the learning system doesn't need to process the exact values of financial indicators, but it's sufficient to use just the information that the indicator value belongs to a certain interval, along with the derivation sign. This makes the system less sensitive to small changes in indicator values and allows it to pick up more significant trends instead.

At the learning stage, ratings assigned to banks in period t are used as an additional source of data. The program is able to recognize relationships between the values and trends of financial indicators and related ratings. Various algorithms could be applied to find the relationships (pattern recognition methods, decision trees, artificial neural networks, PAC learning, etc.); the rating system presented here relies on the Support Vector Machines method. It is based on a simple principle: the learning system will find such a space division by hyperplanes which best separate individual bank groups depending on assigned ratings. If a linear separation of bank groups is not possible, it is appropriate to deform the space in a manner allowing separation. The deformation is given by a selection of a scalar product in a given space, called a kernel function in the learning systems theory. The relationships identified are then used at the second stage where, based on the learned causality, a rating is assigned according to the current values of financial indicators.

The advantage of a learning system is that it can generalise discovered relationships and evaluate even a combination of financial indicator values, which did not appear in the training set. Its another advantage is that financial indicators are not considered separately, but rather as a whole. It can reveal complex interactions among indicators, which are hard to detect by common analytical methods.

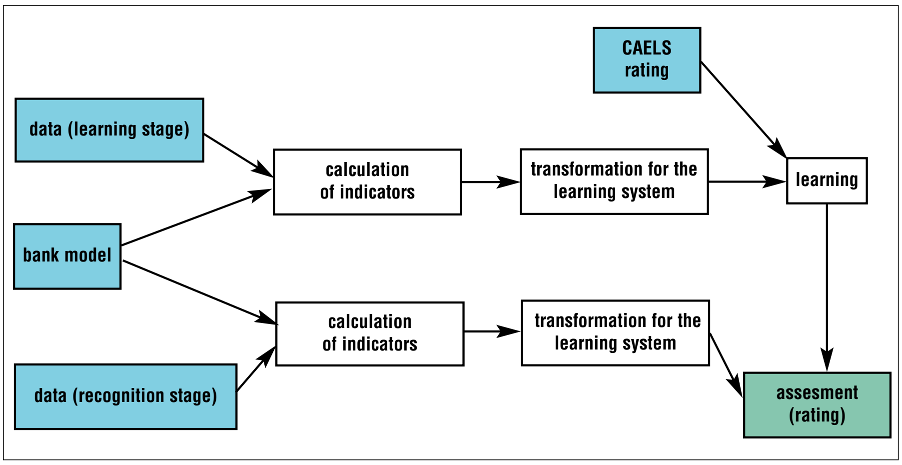
At the learning stage, the original CAELS rating used by banking supervision was applied in order to maintain rating continuity and the link to the CAELS rating system.

In the calculation, one can choose from different settings of the learning system – the type of kernel function (lineal kernel, which offers better economic interpretation, or exponential for higher recognition rate) and optimise its other parameters, where necessary.

The basic workflow of the system is described in Figure 2.

The result is a numerical rating for each bank in respect of individual areas defined in the bank model (e.g. C, A, E, L, S) at a given point in time.

Figure 2



Results

The new rating system has been in place at the NBS banking supervision division since the second half of 2004. Its results have been compared to regular independent analyses of both individual banks and the banking sector. Where major differences occurred between analyst and the rating system assessment, the model was modified (tangent calculation method, calibration of interval boundaries) and the outcome was compared again.

The table below sums up the result of comparison (100 data items compared at each date (20 banks, 5 areas)):

	Analyst agrees with rating	Analyst disagrees with rating
30. 6. 2004	95	5
30. 9. 2004	93	7
31. 12. 2004	96	4
31. 3. 2005	96	4

In final calibration, the very nature of the learning system allows to extend the training set to include analyst-revised ratings. This ensures feedback: the rating triggers an in-depth analysis of a bank, the outcome of the analysis re-enters the rating system as a new input into the next rating assessment.

Further perspectives

Even though the rating system has been successfully tested and operated, several areas remain for further development:

• introduction of fuzzy logic principles. Fuzzy logic is a tool for describing a world with no sharp borders between black and white, good and bad, but rather smooth transitions between extreme values. Although some exact thresholds exist in the banking universe (e.g. the 8% limit for capital adequacy), for the most part it is difficult to draw a line to call an indicator value “good” or “bad”. If, for instance, we made a simplified rule saying that return on equity (ROE) is good if higher than 12M LIBOR, we may find two very similar banks where one has ROE just above and the other just below the LIBOR rate. With traditional logic, the banks would be rated differently, despite their high similarity. In contrast, fuzzy logic would say: the ROE value in the first bank is 95% good, but 5% bad, while in the other bank it is 99% good and 1% bad. In this case, both banks’ assessments are very similar and better reflect reality. In a rating system, fuzzy logic can come into play in particular when domains of possible values of individual indicators are split into intervals, which would have blurred (fuzzy) boundaries;

• explore alternatives to the Support Vector Machine learning system, such as the Trait Recognition Analysis (TRA), and compare suitability and success rates of individual methods;

• develop the rating system into an Early Warning System (EWS). Already in its current form, the system has some EWS features, in particular the consideration of projected trends of future evolution.

Conclusion

The rating system presented in this article is obviously not the only one there is. Its advantage – as mentioned above – consists in the simplicity of the methods applied, easy interpretation of all intermediate results and on top of that – when using linear kernel – the “added value” of the knowledge gained at the learning stage in form of a linear functional relationship between parameter variables and assignment to a rating grade.

Whenever applying the products of any rating system, one must bear in mind that they can only render a basic picture of the entity being rated and the quality of results is only as good as the quality and content of data inputs. Nevertheless, they can be a good guide for quick orientation and a good start to in-depth analysis.

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