ESTIMATING THE CREDIT RISK SCORE FOR NON-BANK STOCK EXCHANGE INTERMEDIARIES IN THE EVENTUALITY OF CHANGEOVER TO EURO CURRENCY

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Abstract

In this paper we build a system for determining the credit risk score and to estimate the probability of default for Romanian non-bank stock exchange intermediaries using principal component analysis applied on a selected set of financial and prudential indicators obtained from their financial statements and capital adequacy reports. Our approach is useful when dealing with non-listed undertakings, for which the probability of default cannot be derived from market prices. In addition, it can be replicated for the same type of companies in other jurisdictions and can be adapted to other type of non-bank financial intermediaries. The method could be especially useful for central counterparties. Regarding the eventuality of changeover to euro, this will have an insignificant impact on the financial credit risk score of Romanian non-bank intermediaries.

Keywords: credit risk scoring, default probability, principal component analysis

JEL Classification: G17, G23

1. Introduction

As a result of the development of financial markets and implicitly of the increase of the value of financial transactions, regardless of whether these are cleared and settled or not through a central counterparty, there is a growing need to develop internal rating

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systems allowing a financial entity to assess the probability of default of its counterparties in transactions.

Due to the increasing level of sophistication of standardized financial instruments, as well as to the interconnections between various financial entities who are participants in a centralized clearing and settlement system, the infrastructure entities of the financial markets are forced to use more and more sophisticated models in order to assess de probability of default of the participants in that clearing and settlement system.

Panait and Lupu (2009) as well as many other authors argue that in emerging capital markets, as is the case for Romania, an eventual financial crisis will have a significant negative impact on the equity market variables (ex. liquidity, volatility, and capitalisation) that will also reflect, in many ways, on the financial soundness of the intermediaries and their credit worthiness.

The default probability models build for non-bank intermediaries should take into account, among other things, the particularities of the indicators used in the evaluation process, if their dynamics is influenced or not by the exchange rate. In this regard, it should be taken into account that in the component of own funds enters items whose value depends on the exchange rate, and also that the capital adequacy ratio takes into account the value of the risk.

This article presents how a probability of default assessment system was built for a category of financial entities in Romania. This model can be used by various financial entities to assess the probability of default of the counterparties participating in transactions and, at the same time, the methodology can also be applied on the data of other categories of financial entities.

2. Literature Review

Many financial industry professionals and researchers were preoccupied with finding practical methods to assess the credit worthiness of companies.

Such methods are intensely utilized by banks and other non-bank credit institutions (ex. leasing companies) in order to decide which (potential) clients are eligible to receive financing and to what extent, based on an extensive set of information collected from internal and external databases and received from the applicants.

Also, investors in bonds and commercial paper use different approaches to evaluate the probability of default and the loss given default of the issuers of such instruments. Some of them rely on their own analysis, others are taking into account the external ratings given by specialized companies or prices of exchange traded financial instruments, such as credit default swaps or options (which are also based on financial models that incorporate a wide range of detailed financial information).

Estimating the probability of default is the first step in evaluating the credit risk, which is often hampered by the limited information available. Structural models based on Merton Option Pricing Model and fundamental models centred on company's own financial and accounting indicators as determinant factors were developed with this purpose. Inside the latter category, we distinguish macroeconomic models, credit scoring models (the most widely used) and rating models.

Credit scoring models usually are developed based on different statistical and econometric methods that were investigated by many researchers, starting with Beaver (1966, 1968) and Altman (1968) who tested the use of linear discriminant analysis (LDA) for predicting failure of a company. Econometric methods are mainly centred on logit (Ohlson, 1980; Platt and Platt, 1990) and probit (Laitinen, 1999) models.

Bandyopadhyay (2006) employs both the logistic and the Z-score approach, with the aim to develop an early warning signal model, which incorporates financial as well as and non-financial information, to be used for predicting corporate default. The author finds that the Z-score model exhibits a high predictive power outperforming the contesting models, among which the Altman's original. Also, regarding the logit analysis, the author concludes that inclusion of financial and non-financial parameters increases the accuracy of the model.

During the recent years, non-parametric models gained popularity (ex. neural networks, fuzzy algorithms, K-nearest neighbour model) but studies are contradictory on their efficiency. While Galindo and Tamayo (2000) and Trovato and Caiazza (2004) argue that non-parametric model leads to better results, Altman, Marco and Varetto (1994) and Yang (1999) reach opposite conclusions. Also, Abramowicz and Nowak (2003) test the applicability of Bayesian belief networks (BBN) within the credit scoring process conducted in commercial banks, comparing results obtained by employing two techniques: traditional credit-scoring system and BBN structure.

Recently, the counterparty risk also started to represent an important part of the risk management of different entities trading on commercial and financial markets. While the general principles for assessing the counterparty risk are similar with the ones for evaluating credit risk, the methods need to be more practical, easy and fast to apply. At the same time, the information available for this purpose is in general more limited, based mainly on information that is available to the public or resulted from periodical reports filed by the respective company according with their applicable legislation. This is especially the case when the counterparty risk is evaluated for an undertaking that is not listed on a stock exchange. Being a more recent preoccupation, the literature available for this field of research is less developed.

Dardac and Moinescu (2006) offer an overview of the quantitative methodologies used by banks for evaluating the probability of default for loans, under Basel II framework. Their research includes both market-based models and determinant factors models concluding that the availability and the quality of the date have a strong impact on model selection and on the relevance of the results.

Miu & Ozdemir (2007) examined alternative methodologies for estimating and validating Long-Run Probability of Default (LRPD) introduced by the Basel II framework. The authors propose a system based on maximum likelihood estimators incorporating both cross-sectional and serial asset correlations which were found to be consistent with the economic model underlying the Basel II capital requirement formulation. Their simulation-based performance studies revealed that the proposed estimators outperformed the alternatives in terms of their accuracies even under a number of small sample settings. For the purpose of validating the assigned LRPDs, the authors also examined alternative ways of establishing confidence intervals (CIs) and concluded that use of the CIs constructed based on the proposed maximum likelihood estimators results in fewer errors in hypothesis tests.

Danila (2012) proposes a scoring model for estimating the default probability, using the logit model and based on both quantitative and qualitative information, according with the methodology previously developed by Altman et al. (2005).

Latter, Nar (2014) also focused on credit risk management under the Basel framework (this time Basel III) analysing the effectiveness of the models and arrangements put forth to prevent risk.

Haralambie and Ionescu (2016) discuss some specific issues that commercial banks have in the credit risk management process related to the analysis of a corporate client and propose a web application for functioning as a credit scoring system.

3. Data, selection of indicators and methodology

The internal rating system described in this article is built based on the historical data collected from financial statements and from capital adequacy reports filed by the Romanian independent stock brokerage companies. In building the database, the specificity and features of the financial entities were taken into account, since the dynamics of the financial and prudential indicators significantly vary from one category of financial entities to another because of the various complexity levels of the current activities, as well as because of the differences between the business models.

Also, in building the database, the minimum number of necessary data was contemplated, so that the subsequent analyses may be statistically meaningful and, at the same time, be able to grasp its dynamics. Thus, a database containing 150 observations was built, including values of several financial and prudential indicators of Romanian companies providing financial investment services, whose entire scope of business is authorized.

A set of financial and prudential indicators relevant to a time horizon of at least 5 years was selected. Considering that the economic-financial statements are drafted on a biannual basis and that the capital adequacy reports are drafted on a quarterly basis, the data was selected based on 6-month periods (semi-annual) so as to ensure the correspondence between the two categories of indicators used.

Also, because of the amendments made to the capital adequacy regulations, in choosing the time horizon, the guarantee that the prudential indicators used were determined unitarily methodologically speaking, regardless of the amendments having occurred in the applicable legislation, was also taken into account.

Some of the indicators taken into account in building the database were the following:

1. From the category of prudential indicators defined in the capital adequacy legislation: capital adequacy ratio (CAR), liquidity coverage ratio (LCR), largest exposure registered

(LER), Tier 1 Own Funds (T1OF), Tier 2 Own Funds (T2OF), total capital (TC), as well as the leverage effect level (LEL).

2. From the category of financial and accounting indicators included in the financial statements: total asset value (TAV), total income (TI), as well as the profit or loss (P&L).

In selecting the prudential indicators, the following aspects were taken into account:

- Inclusion of the most important prudential indicator, namely CAR. This prudential solvency indicator aims at determining the ratio between a) the level of potential losses that could result if the risks the financial entity's assets are exposed to get materialized, and b) the level of own funds held by that particular financial entity;
- At the same time, besides the prudential solvency issue, financial entities are also exposed to the issue of ensuring the necessary cash for every maturity date of the undertaken obligations. The most important maturity date is that of 30 days, reflected by the ratio between the high-quality liquidity assets and the liquidity need falling due within no more than 30 days, namely LCR;
- To describe the effects of a possible materialization of the market risk and of the credit risk, the indicator of the largest exposure registered by the financial entity (LER) towards a debtor/issuer was used;
- Also, the total capital (TC) value was used, as well as the value of each own funds subgroup, namely the tier 1 own funds (T1OF) and the tier 2 own funds (T2OF). The own funds are the amount of financial resources that the financial entity can use to cover, within a reasonable time span, any debt that could occur as a result of the materialization of a financial and/or operation risk;
- At the same time, to describe also the negative effects of the decrease of the own funds value in the event that the main financial and/or operational risks the financial entity is exposed to get materialized, the leverage effect level (LEL) indicator was used.

In selecting the financial-accounting indicators, the following aspects were taken into account:

- The indicator regarding the total asset value (TAV) was chosen because the value of potential losses that could occur if the risks get materialized is determined for the assets held by the financial entity;
- Also, to be able to see the financial results of the financial entities, the following indicators were chosen total income (TI), profit or loss (P&L).

If, for some reason, the value of an indicator used, relevant to a reporting date, was unknown or could not be collected, it was statistically determined through a linear regression built based on the existing data, so that, subsequently, by adding the indirectly determined value, the correlations existing between the original data series are not affected.

Based on the collected data, the scoring analysis is conducted, based on the Principal Component Analysis (PCA) method as described by Abdi and Williams (2010). Thus, the main elements of the formula and, for each main element, the adjustment (weighting) factors, are identified.

By entering various values relevant to a set of relevant indicators, a range of values was determined, which was subsequently divided into several ranges associated to a certain number of ratings. Later, each rating was associated to a level of the probability of default.

The scoring ranges relevant to ratings were determined so that the better the rating (and implicitly the lower the probability of default), the higher the scoring range. Thus, the better a rating is, the more difficult it is for it to be obtained by a financial entity in its creditworthiness assessment.

One aim of the analysis of the main components is to determine a formula including only one indicator or two at the most, which reflect most of the information, whereas for the analysis of the probability of default of a financial institution applying the capital adequacy rules, this indicator should be the CAR (because it is the most important prudential indicator used in the prudential assessment on capital adequacy).

Also, in the scoring formula, the aim is to include, beside the CAR indicators, the Tier 1 Own Funds indicator because the level of this indicator shows the size of the financial resources available to such financial institution to cover, over a time span of only a few business days, any debt that could result from the settlement of the transactions made.

To determine the relevance of the data sample, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) test is used. For a minimum relevance, the value of this test should be at least 0.60 points. Also, the value of the KMO test must be over 0.75 points so as to cope with a potential stress test.

In the analysis of the main component, the following criteria were taken into account:

- Any formula identified to contain at least the capital adequacy ratio (CAR) and the Tier 1 Own Funds (T1OF), where the capital adequacy ratio is the main component – which is mostly reflected by information relevant to the analyzed data;
- The identified formula should have reasoning from the prudential and economic points of view (depending on the type of data included in that formula);
- The level of the relevance test of the data sample used (KMO) should be as high as possible;
- The level of information included in the main factor (indicator) (CAR) and of the T1OF should be as high as possible.

Based on the criteria mentioned above, a series of simulations are made by eliminating one indicator at a time or/and later by adding another indicator, thus obtaining a set of PCA analyses on various combinations of the data categories, to determine the most relevant combination of indicators so that the minimum value of each combination exceeds 0.75 points. The highest value of the model ensuring the best relevance in terms of the information it is based on, will be chosen.

4. Results

Following the successive PCA analyses, statistically speaking, the best formula that was obtained is:

(-0.464)*CAR + (0.878)*T1OF + (0.782)*P&L + (0.937)*TI + (0.904)*TAV,

because:

- it gives the best result in the Kaiser-Meyer-Olkin Measure of Sampling Adequacy test, i.e. the value of 0.785;
- the CAR indicator shows the largest load of information included in the data sets, i.e. the value of 65.87% and
- the T1OF indicator shows the second largest load of information included in the data sets, i.e. the value of 16.99%.

The scoring value for a financial entity is calculated as the sum of the relevant indicators adjusted by the relevant multiplication factor in the formula. To more easily analyze the scoring ranges of financial entities, the value of the resulting sum is adjusted by dividing it to 100,000 units of value.

Subsequently, based on this identified formula, scoring ranges relevant to each rating type are developed by going through the following stages: determination of the maximum value, determination of the minimum value and, later, determination of the other rating ranges (by using the same number of rating intervals as the one used by the large Rating Agencies).

To identify the lowest scoring level, the minimum levels set forth in the legislation on capital adequacy were used for the CAR and T1OF indicators, whereas for the P&L and TI indicators the value “0” was used and for TAV the T1OF value was used. To identify the highest scoring level, the highest values of the indicators recorded by one of the analysed financial entities were used.

Subsequently, based on this identified formula and on the above, the scoring ranges relevant to each rating type were developed, as follows:

Table 1

The scoring ranges relevant to each rating type

Rating level[1]	PD %	PD + X%	Scoring range/ class	Scoring variation/class	Scoring range/ class category
AAA	0%	0	> 80.000		
AA+	1%	1	60.000,1 - 80.000	20.000	50.000
AA	2%	1	40.000,1 - 60.000	20.000	
AA-	3%	1	30.000,1 - 40.000	10.000	
A+	5%	2	20.000,1 - 30.000	10.000	20.000
A	7%	2	10.000,1 - 20.000	5.000	
A-	9%	2	5.000,1 - 10.000	5.000	
BBB+	13%	4	3.000,1 - 5.000	3,000	6.000
BBB	17%	4	2.000,1 - 3.000	1.000	
BBB-	21%	4	1.000,1 - 2.000	1.000	
BB+	27%	6	600,1 - 1.000	400	700
BB	33%	6	400,1 - 600	200	
BB-	39%	6	300,1 - 400	100	
B+	47%	8	235,1 - 300	65	165
B	55%	8	185,1 - 235	50	
B-	65%	10	135,1 - 185	50	
CCC+	75%	10	110,1 - 135	25	75
CCC	85%	10	85,1 - 110	25	
CCC-	100%	15	60 - 85	25	
CC	115%	15	50,1 - 60	10	20
C	130%	15	40 - 50	10	
D	150%	20	< 40		

Source: Authors' own work

[1] *The same number of rating levels as the one used by the large Rating Agencies was used*

To establish the level relevant to the probability of default associated to the ratings used, the following criteria were taken into account:

- The best rating should be associated to a level of the probability of default of 0%.
- The worst rating should be associated to a level of the probability of default of 150%[2].

Subsequently, by applying this formula to the data relevant to the analysed financial entities, the following situation of the rating/probability of default resulted:

Table 2

The rating for each financial entity

Financial entity	Reference date	Rating T-1	PD (T-1)	Rating T	PD (T_0)	Dynamics
1	T-1	B-	65%			
1	T_0			CCC-	100%	↓
2	T-1	B-	65%			
2	T_0			CCC+	75%	↓
3	T-1	BB+	27%			
3	T_0			BB+	27%	=
4	T-1	BB	33%			
4	T_0			BB	33%	=
5	T-1	CCC	85%			
5	T_0			CCC	85%	=
6	T-1	B+	47%			
6	T_0			BB-	39%	↑
7	T-1	BB+	27%			
7	T_0			BB	33%	↓
8	T-1	B	55%			
8	T_0			B	55%	=

[2] *The highest probability of default provided by the legislation on capital adequacy*.

9	T-1	BB+	27%			
9	T_0			BB	33%	↓
10	T-1	CCC	85%			
10	T_0			CCC+	75%	↑
11	T-1	B+	47%			
11	T_0			B	55%	↓
12	T-1	BB	33%			
12	T_0			B-	65%	↓
13	T-1	BBB-	21%			
13	T_0			BBB-	21%	=
14	T-1	BBB+	13%			N/A
15	T_0			CCC	85%	N/A
16	T-1	A-	9%			
16	T_0			A-	9%	=
17	T-1	AA+	1%			
17	T_0			AAA	0%	↑

Source: Authors' own work

Considering that the level of the KMO test applied to the data sample is 0.785, if a stress scenario of 20% is applied to the data value, the value of this relevance test would be above the minimum value of statistical relevance, i.e. 0.60.

If we rebuild the scoring formula on the same sample of indicators, on the same time span, but without including the last reporting date, the following scoring formula will result:

(-0.462)*CAR + (0.890)* T1OF + 0.798*P&L + 0.938*TI + 0.908*TAV

(the scoring formula relevant to the Rating/PD (T-1) in the table above). The level of the KMO test applied to the data sample, used in determining this formula, is 0.792.

5. The impact of currency risk on the evaluation model

In the building up of the default probability model for non-banking intermediaries have been used financial indicators whose dynamics may be influenced by the exchange rate, respectively the own funds indicator, in which structure are elements that depend on the RON-Euro exchange rate, as well the indicator of the capital adequacy ratio which also takes into account the value of the risk.

The Romanian non-bank intermediaries are not significantly affected by the RON-EURO exchange rate for the following reasons:

- Although the CAR indicator shows the highest load of data included in the data sets, approx. 65%, the level of this indicator, in the vast majority, is above 60% (the legal minimum is 8%), and the median of data is at the level of 44%. Considering the high level of CAR and the low level of the capital requirement related to the foreign exchange risk in the total capital requirement (below 10%), the impact of this risk is insignificant.
- The load of information included in the data sets of the T1OF indicator is approx. 17%. Considering the low volatility of the RON-EURO exchange rate, in conjunction with the load of information included in the data sets of the T1OF indicator, the potential negative impact of the RON-EURO exchange rate on the dynamics of the T1OF indicator is low.
- The level of currency risk is low because the level of transactions with financial instruments made by non-banking intermediaries, in a currency other than the RON, is low.

6. Conclusions

By using the Principal Component Analysis method, scoring formulas can be built, that are applicable in the assessment of the creditworthiness of financial entities. The data sample based on which the model is built must obtain a sufficiently high value in the Kaiser-Meyer-Olkin Measure of Sampling Adequacy test so that there is an additional margin besides the statistical minimum value.

If the intention is to build a methodology to assess the creditworthiness of several categories of financial entities (lending institutions, financial investment services companies whose entire scope of business is authorized, financial investment services companies whose scope of business is restrictively authorized, etc.), a scoring formula must be built (and at the same time different scoring ranges) must be built for each category of financial entities because the value of the financial/prudential indicators varies very much from one category of financial entities to another. This is due both to the difference business models and to the different level of diversification of the business lines that are used by those categories of financial entities.

In establishing the details regarding the probability of default assessment system, one must take into account the prudential legislation relevant to the category of financial entities that system is being built for.

If the intention is to build a probability of default assessment system for entities in a certain economic branch, this procedure of the Principal Component Analysis method can be used only on the financial data of the relevant entities. Also, to determine the lowest scoring level, the values of the financial indicators will be used, which, according to the analysis of the historical data during the recent five years, showed that similar entities of the same economic branch went bankrupt.

Regarding the eventuality of changeover to euro currency, this will have an insignificant impact on the financial credit worthiness of non-bank intermediaries. This is due to the particularities of the activity and the balance structure of the Romanian non-bank intermediaries.

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