MODELS FOR THE IDENTIFICATION AND ANALYSIS OF BANKING RISKS

Prof. Gabriela Victoria ANGHELACHE, PhD
Bucharest University of Economic Studies
Prof. Radu Titus MARINESCU, PhD
Assoc. Prof. Anca Sorina POPESCU-CRUCERU PhD
„ARTIFEX” University of Bucharest
Cristina SACALĂ PhD Student
Bucharest University of Economic Studies

Abstract

A basic property of the rating system is the ability to fit customers risk class to which they belong, namely good payer customers or bad payer clients. The tests establishing the classification methods have been applied beginning with the medical science, biology, engineers starting with 1950 and in the late 1990s they have been adapted to be models of application in the credit rating. Basel Committee (1999) identifies this model as a difficult one to develop quantitative models of credit.

Key words: Receiver Operating Characteristics, cumulative accuracy profile, system, bank, valuation

The most popular measures are: operating characteristics curve ("Receiver Operating Characteristics" - ROC) and profile accuracy accrued ("cumulative accuracy profile" - CAP).

1. Operational characteristics curve ("Receiver Operating Characteristics" - ROC)

The system is a tool for assessing credit institutions in order to analyze and identify banks that are inefficient and will be monitored closely by ASF.

This requires assessment of six components that reflect a uniform and comprehensive manner of banks performance under banking laws and regulations in force.

The components assessed under this system are as follows:

- Capital (C);
- Shareholders (A);
- Assets (A);
- Management (M);
- Profitability (P);
- Liquidity (L)

One can remark that each of the six components, is valued between 1 and 5, so that 1 is the most advanced level, and 5 the lowest. Four of the six components (C - capital adequacy, A - asset quality, P - profitability and L - liquidity) are evaluated according to certain indicators, for which there are five intervals for ratings. The basis for calculating the indicators that define the four components is the prudential financial reporting FINREP and COREP at individual level, submitted monthly by the banks.

During checks procedures other two components are evaluated (mainly qualitative elements), the quality of ownership - A and management - M, which contribute directly to determine the risk profile of banks, and in assessing conformance with prudential requirements. Evaluation of specific performance of the six components (CAAMPL) rating is the basis for determining the composite rating, which also involves giving scores from 1 to 5. An important condition that is taken
into the rating calculation is made as if at least one of the components were evaluated in five ratings, the composite rating assigned to the bank and it may not be an upper (1 or 2). Each bank receives one rating for each indicator analysis for each component and finally a CAAMPL composite rating and a final score that represents the total score for the indicators that define the elements CAAMPL. The ratings defining the CAAMPL components are periodically updated by the actions of bank’s premises. A composite rating, based on aggregated data for financial indicators is set for the banking system. ROC probabilistic interpretation and presentation of an efficient calculation of confidence intervals is based on Article 1975 of Bamber.

AUC comparison test of two different validated rating on the same database is based on Article 1988 of DeLong and Clarke DeLolong Pearson. According to its definition the ROC curve is non-decreasing. It is also known Bamber (1975) that the ROC function is concave if and only if Likelihood Ratio is non-increasing in \( i \).

\[
LR_i = \frac{PD_i}{PN_i}, \quad i = 1, \ldots, k
\]

The property is almost intuitive because the probability of getting a high score should be high for a non-default client and low for a borrower client from default category and it is easy to see that the concavity of the ROC curve is equivalent to likelihood ratio, which is equivalent with the optimality rules of cut off in the sense that there is not a rule of decision to have both type I error and type II error with a low value.

AUC probabilistic interpretation is as follows:
- We consider the following experiment: two borrowers are drawn randomly, the first one is selected from the default distribution and the second one from the non-default distribution. The scores of the default and non-default clients can be interpreted as the achievements of two independent random variables \( SD \) and \( SND \). One must presume which of the debtors are in default. A rational decision maker would assume that the default client is the debtor who scores lower rating. Hence the likelihood that the decision is correct is:

\[
P(SD < SND) + \frac{1}{2} P(SD = SND)
\]

A simple calculation shows that this probability is equal to AUC.

\[
AUC = \sum_{i=1}^{k} \frac{1}{2} (CD_D^{'i} + CD_D^{-'i}) (CD_N^{'i} - CD_N^{-'i})
\]

\[
= \sum_{i=1}^{k} \frac{1}{2} (P(SD \leq s_i) + P(SD \leq s_{i-1})) P(SND = s_i)
\]

\[
= \sum_{i=1}^{k} (P(SD \leq s_{i-1}) + \frac{1}{2} P(SD = s_i)) P(SND = s_i)
\]

\[
= \sum_{i=1}^{k} P(SD \leq s_{i-1}) P(SND = s_i) + \frac{1}{2} \sum_{i=1}^{k} P(SD = s_i) P(SND = s_i)
\]

\[
= P(SD < SND) + \frac{1}{2} P(SD = SND)
\]
2. Heavy Model

HEAVY model type (High-frEquency-bAsed VolatilitY Model) was proposed by Kevin Sheppard, professor in the Department of Economics at Oxford University and Neil Shephard, Professor of Economics and Statistics in 2010.

These two professors have developed the aggregate HEAVY considering Kernel estimator robust despite the noisy effects generated by the markets.

To identify long-term component of volatility we consider two sources of information:
- Information represented by daily profitability (R1, R2, R3 ...... R)
- Information represented by daily measures of the aggregated volatility (RV1, RV2, RV3, … RVt).

HEAVY linear model has two equations:

\[ \text{Var}(\gamma_t; IF_{t-1}^{HF}) = \gamma_t = \beta + \mu R_{t-1} + \pi h_{t-1} \]

where, \( \mu, \beta \geq 0 \) și \( \pi \in [0,1] \)

Where information about past volatility are replaced by a form of daily measures of aggregated volatility RV and the HEAVY model is a GARCH model. Compared with GARCH models, the HEAVY models are more performant because the estimation and the process are more complex.

HEAVY model is considered as a model "GARCH turbo" because it uses the estimator of the daily profitability sum of squares and do not use the estimator of daily profitability square.

- HEAVY-RM – models the expected variance \( Y_t \)

\[ F_{t-1}^{HF} = \gamma_t = \beta + \mu R_{t-1} + \pi R_{t-1} \quad \text{unde} \ \gamma_t, \mu R_{t-1} \geq 0 \quad \text{și} \ \mu R_{t-1} + \pi R_{t-1} \in [0,1] \]

Sheppard and Stephard estimated that, in the empirical studies, the coefficient is in the range (0.6 to 0.7) and the value of the parameter is very close to zero.

In 2011 Nourelidin, Shephard and Sheppard developed an extension of the Sheppard Model called HEAVY multivariate model (multivariate High-Frequency-Based Volatility Model). This model is distinguished according to the two researchers for volatility forecasting performance but not for measuring it. Also, from the research conducted in the development of this model, we could not find a package to provide an efficient method of estimation, as well as R or E-Views statistical programs.

3. The HARRV Model

In 2003 Corsi proposed model HARRV (Heterogeneus Auto-regressive Model), drawing on the model Herogeneous Market Hypothesis built by Muller in 1997 to capture the volatility of the stock market.

The model developed by Muller explains the positive relationship between volatility and market activity capital. In this case the volatility is a financial asset which risk changes its value.

In terms of participants, given the heterogeneity the more participants are, the more different are the offered-asking prices.
The HARRV model manages heterogeneity caused by the participants. They may consider as being important different trading time. Each participant perceives and reacts differently in time. In this regard, Corsi’s model identifies volatility on short term (daily, z) and medium-term volatility (week, s) and long term (monthly, l).

The main purpose of the Model HARRV is forecast volatility for different time intervals, the equation is written as follows:

$$RV_{t+1} = \gamma_0 + \gamma_z RV_{t} + \gamma_s RV_{t-1} + \gamma_l RV_{t-24} + \pi_t$$

- $RV_{t+1}$: aggregate volatility for t moment for forecast time t+1
- $\gamma_0$: the constant of the model
- $\gamma_z$, $\gamma_s$, $\gamma_l$: the coefficients for 1 day, 1 week, 1 month.
- $RV_t$: aggregate volatility
- $RV_{t-1}$: aggregate volatility for 1 week
- $RV_{t-24}$: aggregate volatility for 1 month
- $\pi_t$: the errors of the model

In 2012, the model HARRV was improved by Corsi, Audrino and Reno (2012) being easier to be used in terms of providing economic information of value, on the assumption that the estimator RV may depend on continuous variation of prices and negative profitability impact.

Thus, in the HARRV model, RV estimator is influenced by volatility, leverage and the effect of jump sites. These effects can be studied by day, week and month.

4. Identification and analysis of risk management in the banking system

To emphasize risk management analysis model we use data obtained from the Bank Vento. In this context we present data analysis support.

In December 2012 - February 2013, the annual growth of credit to the private sector continued to increase reaching negative level -4.7% compared to -1.3% in September-November 2012.

The negative development is found both in the population and at the companies, so in relative terms is highlighted the diminishing volume process of new loans to these entities. Between August 2012 to August 2013 the funding has accumulated about 6 billion lei, the private sector credit decreased and reaching to negative values in March 2013 (by - 6.11% in August 2013 in real terms).

At the first class of customers the currency loans were important and reflects a slow economic recovery and a rise in credit risk adjustments that leads to financial and non financial balance sector. Based on currencies and foreign currency loans structures the rhythm of decreasing was important, in which context their average share in total credit to the private sector reached the minimum last year and a half.

The analysis of household credit extension reflects the effects of changes to the end of 2012 in accordance with Regulation no. 17/2012, published in the Official Gazette, Part I, no. 855, regarding the household loans dynamics that increased the expense of loans in domestic currency. In today’s banking system two trends are outlined, that give a positive note in the Romanian credit system: corporate and SME customers orientation and quality lending businesses operating in specific sectors of goods trade. The access of SMEs to the credit system is still a concern, because the loans in this sector were reduced by sales of both inertia and through financial
intermediaries collaborating firms. Commercial banks in our country provides the following types of funding by, depending on the purpose for which they are required:
- short-term funding, with repayment period up to two years;
- medium-term funding, with repayment period of 1-5 years;
- long-term financing, with a tenor of 5 years.

Loans to non-financial corporations - Loans in lei - existing loan balance (% P.A.) are shown in the following charts:

Source: NBR, NIS data reports

Loans to non-financial corporations - loans in euros - existing loans outstanding are reflected in the chart below:

Source: NBR, NIS data reports

Developments in the main categories of customers have confirmed the NBR survey on lending to households and non-financial companies that banks anticipated for the first quarter of 2013, meaning a decrease in loan applications to non-financial corporations and demand for real estate loans population, along with the tightening of credit standards for both sectors.

Against this background, the annual change of loans to non-financial corporations declined further to -3.4% for January-February of 2013, compared with -0.6% in the fourth quarter of 2012, due solely to currency component to -4.1% from -3.0% based on values expressed in euro.
In contrast, loans in lei to these entities had a favorable evolution of 5.1% compared to 4.9% in the fourth quarter of the year 2012. The loans dynamic to households widened to -6.5% decline from -3.4% in the fourth quarter of 2012.

Loans to households - loans in lei - outstanding loans

Source: NBR, NIS data

Loans to households - loans in euro - outstanding loans

Source: NBR, NIS data

References
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