Academy of Economic Studies

Doctoral School of Finance and Banking

- Dissertation paper -

Early Warning Models for Banking Supervision in Romania

MSc Student: Radu Muntean

Supervisor: Ph.D. Professor Moisă Altăr

Bucharest, July 2009

Table of contents

Abstract

In this paper we propose an early warning system for the Romanian banking sector, as an addition to the standardized CAAMPL rating system used by the National Bank of Romania for assessing the local credit institutions. We aim to find the determinants for downgrades as well as for a bank to have a weak overall position, to estimate the respective probabilities and to be able to perform rating predictions. Having this purpose, we build two models with binary dependent variables and one ordered logistic model that accounts for all possible future ratings. One result is that indicators for current position, market share, profitability and assets quality determine rating downgrades, whereas capital adequacy, liquidity and macroeconomic environment are not represented in the model. Banks that will have a weak overall position in one year can be predicted using also indicators for current position, market share, profitability and assets quality, as well as, in this case, capital adequacy and macroeconomic environment, the latter only for the binary dependent variable model, leaving liquidity indicators out again. Based on the ordered logistic model's capacity for rating prediction, we estimated one year horizon scores and ratings for each bank and we aggregated these results for predicting a measure of assessing the local banking sector as a whole.

1. Introduction

Banking is one of the most intensively supervised industries world-wide due to the high impact of bank failures on economic activity. Financial stability, a wide variety of markets, infrastructure and even people's personal comfort and safety depend on the credit mechanism and the soundness of the banking sector. Therefore, all over the world, governments grant authority to financial supervisory bodies and put them in charge with the regulation, authorization and supervision of the financial institutions, in order to limit the risks they undertake and the negative effect they might have on other economic sectors.

Bank supervisors develop their knowledge about the banks running in their jurisdictions by the means of on-site examinations and off-site surveillance. Although useful in order to provide current and detailed data, the on-site examinations can be costly for the supervisory authority by requiring the on-site teams to be sent at the premises of the examined bank in order to have meetings, access files, check data quality, analyze systems' integrity and obtain results that can be used in assessing the bank's current situation. Moreover, on-site examinations can be burdensome to bankers because of the human and logistical resources that they need to withdraw from their current activities and make available to the on-site team demands.

Off-site surveillance aims at making the supervisor aware also of the bank's situation between on-site examinations. Financial data and other changes that occur at the bank's level are reported to the supervisory authority where are recorded and analyzed. This way, the assessment of each bank is continuously updated and the supervisors may decide whether and when another on-site examination is needed. This dual approach might save resources for both, supervisor and supervised bank, and might provide a clear picture of the risks undertaken by each bank as well as inputs to assessing stability of the banking sector.

Some of the tools highly used in the off-site surveillance refer to the gathering of relevant information within screens such as risk matrices and other specific tables that assess each bank after a wide range of criteria. Historical experience and expert opinion are some of the methods for selecting relevant criteria and their benchmarks. Each bank is granted with an assessment as low-to-high, or a numerical rating for each of the criteria employed. Then, all criteria-based ratings lead to the overall rating of the bank.

Rating systems used by supervisory authorities provide valuable information about the credit institutions analyzed within the same framework. Separating problematic of well performing banks allow the supervisor to save resources by having the possibility to focus more on the banks that are currently in distress. However, ratings carry information about past situations and are more of an *ex-post* measure of the banks status. Therefore, supervisors always need to consider expert opinion and recent developments in order to have a better assessment of the credit institution. Additionally, supervisors have come up with a class of tools that are able to predict negative future events, thus gaining more time to act. Early warning (EW) models have been used to predict negative events like bank failure, rating downgrade and inadequate capitalization.

For the purpose of this paper we aim to find the determinants for rating downgrades and the ones for a bank’s future overall position, in order to be able to estimate probabilities for downgrades, bad ratings and also for each possible rating; these results will then allow for rating prediction.

This paper is structured as follows: the next chapter is a brief introduction to current practices and some of the literature relevant for the presented subject and chapter 3 presents the methodology highlighting the used models, the variable selection process and model validation. Next chapter refers to data, as analyzed variables, periods and discretions and is followed by Chapter 5 which presents the results focused on both rating downgrade and weak overall position as main dependent variables. In this chapter we show some of the intermediary results, the final models, validation, prediction and other results. Chapter 6 highlights the most important results and conclusions.

2. Practice and literature review

Supervisory authorities around the world have developed their own rating systems aiming for a standardized approach to the different banks running business in their jurisdictions as presented by BIS (2000). The CAMELS rating system was implemented in 1980 in the United States of America by all three supervisory authorities: Federal Reserve System (Fed), Office of the Comptroller of the Currency (OCC) and Federal Deposit Insurance Corporation (FDIC). The rating system has six components, referring to capital protection (C), asset quality (A), management competence (M), earnings strength (E), liquidity risk (L) and market risk sensitivity (S); to each of these components a grade from 1 (best) trough 5 (worst) is assigned. CAMELS was followed by other rating systems like ORAP (Organization and Reinforcement of Preventive Action) implemented by French Banking Commission in 1997, RATE (Risk Assessment, Tools of Supervision and Evaluation) implemented by UK Financial Services Authority in 1998, RAST (Risk Analysis Support Tool) implemented by Netherlands Bank in 1999, etc.

In the United States, the FDIC implemented the SCOR (Statistical CAMELS Off-site Rating) model in 1995. SCOR is quarterly run based on data reported by credit institutions and uses an ordered logit model of CAMELS ratings to estimate likely downgrades of banks with a current composite CAMELS rating of 1 and 2. This is explained by the higher attention already given by the supervisor to banks with on-site examination rating of 3, 4 or 5. The model flags for review banks that are currently strong or satisfactory but have a probable downgrade. The current rating is compared to the one-year prior financial data and the coefficients found are employed to estimate future ratings. The assumption is that the relation between current rating and prior data will hold for future rating and present data.

SCOR uses a step-wise estimation in order to eliminate not statistically significant variables. Many of the variables that are input to this model are also input to the SEER (System for Estimating Examination Rating) model of the Federal Reserve, although the prior CAMELS rating is included only in the SEER rating model.

The time horizon for rating estimation under SCOR is between four and six months. Accuracy of the output has been shown to decrease beyond the six month period.

The output of this model is a table giving the probabilities that the next rating will be each of the five possible ratings. A downgrade appears when a bank with a rating of 1 or 2 goes to a rating of 3,4 or 5. Also, the model provides a SCOR rating as the sum of the possible ratings weighted with their probability. Areas of concern are highlighted by comparing the bank with a “Median 2 Bank”, which is a typical bank with a rating of 2.

Rating downgrade models share strong similarities with bankruptcy prediction models. Beaver (1966) performed an early univariate discriminant analysis using 30 financial ratios for 158 firms, which found that cash-flows/equity and debt/equity can be useful in default prediction.

Altman (1968) developed a scoring function, using multivariate discriminant analysis (MDA), in order to discriminate between the two possible events. The variables used together within the function were also specific for the purpose of bankruptcy prediction.

The logistic regression was first used within a bankruptcy prediction framework by Ohlson (1980). The variables are used in a multivariate framework as it is the case for MDA but the scoring function is linear with regard to the log odd of default. Logit models are preferable to MDA as the latter assumes that the covariance matrices are the same for bankrupt and non bankrupt firms, it also assumes normally distributed variables and, most important, are not able to provide a framework for performing significance tests for the model parameters.

Over the last decades, the increasing interest of both supervisors and academics in rating models and early warning systems has led to an economic literature able to provide new methods and to raise new issues with respect to models used in bank supervision.

As credit institutions are not usually defaulting often enough in order to provide for a significant data base and therefore a significant statistical model, many papers refer to inadequate capitalization, rating downgrades or other lesser negative events that are also of high interest for assessing the stability of a bank.

In this respect, Jagtiani et al (2000) tested the efficacy of EW models as tools for the prediction of capital inadequate banks using a sample of U.S. banks with capital between \$300 million and \$1 billion. Logit and trait recognition analysis (TRA) models were generated and compared trough a testing period. Findings showed the importance of TRA in highlighting complex interaction variables useful in predicting banks with deficient capital. Both the logit and the TRA models had a reasonable degree of accuracy and they were considered a powerful tool for detecting one year in advance inadequately capitalized banks.

Kolari et al (2000) used logit and TRA models to predict large U.S. bank failures. The models were developed from an original sample and tested for predictive ability in the holdout sample. Both models performed well, but TRA outperformed logit models in overall accuracy, large bank failure accuracy, weighted efficiency scores. The paper concluded that TRA models can identify variables interactions relevant for prediction and therefore can provide valuable information about the future large bank failures.

Regarding rating downgrade, Gilbert et al (2000) compared such a model with a currently employed banking failure prediction model (SEER) in use at the Federal Reserve. Because of the small number of bank failures, the SEER coefficients are mostly "frozen" and over time, the ability of the downgrade model in predicting downgrades improves relative to that of the SEER model in predicting failures. This paper concludes that a downgrade model may be useful in banking supervision and shows the higher accuracy of a frequently re-estimated model.

Other studies like Gilbert et al (2002) argue that rating downgrade prediction models may not clearly outperform failure prediction models, especially in tranquil periods. However, it should be noted that there is a consensus over the fact that a rating downgrade prediction model is an important informational supplement to supervisors and even though it should not rule out expert opinion and other supervisory tools, it should be used for highlighting possible problematic banks.

The models employed for rating systems can be validated through variety of techniques. Engelmann et al (2003) analyzed useful tools for discriminatory power such as the Cumulative Accuracy Profile (CAP) and the Receiver Operator Characteristic (ROC). The summary statistics of CAP and ROC were proved to be equivalent and the comparability of different models according to both statistics is stated only for the same input data. For this reason, one could use Area Under ROC (AUROC) alone in order to capture the discriminatory power of a model.

With respect to statistical issues concerning early warning models we refer to Hosmer and Lemeshow (2000) who have thoroughly presented practical steps, problems and discretions available when working with a logistic regression.

Studies performed on U.S. banks or cross-European banks samples have met with the choice between different types of early warning system models. That is because on such samples one could identify bank failures or inadequate capitalized banks and therefore develop a model for predicting these events.

Banking sectors in most emerging countries have fewer banks and the data history is shorter. Supervisors in these jurisdictions also employ tools based on current assessment of banks but due to this issue they are usually not able to predict bank failures or inadequate capitalization as early warning models, as these kind of negative events have not happened enough to provide for a significant database. However, implementation of rating downgrade prediction models is possible.

In Romania, in accordance with the Government Emergency Ordinance no. 99/2006, the banking supervisory authority is granted to the National Bank of Romania (NBR). Within the NBR there are several Departments directly connected to the banking sector, with respect to regulation, authorization, financial stability and prudential supervision. Changes in management, shareholders, financial situation of banks, as well as current and past financial data and other relevant information are all actively analyzed by the NBR, mainly within the Supervision Department (SD).

Commercial banks are assessed regarding the risks they undertake both by on-site examinations and by off-site surveillance. The CAAMPL uniform rating system refers to six components that are checked by the supervisor and rated in order to obtain a final score and then an overall rating of the bank:

- capital adequacy (C);
- shareholders' quality (A);
- assets' quality (A);
- management (M);
- profitability (P) and
- liquidity (L).

Banks are rated from 1 (best) to 5 (worst) for each indicator included in each of the six components and then the supervisor calculates aggregated ratings for the components and an overall rating for the bank.

3. Methodology

3.1. Binary dependent variable model

In order to build an early warning model for the prediction of CAAMPL rating downgrades we have employed a logit methodology. Then, the same methodology has been applied for prediction of banks receiving a bad rating in one year horizon.

Firstly, we assume an unobservable dependent variable y* related to a binary observed variable y, which represents a CAAMPL rating downgrade (y=1) versus a constant or upgraded CAAMPL rating (y=0).

(1) $$\begin{cases} y_i = 1, if : y_i^* > 0 \\ y_i = 0, otherwise \end{cases}$$

The latent variable y^* is explained by the vector of bank's financial ratios and other individual figures as well as macroeconomic environment x_i and the vector of estimated coefficients β.

(2) $$\begin{aligned} y_i^* &= x_i^{'}\beta + \varepsilon_i, or: \\ y_i^* &= \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_n x_{in} + \varepsilon_i \end{aligned}$$

The term ε_i is logistic distributed, thus having the logistic cumulative distribution function:

(3) $$F(x) = \frac{1}{1 + e^{-x}}$$

The probability that a bank will have a downgraded rating can be expressed as follows:

(4) $$\begin{aligned} & P(y_i = 1 \mid x_i, \beta) = P(y_i^* > 0) \equiv P(-\varepsilon_i < x_i^{'}\beta) \\ & \Rightarrow P(y_i = 1 \mid x_i, \beta) = F(x_i^{'}\beta) \equiv \frac{1}{1 + e^{-x_i^{'}\beta}} \end{aligned}$$

The model's coefficients are contained in the β vector and they need to be estimated. The maximum likelihood method (MLE) assumes that each observation is extracted from Bernoulli's distribution. Therefore, a rating downgrade event has the attached probability *$F(x_i'\beta)$* making the probability of a non-downgraded rating event *$1-F(x_i'\beta)$*. The probability mass function is the product of the individual probabilities:

(5) $$P(Y_1 = y_1, Y_2 = y_2, \ldots, Y_n = y_n) = \prod_{y_i=1} F(x_i^{'}\beta) \times \prod_{y_i=0} (1 - F(x_i^{'}\beta))$$

The likelihood function should be maximized with respect to the vector of coefficients.

(6) $$L(\beta) = \prod_{i=1}^{N} \left[F(x_i^{'}\beta)\right]^{DN} \times \left[(1 - F(x_i^{'}\beta))\right]^{NDN}$$

In order to obtain a more convenient expression to maximize we employ the logarithm:

(7) $$\ln L(\beta) = \sum_{i=1}^{N} \left\{y_i \ln(1 - F(-x_i^{'}\beta)) + (1 - y_i)\ln(F(-x_i^{'}\beta))\right\}$$

The coefficients have been estimated using the quadratic hill climbing algorithm, which, in order to achieve convergence, employs the matrix of secondary differentials of the log likelihood function.

The estimated coefficients should be analyzed carefully noting that their size does not necessarily carry significant economic information. However, the sign of each coefficient is important as it shows how the dependent variable is influenced by a variation in each variable. For instance, positive coefficients show that their respective variables' variations influence the downgrade probability in the same direction as that of the variations which took place.

The marginal effect of the explanatory variables x_j on the dependent variable is given by β_j weighted with a factor f depending on all the values in x.

(8) $\dfrac{\partial E(y_i \mid x_i, \beta)}{\partial x_{ij}} = f(-x_i^{'}\beta)\beta_j$, where $f(x) = \dfrac{dF(x)}{dx}$ is the density function corresponding to F.

3.2. Ordered logistic model

Secondly, we considered an ordered logistic model. In this approach, the dependent variable is assumed to represent ordered or ranked categories. The one year future CAAMPL rating is mapped into the different values of y. The dependent variable in an ordered logistic model is considering a latent variable, like in the case of the binary dependent variable model previously presented.

(9) $$y_i^* = x_i^{'}\beta + \varepsilon_i$$

The observed response y_i is obtained from y_i*, based on the following rule:

$$(10) \qquad y_i = \begin{cases} 1, if: y_i^* \le \gamma_1 \\ 2, if: \gamma_1 < y_i^* \le \gamma_2 \\ \vdots \\ M, if: \gamma_{M-1} < y_i^* \end{cases}$$

The probabilities for the dependent variable to take each of the values allowed for are given as follows:

$$(11) \qquad \begin{cases} P(y_i = 1 \mid x_i, \beta, \gamma) = F(\gamma_1 - x_i^{'}\beta) \\ P(y_i = 2 \mid x_i, \beta, \gamma) = F(\gamma_2 - x_i^{'}\beta) - F(\gamma_1 - x_i^{'}\beta) \\ \vdots \\ P(y_i = M \mid x_i, \beta, \gamma) = 1 - F(\gamma_{M-1} - x_i^{'}\beta) \end{cases}$$

, where *F* is the cumulative distribution function of *ε*. For the purpose of this application, *F* was selected as being the logistic cumulative distribution function.

The threshold values *γ* are important by determining the value of the dependent variable, based on the score $x_i'\beta$. In order to estimate the threshold vector *γ*, as well as the *β* coefficients, the log likelihood function has to be maximized.

$$(12) \qquad \ln L(\beta) = \sum_{i=1}^{N} \sum_{j=1}^{M} \ln\left(P\left(y_i = j \mid x_i, \beta, \gamma\right)\right) \cdot 1\left(y_i = j\right),$$

where *1(x)* is an indicator function which takes the value 1 for a true argument and 0 for a false argument.

3.3. Variable Selection

While building a logit model, a key issue is the selection of explanatory variables. In this regard, we considered to steps structured by Hosmer and Lemeshow (2000) for the process of variable selection as well as other useful filters aimed to discriminate between relevant and irrelevant explanatory variables.

For the first filter we considered the attribute of the explanatory variables to discriminate between downgrades and non-downgrades. In this respect, we employed a two-sample one-sided Kolmogorov-Smirnov test to determine whether the two groups are drawn from the same underlying population, the null hypothesis of the K-S test. We calculate the percentage of X_{ND} and X_D less than each value *x* of the tested variable and we record *x* for which the difference between the two figures is maximum. The K-S statistic equals the maximum difference between X_{ND} and X_D.

$$(13) \qquad KS = \max_x \left[X_{ND} - X_D\right]$$

The p-value of the test is $p=e^{-2*\lambda\wedge 2}$, where *λ* is given by:

(14) $\lambda = \max\left(\left(\sqrt{\frac{ND \times D}{ND + D}} + 0.12 + \frac{0.11}{\sqrt{\frac{ND \times D}{ND + D}}}\right) \times KS, 0\right)$, where ND is the number of non-downgrades and D is the number of downgrades.

The main purpose of the K-S test filter is to eliminate variables that clearly do not discriminate between downgrades and non-downgrades. However, this test is also used in order to obtain the sign of the discrimination, explicitly whether the variable is generally higher for future downgraded banks or lower. This result will be compared to the following tests so that the sign of the explanatory variable with regard to the dependent variable could be examined more carefully. The threshold for this test was set at the 0.1 level of the p-value so that variables without a clear economic sense to be eliminated, but was not set lower to avoid excluding potentially relevant variables.

As second filter, we analyzed the monotony assumed by a logit model. In this respect, for each explanatory variable, we built a linear regression between the logarithm odd against the mean values for several data subsets and checked if the assumptions made for the relation between the dependent variable and explanatory variable are respected.

(15) $\ln\left(\frac{RD_i}{1 - RD_i}\right) = \beta_0 + \beta_1 x_i$, where RD is the historical rate of Downgrade and x_i is the average of the explanatory variable, both built on the data subsets.

The variables selected after these two filters are analyzed within a univariate logit model framework. Hosmer and Lemeshow (2000) proposed a threshold of 0.25 for the p-values of variables in univariate models. Variable selection can take into account p-values, likelihood values, as well as AUROC calculated for each univariate model.

(16) $\ln\left(\frac{PD_i}{1 - PD_i}\right) = \beta_0 + \beta_1 x_i$, where PD is the probability of Downgrade and x_i is the explanatory variable, both chosen over the entire estimation sample.

A fourth filter is given by colinearity tests. It should be noted that any correlation between selected variables should make economic sense. Variables with a correlation coefficient above a threshold are analyzed and the one which has a higher performance in univariate models is selected.

Explanatory variables which have passed all the filters are subsequently analyzed in a multivariate framework.

Backward selection method implies continuing with all the selected variables in a multivariate model. Like structured in Hosmer and Lemeshow (2000), we examined the Wald statistic for each variable and we compared the coefficient of each variable with coefficients obtained in univariate models. It is important to see whether the signs of the coefficients change or whether its size is highly volatile.

Variables that pass these tests are employed in a new multivariate model, for which again the coefficients are examined. A new model is compared with the previous larger model and in case the analyzed variable is considered not providing additional information to the model, it will be rejected.

This process of eliminating, refitting and comparing continues until all the variables included in the model are statistically significant as well as economically significant, also checking whether other relevant variables remained outside the model.

In a forward selection method, after we decided which variables will be used in a multivariate model, we introduced one variable at a time, in their univariate performance order. If the new model is superior to the old model and if all the estimates are significant, the variable is accepted and therefore other variable is analyzed for selection in the new model.

Variable selection for predicting banks receiving a bad rating in one year horizon is similar to the methodology presented for the prediction of rating downgrades.

In this case, a Kolmogorov – Smirnov test is applied to observe the discrimination of each variable between the different one year future ratings. Analyzing variables in this respect is more complex as it is required that they discriminate between banks in high and low ratings, also having the option to check the downgrades discrimination.

Monotony must also be respected for each selected variable compared to the logarithm odd of historical rate of each future rating.

A third test is based on the univariate models and checks the significance of each parameter estimated in the univariate model built for each tested variable.

The colinearity filter is similar to the filter employed for rating downgrades prediction, therefore the variables with a correlation above the threshold are analyzed and the one with a lower performance in a univariate framework is rejected.

The variables selected after the four filters are used in order to build a multivariate model. Both backward and forward selection methods are similar to the methods used for the rating downgrades prediction, noting that the dependent variable is in the case of binary dependent variable model the probability to receive a bad rating, respectively the probability of each rating, in a one year horizon, for ordered logistic model.

3.4. Validation

When the steps within the variable selection are completed, the remaining variables enter the final model, which has to be validated in order to be considered proper for the intended purpose and to be used for prediction.

While the models are useful in estimating probabilities of downgrades, it is necessary to select a threshold above which the dependent variable will be estimated as 1, meaning a rating downgrade. This threshold will be estimated based on the minimization of a loss function which assesses the "*loss*" of the supervisory authority using the model, depending on the Type I (downgrades occurred when non-downgrades were estimated) and Type II (non-downgrades occurred when downgrades where estimated) errors.

Estimated Equation	Dependent variable = 0	Dependent variable = 1	Total estimated
Estimated dependent variable = 0	Correctly estimated non-downgrades	Unexpected downgrades (Type I Error)	Estimated non-downgrades
Estimated dependent variable = 1	Unexpected non-downgrades (Type II Error)	Correctly estimated downgrades	Estimated downgrades
Total	Non-downgrades	Downgrades	Total Sample

Therefore, the loss function of the supervisory authority has the following specification:

(17) $\varphi(c) = \varepsilon_1(c) \times \omega_1 + \varepsilon_2(c) \times \omega_2$, where $\varepsilon(c)$ are Type I and Type II errors, depending on the cutoff value c and ω are their respective weights.

These weights will be selected by the decision maker and the cutoff will have the value of c when the loss function is minimized.

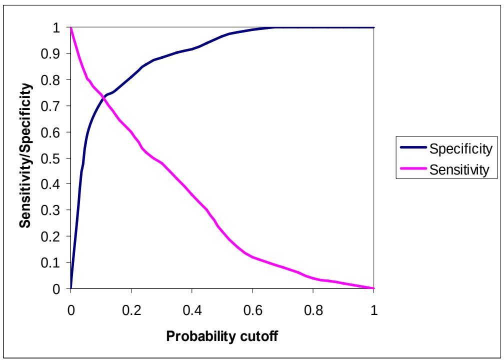
Another tool used for validation is the Receiver Operator Characteristic (ROC) Curve. This method has the advantage of an easily understandable graphic representation as an area part of the area of a square, which represents the performance of the perfect model. In order to calculate the area under the ROC Curve (AUROC), we need the following relations:

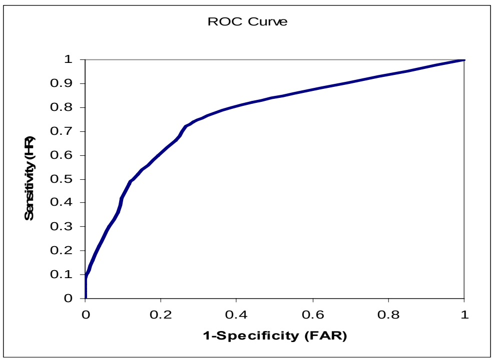
(18) $HR(c) = \dfrac{H(c)}{ND}$, where HR(c) is the hit rate for cutoff c, H(c) is the number of rating downgrades estimated correctly with cutoff c and ND is the total number of rating downgrades. Hit rate is corresponding to the concept of sensitivity, as the probability of detecting a true signal.

(19) $FAR(c) = \dfrac{F(c)}{NND}$, where FAR(c) is the false alarm rate for cutoff c, F(c) is the number of false alarms with cutoff c and NND is the total number of rating non-downgrades. False alarm rate is corresponding to the concept of specificity, as FAR=1-Specificity is the probability of detecting a false signal.

Having calculated the hit rate and the false alarm rate and plotting them together we obtain the ROC Curve and the AUROC is subsequently calculated.

(20) $$AUROC = \int_0^1 HR(FAR)d(FAR)$$



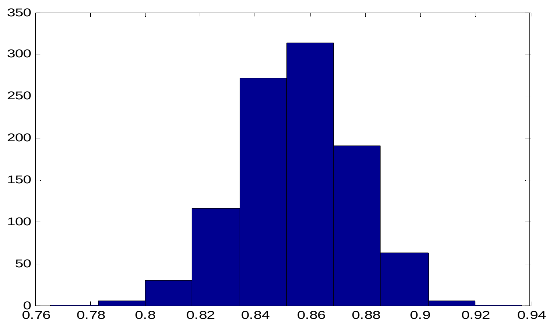


ROC Curve is obtained plotting HR and FAR over all possible probability cutoffs. Area under ROC ranges from zero to one and provides a measure of how the model discriminates between the realization of the dependent variable and the opposite event.

As general rule for model performance, we use the following thresholds for AUROC:

If AUROC<0.5	Failed test – less than chance
If 0.5<=AUROC<0.6	Failed test
If 0.6<=AUROC<0.7	Poor test
If 0.7<=AUROC<0.8	Fair test
If 0.8<=AUROC<0.9	Good test
If 0.9<=AUROC	Excellent test

While the AUROC indicates the discriminatory power of the model, this figure alone may need to be analyzed with respect to the sample used in its calculation. Therefore, we used a Bootstrap methodology, generating 1000 AUROC figures based on different samples from a distribution identical to the empirical distribution of the original sample.



This method allows us to assess the stability of the AUROC around the original estimated value and to obtain variation intervals around this value.
In order to assess the goodness-of-fit of the model we used a Hosmer-Lemeshow test. In this respect, we divided the sample in g groups and we compared the estimated probability of downgrade with the empirical percentage of downgrades for each group. The HL Test statistic for a model with correct specification follows a Chi-square distribution with *(g-2)* degrees of freedom and is calculated as follows:

(21) $\hat{C} = \sum_{k=1}^{g} \frac{\left(o_k - n_k^{'}\overline{\pi}_k\right)^2}{n_k^{'}\overline{\pi}_k\left(1-\overline{\pi}_k\right)}$, where n_k' is the total number of subjects in the k^{th} group,

$o_k = \sum_{j=1}^{k} y_j$, y_j is the indicator of rating downgrade, $\overline{\pi}_k$ is the average estimated probability for group k.

3.5. Predictions

Once the variables have been selected and the model has been validated, for both binary dependent variable and ordered logistic models, the dependent variable is calculated. In sample, this is done using the values of the ratios already used in estimation, while out of time the dependent variable is calculated based on values of the ratios not included in the estimation.

The estimated dependent variables are compared to the realized values in sample and, particularly, out of time. While for the binary dependent variable model the dependent variable is easily comparable with the percentage of rating downgrades/number of banks receiving a bad rating, for the ordered logistic model the probabilities calculated for each possible rating have to be manipulated in order to obtain values comparable with an observable variable.

Firstly, the ordered logistic model can be used for the same purpose as the binary dependent variable model, for instance, in calculating a probability of rating downgrade.

(22) $PD_i = \sum_{j=r}^{M-1} P_{i,j+1}$, where M is the total number of ratings, r is the current rating of the observed bank i and $P_{i,j}$ is the probability that the observed bank i will have the rating j in one year horizon.

Moreover, the probability of downgrade estimated with the ordered logistic model can be compared to the one estimated with the binary dependent variable model and the validation results can be analyzed as well. This can also be done in the case of predicting bank receiving a bad rating.

The ordered logistic model can also provide for a *shadow* rating which is the average of the possible ratings, weighted with their respective estimated probabilities.

(23) $SR_i = \sum_{j=1}^{M} P_{i,j} \times R_j$

Considering a naive model predicting the one year horizon rating to be the current rating, the estimated shadow rating is expected to perform better. Both predictions are comparable with the realized rating, observable in one year, using a distance function as following:

(24) $D = \sum_{i=1}^{N} \left(\overline{R_i} - R_i\right)^2$, where $\overline{R_i}$ is the estimated rating for observation i, N is the number of analyzed observations and R_i is the observed respective rating.

4. Data

For the purpose of this paper, the input data contains both microeconomic and macroeconomic variables (Annex 1) from December 2002 to December 2008.

Most of the microeconomic data is taken from the reports provided by a sample of about 30 Romanian banks to the National Bank of Romania, their supervisory authority. These financial ratios are structured on the following four main components: assets quality, capital adequacy, profitability and liquidity. Other variables with specific values for each bank and therefore considered to be microeconomic are the CAAMPL rating and the bank's position in the market, as both assets and loans based market share.

The other part of the input data consists on several indicators at macroeconomic level which have the same values for different banks at the same moment in time. These variables are current values and last variations of indicators related to interest rates, exchange rates, wage, industrial production, unemployment rate and inflation.

It should be noted that the financial ratios are also comparable because of the reporting regulations and procedures maintained by the National Bank of Romania. Moreover, the data only takes into account banks which are Romanian legal entities, excepting the savings banks for housing. We have not selected branches of foreign banks that are not Romanian legal entities because these banks have different reporting regime and also a different overall status, due to the direct involvement of the parent bank and home country supervisory authority.

The banks selected into analysis have a cumulative assets market share between 90.95% and 94.66% over the period making the results obtained for this sample relevant for the entire Romanian banking sector.

The available data was divided into three samples. The first period from December 2002 to December 2006 containing 480 observations for financial ratios and indicators is used to estimate the parameters, with the help of the one year future CAAMPL Rating. The models built based on these parameters are then tested in the following period, 114 observations until December 2007, with the help of the one year future CAAMPL Rating, until December 2008. Subsequently, 116 observations data until December 2008 is used to make predictions for the following period.

5. Results

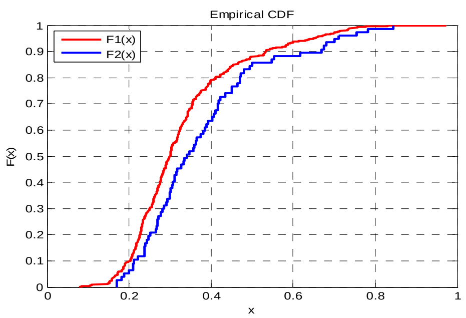
5.1. Rating downgrade

Firstly, we have built an early warning model for predicting CAAMPL rating downgrades in one year horizon. In this respect, we used a set of tests in order to eliminate variables that do not comply with the assumptions made for them. The purpose of this method is to obtain a set of variables that explain future rating downgrades reasonably well individually and to use them in a multivariate framework so that, at the end, to build a early warning model for rating downgrade.

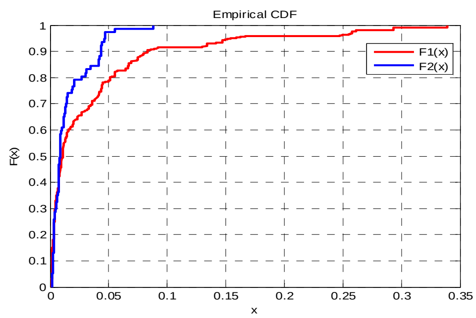
Kolmogorov – Smirnov Test

Following the steps presented in the methodology section, we have started with a Kolmogorov – Smirnov test to find the variables able to discriminate between banks that will have their ratings downgraded in one year horizon and banks that will have at least the same rating after that period. The results show that for a threshold of 0.1 for the test p-value, only 15 variables will be selected (see Annex 2). We show in a graphic representation for two of the selected variables – *a)Loans and deposits placed with other banks/ Total assets (v14)* and *b)Assets market share (CotaActive)* – compared to the graph of a rejected variable – *c)Customer loans/Customer deposits (v44)* – the difference between the cumulative distribution functions *F(x)* for downgrades (blue line) and non-downgrades (red line).

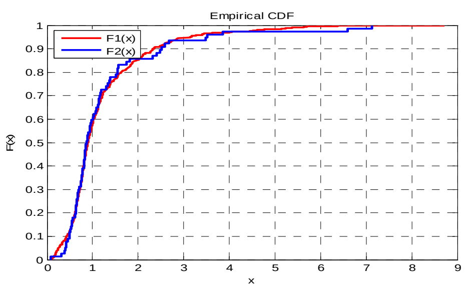
a)



b)



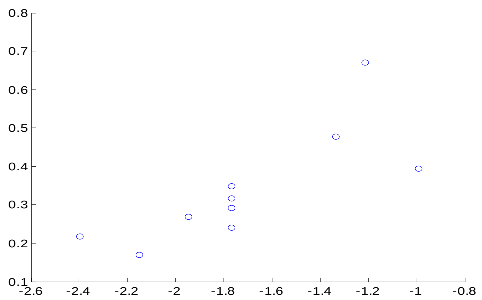
c)



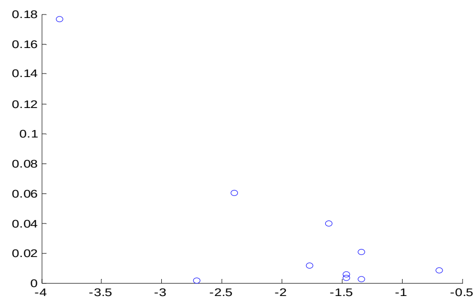
Monotony

For the purpose of the monotony test we built subgroup regressions for the logarithm odd over the explanatory variables which passed the first test. The result is highly dependent on the number of subgroups used; therefore the test results will not be given categorical power of variable rejection. Nevertheless, for a small number of subgroups, such as ten, we selected a threshold for p-value at 0.1. The values for p-value reached a wide variety of values for selected and rejected variables, like for *a) Loans and deposits placed with other banks/ Total assets (v14)* and *b)Assets market share (CotaActive)* – compared to the graph of a rejected variable – *c) Customer loans/Total liabilities (v13).*

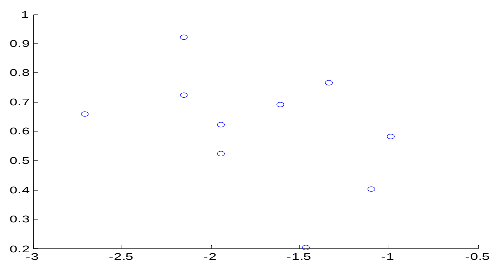
a)



b)



c)



This test for monotony is used to reject only those variables which clearly do not fulfill the logit assumptions. Both the number of subgroups and the threshold of p-value were selected in such manner to allow for variables with present but weaker monotony to pass and enter the next filter of univariate models.

Univariate framework

The variables tested in a univariate framework performed well, with only one being eliminated because of a p-value of 0.23 and a relatively small AUROC. The tests already performed eliminated variables that clearly do not explain future rating downgrades, so that now is possible to analyze to correlation between the selected variables and then build a multivariate model.

Multicolinearity

The correlation matrix for the so-far selected variables shows high correlations between some of them.

	Rating	v31	v33	v14	v32	DIPI	CotaCredite	CotaActive
Rating	1.000	-0.576	-0.473	-0.070	-0.573	0.013	-0.301	-0.284
v31	-0.576	1.000	0.609	-0.006	0.788	-0.161	0.258	0.261
v33	-0.473	0.609	1.000	0.068	0.622	-0.057	0.220	0.262
v14	-0.070	-0.006	0.068	1.000	0.009	-0.007	-0.086	-0.001
v32	-0.573	0.788	0.622	0.009	1.000	-0.154	0.321	0.358
DIPI	0.013	-0.161	-0.057	-0.007	-0.154	1.000	-0.002	-0.008
CotaCredite	-0.301	0.258	0.220	-0.086	0.321	-0.002	1.000	0.964
CotaActive	-0.284	0.261	0.262	-0.001	0.358	-0.008	0.964	1.000

The threshold set for this step is a correlation coefficient of maximum 0.7. However, high values will be further analyzed even if within this threshold.

First of all, the *loans market share (COTACREDITE)* is highly correlated with the *assets market share (COTAACTIVE)* but it will be selected first due to a higher univariate AUC: 57.5% compared to 55.6%. The correlations between *ROA (v31), ROE (v32)* and *Operational return rate (v33)* are very high, but they will be accepted for now, highlighted and analyzed in the model building. It should be noted that the CAAMPL *Rating* is highly correlated with this three profitability ratios as expected, the higher the profitability, the lower the *Rating* (lower rating indicates better performing banks).

Multivariate model

The remaining variables were introduced in a multivariate logit model. In a backward selection methodology, variables with the highest p-values were eliminated one at a time, examining the values of the model's likelihood and Akaike Information Criterion. If the new model is better, the variable is eliminated and a new iteration is done.

After several iterations, and after reconsidering the eliminated variables in order to assess whether they perform better in a multivariate framework, we decided to replace

the loans market share with the assets market share, as the latter was statistically significant and allowed for a model with higher likelihood and smaller AIC.
The final model has the following specifications:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.303176	1.168088	5.396149	0.0000
RATING	-3.196101	0.429761	-7.436924	0.0000
ROE	-4.033393	2.002130	-2.014551	0.0440
Loans and deposits placed with other banks/ Total assets	1.865809	0.954702	1.954337	0.0507
Assets market share	-36.79551	9.938265	-3.702408	0.0002

Mean dependent var	0.160417	S.D. dependent var	0.367375
S.E. of regression	0.315838	Akaike info criterion	0.648043
Sum squared resid	47.38290	Schwarz criterion	0.691520
Log likelihood	-150.5304	Hannan-Quinn criter.	0.665133
Restr. log likelihood	-211.3729	Avg. log likelihood	-0.313605
LR statistic (4 df)	121.6850	McFadden R-squared	0.287844
Probability(LR stat)	0.000000		

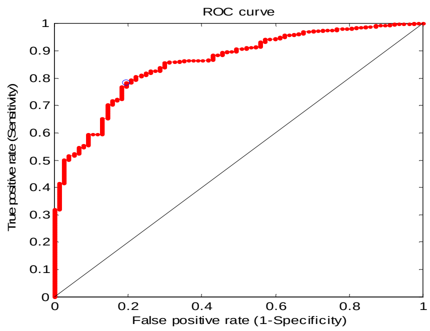
As expected, better CAAMPL Ratings increase the probability of rating downgrade, meaning that banks with modest performance have lower probability to downgrade than the better performing banks. In fact, this can be explained by the direct involvement of the stakeholders as well as the increased supervisory measures always applied to a bank with poor performance. A rating downgrade from Rating 1 to 2 or even from Rating 2 to 3 is accepted with more ease than a downgrade in the lower end of the scale.
The influence of *ROE* indicator on the probability of downgrade is negative, meaning that the higher ROE, the lower the probability, which can be explained by the fact that banks with higher profitability have a stronger financial position and therefore are less likely to encounter a rating downgrade.
Higher *Loans and deposits placed with other banks/ Total assets* may increase the contagion risk but may also be evidence that the bank has some problems in the

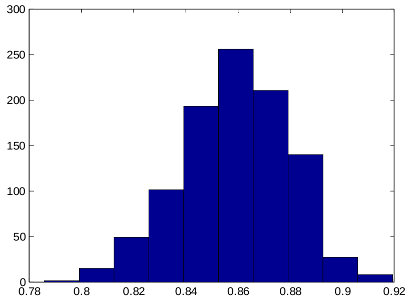
customer loan sectors or in other areas that are commonly more efficient and have a higher return rate.

The sign of the *Assets market share* variable indicates that smaller banks are more likely to downgrade. Usually, bigger banks have solid portfolios and are safe of tensions generated by fast development or simply operational problems that are more costly to smaller banks.

Validation and results

After the model was built, we checked its discriminatory power using the ROC curve and the Area under ROC.

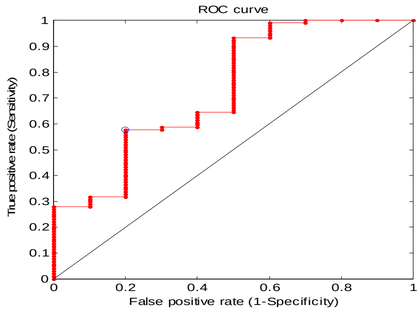




The AUROC of this Early Warning Model is 85.84%, statistically greater than 0.5, which is the value for a random model. In order to check the stability of this figures, compared to the estimation sample, we employed a bootstrap exercise, with 1000 iterations. The 95% confidence interval is (80.41%, 91.27%), so that the model is assessed as having a good discriminatory power, with little variations due to the estimation period.

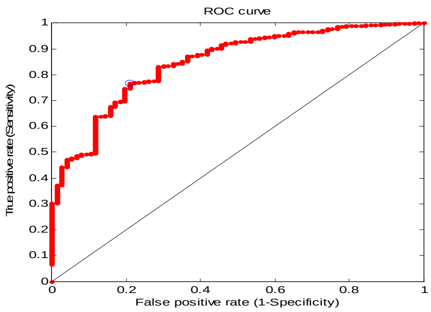
The EW Model was assessed as good with respect to its discriminatory power and stability in sample. However, in order to be used in predicting future rating downgrade, the model should be tested for predictive power, in out of time settings. Using the values of the selected variables in the year 2007, we predicted downgrades for the year 2008 and compared them with the observed downgrades in the respective period.

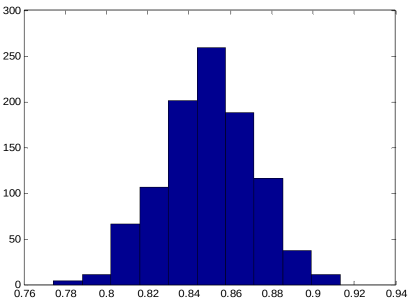
The AUROC for the out of time sample is 74.81% with 95% confidence interval of (56.74%, 92.87%). The model is fair in predicting out of time downgrades, with AUROC statistically greater than 0.5.



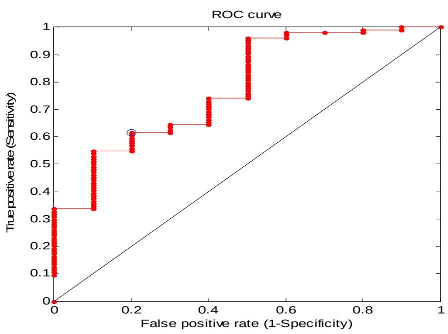
Due to the small out of time sample of downgrades, the ROC curve is not concave and it should be interpreted with care.

The ordered logistic model developed in next section delivers probabilities for each possible rating so that we can compute a probability of downgrade by adding all the probabilities for each rating worse than the current value.





The AUROC of this Early Warning Model is 84.87% and the 95% confidence interval is (79.3%, 90.45%), so that the model is assessed as having a good discriminatory power, with little variations due to the estimation period. The AUROC for the out of time sample for this model is 80.39% with 95% confidence interval of (63.6%, 97.17%).



Due to the small out of time sample of downgrades, the respective ROC curve is not concave and it should be interpreted with care. However, the out of time AUROC values for the ordered logistic model are higher than those of the binary dependent variable model, indicating that even though the models perform closely in sample, the ordered logistic model predicts more accurate the downgrades of the CAAMPL Rating in one year horizon.

With respect to the "loss" function of the supervisory authority, the model was used in order to assess a threshold for a probability of downgrade, which will be, with the same notation: $c = \arg\min_{c} \varepsilon_1(c) \times \omega_1 + \varepsilon_2(c) \times \omega_2$

The weights used for Type I and Type II Errors depend on the importance given by the supervisory authority to unexpected downgrade events. If this weight is 0.5 the probability threshold will be 20.2%, where as for the weight of 0.6667 it is 11.0%.

Included observations: 480

Prediction Evaluation (success cutoff C = 0.202)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	319	16	335	403	77	480
P(Dep=1)>C	84	61	145	0	0	0
Total	403	77	480	403	77	480
Correct	319	61	380	403	0	403
% Correct	**79.16**	**79.22**	**79.17**	100.00	0.00	83.96
% Incorrect	**20.84**	**20.78**	**20.83**	0.00	100.00	16.04
Total Gain*	-20.84	79.22	-4.79			
Percent Gain**	NA	79.22	-29.87			

Included observations: 480

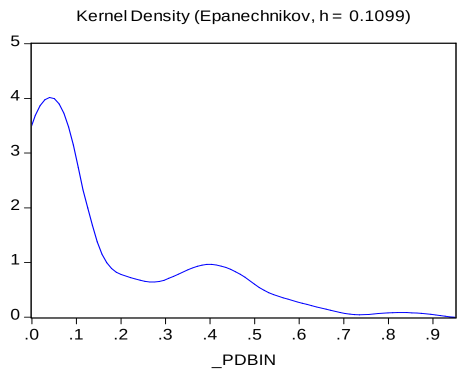
Prediction Evaluation (success cutoff C = 0.11)

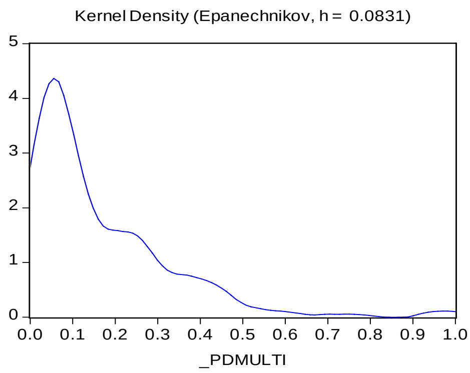
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	283	11	294	0	0	0
P(Dep=1)>C	120	66	186	403	77	480
Total	403	77	480	403	77	480
Correct	283	66	349	0	77	77
% Correct	**70.22**	**85.71**	**72.71**	0.00	100.00	16.04
% Incorrect	**29.78**	**14.29**	**27.29**	100.00	0.00	83.96
Total Gain*	70.22	-14.29	56.67			
Percent Gain**	70.22	NA	67.49			

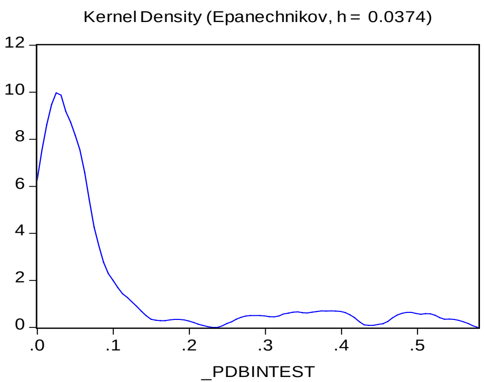
Using the ordered logistic model presented in the next chapter to estimate probabilities of rating downgrades, the thresholds will be 18.7% and 11.5%, respectively. For the first case, the errors will be 19.48% (Type I) and 25.31% (Type II) and for the second, in which the weight for Type I error is higher, the errors will be 11.69% (Type I) and 36.23% (Type II).

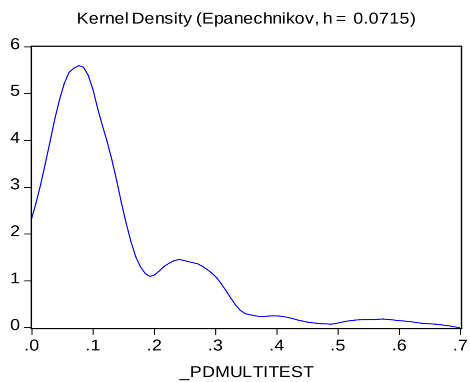
Type I Error Weight	Binary dependent variable model for probability of downgrade			Ordered logistic Model (see next section) for probability of downgrade		
	Cutoff	Type I Error	Type II Error	Cutoff	Type I Error	Type II Error
50.00%	20.2%	20.78%	20.84%	18.7%	19.48%	25.31%
66.67%	11.0%	14.29%	29.78%	11.5%	11.69%	36.23%

With respect to the probability of downgrade, both types of models can provide useful results. Generating the Kernel densities for the two models allow us to draw the following representations for estimation period and for test period.

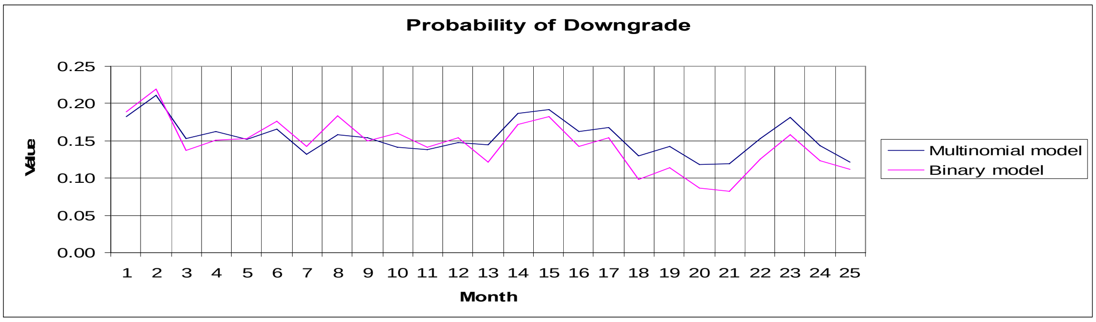








Comparing the average probabilities of downgrade estimated by the two models, we find that the ordered logistic model is more conservative to the end of the analyzed period.



5.2. Weak overall position

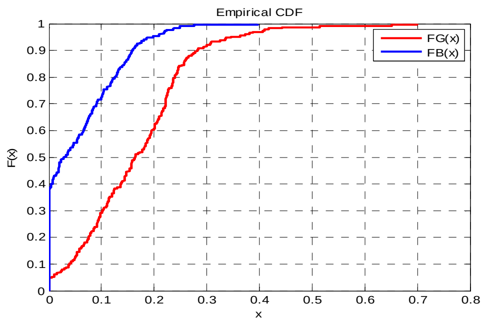
At this point, we have built a model designed for predicting CAAMPL rating downgrades, which can be a useful tool in banking supervision. However, this model should always be doubled by expert opinion and used just as the early warning model which it is. In fact, the output of the model is a probability of rating downgrade, without specifying how many grades the downgrade could be and what could be the probability that the one year horizon rating will be better. A much more useful tool will be a model that can not only predict rating downgrades, but can also provide a probability for each possible rating. This issue is particularly helpful as one can obtain an estimated one year horizon CAAMPL rating, weighting the possible ratings with their estimated probabilities.

For these reasons we employed an ordered logistic model, considering the theoretical background presented in the methodology section as well as the general filters used in the variable selection for rating downgrades. In this case, the variable selection methodology seeks variables that explain a "bad" future rating in one year horizon.

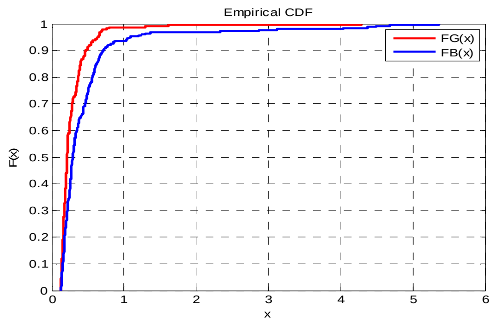
Kolmogorov – Smirnov Test

Both models have to discriminate between banks with higher ratings and banks with lower ratings in one year horizon. We used a Kolmogorov – Smirnov test to check whether the variables fulfill this requirement and we divided the possible ratings into good (1-2) and bad (3-4) ratings. The test was passed by 40 variables, at a 0.1 threshold for the test p-value. For this mode, we also present a graphic overview of two selected variables – *a)ROE(v32)* and *b)Solvency ratio(v23)* – and one rejected variable – *c)Customer loans/Customer deposits(v44)*:

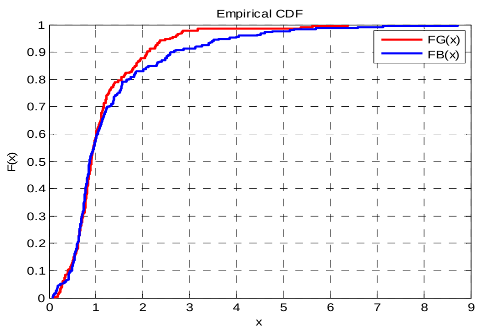
a)



b)



c)

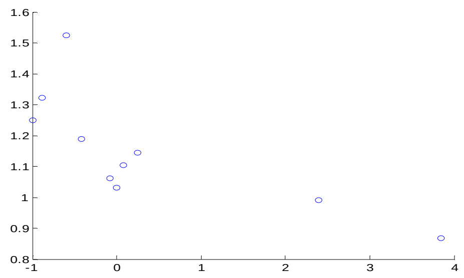


The maximum difference between the distribution of good banks (red line) and bad banks (blue line) is visibly higher for selected variables compared to the variables rejected at this step.

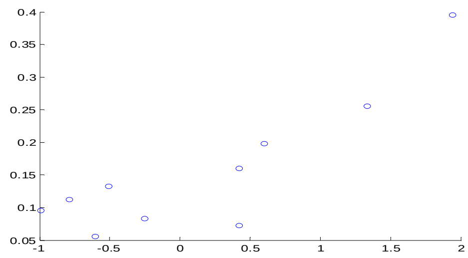
Monotony

With respect to monotony, we considered dependent variable takes the value 1 if the bank will have a bad rating and 0 otherwise, in one year horizon. Similar to the methodology for predicting probability of downgrade, we used a regression for the average logarithm odd of the dependent variable with the average of each explanatory variable, on the ten created subgroups. The number of subgroups was selected considering the size of the estimation sample and the purpose of building the monotony test, with limited discrimination, so that to be sure we will not exclude variables that might perform well in a multivariate framework. We selected a threshold for p-value at 0.1 and the test showed the a wide variety of values for selected and rejected variables, like for *a)ROE (v32)*, *b)Solvency ratio (v23)*, respectively *c) Level 1 Own Funds Index (v26)*.

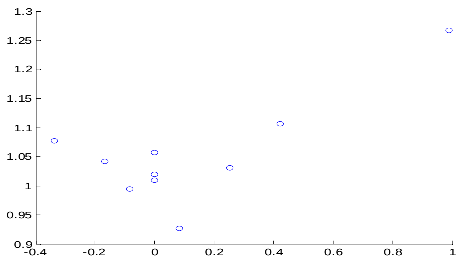
a)



b)



c)



This test was passed by 24 variables which entered the univariate models.

Univariate framework

The next filter used was similar to the case of the rating downgrade prediction. We generated univariate logistic models for the tested variables and we set up a threshold at 0.1 for their p-values. The univariate models assume a dependent variable given by the one year horizon rating, as 0 for a good rating and 1 for a bad rating. We then construct logit models with this dependent variable and each tested explanatory variable and we also check the AUROC for these models. Most of the variables performed well so that 23 variables passed this test, having only two variables rejected.

Multicolinearity

Next, the selected variables were analyzed based on their correlations. The competing variables have been ordered with respect to their AUROC in the univariate models and then the correlation matrix has been used to eliminate variables with a correlation higher than the 0.7 threshold when compared to variables with higher univariate AUROC. However, variables eliminated at this step were highlighted and compared in model building with the variables they were correlated to.

Multivariate models

At this step, we eliminated variables that clearly do not explain the dependent variable, which in this case is the probability of a bank to be "bad" in one year horizon.

As presented before for rating downgrades, we build a multivariate binary dependent variable model for this particular case.

In a backward selection methodology, variables with the highest p-values were eliminated one at a time, examining the values of the model's likelihood and Akaike Information Criterion. If the new model is better, the variable is eliminated and a new iteration is done.

After several iterations, and after reconsidering the eliminated variables in order to assess whether they perform better in a multivariate framework. The final binary dependent variable model, for good/bad banks has the following specifications:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROE	-6.445561	1.655071	-3.894432	0.0001
Rating	1.411898	0.245887	5.742063	0.0000
Loans market share	-14.41244	4.445902	-3.241735	0.0012
Solvency ratio	0.630858	0.319149	1.976685	0.0481
General risk rate	2.174651	0.842999	2.579659	0.0099
Consumer price index	-0.033098	0.008284	-3.995511	0.0001

Mean dependent var	0.527083	S.D. dependent var	0.499787
S.E. of regression	0.389287	Akaike info criterion	0.931655
Sum squared resid	71.83203	Schwarz criterion	0.983827
Log likelihood	-217.5971	Hannan-Quinn criter.	0.952163
Avg. log likelihood	-0.453327		

The variables selected after the above presented methodology were also introduced in a multivariate ordered logistic model, with the one year horizon rating being the dependent variable, which resulted in the following final model:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ROE	-5.167666	1.449624	-3.564831	0.0004
Rating	1.819074	0.226134	8.044220	0.0000
Loans market share	-11.37554	3.144244	-3.617893	0.0003
Solvency ratio	0.455977	0.214223	2.128515	0.0333
General risk rate	2.365373	0.807940	2.927658	0.0034
		Limit Points		
LIMIT_2:C(6)	-2.646104	1.264853	-2.092025	0.0364
LIMIT_3:C(7)	4.883068	0.843593	5.788415	0.0000
LIMIT_4:C(8)	9.216655	0.969939	9.502302	0.0000

Akaike info criterion	1.255066	Schwarz criterion	1.324630
Log likelihood	-293.2159	Hannan-Quinn criter.	1.282410
Restr. log likelihood	-422.8128	Avg. log likelihood	-0.610867
LR statistic (5 df)	259.1938	LR index (Pseudo-R2)	0.306511
Probability(LR stat)	0.000000		

These selected variables passed all the tests in a constant manner, having the same sign both in univariate settings and in multivariate framework.

The dependent variable of this ordered logistic model is the one year horizon rating so that the variables' signs have different meaning than in the rating downgrade model. As expected, the relation between current *CAAMPL Rating* and the one year horizon rating is direct so the better the current *CAAMPL Rating*, the better the one year horizon rating. This issue can also be explained by the fact that the rating is not so volatile in time. A bank with strong current position is less likely to be weak in one year time than a bank that is currently already weak.

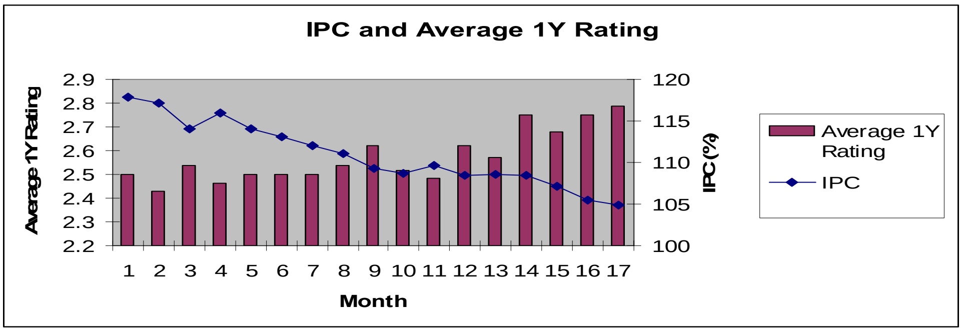
Banks with high profitability, as indicated by *ROE*, are more likely to have a strong position in one year horizon. The same goes for banks with higher market share which, due to their size, have the means to properly manage their portfolio in order to find ways in maintaining a strong overall position.

Loans market share affects the future one year rating in the sense banks with higher market share are less likely to receive a bad rating in one year horizon.

The *Solvency ratio* for the analyzed banks has always been above the regulatory threshold therefore its distribution has longer tail on the higher values. Banks with higher values for the *Solvency ratio* may have difficulties in finding destinations for its resources and therefore may be in the situation of having a worse position than banks with lower but appropriate values of this indicator, due to a weaker management of resources.

The *General risk rate* sign indicates that lower risk banks will generally have a higher probability to have a good (small value) rating in one year horizon. Bad loans and other assets with high risk weight can easily affect the bank's situation generating higher provisions and even losses, in case of defaults.

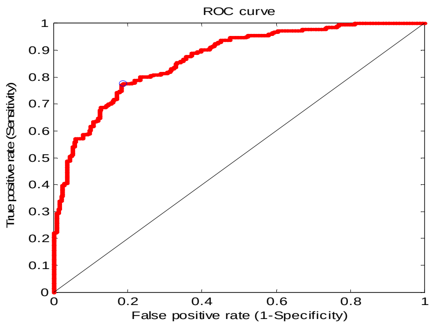
The influence of the *Consumer price index* (IPC) on the dependent variable is negative, meaning that the higher IPC, the lower (therefore better) the one year horizon rating. For the estimation period, this relation can be observed empirically:

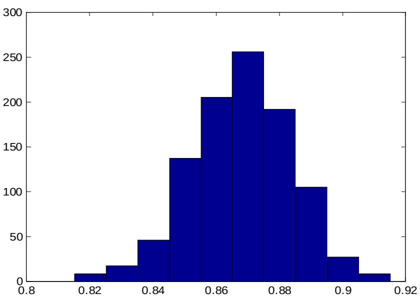


During the analyzed period the Consumer price index decreased while the ratings reached higher values, meaning weaker banks. In the first part of this period the higher inflation allowed the banks to have higher margins, therefore higher profitability and stronger position. The last months were characterized by lower inflation as well as lower profitability, while the banks had to strive more for each market share point and also for maintaining their sound position. The proc-cyclical nature of inflation can help us explain this result by connecting economic growth with inflation and, in the same time, stronger banks. Inflation is also favoring the reimbursement of loans, decreasing this way the credit risk undertaken by banks. This variable did not enter the ordered logistic model but only the binary dependent variable model and is therefore useful to analyze both of them.

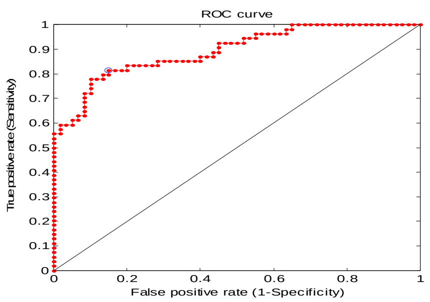
Validation and results

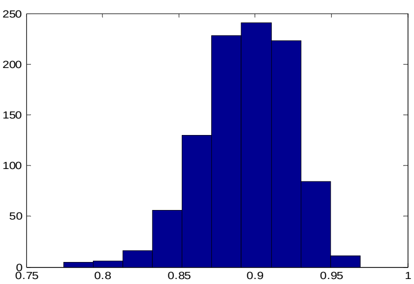
As it was the case for the first binary dependent variable model for probability of downgrade, we have also built a ROC curve for this second binary model.



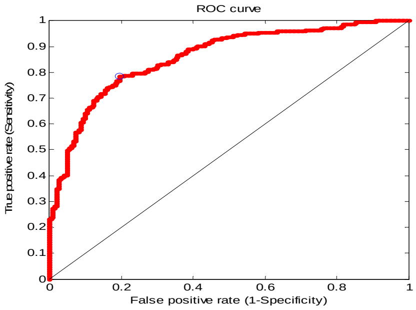


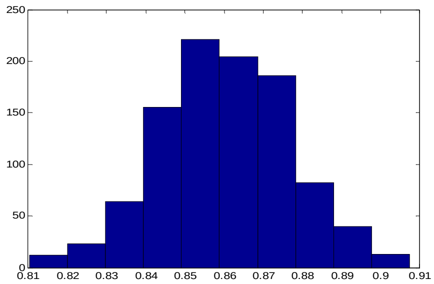
The AUROC of this Early Warning Model is 86.86%, statistically greater than 0.5, which is the value for a random model. The 95% confidence interval is (83.65%, 90.08%), so that the model is assessed as having a good discriminatory power. The out of time AUROC for this model is 89.41% with 95% confidence interval of (83.45%, 95.38%). This method shows that the model has high discriminatory power with little variations due to the estimation period.



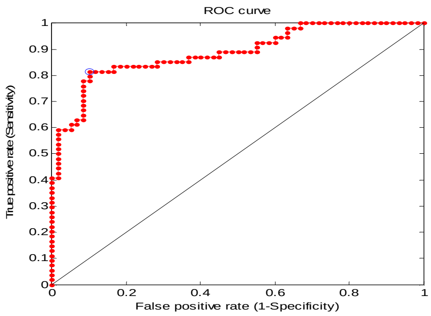


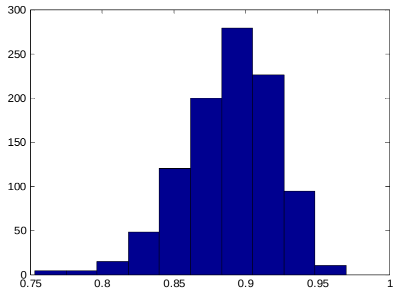
In order to assess the goodness of fit of the ordered logistic model we employed a ROC based approach, similar to the case of the binary dependent variable model. The ordered logistic model can target a dependent variable that takes the value 0 for good banks and 1 for bad banks. Using the calculated probabilities, we can obtain the estimated probability for a bank to be bad (rating 3-4) and then draw the ROC curve for this probability and the percentage of banks that were bad in one year horizon.





The AUROC of this Early Warning Model is 86.07% and the 95% confidence interval is (82.77%, 89.38%), so that the model is assessed as having a good discriminatory power, with little variations due to the estimation period. The out of time AUROC for this model is 88.8% with 95% confidence interval of (82.67%, 94.93%).





This method shows that the model has good and stable predicting power.

Considering the models' in sample performance, we conclude that the binary dependent variable model does not strongly outperform the ordered logistic model, which has the advantage of being able to provide probabilities for each possible rating. This feature may be useful in modeling banks that will have a bad rating in one year horizon and this model is also well behaved in sample, with high AUROC values. For this reason, the ordered logistic model may be selected for further use. However, we tested both models in an out of time setting.

With respect to the "loss" function of the supervisory authority, these models were also used in order to assess a threshold for a probability of receiving a bad rating. The weight for Type I Error represents the importance given by the supervisory authority to unexpected bad ratings events and if this weight is 0.5 the probability threshold will be 47.5%, where as for the weight of 0.6667 it is 27.2% - for binary dependent variable model.

Included observations: 480
Prediction Evaluation (success cutoff C = 0.475)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	176	49	225	0	0	0
P(Dep=1)>C	51	204	255	227	253	480
Total	227	253	480	227	253	480
Correct	176	204	380	0	253	253
% Correct	**77.53**	**80.63**	**79.17**	0.00	100.00	52.71
% Incorrect	**22.47**	**19.37**	**20.83**	100.00	0.00	47.29
Total Gain*	77.53	-19.37	26.46			
Percent Gain**	77.53	NA	55.95			

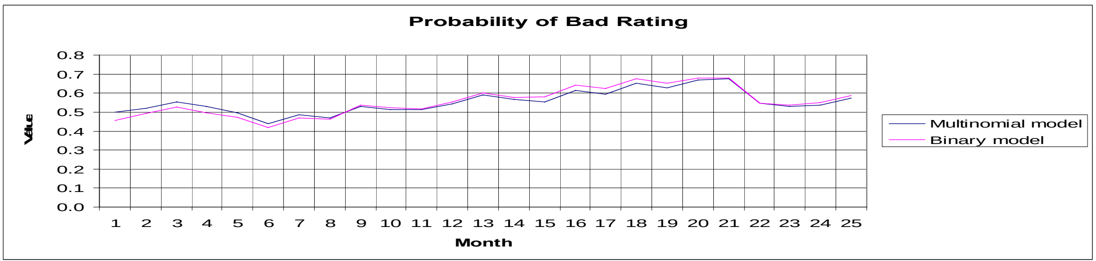
Included observations: 480
Prediction Evaluation (success cutoff C = 0.272)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	129	15	144	0	0	0
P(Dep=1)>C	98	238	336	227	253	480
Total	227	253	480	227	253	480
Correct	129	238	367	0	253	253
% Correct	**56.83**	**94.07**	**76.46**	0.00	100.00	52.71
% Incorrect	**43.17**	**5.93**	**23.54**	100.00	0.00	47.29
Total Gain*	56.83	-5.93	23.75			
Percent Gain**	56.83	NA	50.22			

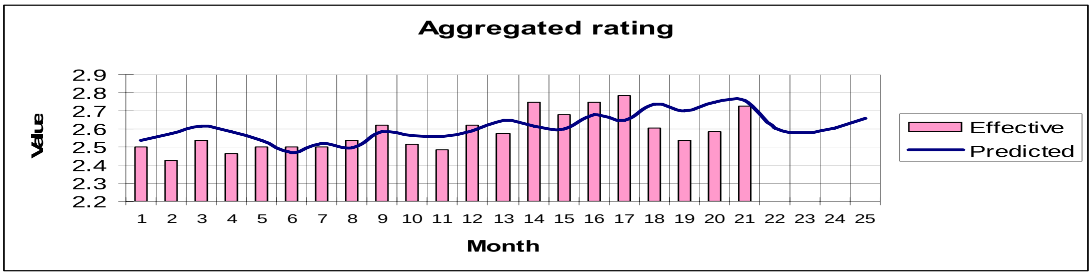
For ordered logistic model, the probability threshold will be 47.6% and 31.7%, respectively. For the first case, the errors will be 19.76% (Type I) and 21.59% (Type II) and for the second, in which the weight for Type I error is higher, the errors will be 10.28% (Type I) and 34.36% (Type II).

Type I Error Weight	Binary dependent variable model for bad future rating			Ordered logistic Model for bad future rating		
	Cutoff	Type I Error	Type II Error	Cutoff	Type I Error	Type II Error
50.00%	47.5%	19.37%	22.47%	47.6%	19.76%	21.59%
	out of time	3.33%	40.74%	out of time	5.00%	38.18%
66.67%	27.2%	5.93%	43.17%	31.7%	10.28%	34.36%
	out of time	0.00%	64.81%	out of time	1.67%	40.00%

The average probabilities estimated for bad future ratings by the two models are similar, confirming this way that the ordered logistic model is not outperformed and, therefore, considering the multiple results available through this model, it may be used in further applications.



The probabilities provided by the ordered logistic model for each possible rating can be used for rating prediction.



Both binary dependent variable and ordered logistic models perform well in sample and out of time. For the purpose of estimating and predicting rating downgrades, both of them are useful tools. However, the ordered logistic model has important features that may recommend it for further analysis and use. The ordered logistic model provides probabilities for each possible rating and these can be employed to obtain a rating downgrade probability but also a probability of reaching one particular group of ratings, such as the top two ratings, or the bottom ones. The discriminatory power of this model with respect to good/bad banks has proven to be high, so that the ordered logistic model has at least one important supplemental use than the binary dependent variable model. Also, the simple estimated probabilities can be useful in order to obtain an estimated rating, as the weight of the possible ratings.

One particular result of the ordered logistic model is rating prediction. In the previous sections we compared the ordered and binary dependent variable models with respect to Type I errors and Type II errors for the cutoffs calculated by minimizing the loss function of the supervisory authority. However, ordered logistic model can also provide a score for each bank, which can subsequently be transformed in a rating prediction. We then analyzed whether the banks will have a future weak overall position or not. For each bank we calculated the Type I errors (E1) as being generated by unexpected future bad ratings and the Type II errors (E2) as for unexpected future good ratings. The total error rate is calculated as total errors to number of records, for each bank.

Bank Code	E1	E2	Total error rate
1	0.0%	0.0%	**0.00%**
2	0.0%	0.0%	**0.00%**
3	5.6%	100.0%	**19.05%**
4	30.8%	0.0%	**19.05%**
5	33.3%	5.6%	**9.52%**
6	100.0%	16.7%	**28.57%**
7	11.1%	41.7%	**28.57%**
8	33.3%	77.8%	**52.38%**
9	0.0%	0.0%	**0.00%**
10	100.0%	16.7%	**28.57%**
11	50.0%	0.0%	**8.33%**
12	16.7%	100.0%	**28.57%**
13	35.7%	85.7%	**52.38%**
14	0.0%	4.8%	**4.76%**
15	22.2%	100.0%	**33.33%**
16	0.0%	100.0%	**4.76%**

Bank Code	E1	E2	Total error rate
17	44.4%	8.3%	**23.81%**
18	43.8%	60.0%	**47.62%**
19	20.0%	45.5%	**33.33%**
20	6.3%	80.0%	**23.81%**
21	0.0%	0.0%	**0.00%**
22	16.7%	100.0%	**28.57%**
23	33.3%	26.7%	**28.57%**
24	16.7%	100.0%	**28.57%**
25	0.0%	0.0%	**0.00%**
26	28.6%	0.0%	**19.05%**
27	100.0%	20.0%	**23.81%**
28	0.0%	100.0%	**14.29%**
30	0.0%	100.0%	**23.08%**
33	0.0%	0.0%	**0.00%**
Total	18.2%	24.6%	21.21%

The first four banks according to assets market share which hold together 48.75% of the local banking assets have an average of only 13.1% for total error rate. Banks numbered 8, 13, 15, 18, and 19 which have the highest total error rate hold together a market share of 4.84%, being in fact some of the smallest local banks. Banks with total error rate below 25% account for an assets market share of 69.79%. These results show that the model performs best for bigger banks and records the highest errors for some of the smaller credit institutions, while the overall errors are considered to be acceptable.

6. Conclusions

In this paper we aimed to find the determinants for rating downgrades and the ones for a bank's future overall position.

After conducting the selection process we obtained two sets of variables that explained reasonably well the dependent variables, which were related to future rating downgrades and future bad ratings, respectively. We then generated multivariate models and after the final models were constructed we were able to highlight the determinants assumed for the dependent variables.

In this respect, we found that rating downgrades are negatively affected by the current *Rating*, *ROE* and *Assets market share*, while *Loans and deposits placed with other banks/ Total assets* have a positive impact on the probability of downgrade. We note that all selected variables have the expected influence on downgrades, with only profitability and assets quality being represented, besides market share and current position. Capital adequacy and liquidity have no influence in this model, perhaps due to a higher degree of regulation for the two microeconomic fields which does not allow for banks to fall under some strict thresholds that are frequently monitored and set at levels avoiding distress. Macroeconomic environment was also not included in the model, meaning that the overall position of a Romanian bank is mostly determined by its characteristics.

Also, an important point of interest was finding the banks that will receive a bad rating in one year horizon. We found that *ROE*, *Loans market share* and *Consumer price index* negatively affects the respective probability, while the current *Rating*, *Solvency ratio* and *General risk rate* have a positive impact. In this case, the model allows for the influence of profitability, assets quality and capital adequacy, besides the current position and market share. All variables have the expected signs, with *Solvency ratio* signaling an opportunity cost for banks that do not properly manage their resources. The macroeconomic environment is again found less influential than a bank's characteristics, having the *Consumer price index* only included in the binary dependent variable model estimating bad future ratings, while the ordered logistic model keeps all the other variables with the same influence on the future overall position. These results highlights as well the fact the Romanian banks are dependent more on their individual business than on macroeconomic elements.

With respect to probability estimation, the binary dependent variable models built for rating downgrades and bad future ratings have not outperformed the ordered logistic model and all of them had good performance both in sample and out of time, as shown by AUROC results as well as analyzing Type I and Type II errors for each model.. The ordered logistic model has the important characteristic of being able to estimate probabilities for each possible rating and is therefore particularly useful in rating prediction, providing a score for each bank so that the supervisors are able to sort the credit institutions based on this criteria. The errors recorded by this model are acceptable overall, with very good performance for bigger banks, but with significant errors for some of the smaller banks.

The results generated by the ordered logistic model can be aggregated in order to obtain an expected rating for banking sector level. This model was able to predict worse ratings and more downgrades for the end of 2007 and for 2008.

Regarding the value that can be added by an early warning model to the activities run in banking supervision, we found that both binary dependent variable and ordered logistic models provide important information about future evolutions and therefore can be a useful tool in this field. However, the results generated by these models can also be manipulated trough a consensus method or by analyzing other models and techniques and they should always be doubled by expert opinion.

This paper provides a framework for building an early warning system regarding the Romanian banks, as well as for the banking sector as a whole. Therefore this methodology and subsequent results should be analyzed considering the characteristics of the local banking sector, which has a small number of banks, mostly retail oriented, with not enough adverse events to allow for modeling defaults or even capital inadequacy. Further research with the intended purpose should consider revising the data set, including new available data based on which the models should be redeveloped and analyzing other comparable parametric or non-parametric (e.g. TRA) methods.

Bibliography

Altman, E. (1968), “Financial ratios, discriminant analysis and the prediction of corporate bankruptcy”, *The Journal of Finance*, *23, 589-609.*

Beaver, W. (1966), “Financial ratios as predictors of failure”, *Journal of Accounting Research, 4, 71-111* .

Berger, A. N., M. K. Kyle, and J.M. Scalise (2000), “Did U.S. Bank Supervisors Get Tougher During the Credit Crunch? Did They Get Easier During the Banking Boom? Did It Matter to Bank Lending?”, *NBER Working Paper no. 7689.*

BIS (2002), “Supervisory Guidance on Dealing with Weak Banks”, *Basel Committee on Banking Supervision, Report of the Task Force on Dealing with Weak Banks.*

Cashin, P. A. and R. Duttagupta (2008), “The Anatomy of Banking Crises”, *IMF Working Papers,WP/08/93.*

Čihák, M. and K. Schaeck (2007), “How Well Do Aggregate Bank Ratios Identify Banking Problems”, *IMF Working Papers, WP/07/275*.

Derviz, A. and J. Podpiera (2004), “Predicting Bank CAMELS and S&P Ratings: The Case of the Czech Republic”, *The Working Paper Series of the Czech National Bank 1/2004.*

Engelmann, B., E. Hayden and D. Tasche (2003), „Measuring the discriminatory power of rating systems“, *Deutsche Bundesbank, Discussion paper 1.*

Gilbert, R. A., A. P. Meyer and M. D. Vaughan (2000), “The Role of a CAMEL Downgrade Model in Bank Surveillance”, *Federal Reserve Bank of St. Louis, Working Paper 2000-021A.*

Gilbert, R. A., A. P. Meyer and M. D. Vaughan (2002), "Could a CAMELS Downgrade Model Improve Off-Site Surveillance?", *Federal Reserve Bank of St. Louis, Review vol. 84, no.1.*

Hammerle, A., R. Rauhmeier and D. Rosch (2003), "Uses and misuses of measures for credit rating accuracy", *Regensburg University.*

Hosmer, D.W. and S. Lemeshow (2000), "Applied Logistic Regression", *John Wiley & Sons, Inc.*

Jagtiani, J., J. Kolari, C. Lemieux and H. Shin (2003), "Early Warning Models for Bank Supervision: Simpler Could Be Better", *Federal Reserve Bank of Chicago, Economic Perspectives, Q3.*

Kolari, J., D. Glennon, H. Shin and M. Caputo (2000), "Predicting Large U.S. Commercial Banks Failures", *Journal of Economic and Business 54:361–87.*

Ohlson, J. (1980), „Financial ratios and the probabilistic prediction of bankruptcy", *Journal of Accounting Research, 18, 109-131.*

Oshinsky, R. and V. Olin (2006), "Troubled Banks: Why Don't They All Fail?", *FDIC Banking Review Series, Vol. 18, No. 1, 2006.*

Poghosyan, T. and M. Cihák (2009), "Distress in European Banks: An Analysis Based on a New Dataset", *IMF Working Papers, WP/09/9.*

Sahajwala, R. and P. van den Bergh (2000), "Supervisory Risk Assessment and Early Warning Systems", *BIS, Basel Committee on Banking Supervision Working Papers, No. 4 – December 2000.*

Schuermann, T. (2007), "Credit Migration Matrices", *Federal Reserve Bank of New York.*

Wheelock, D., and P. Wilson (2000), "Why do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions", *Review of Economics and Statistics 82, no. 1:127–38.*

Worrell, D. (2004), "Quantitative Assessment of the Financial Sector: An Integrated Approach", *IMF Working Paper, WP/04/153.*

Annex 1 – Variables and Signs

Variables	Code	Downgrade Expected Sign	Downgrade Emprirical Sign	“Bad” Bank Expected Sign	“Bad” Bank Empirical Sign
I. Assets quality					
General risk rate (RW exposures/Exposures)	v11	+	-	+	+
Customer loans/Total assets	v12	-	-	-	-
Customer loans/Total liabilities	v13	-	-	-	+
Loans and deposits placed with other banks/ Total assets	v14	+	+	+	+
Overdue and doubtful loans/Loans portfolio	v15	+	+	+	+
Overdue and doubtful customer loans/Customer loans portfolio (net)	v16	+	-	+	-
Overdue and doubtful customer loans/Customer loans portfolio (gross)	v17				
Overdue and doubtful loans/Total assets	v18	+	+	+	+
Overdue and doubtful loans/Total liabilities	v19				
Overdue and doubtful loans/Equity	v110	+	+	+	+
Overdue and doubtful loans and following debtors outside the balance sheet/Total assets	v111	+	+	+	+
Overdue and doubtful loans and following debtors outside the balance sheet/Total liabilities	v112	+	+	+	+
Customers deposits/Total assets	v113	+|-	+	+|-	+
Bank loans//Total liabilities	v114	+|-	+	+|-	+
Fixed factors/Equity	v115				
Fixed factors and materials/Total assets	v116				
Credit risk rate 1 (Exposures…/Loans and interests...)	v117	+	+	+	+
Credit risk rate 1a	v118	+	+	+	+
Credit risk rate 2	v119				
Credit risk rate 2a	v120				
Credit risk rate 3	v121				
Credit risk rate 3a	v122				
Degree of exposures covert by provisions	v123				
Substandard, doubtful and loss loans in equity	v124	+	+	+	-
Rate of covert doubtful and	v125				

loss loans and investments					
Rate of covert substandard, doubtful and loss loans and investments	v126				
Customer loans index	v127	-	-	+|-	+
Overdue loans index	v128	+	+	+	+
II. Capital adequacy					
Equity	v21				
Level 1 own funds/Equity	v22	-	-	-	-
Solvency ratio	v23	+	+	+	+
Level 1 own funds/RW Exposures	v24				
Leverage ratio (Level 1 own funds/ Total assets)	v25	+	+	+	+
Level 1 Own Funds Index	v26	-	-	+|-	+
Assets Index	v27	-	+	-	-
Own Funds	v28				
III. Profitability					
ROA	v31	+|-	+|-	-	-
ROE	v32	+|-	+|-	-	-
Operational return rate	v33	+|-	+	-	-
Cost-to-income ratio	v34				
Staff expenses/Operational expenses	v35				
Interest Incomes/Operational Incomes	v36				
Net Incomes other than Interest/Operational Incomes	v37				
Operational Incomes/Total assets	v38				
Operational expenses/Total assets	v39				
IV. Liquidity					
Liquidity ratio	v41	+|-	-	+	+
Quick liquidity ratio	v42	+|-	-	+	+
Available amounts in banks and government bonds/Total liabilities	v43				
Customer loans/Customer deposits	v44	+|-	+	+|-	+
Liquid assets/Short term liabilities	v45				
V. Rating and Market share					
CAAMPL Rating	Rating	-	-	+	+
Assets market share	CotaActive	-	-	-	-
Loans market share	CotaCredite	-	-	-	-
VI. Macroeconomic indicators					
3M BUBID interest rate	BUBID3M	-	-	-	-
3M BUBOR interest rate	BUBOR3M	-	-	-	-
EUR/RON exchange rate	EUR	+|-	-	+|-	-

USD/RON exchange rate	USD	+|-	-	+|-	-
EUR/RON exchange rate one year variation (%)	DEUR	+|-	-	+|-	-
USD/RON exchange rate one year variation (%)	DUSD	+|-	-	+|-	-
Net monthly nominal wage	SALNOMMEDNET	+|-	+	+|-	+
Net monthly nominal wage one year variation (%)	Dsal	-	-	-	-
Consumer price index based on the same period of last year	IPC	+	-	+	-
Inflation rate	Rinfl	+	-	+	-
Inflation rate one year variation	Drinfl	+	+	+	+
Unemployment rate	Rsomaj	+	-	+	-
Unemployment rate one year variation	Dsomaj	+	+	+	+
Adjusted unemployment rate	Rsomajaj	-	-	+	-
Adjusted unemployment rate one year variation	Dsomajaj	+	+	+	+
Industrial production index	IPI	+|-	+	+|-	+|-
Industrial production index one year variation	DIPI	+|-	+	+|-	+|-
RON Interest rates for non-governmental assets	DA	-	-	-	-
RON Interest rates for non-governmental liabilities	DP	-	-	-	-
RON Interest rates for non-governmental assets one year variation	DDA	+|-	+	+|-	+
RON Interest rates for non-governmental liabilities one year variation	DDP	+|-	+	+|-	+

Annex 2 – KS Test

Rating downgrades

Variables	KS Sign	P-value	μ_{ND}	σ_{ND}	μ_{D}	σ_{D}
Rating	-	0	2.6328	0.606	2.0519	0.4558
v118	+	0.004	0.1522	0.1706	0.1907	0.1778
v117	+	0.0041	0.1495	0.1696	0.1826	0.1733
CotaCredite	-	0.0077	0.0389	0.071	0.0158	0.0193
v23	+	0.0136	0.3608	0.4485	0.5332	0.9065
v14	+	0.0159	0.3321	0.1394	0.3786	0.1541
CotaActive	-	0.0161	0.0365	0.0625	0.0151	0.0168
v25	+	0.0196	0.1535	0.1059	0.1692	0.094
v42	-	0.0459	0.5662	1.3346	0.562	0.271
v13	-	0.0552	0.6178	0.1999	0.5692	0.1961
DIPI	+	0.0631	4.9278	4.2525	6.3078	4.3955
v12	-	0.1091	0.4833	0.1521	0.4476	0.1617
v16	-	0.1091	0.4833	0.1521	0.4476	0.1617
v22	-	0.1385	1.4952	0.7511	1.467	0.7001
v41	-	0.1399	2.9475	2.4682	2.2699	0.8956
IPC	-	0.1471	111.0263	3.7588	110.314	3.8235
Rinfl	-	0.1471	11.0263	3.7588	10.314	3.8235
IPI	+	0.1471	124.4839	8.4145	126.1792	9.3899
DA	-	0.1471	24.3609	6.6304	23.0814	7.2268
EUR	-	0.1598	3.7449	0.2338	3.7167	0.2474
USD	-	0.1748	3.0906	0.2425	3.0408	0.2563
Dsal	-	0.1748	0.2307	0.0349	0.2217	0.0414
v18	+	0.2541	0.0028	0.0041	0.0031	0.0045
v112	+	0.2541	0.0028	0.0041	0.0031	0.0045
DDP	+	0.2904	-5.1913	5.8565	-4.3	5.7445
v110	+	0.3077	0.017	0.0235	0.018	0.0253
v114	+	0.3077	0.017	0.0235	0.018	0.0253
SALNOMMEDNET	+	0.3231	672.6843	170.1884	708.1593	179.0915
Dsomajas	+	0.3257	-1.1387	1.0169	-0.9473	0.9754
Dsomaj	+	0.3431	-1.1538	1.1021	-0.9623	1.0574
v113	+	0.3786	0.0036	0.0061	0.004	0.0057
v26	-	0.3821	1.0605	0.3141	1.0197	0.0661
v124	+	0.4103	0.053	0.0654	0.0584	0.0805
BUBOR3M	-	0.4338	15.045	5.8158	14.2274	5.7848
DP	-	0.4338	11.6378	4.2026	11.0924	4.4311
v127	-	0.4851	1.1356	1.6863	1.031	0.0792
v27	+	0.4871	1.052	0.1195	1.059	0.1004
DEUR	-	0.5208	0.0409	0.1275	0.0311	0.1201
Rsomaj	-	0.5208	6.4764	1.0673	6.3377	1.0994
Rsomajaj	-	0.5208	6.4513	0.9523	6.2942	0.9716
v11	-	0.5797	0.4992	0.1545	0.4753	0.163
v15	+	0.6193	0.0051	0.009	0.006	0.0105
v111	+	0.6535	0.0053	0.0095	0.0063	0.0108
DDA	+	0.7276	-7.6081	5.7691	-7.0432	5.5463

v128	+	0.8229	2.146	10.5955	45.4507	388.5757
v44	+	0.9851	1.2174	1.0213	1.2606	1.1886
BUBID3M	-	0.9863	12.0101	5.0432	11.5815	4.9493
Drinfl	+	0.9893	-4.3363	3.0626	-4.1535	3.1044
DUSD	-	0.9992	-0.0368	0.0702	-0.0386	0.0705

Bad Ratings

Variables	**KS Sign**	**P-value**	μ_{GOOD}	σ_{GOOD}	μ_{BAD}	σ_{BAD}
v117	+	0	0.1312	0.1679	0.1759	0.1702
v118	+	0	0.131	0.1675	0.183	0.1729
v22	-	0	1.8194	0.8042	1.1958	0.5322
v23	+	0	0.2901	0.321	0.4767	0.6837
v25	+	0	0.1241	0.0824	0.1847	0.1131
v31	-	0	0.0222	0.0122	0.0108	0.0133
v32	-	0	0.1691	0.1084	0.0601	0.0712
v33	-	0	1.2188	0.1688	1.0852	0.179
CotaActive	-	0	0.0539	0.0764	0.0144	0.0211
CotaCredite	-	0	0.0596	0.0876	0.0133	0.0199
Rating	+	0.0000	2.1938	0.4954	2.8498	0.5574
v11	+	0.0004	0.4716	0.1477	0.5167	0.1603
v42	+	0.0041	0.4682	0.2912	0.6529	1.6647
v124	-	0.0045	0.0549	0.0614	0.0529	0.0736
IPC	-	0.0206	111.4571	3.7126	110.423	3.7695
Rinfl	-	0.0206	11.4571	3.7126	10.4229	3.7695
v12	-	0.0207	0.4936	0.1446	0.4632	0.161
v16	-	0.0207	0.4936	0.1446	0.4632	0.161
USD	-	0.0235	3.1179	0.2336	3.0509	0.2514
v26	+	0.0257	1.0427	0.164	1.0642	0.3672
DIPL	+	0.0391	4.6207	4.2182	5.6233	4.3276
BUBOR3M	-	0.0442	15.5966	5.7718	14.3013	5.792
SALNOMMEDNET	+	0.0442	653.5084	162.1538	700.686	177.659
IPL	+	0.0442	123.6079	8.2405	125.786	8.7821
DA	-	0.0442	25.0948	6.4587	23.313	6.8835
DP	-	0.0442	12.0393	4.1486	11.1116	4.2812
v14	+	0.0448	0.3308	0.1332	0.3474	0.1506
v111	+	0.0486	0.0045	0.0078	0.0063	0.0111
v13	+	0.0524	0.5994	0.171	0.6195	0.2226
v113	+	0.0586	0.0028	0.0036	0.0044	0.0075
v15	+	0.0598	0.0042	0.0065	0.0062	0.011
v27	-	0.0598	1.0533	0.1399	1.053	0.091
v18	+	0.0618	0.0023	0.0029	0.0032	0.0051
v112	+	0.0618	0.0023	0.0029	0.0032	0.0051
DEUR	-	0.0676	0.0522	0.1302	0.0277	0.1218
Rsomajaj	-	0.0676	6.5553	0.9433	6.3102	0.9546
Rsomaj	-	0.0965	6.5841	1.0765	6.3375	1.0575
v127	+	0.1014	1.0419	0.1064	1.1878	2.1262
EUR	-	0.1147	3.7605	0.2345	3.7223	0.2363
BUBID3M	-	0.1468	12.4431	5.0289	11.4911	4.9897
Dsal	-	0.2374	0.2323	0.033	0.2266	0.0386

v128	+	0.252	2.5653	13.5224	14.9495	214.384
v110	+	0.2794	0.0169	0.0214	0.0174	0.0258
v114	+	0.2794	0.0169	0.0214	0.0174	0.0258
Dsomaj	+	0.2864	-1.207	1.1618	-1.0478	1.0303
DUSD	-	0.2931	-0.0322	0.0683	-0.0415	0.0718
v41	+	0.3741	2.5605	1.2151	3.0885	2.9362
DDP	+	0.4412	-5.4675	6.0119	-4.6722	5.6707
v44	+	0.4524	1.1285	0.8249	1.3103	1.2102
Drinfl	+	0.4749	-4.5006	3.1548	-4.1332	2.9813
Dsomajas	+	0.5082	-1.1875	1.0677	-1.0367	0.9553
DDA	+	0.6387	-7.8104	5.953	-7.2547	5.5249

Annex 3 – Monotony

Rating downgrades

Variable	coef	p-value
Rating	-1.7409	0.0006
CotaCredite	-11.3279	0.0024
DIPI	0.1141	0.0051
CotaActive	-13.2768	0.0058
v14	2.2828	0.0075
v116	-0.8048	0.0084
v115	-0.7939	0.0146
v41	-0.1854	0.0422
DDP	0.0488	0.0532
DDA	0.0407	0.0723
v25	2.1703	0.0897
Dsomajas	0.3245	0.0903

Bad ratings

Variable	coef	p-value
Rating	2.2739	0.0000
SALNOMMEDNET	0.0018	0.0000
v42	0.9990	0.0003
USD	-1.1574	0.0003
v32	-14.5245	0.0005
v22	-1.3865	0.0008
DA	-0.0394	0.0014
v25	7.6877	0.0018
IPI	0.0345	0.0038
v31	-75.2235	0.0039
Rinfl	-0.0723	0.0050
IPC	-0.0723	0.0050
Rsomajaj	-0.2365	0.0057
BUBOR3M	-0.0403	0.0068
DP	-0.0536	0.0096
v33	-6.1236	0.0100
DIPI	0.0460	0.0168
Rsomaj	-0.2219	0.0173
CotaCredite	-14.3810	0.0175
v23	1.2082	0.0201
v27	2.8107	0.0337
DEUR	-1.6693	0.0451
CotaActive	-15.6301	0.0478
v11	2.2591	0.0482
v113	56.9773	0.0942

Annex 4 – Univariate Framework

Rating downgrades

Variable	Coefficient	Std. Error	z-Statistic	Prob.	AUC
Rating	-2.1230	0.3256	-6.5203	0.0000	0.7403
v14	2.0470	0.7915	2.5862	0.0097	0.6016
DIPI	0.0729	0.0285	2.5607	0.0104	0.5888
CotaCredite	-12.2136	4.9837	-2.4507	0.0143	0.5753
CotaActive	-15.0029	5.4122	-2.7721	0.0056	0.5565

Bad ratings

Variable	Coefficient	Std. Error	z-Statistic	Prob.	AUC
v32	-12.8598	1.2220	-10.5234	0.0000	0.8129
Rating	2.4656	0.1931	12.7719	0.0000	0.7820
CotaCredite	-20.1209	3.5301	-5.6998	0.0000	0.7677
CotaActive	-20.0159	3.1546	-6.3449	0.0000	0.7596
v31	-65.9501	7.7643	-8.4940	0.0000	0.7558
v22	-1.4853	0.1657	-8.9628	0.0000	0.7459
v33	-4.4319	0.5853	-7.5715	0.0000	0.7323
v25	5.2074	0.9319	5.5878	0.0000	0.6636
v23	0.4846	0.1622	2.9875	0.0028	0.6480
v11	2.0933	0.5821	3.5962	0.0003	0.5950
IPC	-0.0762	0.0241	-3.1549	0.0016	0.5853
Rinfl	-0.0762	0.0241	-3.1549	0.0016	0.5853
DA	-0.0422	0.0134	-3.1379	0.0017	0.5815
SALNOMMEDNET	0.0017	0.0005	3.2243	0.0013	0.5781
USD	-1.1616	0.3695	-3.1434	0.0017	0.5770
Rsomajaj	-0.2799	0.0949	-2.9486	0.0032	0.5756
IPI	0.0316	0.0106	2.9913	0.0028	0.5731
DIPI	0.0551	0.0210	2.6266	0.0086	0.5727
Rsomaj	-0.2273	0.0847	-2.6834	0.0073	0.5701
BUBOR3M	-0.0401	0.0155	-2.5907	0.0096	0.5637
DP	-0.0552	0.0212	-2.6060	0.0092	0.5607
DEUR	-1.5894	0.7142	-2.2254	0.0261	0.5495
v113	34.6881	14.4214	2.4053	0.0162	0.5487

Annex 5 – Multicolinearity

Rating downgrades

AUC UV	PD	Rating	v31	v14	v32	DIPL	Cota Credite	Cota Active
0.7403	Rating	1.000	-0.576	-0.070	-0.573	0.013	-0.301	-0.284
0.6863	v31	-0.576	1.000	-0.006	0.788	-0.161	0.258	0.261
0.6017	v14	-0.070	-0.006	1.000	0.009	-0.007	-0.086	-0.001
0.5946	v32	-0.573	0.788	0.009	1.000	-0.154	0.321	0.358
0.5888	DIPI	0.013	-0.161	-0.007	-0.154	1.000	-0.002	-0.008
0.5753	CotaCredite	-0.301	0.258	-0.086	0.321	-0.002	1.000	0.964
0.5562	CotaActive	-0.284	0.261	-0.001	0.358	-0.008	0.964	1.000

Bad ratings

Variable	AUROC UV	IPC
IPC	0.59	1.00
Rinfl	0.59	**1.00**
DA	0.58	**0.89**
SALNOMMEDNET	0.58	**-0.93**
USD	0.58	**0.88**
Rsomajaj	0.58	**0.98**
IPI	0.57	**-0.84**
Rsomaj	0.57	**0.92**
BUBOR3M	0.56	**0.81**
DP	0.56	**0.80**
DEUR	0.55	**0.89**

Variable	AUROC UV	v32
v32	0.81	1.00
v31	0.76	**0.79**