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TOWARDS AN EARLY-WARNING SYSTEM OF DISTRESSED NON-BANKING FINANCIAL INSTITUTIONS

Abstract. *In this article we develop a quantitative framework for risk-based supervision of non-banking financial institutions (NFIs). Its main component is represented by an early warning system (EWS) of NFIs' defaults, which consists of a scoring function with a rating scale attached. Using a preliminary univariate and cross-correlation analysis, we select a short list of discriminants for the NFIs' defaults. A further filtering of risk drivers is performed via multivariate logit estimation. The econometric results suggest that three core variables form the risk profile of NFIs in default, namely: low or negative ROA, elevated NPL ratio and a rather reduced share of loans in total assets. The high discriminatory power of the EWS was confirmed by the backtesting results, as its forecasts adequately captured the moderate deterioration of NFIs' performance in the third quarter compared to the first quarter of 2013.*

Key words: *non-banking financial institutions, early-warning system, risk of default.*

JEL Classifications: C38, C81, G23

I. Introduction

This paper is one of the few, if not the first one, that aims at developing early-warning systems for non-banking financial institutions' (NFIs') defaults. It aims not only at modelling the probability of NFIs' default, but, also, at determining when this event is more likely to take place (in a six-, nine- or twelve-months time horizon). At least in Romania, the activity of NFIs has been recently regulated. NFIs are financial entities which engage in lending activities such as: granting of credits, financial leasing, issuance of guarantees, etc. The set-up of such entities has been encouraged by the mother-banks with the aim of making the process of lending more cost-effective (the aim was to create lending entities that would not be classified as credit institutions and, therefore, would not be subject to the credit institutions' applicable legislation). However, the central bank which is responsible with providing the regulatory and supervisory frameworks for the NFIs, took immediate action and, in 2006, carried on continuous measures directed towards the implementation of its regulatory and supervision role in the field of NFIs.

According to legislation currently applicable, NFIs are subject to two supervision methods used by the central bank: reporting-based prudential supervision ("off-site" supervision), supervision by on-site inspections ("on-site" supervision). The main challenge the supervision authority faces when engaging in the prudential supervision of the NFIs' sector is the efficient allocation of its resources (time and personnel). Consequently, there is a need for models for evaluating comparatively the performance of NFIs so that the supervisory authority focuses its attention on institutions that present a lower performance or a high probability of default[1]. We call these models NFIs' performance benchmarking models or NFIs' default early warning systems (NFIs' default EWSs).

In a previous paper (Costea, 2011) we formalized the process of assessing comparatively the performance of NFIs by considering it as a knowledge discovery problem and by following the formal steps of a well-known discovery process called Knowledge Discovery in Databases (KDD) process (Fayyad et al., 1996). We argued that the current system used to evaluate the performance of credit institutions (e.g.: the CAAMPL system – Cerna et al., 2008) is suboptimal when applied to assessing NFIs' performance and that the KDD and Data Mining (DM) processes could offer specific methods - Computational-Intelligence (CI) methods - that may be used to develop better systems.

The Uniform Assessment System or CAAMPL (Cerna et al., 2008), developed by the Supervision Department of the National Bank of Romania constitutes an effective tool for evaluating the performance of credit institutions. However, this system presents some disadvantages:

- it uses simple linear techniques for discriminating the multidimensional space;
- the selection of independent variables is not based on scientific rigor, but rather on the experience of members of the supervisory authority;
- the limits (thresholds) for the explanatory variables which determine the rating are not properly explained.

[1] We consider a NFI to default when it can no longer sustain minimum capital and credit granting requirements

Dardac et al. (2012) apply model validation techniques traditionally employed in relation with rating systems developed by banks to review the scoring system used by NFIs. The study shows how weak areas in credit risk management of NFIs could be identified and removed by scientific calibration of such a scoring system.

Currently, application of the assessment system is limited to the credit institutions (banks). Therefore, the main objective of this paper would be to improve and expand the applicability of the performance assessment systems in the case of NFIs. In this respect, we aim at developing models for classifying NFIs financial performance, by highlighting the results of our previous research (Costea, 2005).
Except the supervision authority, the performance evaluation models would be useful to other actors in financial markets as well: from managers to creditors and investors, all business players are interested in obtaining accurate and timely information about an economic entity (in our case, a NFI).

The rest of the paper is structured as follows. In Section two we present a literature review of models for assessing the financial institutions'/entities' performance (the risk of default). Next, we propose a NFIs' default EWS based on a logit model. In the final Section we draw our conclusions.

II. Literature review

In the literature there are a number of models to assess the financial performance of entities that apply, in particular, to credit institutions. For example, Collier et al. (2003) described the characteristics of an "off-site" monitoring instrument of the FDIC (Federal Deposit Insurance Corporation) and the data used in its development. Doumpos & Zopounidis (2009) proposed a new classification system of financial institutions as a support-tool for analysts from the National Bank of Greece. The system provides a rich set of assessment, visualization and reporting options.

Swicegood & Clark (2001) compared three models (based on discriminant analysis, neural networks and human thought) used to predict the deterioration of commercial banks' financial performance. Neural networks-based model showed better predictive accuracy than the other two models.

The authors proposed in Boyacioglu et al. (2009) several methods for classifying credit institutions based on 20 performance indicators grouped into six dimensions (CAMELS). They used four sets of financial data, the results showing that among the techniques of clustering/classification tested, the best in terms of accuracy rates were the neural networks.

Kumar & Ravi (2007) have done a consistent literature review regarding the research conducted during 1968-2005 on the application of statistical and computational intelligence methods on banks' and firms' bankruptcy prediction problem. The authors show, for each study the source of data, indicators used, country of origin and period of data collection.

Borio & Lowe (2002) developed a very simple early-warning system for banking crises: they relied on three main indicators (credit, asset prices and real exchange rate), set-up some thresholds for these indicators and, if these thresholds were crossed cumulatively then this would be a signal that a crisis might occur. All variables are measured as gaps, ie as a percentage point or percentage deviation from an ex ante, recursively calculated Hodrick-Prescott trend (Borio & Lowe, p. 49). The authors obtained good crisis' prediction rates (up to 60%) with the best results intuitively obtained for the highest time-horizon case (3-years).

Bussière & Fratzscher (2002) developed an early-warning system model for predicting financial crises by applying a multinomial logit model (instead the classical two-case output variable, the authors used a three-case output variable by adding the "post-crisis period" as a new value for the dependent variable). The results show that the model would have correctly predicted a large majority of crises in emerging markets. The dataset consisted of about 32 open emerging market economies for the period 1993-2001. Also, the paper provides some hints about the optimal design of the EWS models for policy-makers.

Candelon et al. (2009) propose a statistical framework for evaluating EWS models for currency crises. The EWS models' evaluating criteria include ROC curves, Kuiper Score, Petra Index and Bayesian Error Rate. Also, the authors propose a method of finding the optimal cut-off rate (the value that signals the crisis) by maximizing simultaneously and conditionally two model accuracy-based measures: *sensitivity* and *specificity*. The data covers 12 countries with monthly frequency, spans from January 1985 to January 2005 and is extracted via Datastream. Based on the above-mentioned criteria, the authors compare two EWS models: panel logit and a Markov switching model, the former outperforming the later.

Davis & Karim (2008) compare two EWS models: the logit and signal extraction EWS and suggest that logit is the most appropriate approach for global EWS, while signal extraction is better for country specific EWS. At the same time, the authors sugest that the policy maker's objectives play an important role in designing the predictive systems and setting-up the related thresholds. The results show that the GDP growth and terms of trade are robust leading indicators for banking crisis. The authors argue that the definition of the output variable (that defines the banking crisis) is essential in designing an effective EWS model.

Kaminsky & Reinhart (1999) propose a set of 15 macroeoconomic variables as predictors (early warning indicators - EWIs) of banking crisis. The data was collected for a number of 20 countries that experienced banking crises during 1970-1995 period. The criterion used by the authors to construct and rank alternative signals is the so-called noise-to-signal ratio (NSR). Demirgüç-Kunt & Detragiache (1999) explore the use of multivariate logit model of banking crisis probabilities for monitoring the banking sector fragility. They propose as a crisis signaling criterion the "loss function of the decision maker" (Demirgüc-Kunt & Detragiache, 1999, p.12) which takes into account three aspects: the probability of type I and type II errors associated with the threshold, the unconditional probability of a banking crisis and the cost to the decision maker of taking preventive action relative to the cost of an unanticipated banking crisis.

Drehmann & Juselius (2013) use the receiver operating characteristic (ROC) curve to evaluate EWIs for banking crises. In particular, the area under the curve (AUC) is used due to its nice interpretability. Also, another advantage of using ROC curves is that, in the literature (eg Janes et al., 2009 and Pepe et al. 2009, cited in Drehmann & Juselius, 2013, p. 3), there are available estimators (parametric and non-parametric), confidence bands and Wald statistics for comparing the AUCs of two signals. The results show that the credit-to-GDP gap was the best indicator in the case of longer horizons, while a new indicator, the debt service ratio (DSR), consistently outperform other measures in the case of shorter ones.

Hardy & Pazarbasioğlu (1998) found that while the main macroeconomic indicators were of limited value in predicting the Asian crises, the best warning signals were given by proxies for the vulnerability of the banking and corporate sectors. The data sample consist of 50 countries, 38 of which suffered a total of 43 episodes of banking system crisis or significant problems. Four episodes were used for out-of-sample testing. The explanatory variables were divided in real sector, banking sector and other potential shocks variables. The empirical findings suggest that a consumption boom in the years preceding a crisis can be a leading indicator and also, that the occurrences of the crises are associated with a sharp decrease of the real effective exchange rate (Hardy & Pazarbasioğlu, 1998, p. 20).

All the above papers related with the development of performance benchmarking and EWS models were focused on credit institutions (banks). Consequently, we identified potential contributions that could be brought to the research field of assessing comparatively the performance of different entities, such as:

- the application of the algorithms proposed in previous research (Costea, 2005) and other Data Mining methods for elaborating classification/EWS models for NFIs' defaults;
- the utilization of clustering in order to have a benchmark model for the classification/EWS models;

- the evaluation of the predictive power of the proposed classification/EWS models;
- the utilization of visualization techniques for analyzing the evolution of NFIs over time;
- the application of clustering techniques for discovering abnormal situations of NFIs.

In this paper we address the first issue mentioned above by applying a multivariate logit technique in order to find distressed NFIs. In Costea (2013) we addressed the last two issues outlined above by analysing the movements of the three largest NFIs.

The degree of originality/innovation of proposed research methods and objectives of our paper is made clear from the literature. The application of Data Mining methods in the classification of financial institutions as to their economic performance is a relatively new area of research. Also, some of the proposed methods are new versions of existing techniques. In the next Section we present the multivariate logit-based EWS model.

III. A multivariate logit-based EWS for NFIs' defaults

Next, we try to develop an early-warning system of NFIs' defaults. We use a binomial logistic regression model, drawing on the methodological framework deployed by Moinescu (2007) for assessing the downgrade probability of Romanian credit institutions. Under this setting, the endogenous variable is binary and it discriminates between defaults and normal functioning in a time horizon of two to four quarters. Conventionally, we assign zero value to the dependent variable when the NFI is functioning normally and the value of one when the NFI goes in default in two, three or four quarters later.

III.1. The data sample used for building the predictive models

The original set of candidate variables comprises 10 elements, i.e. the prudential indicators covering the following performance dimensions: (a) capital adequacy; (b) assets' quality; and (c) profitability indicators (see Table 1).

Table 1 – List of main exogenous variables

Candidate variables	Formula	Expected sign
1. Capital adequacy		
Equity ratio (Leverage)	own capital / assets (net value)	-
Share of own capital in total equity	own capital / equity	-
Indebtedness	borrowings / assets (net value)	+
2. Assets' quality		
Loans to assets (Earning power)	loans (net value) / assets (net value)	-
Loan to borrowings ratio	loans (net value) / borrowings	+
NPLs as share of total loans	past due and doubtful loans (gross value) / (loans portfolio + guarantee commitments)	+
NPLs as share of total assets	past due and doubtful loans (gross value) / assets (net value)	+
3. Profitability		
Return on assets	net income / total assets (net value)	-
Return on equity	net income / equity	-
Cost to income ratio	costs / revenues	+

Relevant variables have been selected according to economic literature on credit institutions performance and the recommendations of staff involved in the supervisory activity of Romanian NFIs. They were empirically tested and eventually only those variables having statistical significance were employed (R^2-McFadden > 2%).

The data sample employed for building the predictive models consists of an unbalanced panel of 68 entities, which covers the entire population of Romanian NFIs. The number of NFIs varied across the estimation period, as the entities in default were expelled from the data for the rest of the estimation period.

For example, for the "three-quarters" case, there were 1111 records available, out of which 18 were defaults. We used quarterly data starting with early 2007, as this record is the oldest available in the NBR' Special register on NFIs, ending with the last quarter in 2012. The last three records in the database (Q2:Q4 2012) were deployed for running the forecasts on Q1:Q3 2013. As in our previous studies, the data has been leveled to a [-20, 20] interval to avoid the algorithms placing too much weight to extreme values.

The preliminary data analysis started with a short investigation of statistical features of each candidate variable (see Table 2) on both sub-groups of NFIs (default/non-default).

Table 2 – Statistics on explanatory variables for the "three-quarters" case

Candidate variables	*Mean*		*Standard deviation*	
	Normal	*Default*	*Normal*	*Default*
Leverage	0.075	0.022	0.2085	3.1006
Share of own capital in total equity	0.977	0.487	7.4915	1.3383
Indebtedness	0.866	0.789	0.6256	2.3338
Earning power	0.911	0.896	0.5921	4.2469
Loans to borrowings ratio	1.039	1.067	1.8804	4.4963
NPLs as share of total loans	0.068	0.112	0.3964	0.2217
NPLs as share of total assets	0.061	0.129	0.2071	1.3555
Return on assets	**0.002**	**-0.026**	**0.0526**	**4.4748**
Return on equity	0.024	-0.164	5.2686	1.1332
Cost to income ratio	0.977	1.098	0.4592	1.7636

Preliminary results show that all selected variables seem good candidates for identifying distressed NFIs, as the mean values differ significantly between the two sub-groups of NFIs. One example is that of return on assets, as its mean value for normal functioning NFIs is around 0.2 percent, while for the defaulted NFIs slips well into negative territory (-2.6 percent). Another example is that of asset quality indicators, as the non-performing loans (NPLs) for the defaulted NFIs are two-time larger than those of normal-functioning NFIs. These results are backed by the standard deviation data, which generally provide evidence of larger homogeneity in the good sub-sample compared with that of defaulted NFIs.

The data was further analyzed by deploying the univariate analysis, based on R-squared McFadden statistic of the logistic regression output. The applied procedure tested variables on one-by-one basis using two to four-quarter lags (see Table 3).

Table 3 – The short list of exogenous variables

Candidate variables	*R-squared McFadden*		
	k=2Q	*k*=3Q	*k*=4Q
Leverage	**4.45%**	**6.85%**	**5.51%**
Share of own capital in total equity	0.06%	0.15%	0.12%
Indebtedness	3.09%	1.60%	1.2%
Earning power	**3.20%**	**4.27%**	**5.06%**
Loans to borrowings ratio	1.57%	1.87%	1.31%
NPLs as share of total loans	**3.86%**	**3.09%**	**2.92%**

NPLs as share of total assets	**6.48%**	**10.30%**	**7.53%**
Return on assets	**1.14%**	**18.63%**	**3.42%**
Return on equity	0.02%	0.20%	0.09%
Cost to income ratio	**1.97%**	**6.74%**	**5.39%**

After performing univariate tests, **six variables** were retained for further analysis, as follows: (i) *leverage*; (ii) *earning power;* (iii) *NPLs as share of the banking book*; (iv); *NPLs as share of the total assets;* (v) *ROA and* (vi) *cost-to-income ratio.* The univariate analysis pointed out that the loans to borrowings indicator does not present material value added in modeling defaults of NFIs. One additional landmark is that almost all short-listed determinants had their best performance when the three-quarters time horizon was used.

The last step of the preliminary empirical analysis was dedicated to the cross-correlations among the short-listed variables in order to avoid any multicolinearity problem when estimating the early warning system (see table 4).

Table 4 – Cross correlations among the short-listed variables

	Leverage	**Earning power**	**NPLs as share of total loans**	**NPLs as share of total assets**	**ROA**	**Cost-to-income**
Leverage	1.00	-0.69	-0.12	-0.72	0.91	-0.18
Earning power	-	1.00	0.09	0.57	-0.69	0.47
NPLs as share of total loans	-	-	1.00	0.66	-0.04	0.06
NPLs as share of total assets	-	-	-	1.00	-0.73	0.15
ROA	-	-	-	-	1.00	-0.15
Cost-to-income	-	-	-	-	-	1.00

The cross-correlations results show, rather not surprisingly, that the equity ratio is intimately linked to the return on assets (0.91), while is strongly affected by the share of loans in total assets (-0.72). Moreover, the ROA is intensely adjusting to the share of past due loans in total assets (-0.73). Such combinations of determinants are to be avoided during the multivariate estimation process.

III.2. The multivariate logit-based EWS

The estimation methodology has the following model design:

$$PD_{i,t} = \frac{1}{1+e^{-\left(\alpha+\sum \beta_i \times Micro_{i,t-k}\right)}}$$

We have denoted with $PD_{i,t}$ the probability of default for the *i* entity in our sample at the moment *t*, while the term $Micro_{i,t-k}$ defines the vector of explanatory variables registered with *k* quarters earlier.

The model validation is based on the assessment of the discriminatory power. In this respect, the ROC curve was applied, as it models the relationship between the percentage of NFIs that defaulted and were accurately identified (HR – Hit Rate) and the percentage of NFIs that did not default, but were wrongly classified (FAR – False Alarm Rate). The concavity of the ROC curve is an indication of scores having discriminatory information content, while a surface under the ROC curve (AUROC) larger than 75% signals rather good modelling performance (Hosmer & Lemenshow, 1999).

The added value for the supervisory activity of the estimated logistic regression model is to provide the score (theoretical default probability) based on which the NFIs are rated. The method employed is that of traffic light approach, as the aim is to obtain a reasonable and time-consistent accuracy both of the NFIs rating procedure and the significant discrimination between probability of default and rating scale granularity. This approach draws on the method deployed by Dardac & Moinescu (2009), which ensures a good segmentation of default risk and, hence, a proper understanding of the signal conveyed by the statistical model.

Using the six criteria to estimate the polynomial *logit* regression, the result obtained following the tests on the multivariate backward procedure resembles those obtained in studies that modeled the credit institutions' performance (see Table 5).

Table 5 - Default model estimation output

Variable	Beta	T-stat.
C	-3.3552	-4.2562
Earning power	-1.9698	-2.0042
NPLs as share of the banking book	2.2967	1.7858
ROA	-11.25	-4.0971
R-squared_McFadden	0.2213	

Statistical test values relative to the training sample are indicative of the fact that the obtained model is in line with the requirements of a good econometric performance. The coefficients are statistically significant and their signs are in accordance with economic theory. The result reflects the capability of most NFIs to capitalize upon positive ROA. Other variable having a negative impact on the probability of default is the earning power, whereas the share of NPLs in total loans has a positive influence on such an event.

Based on the estimated logistic function, the theoretical probabilities of default (PDs) were calculated for each NFI. The reasonable accuracy of the predictions incorporated in the model assessing the probability of default is ensured by the scoring function performance, in terms of discriminatory power of its estimates. The histogram of *logit* score highlights that the model performs rather well in ranking NFIs (see Figure 1), as the histogram displays a log-normal shape, which represents a common result for accurate credit risk models.

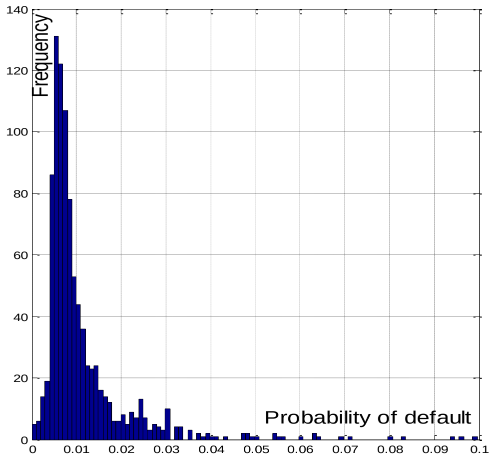

Figure 1 – Histogram of logit score
(Q1 2007 – Q1 2012)

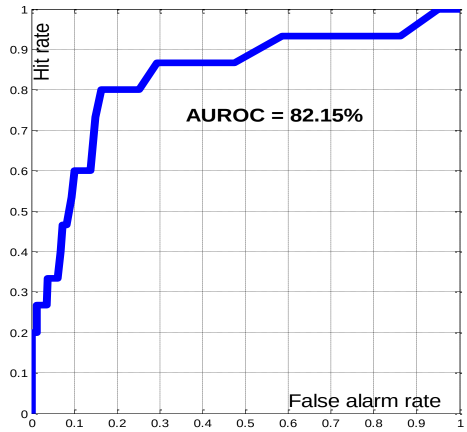

Figure 2 – ROC curve
(Q1 2007 – Q1 2012)

This outcome is supported by the ROC curve test (see Figure 2), which shows a high value of the AUROC indicator (82.6 percent). This performance allows us to reach a level significantly higher than the 75 percent threshold which is considered the benchmark. In addition, the numerical results mentioned above are confirmed by the shape of the ROC curve. The concavity of the ROC curve highlights the fact that the selected variables have a discriminatory power large enough to ensure that the model in its entirety can provide a good ranking of NFIs, based on their probability of default. Thus, the model is successful in concentrating the majority of default cases in the riskiest classes, while the curvature of the ROC test tends to near the unit square margins; in fact, the concavity of the ROC curve is equivalent to highly informational content scores, being a decreasing function.

Forecasting NFIs default events based on the estimated scoring function requires calibrating the rating scale, namely the risk classes. **Having theoretical probabilities and the vector of default events as a starting point, four risk classes have resulted.** The criteria employed here were the homogeneity of events in the same category and the discrimination of empirical probability of default between the different risk classes. The empirical values for the probability of default[2] assigned to each risk class are set out in Figure 3. Thus, there is a chance in fifty that a NFI with a score ranging between 1.14 and 2.64 will be assigned a default over a time horizon of three quarters, bearing in mind that only 2 percent of NFIs classified under "yellow" code recorded a default. On the other hand, **"Yellow" code is a medium risk class**, taking into account that its empirical probability signals a level close to the unconditional probability of default seen in the whole data sample. At the same time, "green" code may be regarded as a low risk class while "orange" and "red" codes can be considered as implying an increased risk of a default.

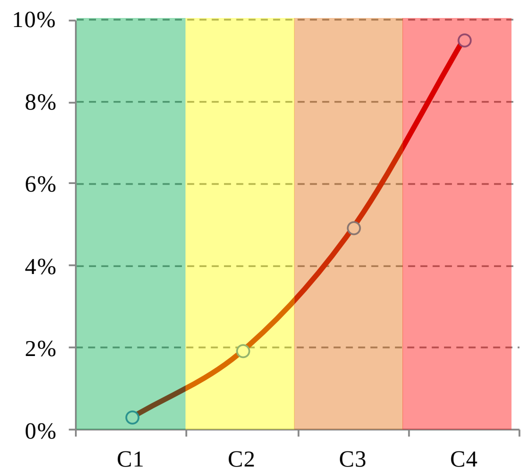

Figure 3 – Segmentation by default risk class

The four risk classes of the rating scale allow the analysis of risks associated with the Romanian non-banking financial institutions stability based on the breakdown of their assets consistent with the probability of default forecast. The traffic light approach also favors an in-depth assessment of the NFIs' performance migration amid a potential worsening of the internal fundamentals.

IV.4. Results of the default events forecasting system

Applying the above-described logistic regression default forecasting system to the data available for the last three quarters in 2012, the breakdown of number of entities forecasted in terms of probabilities of default estimated for the period Q1 – Q3 2013 is dominated by the concentration of NFIs in the low risk category (see Table 6).

[2] The empirical rating downgrade probability is the share of debtors in default in the total number of debtors of a risk class.

Table 6 - Breakdown of NFIs by probability of default using logistic regression

percentage of NFIs	Q1 2013	Q2 2013	Q3 2013
“Green” code	75%	65%	64%
“Yellow” code	18%	27%	18%
“Orange” code	6%	4%	10%
“Red” code	2%	4%	8%

According to the regression model, the share of NFIs classified under “Green” code declined in the run-up to year-end 2013, pointing to a moderate deterioration of performance, against the backdrop of weaker internal developments in 2012. At the same time, estimations show a rise in the share of NFIs with a medium risk of default. The forecast shows a deterioration of the NFIs’ performance in Q3 2013 compared with Q1 2013 which corresponds to the reality since, during 2013, there were 3 NFIs’ defaults, all of them being encountered in the third quarter.

V. Conclusions

This study presents an early warning system (EWS) for the non-banking financial institutions’ (NFIs’) defaults based on a multivariate logit approach. It aims not only at modelling the probability of NFIs’ defaults, but, also, at determining when this event is more likely to take place (in a six-, nine- or twelve-months time horizon). The data sample employed for building the predictive models consists of an unbalanced panel of 68 entities, which covers the entire population of Romanian NFIs. We used quarterly data for the 2007-2012 period for a set of 10 NFIs’ performance indicators (employed to capture three most important performance dimensions: capital adequacy, assets’ quality and profitability). We performed an univariate analysis in order to select the best discriminant variables. After performing univariate tests, six variables were retained for further analysis, namely: (i) *leverage*; (ii) *earning power;* (iii) *NPLs as share of the banking book*; (iv); *NPLs as share of the total assets;* (v) *ROA and* (vi) *cost-to-income ratio.* Following the multivariate estimation procedure we retained three variables as discriminants: earning power, NPLs as share of banking book and ROA. We obtained the best results in terms of model accuracy for the nine-month- (or “three-quarters-”) time-horizon case. In this case we obtained a value of 82.6% for the AUROC accuracy measure which shows that our model has a strong discrimination power. Based on the method deployed by Dardac & Moinescu (2009), we proposed four default risk classes (as a “traffic light” forecasting mechanism) and set-up the limits for the default probabilities for each class. The model is successful in concentrating the majority of default cases in the riskiest classes.

Next, we applied our NFIs' defaults EWS to forecast future defaults. The data for the last three quarters in the database (Q2:Q4 2012) was deployed for running the forecasts on Q1:Q3 2013. The results showed a moderate deterioration of NFIs' performance in Q3 2013 compared to the first quarter of 2013. **This corresponds to the reality since, during 2013, there were 3 NFIs' defaults and all of them were encountered in the third quarter.**

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