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MASTER'S THESIS

What Are the Main Determinants of Banks' Ratings Across CEE Countries?

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature and that the thesis has not been used to obtain another academic degree.

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Prague, May 14, 2015

Signature

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Abstract

This thesis uses data of more than 180 banks from Central and Eastern European Countries (CEE) region to identify the main determinants of long term credit ratings assigned to these banks in period between 2010 - 2012. This is done by employing two frequently used classification methods - Multiple Discriminant Analysis and Ordered Logit Model. The main contribution lies in including explanatory variables from various areas which have impact on financial health of examined banks. Apart from standard spheres of banks' performance such as capital adequacy, asset quality or profitability we investigate relevance of macroeconomic and qualitative factors as well. Although our results suggest that all mentioned areas are relevant for credit risk and hence rating assignment process the bank specific variables, both quantitative and qualitative, still play the key role.

JEL Classification	C25, G21, G24
Keywords	Banks' Ratings, Determinants, Ordered Logit Model, Multiple Discriminant Analysis, Factor Analysis

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Abstrakt

Tato práce využívá data více než 180 bank z regionu střední a východní Evropy k nalezení hlavních faktorů, jež určují kvalitu výsledného dlouhodobého ratingu, jež byl těmto bankám udělen mezi lety 2010 - 2012. Tato analýza je prováděna za pomoci dvou často užívaných klasifikačních metod - vícerozměrné diskriminační analýze a ordinální logistické regrese. Hlavní přínos práce spočívá v zařazení proměnných z různých oblastí ovlivňujících finanční zdraví bank. Kromě standardních ukazatelů bank jako kapitálová přiměřenost, složení aktiv nebo profitabilita zkoumáme rovněž makroekonomické a kvalitativní faktory. Ač naše výsledky naznačují, že všechny oblasti jsou relevantní pro hodnocení kreditního rizika, a tudíž přidělené ratingové známky, jsou to právě specifické kvalitativní a kvantitativní ukazatele bank, jež mají pro výsledný rating zásadní roli.

Klasifikace JEL	C25, G21, G24
Klíčová slova	Ratingy bank, Determinanty, Ordinální logistická regrese, Vícerozměrná logistická analýza, Faktorová analýza

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Acronyms

As Total Assets

CA Capital Adequacy

CART Classification and Regression Trees

CDF Cumulative Distribution Function

CEE Central and Eastern European Countries

CRA Credit Rating Agency

EBRD European Bank for Reconstruction and Development

Eq Equity

GDP Gross Domestic Product

ICAAP Internal Capital Adequacy Assessment Process

LCR Liquidity Coverage Ratio

MDA Multiple Discriminant Analysis

NI Net Income

NPACR Non-Performing Asset Coverage Ratio

NRSRO Nationally Recognized Statistical Rating Organizations

OECD Organisation for Economic Co-operation and Development

OLM Ordered Logit Model

OLS Ordinary Least Squares

ORM Ordered Response Model

ROAA Return on Average Assets

ROAE Return on Average Equity

SIFI Systematically Important Financial Institution

Master’s Thesis Proposal

Author	Bc. Kryštof Wolf
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Proposed topic	What Are the Main Determinants of Banks’ Ratings Across CEE Countries?

Motivation Rating agencies and their decisions in the area of rating assignments have gained a broad attention in last decade. It was mainly due to recent Global Financial Crisis that rating agencies became heavily criticized by broad public for its inability to correctly assess the riskiness of single instruments and companies. Apart from misleading ratings of asset-backed securities the most attention was attracted by bankrupting, supreme graded banks. Such an experience raised several questions which became the foundation stones for this thesis: Are the ratings fair in terms of assessing the true level of risk? What are the true determinants of rating quality for banks? Are the ratings consistent among all rating agencies or do the weights of single determinants differ significantly? Are the ratings foreseeable or is there any systemic bias?

In recent years numerous papers dealing with ratings were published however only minority of them focuses on banking industry (most of works are devoted to sovereign ratings; for banks’ ratings see e.g. Hau, Langfield & Marques-Ibanez 2012 and references therein). This can be attributed to the fact that banks are somewhat specific entities (important macroeconomic role, high leverage, cyclical nature of the industry) and therefore require special approach to assessing their risk profile. Moreover to the author’s best knowledge no work did focus on the Central and Eastern European region which has its specifics affecting perception of riskiness of local enterprises.

In my work I will try to fill this gap in current research and answer all above mentioned questions. The resulting thesis should provide reader with complex review of banks' ratings determinants as well as current situation in rating agencies practices.

Hypotheses

1. Hypothesis 1: Banks' ratings are determined mainly by bank specific characteristics (asset quality, capital adequacy, etc.), macroeconomic and market risk factors hold much less significant role.

2. Hypothesis 2: Assigning of ratings by rating agencies supports the "too big to fail" hypothesis; i.e. large banks achieve better ratings compared to smaller banks with similar characteristics.

3. Hypothesis 3: Banks' ratings are inconsistent among various agencies; i.e. the weights of single variables are different for each agency.

Methodology The above mentioned hypothesis will be tested using data from Bankscope database supplemented by publicly available data from other sources (banks' annual reports, etc.). Although the Bankscope represent quite complex source of information describing financial situation of most banks within the given region, the information concerning development of ratings in time is rather incomplete. An important part of the thesis will be therefore gathering of all necessary data.

The current literature (e.g. Poon, Firth & Hung-Gay 1999 or Hammer, Kogan & Lejeune 2012) suggests that using a simple regression approach is not sufficient when dealing with ratings. Therefore, in order to utilize the above mentioned dataset, we will first specify an order logistic regression model (OLRM) which should best capture the principles of ratings creation. As already mentioned in Hypotheses section the main part of the model will be created by variables signalizing financial health and stability of banks. Further it will be supplemented by macroeconomic and market risk indicators which (at least in theory) should also influence the overall rating, last part should be inclusion of proxy variables for non-quantitative (mostly unobservable) measures which also according to rating agencies enter the rating process. Such a model will be later used for testing stated hypotheses - whether it is testing of significance at examined variables (size of bank or dummy variables distinguishing between single agencies) or using for out-of-sample prediction and verifying the predictability of ratings based on the observed determinants.

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Chapter 1

Introduction

The topic of rating agencies and by them assigned credit ratings attracted a lot of attention especially in the last decade. It was mainly after the outbreak of recent Global Financial Crisis when credit rating agencies became heavily criticized for their inability to provide correct assessment of potential risk of rated subjects. The area which earned most criticism was rating of financial sector with defaulting supreme rated banks. This experience has raised many questions which become a base for current researchers and which are also addressed in this paper, such as: Are ratings provided by credit rating agencies reliable and consistent? What are or should be the appropriate determinants of banks' ratings? or Are the assigned ratings predictable based on publicly available data?

The range of current literature dealing with banks' ratings is rather narrow. Moreover substantial majority of works focuses solely on quantitative, bank specific factors - e.g. Hammer *et al.* (2012) or Öğüt *et al.* (2012) - which indeed are the main, but not the only, indicators of banks' financial health. Poon *et al.* (1999) and Bissoondoyal-Bheenick & Treepongkaruna (2009) already add macroeconomic and market risk variables in their regressions however they coincidently find them not contributing to overall explanatory power of examined models. To the author's best knowledge there are no studies which could provide clear assessment of impact of qualitative factors on assigned rating.

The aim of this study is to fill in this gap in current literature. We attempt to find the main factors responsible for final rating grades of more than 180 banks from CEE region assigned between years 2010 - 2012. Apart from verifying the up to date findings regarding accounting and macroeconomic determinants we also include proxy measures for the main qualitative aspects -

market concentration, relative importance of bank on local financial market, ownership structure and institutional environment.

In order to test the above indicated hypotheses we introduce two different modelling frameworks - Ordered Logit Model (OLM) and Multiple Discriminant Analysis (MDA). OLM is nowadays widely used method employed by majority of current researchers dealing with classification problems which proved to be very accurate under most circumstances and hence will serve as a fundamental model used in this work. MDA is then methodology used in the very beginnings of classification studies which yet provides very good results compared to the rest of models, especially with small data samples, as demonstrated by Kaplan & Urwitz (1979). We include MDA for consistency and robustness check purposes. Result produced by this method should also confirm independence of our findings on used methodology.

Our results suggest that all three areas of our interest are relevant for credit risk assessment process and hence determine the assigned rating grade. The highest significance and share of explained variation was reached by bank specific variables representing *Asset Quality*, *Capital Adequacy* and *Size* of the bank as well as by *Institutional Environment* approximated by *EBRD index* and *Country Rating*. On the other side the macroeconomic variables are contributing significantly less.

The rest of thesis is organised as follows: In the Chapter 2 the reader is provided with basic overview of rating area and its historical development. Chapter 3 summarizes the current research regarding rating modelling, rating determinants as well as banking sector in CEE. In following two parts (Chapter 4 and Chapter 5) we deal with methodology framework and describe variables used in the subsequent analysis. In the empirical Chapter 6 the estimation of models and discussion of obtained results is performed. Finally, the last Chapter 7 concludes the study.

Chapter 2

Theoretical Background

In the first theoretical chapter we will introduce the basic concepts connected with rating issues and describe the system used for transmission of information about credit risk (the rating scale). Later on we will briefly go through the history of rating industry with stress on events important for our future empirical part. In the end of this chapter the basic categories of ratings (with focus on banking industry) are presented.

2.1 Rating Definition

Ratings can be generally seen as a form of assessment of the financial situation or solvency of given subject. The more befitting definition is given by Langohr & Langohr (2008): "Credit ratings are forward-looking opinions about credit risk, i.e. opinions of the evaluator about the ability and willingness of an issuer, such as corporation, state or city government, to meet its financial obligations in full and on time".

Result of such an assessment is usually a letter code (depends on the Credit Rating Agency (CRA)) which match the rated subject with one of the credit risk groups with appropriate level of default probability (and hence probability that the claims will not be satisfied). Advantage of such approach is in the possibility to directly compare riskiness of various subjects, which may be often more intuitive and hence more useful then absolute default probabilities.

However (as rating agencies often stress) rating does not serve as an investment recommendation - when analyzing the investment opportunity the investor has to find optimal proportion between risk and return, credit rating provides information about one part of risk side only (one has to take into account also liquidity, currency, interest rate and other risks).

2.2 Rating Scale

As already mentioned single rating classes are labelled by letter codes consisting of first four characters of the alphabet, each grade can be further specified by +/- sign (S&P, Fitch) or by numbers 1-3 (Moody's)[1] to show a relative standing within the major categories. This approach was suggested by John Moody in the very beginnings of rating history and with small adjustments survived till today.

It is important to emphasize that differences between single grades are not equal, i.e. change in risk, or probability of default, between AAA and AA+ is not the same as between BB- and B+. This can be best seen in case of BBB-/BB+ break which divides the risk classes into Speculative and Investment grades. Getting among investment graded instruments brings many advantages (e.g. some regulated subjects are allowed to invest into these kinds of instruments only) and so we can say that difference between these two classes is biggest among all others.

Figure 2.1: Rating scale

S&P	Fitch	Moody's		Description
AAA	AAA	Aaa		Extremely strong capacity to meet financial commitments.
AA+	AA+	Aa1	Investment grade	Very strong capacity to meet financial commitments.
AA	AA	Aa2		
AA-	AA-	Aa3		
A+	A+	A1		Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances.
A	A	A2		
A-	A-	A3		
BBB+	BBB+	Baa1		Adequate capacity to meet financial commitments, but more subject to adverse economic conditions.
BBB	BBB	Baa2		
BBB-	BBB-	Baa3		
BB+	BB+	Ba1	Speculative grade	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions.
BB	BB	Ba2		
BB-	BB-	Ba3		
B+	B+	B1		More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments.
B	B	B2		
B-	B-	B3		
CCC+	CCC	Caa1		Currently vulnerable and dependent on favourable business, financial and economic conditions to meet financial commitments.
CCC	CC	Caa2		
CCC-	C	Caa3		
CC	RD	Ca		Currently highly vulnerable.
D	D	C		Payment default on financial commitments.

Source: Author; based on Standard and Poors guideline (http://www.standardandpoors.com)

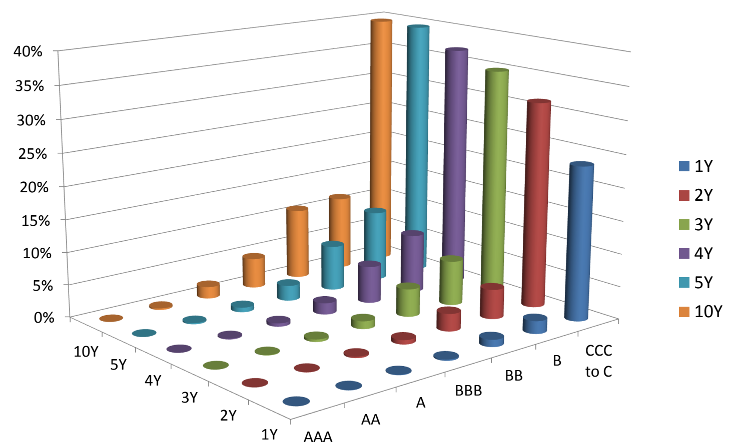
Next signal which helps to specify the exact meaning of the rating to investors is the outlook which describes the expected performance of rated subject

[1] detailed description can be found in Figure 2.1.

and hence its rating in future. Assigned outlook can be either negative (in case of expected downgrade of the rating), stable or positive (in case of expected upgrade).

Apart from ordinal dimension of ratings (i.e. the possibility to rank rated subject from best to worst) the rating classes can provide investor with estimated probability of default in certain future time period. These estimates are obtained from the empirical historical data and are usually expressed as cumulative probabilities of default in ten consecutive years, example of such cumulative matrix (in graphical form) can be seen in Figure 2.2:

Figure 2.2: Global cumulative probability of default rates: 1990 - 2013



Source: Author; based on data from Fitch Ratings (2014)

As we can see the probability of default of AAA subjects is basically zero even in ten years, while almost 40 % of CCC and worse rated subject will default already in five years. Also the above mentioned crucial difference between BBB and BB (investment/speculative) rating proved to be true - the probability of default shows to be more than five times higher in case of BB rating class during all ten years (which is significantly more than for other adjoining classes - A/BBB or BB/B).

2.3 Brief History of Rating, Credit Rating Agencies and Industry Overview

According to Werth (2012) the very foundations for rating industry were laid in the end of first half of 19th century[2] in United States, where the first companies assessing the business credibility of economic subjects, i.e. the ability to repay its operational claims (invoices and other short-term debts) were established. In 1909 John Moody founded the first bond rating agency and started the era of CRAs as we know them today. The main impulse for Moody was the lack of relevant information about performance of companies in those times (no mandatory financial disclosures) which together with rapidly growing amounts of issued debt (especially by railroad companies) resulted in demand for risk assessment from investors' side. In upcoming 20 years the Moody's example was followed by others who hold the majority of market share in these days: the Poor's Publishing Company (1916), the Standard Statistics (1922) and the Fitch Publishing Company (1924).

Another important occurrence for CRAs development took place in late 1930s. Until this time the use of ratings by bond investors was entirely optional - rating served only as a clue helping to simplify the decision process. However, as stated by Sylla (2001), in 1936 the Federal banks, regulators of commercial banks, decided to include risk assessment of private CRAs in their regulatory framework[3]. From now on the regulated banks, which are the most important participants in bond markets, are obliged to invest according to ratings of one of licensed CRAs. Not only that by this decision the agencies were given guaranteed customers for their rating assessments, moreover, due to dominant position of commercial banks on bond markets, also the other participants were interested in rules according to banks have to behave - this have further increased the customer base and hence the importance of CRAs even more. This decision became the origin of today's situation - highly oligopolized industry with insurmountable barriers of entry.

As mentioned by White (2009), the confirmation of dominant position of the "Big Three"[4] was completed in 1975 when new category of CRAs, so called Nationally Recognized Statistical Rating Organizations (NRSRO), was estab-

[2] The very first rating agency was established by Louis Tappan in New York, 1841.

[3] Commercial banks were obliged to invest (i.e. buy and hold) in "Investment graded" bonds only.

[4] Moody's, Fitch and already merger S&P

lished. Ratings of these agencies were allowed to be used for accounting purposes, capital adequacy computations, etc. In the very beginning there were seven such organizations, however due to mergers (four agencies merged with Fitch during 1990s) this number dropped to three in 2003. This step created huge barriers to enter the rating market - no agency was able to attract any customers without NRSRO licence and on the contrary without creditworthiness gained by correct decisions in the past it was very difficult to obtain the licence. This fact led to a perfect oligopoly when the whole (global) market is basically divided between three players, see Figure 2.3. The situation started to change after Global Crisis in 2011 when (mainly due to high political pressure after wrong decisions of the Big Three) the licence was granted to seven other agencies.[5]

Next important occurrence took place around year 1970. As already mentioned from the very beginning the rating industry was based on demand from investors' side (so called "investor pays" model), toward the end of the 1960s the industry gradually moved to reverse model - the "issuer pays" one, i.e. the business model where issuers themselves pay rating agencies to give rating on issued debt. As mentioned in White (2013) the true reason was never persuasively explained, however as the author suggests it was probably mainly due to the effort of CRAs to maximize their profits. This theory is supported by two arguments: Firstly it was the rapidly increasing number of debt issuance which forced issuers to let their debt rated in order to be able to successfully place it on the market, secondly it was the expansion of modern technology which made sharing of information among investors much easier and caused the same problem which is nowadays experiencing the entertainment industry (violation of copyrights). In any case it was an important change in business principles which is nowadays often seen as one of the causes of Global Financial Crisis (2007-2008). Problem of issuer pays model is obvious: rating agencies are paid by rated subjects, in order to keep their customer base, the CRAs are motivated to satisfy customer's wishes, hence to assign better than true ratings. This principle creates obvious moral hazard between true assessment of credit risk and creating profit - according to many researches (among all Kashyap & Kovrijnykh 2014 and references therein) CRAs failed to manage this risk which contributed to recent Financial Crisis.

In following decades CRAs experienced rather calm and prosperous times. The break came in new millennium and was caused by increased number of

[5]The list of current NRSROs can be found in Appendix A.

defaults of subprime or at least A-rated subjects. Among all let us mention two most famous ones:

- Bankruptcy of Enron Corp. in November 2001 which was rated by ”investment” grade by all three big CRAs until five days before bankruptcy and was basically the first case which attracted so much attention.
- Second is of course fall of Lehman Brothers in September 2008 which had the most severe consequences and led (together with bankruptcies of other financial houses) to Global Financial Crisis. Again, rating of this institution was not downgraded sooner than a few days before bankruptcy.

Such bad moves of course resulted in focus on CRAs' performance and attempts to regulate this industry by national governments which is also an issue of these days.

As already mentioned nowadays there are three CRAs which hold the absolute majority of the rating market - these are US based Standard & Poor's Financial Services LLC and Moody's Investors Service and Fitch Ratings Inc which has headquarters both in New York and London and is controlled by French company[6]. The S&P and Moody's both hold approximately 40 % of the market share, Fitch moves between 15 % and 20 % and none of the remaining agencies reaches more than 1% share[7]. However as White (2009) points out, not even situation presented in Figure 2.3 fully reflects the dominant position of S&P and Moody's as the common approach when assessing credit risk is to obtain rating from these two, the third rating is usually used only in exceptionally complicated cases or when the two agencies differ in their decisions significantly.

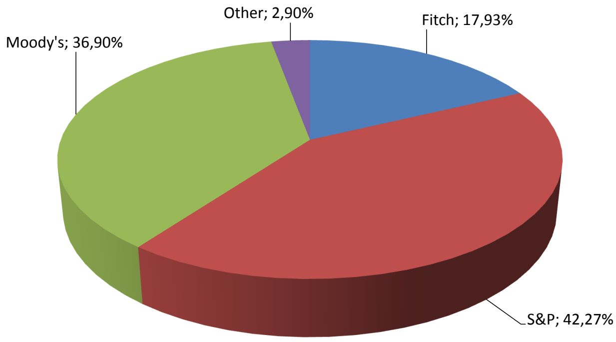
2.4 Rating Classification

With development of rating industry in 20th century, various investors started to demand slightly different type of information that can be obtained from rating assessment. In reaction, the CRAs introduced several classes of ratings which should satisfy investors' needs. Basic division of rating types is usually according to time perspective, denomination of debt, rated subject, rated instrument and finally according to sources used during the rating process (un-/solicited rating).

[6] FILAMAC SA

[7] based on U.S.SEC (2013)

Figure 2.3: Share of total credit ratings outstanding



Source: Author; based on data from U.S.SEC (2013)

- **Time perspective:** Investors generally distinguish between short- and long-term ratings and the division follows general accounting consensus, i.e. instruments with maturity (or horizon in case of enterprises) up to one year are considered short-term, instruments with maturity above one year long-term. Each of the ratings has its specifics and even different rating scale, short- and long-term rating of the same subject can therefore often differ, sometimes even very significantly.

- **Target market and denomination of the debt:** Based on the currency and target market of the rated instrument we can distinguish between local and international rating. While the international is a universal one comparable all around the world (i.e. AA+ describes subjects with the same risk profile in any two countries) the local rating describes relative standing within each country (i.e. the rating of sovereign is always AAA, all other subjects are rated relative to it). In order to distinguish between both ratings at first sight, the local one is always presented with state abbreviation, e.g. czAA+ for Czech Republic.

- **Rated subject:** Specific economic subjects often require individual approach to evaluate their risk profile. Based on these specific needs three basic groups of subjects were formed:
  - Enterprises

  - Government and public sector (countries, cities, districts)
  - Financial institutions (banks, insurance companies, hedge and invest funds)

  Ratings of first two categories are generally known and are not subject of this thesis, we will therefore skip their detailed description. On the other hand the financial institutions ratings deserve our attention. Thede kind of enterprises are generally very difficult to assess (due to high leverage, dependence on macroeconomic environment, etc.), moreover each type within this group is very specific by itself. From this reason a special kind of rating (apart from standard credit rating) for each of them was developed:

  - **Financial Strength Rating** - rating which evaluates financial strength of bank as it is, i.e. does not admit any external help (contrary to credit rating) from parent bank or state, especially in case of Systematically Important Financial Institution (SIFI)
  - **Insurer Financial Strength Rating**[8] - rating describing the ability of insurance company to meet all its obligations from insurance contracts
  - **Fund rating** - fund ratings are based on two basic aspects - first evaluates the ability to return and increase the value of invested capital, second is rather a scoring of the fund which is simply determined by previous profitability and volatility of the fund (i.e. less informative but much more easily available measure)

- **Rated instrument:** The most often rated instruments are fixed income securities (usually bonds, eventually bills), however one can find also rating of preferred stock, project financing, syndicated debt or structured financing.

- **Rating based on publicly (un)available data:** Last class of ratings depends on whether the rated subject itself asks for rating and cooperates with CRA during the rating process, i.e. provides CRA with all data necessary for proper rating process (in this case we talk about solicited rating) or whether the rating is determined based on the publicly available data only (the unsolicited rating). The obvious difference is in the

[8]Mostly issued by specialized CRA - A.M. Best Company Inc.

information value of final rating grade which is generally, due to availability of internal (publicly unavailable) data, substantially higher in case of solicited rating.

2.5 Why Are Ratings So Important?

The main increase of rating popularity and importance came with expansion of debt financing of various subjects (mainly private companies and later countries). With such a growing number of issues investors were not able to analyze every single one of them which created free space for specialized companies on the market which will provide investors with required information. Nowadays rating agencies are inseparable part of financial markets and their assessments are used in many various areas. Their importance and advantages can be seen from three different points of view:

1. **Financial markets**
   - **Help in development of financial markets** - as already mentioned by issuing ratings the CRAs significantly simplify the decision process on debt market which makes it much more flexible and liquid.
   - **Financial market regulation** - credit ratings became a benchmark for regulation of some subjects on the market (banks, funds, etc.). Such subjects can only invest in investment graded instruments, ratings are used for capital adequacy computation, etc.
   - **Improving efficiency of financial market** - by eliminating the informational asymmetry (small investors are, contrary to CRAs, able to get to publicly available data only) CRAs significantly improve efficiency on the borrower's market.
2. **Investors**
   - **Correcting for informational asymmetry** - the biggest advantage for investors is removing the asymmetry between them and issuers (see above).
   - **Save investors' time and effort** - it would take plenty of time and resources for each investor to obtain the same information which is provided by CRAs.

- **Straightforward interpretation** - the information from given rating can be very easily understood and compared among many various instruments. This allows easy and quick orientation on the debt market which, especially nowadays, plays a key role.
- **Updating** - all ratings are regularly updated till the maturity of given instrument. These reviews allow investors to accommodate their investment strategy and optimize the resulting return, again updating of such information by investors themselves would be disproportionately more costly and time demanding.

3. **Rated subjects**

- **Easy and cheaper placement of debt on the market** - from the above mentioned reasons the investors prefer to hold rated debt - it is much easier for them to assess the risk connected with this holding and so they require appropriate (compared to unrated debt lower) risk premium. Moreover, investment graded rating may also significantly decrease the interest cost.
- **Third party assessment** - rating can also be seen as independent assessment of company's performance. This information may be later utilized by its management or owners for improvement of the creditworthiness and investors trust.
- **Marketing tool** - investment graded rating may serve as a marketing tool improving the company's image in the eyes of potential investors and customers.

Chapter 3

Literature Overview

In the chapter devoted to related literature we would like to focus on four main areas: In the first part we will describe the evolution of models used for rating modelling and summarize the prevailing conclusions about their accuracy. The second part will sum up the existing literature dealing directly with banks' rating determinants and motivate the main hypotheses of this work. In the third part we will mention literature devoted to the non-quantitative factors affecting the quality of assigned rating. Last fourth part will provide readers with overview of specifics of banking sector in CEE region with focus on those which are relevant for our future research.

3.1 Development of Rating Modelling

Predicting of credit ratings of various subjects can be generally included among the classification problems which is a widespread issue in economic application (probability of default, behavioural economics, etc.). Application of models suitable for use in economics started in late 1950s first applications to ratings, in the beginning especially to corporate ones, then came in half of 1960s.

One of the pioneering studies exploring rating determinants was written by Horrigan (1966) who used multiple ordinary least squares regression model to predict corporate bond ratings (numbers 1-9 were assigned to each rating class) using primarily accounting ratios. Although the author was able to find some relationships which were confirmed in next studies, his conclusions are rather underestimated - this is due to used regression model which assumes that underlying dependent variable is categorised into equally spaced discrete intervals, i.e. difference between each two adjoining rating classes is equal.

As we have already shown this is not true in case of ratings which is also pointed out by majority of subsequent works (among all Bissoondoyal-Bheenick & Treepongkaruna 2009 or Pinches & Mingo 1975).

One of the papers criticising usage of regression analysis is also Altman (1968) who basically introduced MDA, a statistical technique used to classify and make predictions in classification problems, for predicting corporate bankruptcies and credit ratings (originally MDA was used mainly in biology and sociology). The biggest advantage of MDA compared to regression according to Altman (1968) is the fact it "considers an entire profile of characteristics common to the relevant subjects, as well as interactions of these properties", at the same time it eliminates the above mentioned spacing problem. While Altman used MDA only for two-group analysis (i.e. simple belong/do not belong approach) Pinches & Mingo (1973) generalized this method for any number of groups which already allowed them to apply it for rating determination. Authors in their study showed that MDA is in case of fulfilled assumptions more precise than conventional regression methods.

Slightly different approach was brought by Pogue & Soldofsky (1969) who used binary (0-1) dependent variable signalling model. Using this model authors detected whether the rated subject belongs to higher (1) or lower (0) rating class. Using several separate regression models (i.e. AAA or AA, AA or A, AA or BBB, etc.; only investment grade ratings were examined) the authors were quite successfully able to distinguish between single rating classes. The share of correctly assigned ratings was expectedly increasing with growing interval between rating classes.

Probably most popular methods used are the ordered response models (logit or probit) which started to replace MDA in 1980s. Their biggest advantage is rather simple application with straightforward interpretation (especially in case of logit model), while the precision of estimates remains comparable to other competing methods. In many works this group of models was evaluated as the best performing method for rating estimation and it is therefore used in majority of today's research, at least as a model for comparison with newly developed method, see e.g. Moon & Stotsky (1993) or Gentry *et al.* (1988).

With development of computer technology and statistical software new methods applicable to rating problem were developed and used in some papers - these are primarily data mining methods (e.g. Classification and Regression Trees (CART) - Chandy & Duett 1990; Neural Networks - Huang *et al.* 2004 or Support Vector Machine - Hardle *et al.* 2012). Nevertheless the application of data mining techniques in rating issues is still in very beginnings and so any clear judgement about their usefulness cannot be provided.

Some of the papers focus directly on comparison of accuracy of above mentioned models in assigning correct real-life ratings[1]. Although their results vary quite significantly, we can find one common sign - it is the dominance of Ordered Response Models (ORMs) in most of works. ORM is very often used as a benchmark for other methods and only occasionally is significantly outperformed by them. Example of such work can be Öğüt *et al.* (2012) who compared ORM and MDA with two data mining techniques and ORM outperformed all others under most of circumstances. As the model itself is not a crucial part of this thesis, this evidence is decisive enough for our choice of modelling framework.

3.2 Banks' ratings determinants

Despite the fact that literature dealing with corporate and sovereign ratings is quite extensive, there are only few papers focusing on banking industry. Among reasons for the scarcity of relevant research can be mentioned high complexity and specificity of the industry which require a unique approach or problematic availability of relevant data.

The rating agencies provide investors with basic overview of categories which influence the final decision and assignment of the rating in their guidelines, these are: competition on relevant market, regulatory environment, funding and liquidity, leverage, capital adequacy, profitability, risk management and finally management and strategy of the company[2]. More concrete description of used measures and their weights in final decision are from obvious reasons missing, goal of all below discussed researches was to specify this general areas of interest.

3.2.1 Quantitative Determinants

If we focus on those several papers dealing with determinants of banks' ratings that are available, we find out that conclusions of most of them are in agreement. All the works stress the quantitative bank specific factors as the main determinants of ratings, other groups of variables are mostly found not

[1] In case of interest please see Ravi Kumar & Ravi (2007) who provide the most comprehensive comparison of all commonly used models.

[2] From Standard and Poors guideline (http://www.standardandpoors.com).

contributing to rating quality explanation or are even entirely omitted from the model.

Hammer *et al.* (2012) in their work use 14 accounting variables (in absolute values) and 9 representative financial ratios describing asset quality, profit efficiency, cost efficiency and liquidity. As the work is focused on quantitative bank specific variables only, no other explanatory variables are used. Authors conclude that all areas describing banks' performance has strong predictive power and hence are relevant parts of rating models.

Similar conclusions were drawn also by Öğüt *et al.* (2012) who slightly widened the number of used ratios to 26 (as the research was performed for banks within one country no market risk and macroeconomic characteristics were used as these were the same for all). In this case most significant appeared to be return-on-equity ratio, efficiency ratios (Net Income (NI)/Total Assets (As) and NI/number of employees) and loans/deposits ratio. Based on this finding the CRAs should "reward" with higher rating those banks which are able to generate profit, are efficient with using their resources and have optimal share of loans on totat assets.

The very same results were obtained also by Poon *et al.* (1999) and Bissoondoyal-Bheenick & Treepongkaruna (2009) though with one difference - both teams of authors already included variables not directly connected to rated banks, i.e. the macroeconomic (inflation, Gross Domestic Product (GDP), etc.) and market risk (volatility) measures. Nevertheless it turns out that all of these external variables are insignificant or have a very modest explanatory power.

If we summarize all above mentioned findings we see that majority of works is dealing with strictly quantitative variables only, using proxy for qualitative aspects (which are according to CRAs inseparable part of assessment) is mostly omitted. From the quantitative part then play the key role accounting numbers of each bank, namely ratios describing asset quality, liquidity, profitability, efficiency and capital adequacy.

3.2.2 Qualitative Determinants

If we want to make an overview of relevant qualitative determinants and possible proxy variables which may help us to account for them in econometric modelling we have to look outside the current banks' rating literature which, as already mentioned, is almost exclusively focused on accounting numbers and ratios.

The only exception is Kick & Pfingsten (2011) who investigated the influence of non-quantitative aspects on credit risk modelling among German banks. Apart from standard CAMEL[3] - explanatory variables the authors also include set of qualitative aspects - among all internal governance, Internal Capital Adequacy Assessment Process (ICAAP) (for details see Hassan 2009) or interest rate risk. The conclusion is that the vector of non-quantitative variables significantly improves explanatory power of examined models. Unfortunately authors utilize internal, confidential data of included banks. From this reason no details regarding the data are provided and hence the paper does not bring any tangible findings which can be further utilized and verified.

The group of papers dealing with qualitative determinants of corporate ratings is significantly wider. Although their findings may not be fully relevant for the banking sector, there is, among all, one paper which is worth mentioning. Gabbi *et al.* (2006) use 49 qualitative variables from various fields such as sector situation (competition), corporate governance, learning and growth, internal business processes, etc. to better capture ratings published by rating agencies. Their conclusion is unambiguous - inclusion of qualitative factors significantly improves the predictive ability of examined models.

Last source, that may help us to better understand the importance of qualitative factors are methodical manuals of rating agencies or particular rating reports. Among all we would like to mention Moody's (2000) and KBRA (2014) which offer two different views on this issue. While Kroll in its rating report devotes to qualitative variables[4] the same space as to quantitative ones, Moody's claims that many of these factors are left outside the rating model as they are very difficult to measure consistently and the availability of such data is very limited anyway.

Despite this fact in our work we would like to find and include proxies at least for the most important qualitative factors mentioned above - i.e. competition, ownership and regulatory framework.

[3]Capital Adequacy, Asset Quality, Management, Earnings and Liquidity

[4]Mainly the Industry situation and competition, Economic and regulatory framework and Governance and risk management which are most frequently mentioned areas among all agencies.

3.3 Specifics of banking sector in CEE

In the following chapter we would like to discuss characteristic features of banking industry which are typical for CEE region and which may have impact on bank stability and hence assigned ratings. We will also try to find proxy variables for some of the characteristics and so account for them in our future investigation.

First of all we should define the region of our interest - Central and Eastern European countries - as its perception typically varies among different sources. In our paper we use the broader definition of the region containing apart from "core" CEE countries[5] also Belarus, Moldova, Ukraine and Russia which also belong to category of Eastern Europe but are not always considered among CEE. The reasons for inclusion of four above mentioned countries are straightforward - not only that we consider banking sectors of these countries similar in many aspects to the rest, it also allows as to significantly broaden our dataset and hence increase the credibility of obtained results. In some sources also Eastern Germany and Austria (due to its geographical location) are included however the level of banking sector development in these countries is far from the rest which could distort our results and so we decided to exclude them from our sample.

If we look at all countries from our sample we can find four aspects which have majority of them in common. First of all it is the common History, the rest of characteristics - Foreign ownership, Regulation and Supervision and Competition - are then mostly its implications.

1. **History**

   The common sign which influenced all above mentioned countries is the political history of the region - all of them experienced communist regime and the major difficulties connected with recovery after its fall. The usual model of communist banking sector was created by 100 % stately-owned institutions, usually in form of so called monobanks (i.e. monopolistic banks) or two large banks - one focused on households, second one on productive sector (for detailed description of socialistic banking system see Delis 2008).

[5] Estonia, Latvia, Lithuania, Czech Republic, Slovakia, Hungary, Poland, Romania, Bulgaria, Slovenia, Croatia, Albania, Bosnia-Herzegovina, Kosovo, Macedonia, Montenegro and Serbia

In early 90's, after the fall of regime in most of the CEE countries the sector was transformed into standard two-tiered system - a system with one central bank responsible for monetary policy and regulation of financial markets and various number of commercial banks. Unfortunately most of new governments adopted, in order to increase the competition, very lax licensing and regulatory policy. The above mentioned fact together with general macroeconomic conditions of 1990's, political pressure to support often uncompetitive enterprises and rather insufficient risk management led to severe bad debt problems. To prevent crush of the whole economy many local governments approached to massive bail-outs[6].

2. **Foreign Ownership**

   This development gave rise to one of the most significant specifics of CEE banking sector - abnormally high percentage of foreign ownership. It turned out that banks controlled by state heavily lack competitiveness and efficiency and that costs connected with necessary recapitalization would far exceed the costs of potential privatisation. As there were only few subjects with sufficient funds to privatise a bank this led to massive inflow of foreign investors and banking groups resulting in many countries in more than 80% foreign ownership of the banking sector. Among the most affected countries belongs Albania, Bosna and Hercegovina or Hungary where the foreign ownership reaches almost 90 %, on the other side there is Slovenia with less than 40 % (as of 2011; based on Raiffeisen 2012). The effect of foreign ownership is twofold - on one hand the large financial groups helped to stabilize the economy and have radically improved the efficiency, on the other one in bad times there is a possible threat of contagion of potential crises from the foreign parents to local subsidies (see e.g. Gabrieli *et al.* 2014 or OECD 2012).

3. **Regulation and Supervision**

   The problem of financial sector regulation and supervision can be basically divided into two levels - national and international. The international regulation was brought with entrance of cross-border financial groups which very often entered into CEE countries via opening branch (which is subordinated to regulator of mother company) instead of classic

[6] Concrete amounts provided by governments as well as more detailed information regarding the bad debt problems can be found in Altmann (2006).

subsidiary. In large international banking groups the usual model is to transfer back-office and strategic decisions from local branches to European (or global) group level. The management of liquidity, assets and liabilities, exposure to risk and others is therefore done outside the branches which obviously further decreases the influence of local regulators and basically transfers it to the ones of mother companies (nowadays very often to European Central Bank - regulator of most of banking groups active in CEE region)[7]. However this aspect is common for all countries and therefore does not have any impact on our following research.

On the other hand the level of national regulatory institutions may differ significantly. As we have already mentioned after the fall of communist regime the quality of set rules and requirements was rather insufficient in most of countries. From that time however development of these institutions had very heterogenous development. While in most of the countries the standards got close to those of developed western economies (especially in Central Europe or the Baltics), countries like Albania, Belarus or Ukraine still lag behind (see comparison provided by (Bonin *et al.* 2013)).

To account for this qualitative aspect we include in our models European Bank for Reconstruction and Development (EBRD) index[8] which on scale from 1 to 4+ (with 1 representing no progress and 4+ the level of regulation of developed economies) "measures" the liberalization and institutional reform of local banking sectors. Among the assessed criteria belongs according to EBRD i) improving of supervision efficiency, ii) privatization of state-owned banks or iii) adoption of international standards in regulation and licensing policy.

4. **Competition**

   Last common factor of CEE banking we would like to mention is higher than average level of concentration. Basis for this fact was set in 1990s in connection with already mentioned banking crisis. Apart from entrance of foreign financial groups also numerous mergers took place. As a result the competition stipulated by loose regulation was again reduced. Although nowadays there are significant differences we can state that the market

[7]The internationalization brings also many other negative aspects for local regulation, for their complex discussion please see Altmann (2006).

[8]EBRD index of banking sector reform, its detailed description can be found in EBRD (2006)

concentration (expressed as market share of 5 largest banks) is rather high. The average of the region is between 50 - 60 %[9] while e.g. in United States the number only slightly exceeds 40 %. Among the countries with lowest competition belong Slovakia, Croatia and Albania with over 70% level of concentration, on the other side there is Lithuania or Ukraine will levels comparable to USA. Interesting case is Russia which although it has one of the highest shares of the largest bank[10] belongs among average regarding the TOP 5 market share - this shows a significant market position of this one single bank.

In our future investigation Herfindal index of single national markets will be included as an explanatory variable to account for influence of market concentration. We will follow the usual convention and measure the market share using total assets, i.e. market share of a bank = share on total assets of whole national banking sector.

[9] as of 2013, source: Raiffeisen (2014)

[10] Sberbank of Russia with almost 30% market share

Chapter 4

Methodology

The following chapter is divided into two main parts. In the first one we will briefly motivate our choice of modelling framework (ordered logit model and multiple discriminant analysis) and describe its main advantages over other competing methods. In the second part an introduction to technical background for above mentioned models as well as factor analysis which will used to reduce number of explanatory variables is provided.

4.1 Model Choice Motivation

As already indicated in the part summarizing existing findings from current literature the ordinary least square approach turned out to be insufficient for modelling of the credit ratings. In line with majority of papers dealing with rating estimation we therefore decided for two models which offer the best trade-off between consistency of results and applicability in real life situations - ORM and MDA.

According to several works (see e.g Bellotti *et al.* 2011 among all) both ordered response models - logit and probit - provide very similar results in rating area. However as the distribution of our dependent variable is not expected to follow normal distribution the logit model is preferred as it should fit the data better. The biggest advantages of OLM are usually feasible assumptions (will be discussed later) and ease of its use. If we compare it to MDA next significant advantage is possibility to use various interactions and power terms of explanatory variables which may reveal its more complicated relationship to dependent variable and possibility to use variety of statistical tests to verify significance of single variables, etc.

While the basic principle of our second method (MDA) is very similar to OLM, there are several important differences. On one hand MDA has much more restrictive assumptions which are not always fulfilled, on the other one when these are met it may produce more accurate results. Next significant advantage of MDA is also its ability to better perform with smaller data samples. Inclusion of MDA in this paper has a straightforward explanation. Results obtained using this model should serve as a consistency check, i.e. should confirm that our findings have a broad validity and are not dependent on chosen modelling framework.

4.2 Theoretical Background

In the following subchapter we will provide reader with necessary basic overview of methodology used in our paper. For each of the two models we mention step by step the assumptions which are made about used dataset, introduce its simplified derivation and finally discuss its main weaknesses and possible problems arising from its use.

4.2.1 Ordered Logit Model

1. **Model Assumptions**

   As already mentioned the Ordinary Least Squares (OLS) models proved to be inappropriate for modelling ordinal response variables. There are two main (among others) reasons for that:

   - the OLS assumptions are mostly violated due to ordinal character of dependent variable (especially errors proved to be heteroskedastic when modelling ordinal variables using OLS)
   - OLS fails to model the true nonlinear relationship in the data and hence provides misleading results (under/overestimates the relative impact of explanatory power of independent variables)

   When using the ordered logit model both of the above mentioned shortcomings should be eliminated. Firstly the OLM generally eliminates two main breaches of OLS assumptions:

   - **Heteroskedastic errors**: This is due to the fact that OLS assumes continuous dependent variable, when this assumption is not fulfilled the errors will obviously vary among various observations; ordered logit which treats this kind of variables correctly does not face similar problem.

- **Normal distribution of dependent variable**: Distribution of discrete variables generally cause troubles and is only rarely normal, in our case this is even deepened by character of ratings (of which distribution is usually skewed). Logit model brings two benefits - it assumes logistic regression which better (although not perfectly) captures character of ratings, moreover it is also less sensitive to distribution breaches.

The second problem is connected to arbitrary, non-evenly spaced categories of dependent variable[1]. Contrary to OLS ordered logit model considers the floor and ceiling effects of single categories and therefore helps to overcome this problem. It means that OLM is able to recognize the true spacing interval of dependent variable (in our case differences in riskiness assigned by single rating categories) and take it into account.

The summary of all OLM assumptions as mentioned in Healy (2006) can be found below:

(a) **Ordinal Character of Dependent Variable** Obviously the OLM requires the dependent variable not to be continuous. Eventual transformation (e.g. rounding) of continuous variables into ordinal is also unacceptable.

(b) **Correct Fit of the Model** The model should be fitted correctly, i.e. all meaningful variables are included and at the same time there are no irrelevant ones.

(c) **Independent Error Terms** Logistic regression requires each observation to be independent. That is that the observations should not be drawn by any dependent sample design.

(d) **No Multicollinearity** No explanatory variables should be highly correlated among each other.

(e) **Large Sample Size** It is recommended to have at least 30 observations per each independent variable.

[1] for explanation see Section 2.2

2. **Model Derivation**

Following Fok & Franses (2002) we motivate the ordered logit model by considering simple regression model satisfying:

$$\begin{aligned}
\hat{y} &= \beta x + \epsilon \\
where: &\quad \beta\ is\ a\ vector\ of\ regression\ coefficients \\
&\quad x\ is\ vector\ of\ explanatory\ variables \\
&\quad \epsilon\ is\ the\ logistically\ distributed\ disturbance\ term \\
&\quad and\ \hat{y}\ is\ an\ unobservable\ (latent)\ underlying\ dependent \\
&\quad variable.
\end{aligned} \tag{4.1}$$

While $\hat{y}$ (in our particular case the true probability of default) is assumed to be continuous and hence satisfies a linear regression model, its observable realization y (the assigned rating) is discrete and therefore requires a special treatment. The relationship between $\hat{y}$ and y can be described as:

$$\begin{aligned}
y_i &= 1\ if\ \hat{y}_i \leq \mu_1 \\
&\quad 2\ if\ \mu_1 < \hat{y}_i \leq \mu_2 \\
&\quad 3\ if\ \mu_2 < \hat{y}_i \leq \mu_3 \\
&\quad \vdots \\
&\quad N\ if\ \mu_{N-1} < \hat{y}_i \leq \mu_N
\end{aligned} \tag{4.2}$$

where $\mu_1 < \mu_2 < \mu_3 < \ldots < \mu_{n-1} < \mu_n$ are unknown threshold (or cut-off) parameters distinguishing between single categories. In order to simplify notation we introduce $\mu_0 = -\infty$ and $\mu_N = \infty$. Now we can generalize and state that individual i belongs to category n if $\mu_{n-1} < \hat{y}_i \leq \mu_n$ for all n = 1, 2, ..., N.

In order to analyze ordinal responses the proportional odds model is introduced. Its rationale comes from expressing of probability of single outcomes. Let's consider the general formula for $y = n$, we observe such an outcome in case $\hat{y}$ falls between μ_{n-1} and μ_n, hence:

$$P(y_i = n|x_i) = P(\mu_{n-1} < \hat{y}_i \leq \mu_n|x_i) \tag{4.3}$$

After substituting for $\hat{y} = \beta x + \epsilon$ we obtain:

$$P(y_i = n|x_i) = P(\mu_{n-1} < \beta x_i + \epsilon_i \leq \mu_n|x_i) \tag{4.4}$$

which after some rearrangements results in:

$$P(y_i = n|x_i) = P(\mu_{n-1} - \beta x_i < \epsilon_i \leq \mu_n - \beta x_i|x_i) \tag{4.5}$$

As the probability of a random variable being between two values is a difference of values of Cumulative Distribution Function (CDF), defined as $\Lambda = 1/(1 + exp(-(\mu_n - \beta x_i)))$, at these points, we have:

$$\begin{aligned} P(y_i = 1|x_i) &= P(\epsilon_i \leq \mu_n - \beta x_i|x_i) - P(\epsilon_i < \mu_{n-1} - \beta x_i|x_i) = \\ &= \Lambda(\mu_n - \beta x_i) - \Lambda(\mu_{n-1} - \beta x_i) \end{aligned} \tag{4.6}$$

where $\mu's$ and $\beta's$ are to be estimated.

Note that this model does not assume any heterogeneity among coefficients across single categories (i.e. $\beta's$ are always identical regardless of thresholds the observation falls between). This represents the already mentioned assumption of proportional odds. To allow such a heterogeneity one may include the random coefficients allowing for different thresholds as introduced by Jain *et al.* (1994).

3. **Parameter Estimation**

To estimate the above mentioned parameters of ordered logit model the maximum likelihood estimation proved to be the most efficient way.

As long as we assume independent observations, the sample likelihood is simply a product of above derived probabilities. First let us recall that probability of each observation depends directly on category of y it falls into. The simplest way to assure that we assign each observation the right probability function is to introduce N dummy variables for each of the categories (d_{in}) which take value 1 when observation i falls into category n and value 0 otherwise. After doing so the likelihood is just a product over all observations (i) and categories (n) raised to d_{in}:

$$L = \prod_{n=1}^{N}\prod_{i=1}^{I} P(y=i)^{d_{in}} = \prod_{i=1}^{I} P(y=1)^{d_{i1}} * \ldots * \prod_{i=1}^{I} P(y=N)^{d_{iN}} \quad (4.7)$$

To create a log-likelihood we simply logarithmize both sides of the equation and obtain:

$$lnL = \sum_{n=1}^{N}\sum_{i=1}^{I} d_{in}ln[P(y=i)] = \sum_{n=1}^{N}\sum_{i=1}^{I} d_{in}ln[\Lambda(\mu_n-\beta x_i)-\Lambda(\mu_{n-1}-\beta x_i)] \quad (4.8)$$

which is to be maximized in order to estimate the parameters ($\mu's$ and $\beta's$).

4. **OLM drawbacks**

   The most important drawback compared to MDA is necessity of significantly larger datasets. While MDA is able to perform successfully even with number of observation which is 4-5 multiple of explanatory variables, the recommended amount for OLM is even 5 times higher.

4.2.2 Multiple Discriminant Analysis

1. **Model Assumptions**

   As already mentioned earlier the assumptions of MDA are much more restrictive than those of OLM. In the following subchapter we will briefly discuss these and try to assess the consequences of their eventual violation.

   (a) **Sample size:** Although the MDA is able to perform also with relatively smaller sample sizes, there remain some minimal requirements on proportion between sample size and number of explanatory variables - the marginal situation is $n-2$ predictors (where n is number of observations). Nevertheless in most of works (among all Poulsen & French 2004) it is recommended to have approximately 4 - 5 times higher number of observations than independent variables for optimal performance of the model.

(b) **Homogeneity of (co)variances:** MDA assumes covariance matrixes to be homogenous among all classification groups. Violation of this assumption may have significant influence on obtained results, appropriate transformation in such case is therefore necessary[2].

(c) **Normal distribution:** The examined sample is assumed to come from a multivariate normal distribution. Although the normality assumption belongs among fundamental assumptions of all statistical methods, its violation does not bring any severe distortion of results nor decreases reliability of significance tests (as shown by Lachenbruch & Goldstein 1979).

(d) **Outliers:** Outliers mean for classification methods (such as MDA) quite serious problem. Especially in smaller samples even several outliers within one classification group may cause significant increase in variance which on one hand decreases accuracy of the model (erroneous classification) and on the other one distorts the statistical significance tests. In case of detected outliers its elimination or transformation (e.g. logarithmization if possible) is a preferable solution.

(e) **Non-multicollinearity:** The classical assumption of no perfect multicollinearity holds also for MDA. Moreover neither higher values of correlation between independent variables are desired in case of MDA as these may cause misleading assessment of relative importance of classification coefficients.

2. **Model Estimation**

The very basic idea of classification methods is to find an appropriate (in our case linear) transformation of multi-dimensional observations which is best able to discriminate among classes of dependent variable. Technically this idea is represented by scatter matrices analysis.

[2]For complete overview of methods how to handle this problem please refer to Wahl & Kronmal (1977).

The pioneering study on classification methods was introduced by Fisher (1936) who came with discriminant analysis for two classes. He considered a multivariate observations x (vector of explanatory variables) related to univariate realizations y randomly drawn from two different classes, namely k_1 and k_2. Goal of the analysis was to correctly separate (based on vector x) observations y between the two classes.

For the two classes k_i, $i = 1, 2$ the scatter matrices are:

$$S_i = \sum_{x \in k_i} (x - x_i)(x - \bar{x}_i)^T \tag{4.9}$$

where $\bar{x}_i$ is a mean of each class given by $\bar{x}_i = \frac{\sum_{x \in k_i}}{n_i}$ and n_i is the number of observations in k_i. The total intra-class scatter matrix is then given by:

$$S_w = S_1 + S_2 = \sum_{i=1}^{2} \sum_{x \in k_i} (x - x_i)(x - \bar{x}_i)^T \tag{4.10}$$

and the inter-class scatter matrix by:

$$S_b = (\bar{x}_1 - \bar{x}_2)(\bar{x}_1 - \bar{x}_2)^T \tag{4.11}$$

Fischer's solution lies in construction of linear transformation (Φ) maximizing the ratio of determinants of inter-class to intra-class scatter matrices of the samples:

$$J(\Phi) = \frac{|\Phi^T S_b \Phi|}{|\Phi^T S_w \Phi|} \tag{4.12}$$

If S_w is non-singular, the above mentioned equation can be converted to a conventional eigenvalue problem.

The natural extension of Fisher's two-class solution is the MDA as derived e.g. in Johnson & Wichern (1988). Similarly to the Fisher's solution the projection is from high dimensional space to a low dimensional one and the optimal transformation maximizes inter-class to intra-class scatter - however now the maximization is done among several classification classes.

Considering m classification classes, the intra-class matrix becomes:

$$S_w = S_1 + \ldots + S_m = \sum_{i=1}^{m} \sum_{x \in k_i} (x - \bar{x}_i)(x - \bar{x}_i)^T \tag{4.13}$$

The calculation of inter-class matrix takes slightly different form:

$$S_b = \sum_{i=1}^{n} m_i (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})^T \tag{4.14}$$

where m_i is number samples within each class, $\bar{x}_i$ mean of each class as described above and $\bar{x}$ mean over all classes.

As already mentioned the transformation should again satisfy following ratio:

$$J(\Phi) = \frac{|\Phi^T S_b \Phi|}{|\Phi^T S_w \Phi|} \tag{4.15}$$

If the S_W is non-singular, the same as in the two-class case holds.

As already shown the MDA provides, under the condition of satisfied assumptions, quite simple and elegant way for classification using discrimination.

3. **MDA Drawbacks**

Although MDA is quite frequently used to solve classification problems, it has many shortcomings or pitfalls which may cause misinterpretation of results obtained using this method and which are very often ignored though. Following Eisenbeis (1977) we will introduce the most relevant ones.

First of them are quite demanding assumptions which are not always met. As we have already discussed these earlier, let us only mention that among those which are frequently violated belong multivariate normal distribution of observations and equal group dispersion (variance-covariance matrices).

Second drawback is a complicated interpretation of significance of individual variables. Compared to the regression methods (such as OLM) where testing and interpretation of explanatory variables is straightforward this is a clear disadvantage of MDA. Nevertheless there are several ways (according to Eisenbeis *et al.* 1973; a complete overview of significance testing methods can be found therein) how to assess the significance which are sufficient for purposes of this paper. Among all let us mention the possibility to rank variables according to their univariate F-statistic and conditional deletion method. While using F-statistic is the simplest and hence most appealing way how to test significance it turns out that it may provide misleading results - as Cochran (1964) has shown some variables, while seemingly insignificant on their own, may have important discriminative power when combined with other ones. However the F-statistic may serve quite well as a simple, high level indicator of significance. More reliable is then conditional deletion method which assesses the importance of variables based on changes of overall discriminatory power of the model when removed. As shown by Kshirsagar (1972) this method is not only intuitive but has a solid theoretical background, however its description is beyond the scope of this text and so we refer readers to above mentioned paper for details.

Thirdly there is a common problem with definition of groups of dependent variable. The MDA assumes that groups are discrete and identifiable - in many cases this does not hold. Fairly usual approach is to divide continuous variable into several groups (e.g. according to particular quantiles) and then apply MDA. This procedure obviously violates the assumption of discreteness. Ratings on the other hand surely satisfy both of the above mentioned conditions.

Last noteworthy pitfall is the assessment of classification error rates. As mentioned in Eisenbeis (1977) using the reclassification of the original sample (i.e. the one used for estimation) is an inappropriate procedure which generally leads to biased and exaggeratedly positive results. To overcome this issue the most frequent way is to test the discriminant function using out-of-sample data.

4.2.3 Factor Analysis

As the number of explanatory variables which can potentially be a relevant determinants of banks' ratings is rather high (especially compared to number of observations) we introduce varimax rotation factor analysis in order to operationalize our models. Factor analysis is a statistical method used to describe variability explained by observed (very often correlated) independent variables by terms of lower number of uncorrelated, unobserved factors which are common for two or more variables. Factor analysis is a common method accompanying classification problems as demonstrated by Mileris & Boguslauskas (2011) or Teker *et al.* (2013).

1. **Factor Analysis Model**

To motivate the factor analysis we follow Tucker & MacCallum (1997) and assume n observed explanatory variables $X_1, X_2 \dots X_n$, m common factors $F_1, F_2 \dots F_m$ and n unique factors $U_1, U_2 \dots U_n$. Now each explanatory variable can be expressed as linear combination of all common factors and a specific unique factor:

$$
\begin{aligned}
X_1 &= \beta_{11}F_1 + \beta_{12}F_2 + \ldots + \beta_{1m}F_m + \beta_1 U_1 \\
X_2 &= \beta_{21}F_1 + \beta_{22}F_2 + \ldots + \beta_{2m}F_m + \beta_2 U_2 \\
&\vdots \\
X_n &= \beta_{n1}F_1 + \beta_{n2}F_2 + \ldots + \beta_{nm}F_m + \beta_n U_n
\end{aligned}
\tag{4.16}
$$

Each of these equations can be considered a regression equation. Goal of the factor analysis is to find regression coefficients ($\beta_{11} \dots \beta_{nm}$) which best replicate the observed variables. Each coefficient represents[3] the correlation between each variable and a given factor. The sum of squares of these correlations for one variable X_n (i.e. $\beta_{n1}^2 + \ldots + \beta_{nm}^2$) then show the overall variance of variable X_n which is accounted for by the common factors. Obviously the higher share of captured variance the more successful factor analysis.

Solution to the above mentioned problem uses correlation matrix of the explanatory variables and seeks for "clusters" of intercorrelated ones (i.e. groups of two or more variables which are mutually highly correlated - usually with correlation at least 0.3), these can be potentially replaced using common factors. The mathematical algorithm of obtaining factor solution from a correlation matrix assigns each successful factor, which is uncorrelated with all other factors, as much of the variance of the observed variable as possible. This process very often leads to all variables having substantial correlations (coefficients) with

[3]Under the condition of factors beeing uncorrelated among each other which for orthogonal rotation holds always as will be discussed later.

the first factor. While this solution is valid and consistent with method requirements its interpretation is usually quite complicated (as advised by Field 2000). The rotation - adjustment which ensures that each variable has substantial correlations with as few factors as possible (in optimal case with only one) - is therefore usually applied. Graphically one can easily imagine this procedure as rotating of axes representing single factors so that correlations with explanatory variables are evenly distributed. There are several ways to do this - in our work the most conventional orthogonal varimax rotation is used. The technical description of factor rotation is beyond the scope of this text, for details see refer to Tucker & MacCallum (1997).

The frequently discussed issue regarding factor analysis is the rule defining number of factors which should be retained and used in following investigation. Among the most frequently used criteria belongs Guttman-Kaiser one which suggests to retain those factors of which sum of captured variation is equal or higher than one (see Kaiser 1958). As shown by Yeomans & Golder (1982) it is not only the ease of use and intuitively acceptable justification which make this criterion more favourable, in many cases it also outperforms theoretically more appropriate methods. Therefore we will in our study rely on this criterion as well.

Last step of factor analysis is obtaining factor scores (i.e. fitted values of factors for all observations). Given the Equation 4.16 with estimated parameters β and after disregarding unique factors U_n, solution expressing factors as a functions of explanatory variables should be available:

$$
\begin{aligned}
F_1 &= \gamma_{11}X_1 + \gamma_{12}X_2 + \ldots + \gamma_{1n}X_n \\
F_2 &= \gamma_{21}X_1 + \gamma_{22}X_2 + \ldots + \gamma_{2n}X_n \\
&\vdots \\
F_2 &= \gamma_{m1}X_1 + \gamma_{m2}X_2 + \ldots + \gamma_{mn}X_n
\end{aligned}
\tag{4.17}
$$

Using this we are easily able to estimate factor scores and use them is further research as new explanatory variables. As already mentioned the main advantages of using factors is possibility to significantly decrease number of explanatory variables with only negligible loss of information (variation) and certainty that we are nor facing multicollinearity problem as factor scores are uncorrelated by definition (due to orthogonal rotation, see Taherdoost *et al.* 2014).

Chapter 5

Dataset and Variables

The following part of our thesis will be devoted to description of variables and overall dataset used for modelling of credit ratings. In the first part we will summarize all aspects which according to prior research and our opinion should determine the risk of potential default and hence assigned ratings and also state hypotheses connected to them. Apart from that we will also describe the dataset and process of its formation, i.e. criteria used for data selection, necessary adjustments as well as basic statistical overview of dependent variable.

5.1 Dependent Variable

Our dependent variable are long-term ratings assigned by one of "Big Three" rating agencies - Moody's, S&P or Fitch, period of our interest is then 2010 - 2012. As we are interested in generally valid determinants of rating, we disregard the information about rating agency which has assigned the rating. In our dataset we utilize end-of-year data from financial statements hence we take as a corresponding rating the one which was assigned in following 3 - 6 months after the disclosure. As rating for each bank in each year was not available (or due to unavailability of some of explanatory variables) the final dataset creates an unbalanced panel with some observations missing.

In order to be able to use our dependent variable in regression and classification analysis we follow the general conventions in most of related works (among all Bissoondoyal-Bheenick & Treepongkaruna 2009) and introduce Figure 5.1 which assigns each rating grade a number in ascending order (i.e. 1 being AAA rating; 21 being default - D):

Figure 5.1: Rating grades

S&P	Fitch	Moody's	Rating Grade
AAA	AAA	Aaa	1
AA+	AA+	Aa1	2
AA	AA	Aa2	3
AA-	AA-	Aa3	4
A+	A+	A1	5
A	A	A2	6
A-	A-	A3	7
BBB+	BBB+	Baa1	8
BBB	BBB	Baa2	9
BBB-	BBB-	Baa3	10
BB+	BB+	Ba1	11
BB	BB	Ba2	12
BB-	BB-	Ba3	13
B+	B+	B1	14
B	B	B2	15
B-	B-	B3	16
CCC+	CCC	Caa1	17
CCC	CC	Caa2	18
CCC-	C	Caa3	19
CC	RD	Ca	20
D	D	C	21

Source: Author

If we focus on distribution of single rating classes within our sample we see its histogram presented in Figure 5.2 is significantly skewed towards worse ratings. Based on that we can assume that our dependent variable is likely not going to be normally nor log-normally distributed which has to be taken into account while interpreting our findings. On the other hand this situation was, due to character of ratings, expected and therefore does not represent any severe complication.

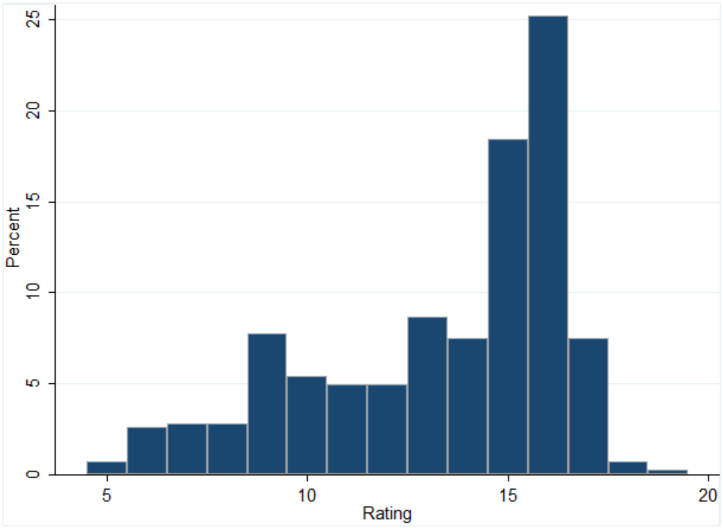
If we look at basic statistical properties of our dependent variable we see that it ranges from 5 (A+) to 19 (CCC-) with mean value of 13.387 which again confirms our assumption about its non-normal distribution:

Table 5.1: Rating - summary

Variable	Min	Max	Mean	Median	St. Dev.
Rating	5	19	13.387	9	3.129

Source: Author's computations.

Figure 5.2: Ratings distribution



Source: Author

5.2 Explanatory Variables

As already described earlier in our analysis we will include three groups of explanatory variables i) the accounting numbers and ratios signalizing the performance of each bank, ii) proxy variables for non-measurable characteristics of single banks or national banking sectors and finally iii) macroeconomic and country specific measures describing local economy which banks heavily depend on.

In the following sub-chapter we will briefly describe all areas which we believe are relevant for rating estimation, describe particular variables which represent them and state the expected influence on credit rating quality (i.e. hypotheses which will be later confirmed or disproved).

5.2.1 Quantitative Bank Specific Variables

Profitability & Efficiency: Profitability is one of the first subjects of interest when it comes to assessing performance of any corporation and banks are not an exception. The fact whether or not the bank is able to generate profit signalizes its health, competitive character and effective treatment of entrusted resources - profitability and efficiency ratios may therefore serve as rule of thumb distinguishing between safe and risky banks. We believe that apart from comparable profitability ratios also the absolute amount of generated profit plays an important role that is why we include absolute value of Net Income. From relative measures we picked Net Interest Margin which shows what margin the bank is able to maintain and hence approximates for strength of market position and Non-interest income/Revenues. The income from non-interest operations is considered much more volatile than income from borrowings and its high share can be therefore viewed as potential danger.

The most common ratios describing effective performance are Return on Average Assets (ROAA) respectively Return on Average Equity (ROAE) which will be part of our model as well. Apart from these we consider also Cost to Income Ratio and Non-Interest Expenses/Gross Revenues. While the first ratio describes the general costs (and hence effectiveness) needed to produce one "unit" of income, the second one focuses only on non-interest expenses (salaries, equipment or loan loss provisions) which can be much more easily influenced by the bank[1] and show therefore the true effectiveness of its operations.

H1: Efficiently performing banks which are able to generate profit are awarded by better ratings due to higher probability of sustainability of their operations.

Asset Quality (Credit Risk): Borrowing money to final customers creates the main activity of most of banks. Therefore the quality of provided loans (main part of asset side) is one of the key measures signalizing the financial health or possible troubles with meeting the obligations of each institution. In our model this aspect will be represented by two basic ratios: i) Impaired Loans/Gross Loans which represent the historical performance and current state of loan portfolio and provides with expected loss from non-performing loans compared to overall pool and ii) Loan Loss Reserves/Gross Loans which allows us to take into account expected future development of the above mentioned. As supportive measure we also include Net Loans/As which serves as a "magnifier" of bad loans problem - high share of impaired loans causes the more trouble the higher share of assets is created by loans and vice versa[2].

H2: Share of bad loans on its total amount is one of the most important factors for credit risk assessment - the lower it is the better rating is assigned.

[1]Compared to capital or liquidity costs which are mostly given.

[2]Another possible indicator is Non-performing loans ratio however due different definitions of this measure across the Europe - as described e.g. in Barisitz (2013) - we decided to drop it from our dataset

Liquidity (Funding): Another important aspect signalizing the ability of a bank to meet all its obligations is liquidity. To hold enough liquid assets to cover sudden high withdrawals (so called "runs on a bank") became a very popular topic in recent years and several regulatory measures[3] were set in order to assure it. In line with this we introduce two measures of bank liquidity - Liquid Assets/Total Deposits and Borrowings and Net Loans/As (as used e.g. by Poon *et al.* 1999) which was already mentioned in regard with asset quality, however can be used as approximation of banks' liquidity as well.

H3: Higher stock of liquid assets increases the probability of bank surviving unexpected outflows and hence decreases probability of potential default (=results in better rating).

Capital Adequacy: Capital Adequacy (CA) is one of the very basics of Basel III regulation which generally compares capital of the bank to its risk weighted assets. Regulators then require to maintain this ratio at certain level which should prevent banks from excessive leverage and hence potential insolvency. As the most common measures of CA (Tier 1 and Capital Adequacy Ratios) are not available for most of banks in our sample, we decided to include alternative measure proposed by Chernykh & Cole (2015) - Non-Performing Asset Coverage Ratio (NPACR). This ratio is calculated as:

$$
\begin{aligned}
NPACR &= \frac{Eq + LLR - IL}{TA} \\
where: \quad & Eq...Equity \\
& LLR...Loan\ Loss\ Reserves \\
& IM...Impaired\ Loans \\
& TA...Total\ Assets
\end{aligned}
\tag{5.1}
$$

In their work authors show that it has even better information and predictive value than the two above mentioned measures, moreover it has one crucial advantage - data for its calculation are much easier to obtain. Apart from

[3] Among all Liquidity Coverage Ratio (LCR) - ratio of high quality liquid assests and possible cash outflow in short term (see e.g. (BIS 2013))

NPACR we also consider as a supportive measure the ration of Equity to Total Assets which usually serves as a high level indicator of capital adequacy.

H4: Capital adequacy assures manageable levels of leverage and hence prevents banks go bankrupt - the higher CA ratios, the better rating.

5.2.2 Qualitative Bank and Banking Sector Specifics

Size: As shown in several papers (among all Marques Ibanez *et al.* 2012 and references therein) one of the factors contributing to rating quality is absolute size of the institution. This finding can be viewed from two different points: Not only that large banks are generally less likely to default as they have broad capital backup which makes them less sensitive to market changes, there is also the aspect of potential state interventions. Eventual default of locally significant bank[4] would cause severe problems to national financial market and it can be expected that governments would approached (as they did during last financial crisis) to bailing-out of such a bank. Although this creates a clear moral hazard as the large banks can a priori count with such a help, it may decrease potential credit risk of these large banks. This phenomenon is in recent times known as "too-big-to-fail" problem. In order to approximate for size and importance of single banks we introduce three variables - Natural Logarithm of Total Assets, Market Share (measured as share on total assets of whole banking sector) and Rank Within Each Country (i.e. banks in each country were ranked from largest to smallest and their standing is taken as a explanatory variable).

H5: Their stability as well as too-big-to-fail aspect help large banks to achieve better ratings.

Growth potential: Apart from the actual size (as described above) also its relative changes play a key role. Certainly there is big difference between a large bank which constantly looses its dominant position and bank of half size which grows by two-digit speed every year. That is why we include the Growth Rate of Total Assets and Gross Loans (Y-o-Y) as independent variables.

H6: Constantly growing banks are assessed better than stagnating or even dwindling banks - regardless on their absolute size.

[4] so called SIFI

Market concentration: While market with dominant position of several few banks would not be very favourable for customers (due to higher prices allowed by low competition) it would significantly improve financial position of all market players and hence stabilize the financial market. Our assumption therefore is that market concentration may have influence on rating assigned to banks of single countries. To confirm it we add the Herfindahl index which measures concentration of industry as a sum of squares of market shares of all subjects on the market:

$$HI = \sum_{i=1}^{N} S_i^2$$

$$\begin{aligned} where: \quad & S_i ...market\ share\ of\ i-th\ company \\ & N...number\ of\ companies\ on\ the\ market \end{aligned} \tag{5.2}$$

Due to its construction the index takes value belonging to interval $(0, 1\rangle$ where value close to zero signalize the perfect competition while 1 the monopoly.

H7: Banks in more concentrated markets are pushed to decrease their margins which may result in insolvency problems, they are therefore rated worse.

EBRD index: As already mentioned earlier we include EBRD Banking Reform Index as a proxy variable for quality of institutional and regulatory framework (use of this index as a proxy for banking sector reform was used e.g. Brissimis *et al.* 2008 among all). Using the scale 1 - 4+ the index assesses the process of liberalization of national banking sectors and its move towards the developed systems of western economies. In order to be eligible to obtain particular evaluation the institutional environment has met following criteria[5]:

1 - Little progress beyond establishment of a two-tier system.

2 - Significant liberalisation of interest rates and credit allocation; limited use of directed credit or interest rate ceilings.

3 - Substantial progress in establishment of bank solvency and of a framework for prudential supervision and regulation; full interest rate liberalisation

[5] as adviced by EBRD in Methodological Manual at http://www.ebrd.com

with little preferential access to cheap refinancing; significant lending to private enterprises and significant presence of private banks.

4 - Significant movement of banking laws and regulations towards BIS standards; well-functioning banking competition and effective prudential supervision; significant term lending to private enterprises; substantial financial deepening.

4+ - Standards and performance norms of advanced industrial economies: full convergence of banking laws and regulations with BIS standards; provision of full set of competitive banking services.

H8: Banks operating within developed institutional and regulatory framework are assigned with better ratings.

Control: An important difference between banks determining their safeness is institutional type of its owners. For our purposes the main difference is in state vs. private ownership - while the privately owned banks may rely on state help only in case their eventual default would have impact on whole financial market, the state ones will be bailed-out always. We therefore introduce simple dummy variable which takes value 1 for banks where majority is hold by a public authority (state, government, etc.) and 0 otherwise.

H9: Banks with majority hold by public authority are generally assessed better than the privately owned ones.

5.2.3 Macroeconomic Measures

GDP Growth Rate: Growing economy offers much more convenient conditions for banking business - there is lower risk of default of the borrowers, the demand for financing as well as margins are increasing. Under such circumstances the probability of default of all banks within the economy is generally lower than in case of stagnating or even decreasing economy. That is why we include GDP Growth Rate in our model.

H10: Banks operating in growing economy are less likely to default due to lower share of unpaid loans.

Public Debt to GDP: The overall indebtedness of public sector has direct influence on amount of money it transfers back to economy, whether it is in form of direct payments, investments or wages of state employees. High indebtedness (measured as an absolute Public Debt to GDP) may therefore prefigure the upcoming cost-saving measures which may significantly worsen the economic situation of certain groups of subjects (state employees, retirees, construction companies, etc.) and hence disrupt the stability of banks.

H11: Banks operating in less indebted countries are likely to have better credit ratings.

Inflation: Stable price level significantly helps to maintain stable environment on financial market of which benefits for banks were already discussed. However the exact value of inflation which is the most beneficiary for economy is not clear as shown e.g. by Saymeh & Orabi (2013). Generally inflation rate around 2 % p.a. is seen as optimal for stipulating the economic growth. Higher inflation (two- or even three-digit one) may cause uncertainty among consumers - their logical reaction in order to preserve value of their resources is to withdraw money and exchange them for goods, this may cause severe liquidity problems for banks. Inflation close to zero (or even deflation) than slows down the economy as consumers are motivated to wait for prices drop down. Banks generally prefer low and stable inflation as well - that is when they can easily settle the lending rates and money repaid in several years horizon do not lose much of their value.

H12: Low inflation improves banks' operations and hence results in better rating.

Interest Rates: The influence of interest rates on performance of banks seems to be twofold. Generally banks rely on wide spreads between long- (loans) and short-maturity (deposits) yields to make profit. It is therefore obvious that environment of low rates is challenging and has clearly negative impact. As shown by Genay & Podjasek (2014), this effect outweights the potential benefit from positive influence on whole economy which low i.r. have. The final effect of our variable - Real Interest Rate - remains unclear, however based on the above mentioned study we expect it to be directly related (i.e. higher rates imply better situation of banks).

H13: Low interest rates eliminate possibilities of banks to create profit which worsen the outlook of financial health of banks.

Unemployment: Growing unemployment usually signalizes troubles of the whole economy. Not only that overall ability of natural persons to repay their obligations is obviously worse with higher unemployment, it also shows the poor performance of companies which do not hire any new workers or even dismiss the current ones. Both factors may have cardinal effect on performance of banks.

H14: Higher unemployment increase risk of bad loans problem which has negative impact on the assigned rating.

Country Rating: Reasons for inclusion of Country Rating may be viewed from several different angles:

- Many banks are still owned (or partially owned) by the state. If this is the case the final rating is very often very similar to the country one (bank takes over rating of its owner, the final result is than adjusted to real state of the bank).
- Countries with good rating are more likely to have funds to bail-out banks in troubles.
- Healthy public finances can better support the economic growth through public investments - see Public Debt/GDP description.

In any case the Country Rating seems to be closely related to the one of participants on financial markets, especially banks. We therefore include it as an explanatory variable considering the same logic as in case of dependent variable (i.e. each rating class was assigned with number from 1 - 21 with one being the best).

H15: Quality of country rating influences quality of the banks' one in direct proportion.

Chapter 6

Empirical Part

In the following chapter we will focus on modelling of banks' ratings itself and will try to reveal the true factors which determine their quality. In the beginning we will reduce number of explanatory variables with use of factor analysis. Later on we will check the basic assumptions on the data used for our two above mentioned models (OLM and MDA) and finally apply these to our dataset and assess the relevance of single explanatory variables.

6.1 Factor Analysis

As already mentioned the factor analysis looks for variables which are mutually highly correlated and tries to replace them with several common factors which have the same (or very similar) explanatory power. The advantage of factor analysis is not only in reduction of variables it also eliminates the multicollinearity problem (for details see Subsection 4.2.3) which is especially required in case of MDA.

In our study we perform two separate analyses according to nature of the variables - one for bank specific variables (accounting ratios as well as proxy variables for qualitative aspects) and macroeconomic and country-specific ones. Performing one single factor analysis for all the variables would lead to more complicated results which would be interpretable only with difficulties. As we need clear assessment of every aspect's relevance we decided to split our data into two groups.

In the first analyses of bank specific numbers 19 variables describing areas mentioned in previous chapter was included. As can be seen in Figure B.1 and Figure B.2 the factor analysis produced 7 factors with sum of captured variance one or higher which were retained. Based on the correlations between single variables and retained factors after rotation we can easily and clearly assign each factor an area it represents:

- **Factor 1 = Capital Adequacy** (*Cap_adeq*) The first factor is almost solely determined by our two measures of capital adequacy (NPACR and Equity (Eq)/As, both with correlation over 80 %), the rest of the variables contributes only minimally.
- **Factor 2 = Growth Potential** (*Growth*) Similar situation as in the previous case, also the second factor is mainly determined by two variables - Growth of Assets and Gross Loans - which are almost perfectly correlated with the factor (correlations exceeding 90 %).
- **Factor 3 = Efficiency and Profitability** (*Effic_Profit*) The third factor represents the ability of banks to effectively use their resources and make profit. Mostly correlated with the factor are ratios of Non-interest Expenses/Revenues and Cost-to-Income. Next contributing, although less significantly, indicators are ROAA and ROAE (correlation around 40 %). Quite surprisingly there are also two related variables which seems not to be correlated with the rest - Net Interest Margin and Net Income.
- **Factor 4 = Liquidity** (*Liquid*) Leading variables determining the fourth factor are Net Loans/As and Liquid As/Total Deposits - our two proxies for liquidity.
- **Factor 5 = Size** (*Size*) The fifth factor is again clearly connected with variables signalizing the size of bank. The factor scores have high positive correlation with logarithm of Assets, Net Income and Market Share and high negative one with Country Rank (which follows the logic of variable construction).
- **Factor 6 = Asset Quality** (*Asset_qual*) Only two variables with high rate of correlation are Loan Loss Reserves/Gross Loans and Impaired Loans/Gross Loans, the assets quality character of the factor is therefore obvious.
- **Factor 7 = Market Position** (*Market_pos*) Last factor then reflects the position of a bank as well as overall situation on the market. The most contributing variables are here Herfindahl index (index of market

concentration), Market Share and partially also Country Rank of each bank.

In the second group we factor-analyse the five country specific variables which result in two common factors with significant inter-correlations as can be found in Figure B.4 and Figure B.5. While the rest of variables is clearly divided between these two factors, Unemployment seems to contribute to both of them equally and therefore we cannot provide reader with any clear conclusion regarding this variable.

- **Factor 8 = Inflation and Interest Rates** ($Infl\_Inter$) The first factor correlates mostly with Inflation and Real Interest Rates and can therefore be seen as variable describing money related sphere. In compliance with general economic rules these two aspects have opposite relation, i.e. increase of Inflation induces decline of Interest Rates.

- **Factor 9 = Public Finance and Economic Growth** (GDP_debt) The second factor is determined mainly by GDP Real Growth Rate as well as Public Debt/GDP and represents therefore variable describing the overall state of economy. As already mentioned also Unemployment (which should be closely related to economic growth) is significantly contributing to Factor 2.

Having all factors set we simply estimate the scores for each of them which will be later used as explanatory variables in our models.

6.2 Ordered Logistic Regression

6.2.1 Model Assumptions

As the assumptions of OLM are rather theoretical let us only briefly discuss on these:

1. **Ordinal Character of Dependent Variable** Ratings perfectly satisfy the requirements of ordered ordinal variable as it is the only observable realization of latent unobservable variable which is the probability of default.

2. **Correct Fit of the Model** Unfortunately the inclusion of all relevant variables cannot be guaranteed. At least we are aware of several factors which may play a significant role but which are difficult to account for, among all Quality of risk management or Organizational structure of single banks. On the other hand elimination of all redundant variables is assured by significance testing.

3. **Independent Error Terms** Choice of our sample cannot be considered fully random as it was not made from all banks within CEE region but only from those with assigned rating from one of the CRAs. However this is an inevitable fact that has to be accounted for.

4. **No Multicollinearity** Zero correlation between single factors is assured by definition as indicated above. Correlation with the rest of variables can be found in Figure B.7. Based on this correlation matrix as well as consecutive test we can confirm that multicollinearity is not an issue in our sample.

5. **Large Sample Size** Number of observations is almost exactly 30 times higher than the one of explanatory variables, which is the recommended proportion.

The assumptions made on OLM should therefore create no significant obstacle in our following research.

6.2.2 Model Specification

The initial form of the model for our analysis comprises of fifteen explanatory variables. We include all nine factor scores estimated by factor analysis and three additional variables which we consider important and which at the same time were not covered by factor analysis due to their discrete character - these are EBRD index, Country Rating and Control. Apart from these we also include three additional bank specific accounting ratios which were part of factor analysis however their maximal correlation with any of the factors was less than 0.5 and hence are not fully covered by any factor score - ROAE, Liquid Assets/Total Deposits ($LiqAs\_TotDep$) and Net Interest Margin (Net_Int_Mrg). As we are looking for generally valid determinants of the ratings we do not include on purpose any dummy variables indentifying the year of observation or rating agency which assigned the rating.

The estimated equation therefore looks as follows[1]:

$$
\begin{aligned}
Bank\_rating_i = \; & \beta_1 * Cap\_adeq_i + \beta_2 * Growth_i + \beta_3 * Effic\_Profit_i + \\
& + \beta_4 * Liquid_i + \beta_5 * Size_i + \beta_6 * Asset\_qual_i + \\
& + \beta_7 * Market\_pos_i + \beta_8 * Infl\_Inter_i + \beta_9 * GDP\_debt_i + \\
& + \beta_{10} * Country\_rating_i + \beta_{11} * EBRD\_index_i + \\
& + \beta_{12} * Control_i + \beta_{13} * ROAE_i + \beta_{14} * LiqAs\_TotDep_i + \\
& + \beta_{15} * Net\_Int\_Mrg_i + \epsilon_i \qquad (6.1)
\end{aligned}
$$

6.2.3 Discussion of Results

Based on the results of the above mentioned regression we identified four variables which turned out to be highly insignificant and are therefore removed from the model:

- Net Interest Margin (*Net_Int_Mrg*)
- Growth (*Growth*)
- Market Position (*Market_pos*)
- GDP and Public Debt (*GDP_debt*)

Based on this we may conclude that credit rating of a bank does not depend neither on the speed by which the bank expand its activities (represented by growth of assets and loans) nor on the position of the bank within the national market and its concentration. Especially the first finding is surprising as growth indicators should signalize the future situation of the bank. The insignificance of GDP_*debt* can be attributed to "doubling" with $Country\_rating$ which includes similar information. Removal of these variables brings only negligible decrease in share of captured variance (R-squared) amounting circa 0.5 p.p., moreover the predictive power of the model increased by more than 3 percentage points which confirms the irrelevance of these determinants and resulting misspecification of the model.

The final form of estimated model is presented in Table 6.1. Number of observations is 428, $R^2 = 0.1917$ which can be considered a good result considering character of the model.

[1]Definition of all variables can be found above.

Table 6.1: Ordered Logistic Regression - model

Variable	*Coef.*	*Std. Error*	z	$P \succ \|z\|$
cap_adeq	-.435	.127	-3.43	0.001
effic_profit	.953	.220	4.33	0.000
liquid	-.514	.133	-3.85	0.000
size	-1.122	.133	-8.39	0.000
asset_qual	.895	.142	6.30	0.000
infl_inter	.315	.118	2.67	0.008
country_rating	.456	.055	8.26	0.000
ebrd_index	-2.112	.262	-8.04	0.000
control	-.697	.320	-2.18	0.029
roae	.028	.005	4.83	0.000
liqas_totdep	-.011	.003	-2.88	0.004

Source: Author's computations.

As we can see all variables except Control are significant even on 1% level of significance now which confirms importance of all included determinants. As we are interested in relevance of used variables rather than in their absolute values, we just briefly discuss direction of their impact and resulting confirmation/disproval of hypotheses stated in Subsection 5.2.1[2]:

H1: Efficiently performing banks which are able to generate profit are awarded by better ratings due to higher probability of sustainability of their operations.

This hypothesis is confirmed by strongly significant and positive coefficient of Factor 3. Considering results of factor analysis we may claim that decrease in Cost-to-Income and Non-Interest Expenses/Revenues and partially increase in ROAA improve the rating quality. Hypothesis is also supported by significant ROAE which stands separately in the regression.

H2: Share of bad loans on its total amount is one of the most important factors for credit risk assessment - the lower it is the better rating is assigned.

Positive and significant Factor 6 together with high and positive correlation with its two main determinants (Loan Loss Reserves/Gross Loans and Impaired Loans/Gross Loans) again suggests that our hypothesis has support in the data. According to our results decrease in bad loans (or reserves created for them) provides with significantly improved chances of the bank for better rating.

[2]Influence and impact of all variables is discussed ceteris paribus, i.e. all other factors being fixed.

H3: Higher stock of liquid assets increases the probability of bank surviving unexpected outflows and hence decreases probability of potential default (=results in better rating).

Negative coefficient at Liquid Assets/Total Deposits as well as positive relation of Net Loans/As (which is main determinant of liquidity Factor 4) again confirms our hypothesis - safe liquidity position of the bank significantly decreases probability of getting into financial distress.

H4: Capital adequacy assures manageable levels of leverage and hence prevents banks go bankrupt - the higher CA ratios, the better rating.

Negative coefficient of Factor 1 together with high positive correlations of both Capital Adequacy proxies (NPACR and Equity/Assets) signalizes that this measure indeed is an essential determinant of banks' ratings quality - the higher coverage by capital, the lower probability of financial distress, the better rating.

H5: Their stability as well as too-big-to-fail aspect help large banks to achieve better ratings.

Also in case of H5 our results suggest that our assumptions were correct - single variables as well as Factor 5 (which refers to all size-related variables) were even one of the most significant determinants among all. It confirmed that larger banks have better ratings than their smaller competitors with comparable performance.

H6: Constantly growing banks are assessed better than stagnating or even dwindling banks - regardless on their absolute size.

This hypothesis was disproved. Our model suggests that rate of growths of both Total Assets and Gross Loans is not contributing to credit risk assessment. If combined with previous hypothesis we can claim that it is the absolute size rather than rate of growth that matters.

H7: Banks in more concentrated markets are pushed to decrease their margins which may result in insolvency problems, they are therefore rated worse.

Based on the unambiguous insignificance of Factor 9 we reject H9. According to our results the Market Concentration is not a relevant determinant of credit rating. More than concentration of single national markets plays role the standing of each bank within this market (which correlates with its absolute size as described in H5).

H8: Banks operating within developed institutional and regulatory framework are assigned with better ratings.

Although the EBRD index only roughly approximates the true institutional environment it proved to be an important aspect. Quality of regulatory framework, licensing policy or supervision - these are factors which directly determine the riskiness of whole financial sector. For illustration the upward shift by one point in EBRD index results (ceteris paribus) in improvement by approximately 2-3 notches.

H9: Banks with majority hold by public authority are generally assessed better than the privately owned ones.

The character (public vs. private) of majority holders also proved to be a significant aspect of rating assessment, especially in combination with Country Rating. Our model suggests that stately owned banks have, all other being fixed, ratings better by approximately one notch. As already indicated the improvement depends heavily on sovereign rating of that each state but generally we can say that these are of better quality and therefore "improve" those of owned banks.

H10: Banks operating in growing economy are less likely to default due to lower share of unpaid loans.

Our findings regarding the macroeconomic variables (apart from monetary ones - inflation and interest rates) partly support conclusions of majority of current papers which found these as not contributing to banks' credit risk assessment. However we believe that the insignificance of these variables is mainly caused by inclusion of Country Rating which already incorporates similar information about national economy performance.

H11: Banks operating in less indebted countries are likely to have better credit ratings.

The same as for GDP growth rate (see H11) holds also for country indebtedness.

H12: Low inflation improves banks' operations and hence results in better rating.

Money related macroeconomic variables turned out to contribute to overall explanation of rating assignment (due to significance of Factor 8). It confirmed that low inflation suits banks better as they are easily able to set appropriate interest rates (so that money repaid from loans do not loose real value) and hence with decreasing level of inflation chances to obtain better rating increase.

H13: Low interest rates eliminate possibilities of banks to create profit which worsen the outlook of financial health of banks.

The same as for inflation (see H12) applies also for interest rates with the only exception - the direction of relation to credit ratings is opposite, i.e. higher i.r. result (ceteris paribus) in better rating. Our findings follow the general fact than banks earn money on spreads between short- and long-term rates[3] which are obviously increase with increasing absolute values.

H14: Higher unemployment increase risk of bad loans problem which has negative impact on the assigned rating.

As already mentioned in chapter devoted to factor analysis the contribution of unemployment is rather ambiguous and so no clear judgement regarding this variable can be provided.

H15: Quality of country rating influences quality of the banks' one in direct proportion.

A high interconnection of financial sector and sovereign creditworthiness was proven thanks to highly significant Country Rating variable. According to our results an improvement by one notch in country rating results in improvement of banks' one oscillating between 0,5 - 1 notch (depending on rating class). This can be considered as a significant impact and Country Rating proves to be one of the main determinants.

Apart from regression using factor scores we also performed analysis using directly single variables. However as many of them turned out to be insignificant and also overall results of the model were much worse we do not comment on results of this regression.

6.2.4 Prediction Success Rate

Apart from the significance of particular determinants next subject of our interest is the precision of rating prediction that we are able to achieve with given model and set of explanatory variables. For our purposes we divide the discussion into two parts - prediction for observations used for model estimation ("in-sample" data) and out-of-sample data. For each case we present an overview of our results in form of table summarizing the distance of predicted ratings from real ones[4] and a confusion matrix (which can be found in Figure B.12).

Prediction performed using in-sample data produced results which can be found in Table 6.2. As we can see our model was able to correctly assess 192

[3]i.e. between interest paid-out on deposits (short-term) against interest earned on loans (long-term)

[4]Where distance 1 mean mis-estimation by one notch.

observations which account for almost 45 % of whole sample. Moreover 107 observations were mis-estimated by only one notch which can be attributed to statistical mistake. These two groups (with distances 0 and 1) then create almost exactly 70 % of whole sample which can be considered a very good result. This statement is also supported by the fact that only 39 (9 %) observations were mis-estimated by more than 3 notches and the maximal error was 7 notches. If we focus on the confusion matrix we can see that OLM is clearly doing poorly in border groups (i.e. top and worst rating classes) while its results in most frequent ones is highly above average. The only unexplained exceptions are ratings BB+ and BB- which, even though belong among larger groups, show significantly worse success rates. Last noteworthy information that can be gained from confusion matrix is the fact that out of 236 mis-estimated ratings our model underestimated (i.e. predict worse than real) 127 ratings and improved 109 of them.

Table 6.2: Prediction success rate - OLM

Distance	In-sample	In-sample (%)	Out-of-sample	Out-of-sample (%)
0	192	44.9 %	40	40 %
1	107	25 %	33	33 %
2	64	15 %	12	12 %
3	26	6.1 %	5	5 %
4	19	4.4 %	4	4 %
5	7	1.6 %	2	2 %
6	8	1.9 %	2	2 %
7	5	1.2 %	2	2 %
Total	428	100 %	100	100 %

Source: Author's computations.

For the out-of-sample prediction 100 randomly drawn observations were separated from the original sample. When we look at evaluation of their successfulness we can see a slight decrease in correctly assigned rating which dropped from by 5 p.p. from 45 % to 40 %. On the other hand the share of "by-one-notch" mis-estimated ratings increased significantly and more than outweighted the decline - these two groups now create 73 % of whole sample. This result is comparable to most of competing studies where the success rate varies usually between 40 - 70 % (see e.g. Bissoondoyal-Bheenick & Treepongkaruna 2009 or Öğüt *et al.* 2012). However it is important to stress that many of these works are using 9 scale system for rating grades[5] which significantly simplifies situation and increase the overall successfulness. The look at confusion matrix in Figure B.14 only confirms our findings from in-sample data - OLM is doing poorly in outer classes with only few observations and on the other hand exceeds in those with sufficient number of representatives.

6.2.5 Summary

Our findings from OLM analysis confirm that bank specific accounting ratios are the main drivers of probability of default of single institutions and hence of ratings assigned to them. The most contributing turned out to be Capital Adequacy, Asset Quality and Liquidity followed by Profitability and Efficiency of banks' operations. Quite surprisingly the Growth rates of As as well as Gross Loans seem to be absolutely irrelevant.

When assessing importance of macroeconomic measures in the OLM we have divide them into two groups:

- GDP and Public Debt: Here the model suggests that variables are not contributing to rating determination which would coincide with most of current literature (Poon *et al.* 1999 among all). However as already explained we see the reason of insignificance in the fact Country Rating, which carries similar information as GDP and Public Debt is also included in the regression (which was also confirmed by increase in significance of the variable when Country Rating was removed from the model).

- Inflation and Interest Rates: By contrast, the second set of (monetary) macroeconomic variables seems to be an important part of the model explaining rating quality.

Last part of our analysis was devoted to qualitative variables and here the results are clear - all variables except Market position & concentration proved to be important determinants of examined ratings. As the most important we highlight Size of rated banks, however also Control (ownership) and EBRD index (institutional framework) do not lag behind significantly.

Using the above mentioned variables OLM was able to correctly reproduce 40 % of out-of-sample ratings assigned by CRAs, moreover next 33 % of observations were misclassified by only one notch. These results are comparable or even outperform most of the current papers (as described in Subsection 6.2.4)

[5] i.e. each rating class (BBB+, BBB, BBB-) is grouped together, +- signs are disregarded

and we can therefore claim that our model is well able to capture the underlying principles of rating assignment and hence that our explanatory variables are determinants of banks' rating quality.

6.3 Multiple Discriminant Analysis

6.3.1 Model Assumptions

In the following subchapter we will discuss the five basic requirements on the data used for MDA which were stated in Subsection 4.2.2 and investigate whether our dataset satisfies these.

1. **Sample size:** Our final dataset comprises of 428 observations and will utilize up to 15 explanatory variables which is according to all recommendations ratio sufficient for consistent results.

2. **Homogeneity of (co)variances:** The equality of covariance matrixes among all classification groups was tested using the Box's M test which calculates covariance matrix for each rating class and compare them. Based on the results of the test (see Figure B.8) we cannot reject the null hypothesis of equality of covariance matrices on any reasonable significance level. The requirement of homogenous covariance is therefore considered to be fulfilled.

3. **Normal distribution:** To test for multivariate normality of our dataset we use complex procedure using four various criteria for multivariate skewness and kurtosis (see Figure B.9). Results of the test suggest to reject the null hypothesis of normally distributed data on any significance level and we can therefore claim that our data break this assumption. However as already mentioned (and shown by Poulsen & French 2004 or Tabachnick & Fidell 2007) this violation is not "fatal" and usually causes only minor misclassifications of the model.

4. **Outliers:** Check for outliers was performed using the Box-and-Whisker plots (e.g. Massart *et al.* 2005). Based on these all observations which significantly differed from the rest were removed. As the number of outliers was rather small no complex modification of the data was required.

5. **Non-multicollinearity:** The assumption of no perfect collinearity is partially guaranteed by use of factor analysis. Thanks to it all factors are

uncorrelated within each other. To test the rest of variables we investigate their correlation matrix (see Figure B.7). Based on this we can conclude that there is only one higher correlation (over 0.7) between variables which is however still far from being considered perfect.

6.3.2 Model Specification

The initial set of variables for Multiple Discriminant Analysis coincides with the one used for OLM. Unfortunately MDA does not provide such a straightforward way for assessment of significance of single variables as it is in case of regression methods. In order to prevent misspecification of the model we therefore follow Michel (1977) and eliminate those variables whose mean is statistically identical across rating groups. If this is the case such a variable is only poorly able to discriminate between single groups and has therefore no explanatory power.

After performing Wilks' Lambda test (see e.g. Field 2000) we are not able to reject the null hypothesis of identical group means for three variables - $Net\_Interest\_Margin$, $Market\_Position$ and $Control$. While in case of $Control$ this is an expected outcome (due to dummy characteristic of the variable) and we therefore retain it, the remaining variables are disregarded. This result mostly coincides with our findings during OLM with two differences: Both $Growth$ and GDP_$Debt$ variables are retained in the model. Its final form therefore is:

$$\begin{aligned} Bank\_rating_i &= \beta_1 * Cap\_adeq_i + \beta_2 * Growth_i + \beta_3 * Effic\_Profit_i + \\ &+ \beta_4 * Liquid_i + \beta_5 * Size_i + \beta_6 * Asset\_qual_i + \\ &+ \beta_7 * Infl\_Inter_i + \beta_8 * GDP\_debt_i + \\ &+ \beta_9 * EBRD\_index_i + \beta_{10} * Control_i + \beta_{11} * ROAE_i + \\ &+ \beta_{12} * LiqAs\_TotDep_i + \beta_{13} * Country\_rating_i \end{aligned} \tag{6.2}$$

6.3.3 Discussion of Results

The above mentioned equation is estimated using the same sample (comprising of 428 observations) as in case of OLM. The number of estimated discriminant functions is generally a minimum of number of groups of dependent variable less one (14 in our case) and number of discriminating variables (13). That means that in our particular analysis 13 discriminant functions are to be estimated.

Overview of standardized[6] estimated coefficients is displayed in Table 6.3 below. The choice of standardized coefficients was based on the fact that we are interested, rather than in absolute, in relative contribution of single variables.

Table 6.3: Multiple Discriminant Analysis - model

Variable	Func1	Func2	Func3	Func4	Func5	Func6
country_rating	.622	-.223	-.546	.111	-.294	-.132
control	-.078	-.131	-.604	-.065	-.125	.646
ebrd_index	-.483	-.084	-.033	.147	.027	-.326
roae	.385	.691	.393	.597	.112	.224
liqas_totdep	-.247	-.359	-.431	.501	.829	.034
cap_adeq	-.187	-.307	-.381	-.188	-.448	-.489
growth	.073	-.142	.107	-.379	-.402	.144
effic_profit	.290	.508	.078	.977	.363	.347
liquid	-.282	.005	-.561	.242	.985	-.200
size	-.720	-.509	.019	.488	-.056	-.175
asset_qual	.468	.561	.171	.262	-.042	-.247
infl_inter	.198	.073	-.580	-.354	.035	.431
gdp_debt	-.249	.703	-.229	-.013	-.365	.260

Func7	Func8	Func9	Func10	Func11	Func12	Func13
.317	.823	.300	-.165	-.247	-.111	.001
-.011	-.274	.214	-.142	-.388	-.348	-.137
.146	.094	1.121	.057	-1.201	-.468	.162
-.353	-.038	-.004	-.698	.010	-1.198	-.376
-.263	-.192	.380	-.305	.438	-.168	.664
.402	.210	-.516	.594	-.371	-.186	.128
-.476	.126	-.430	.237	-.534	.186	.502
.006	-.049	-.177	.064	-.281	-.212	-.030
-.112	.201	-.187	-.514	-.191	.323	.292
-.116	-.491	-.127	-.163	.141	.434	-.131
-.881	.472	.188	-.139	.109	-.374	-.466
-.383	-.551	-.615	.364	.422	-.097	-.259
-.164	-.249	-1.030	-.031	1.031	.087	.441

Source: Author's computations.

As the direction by which all our variables influence the assigned rating is as expected and the same as in case of OLM, in the following discussion we focus solely on assessing importance of single variables. This can be done based on the above mentioned standardized MDA loadings - high coefficients signalize

[6]Standardization in performed by multiplying unstandardized coefficients by their standard deviation.

large differences among the groups for that particular variable which then poses high discriminative power.

Based on the above presented results we may divide our explanatory variables into three main groups. In the first one there are variables with rather high coefficients through all discriminant function which can therefore be seen as the main determinants of banks' ratings. These are *Country_Rating, Capital_Adequacy, Size, Asset_Quality, Inflation_InterestRates* and *GDP_Debt*. While in case of first five variables our findings coincide with those obtained during OLM analysis, the importance of *GDP_Debt* is rather surprising as it turned out to be insignificant previously.

The second notional group comprises of variables with rather low coefficients and hence only minor discriminative impact. First of such variables is *Growth* - this result is again in line with our previous findings as in OLM *Growth* was a highly insignificant variable. Second negligible variable is unexpectedly $Efficiency\_Profitability$ which also contributes to model discrimination only weakly.

In the last third group there are variables of which coefficients vary among single discriminative functions significantly and where belongs the rest of included variables. While all of these are an important part of the model and help to correctly assess single observations we cannot, contrary to the first group, say that these are the key determinants.

6.3.4 Prediction Success Rate

We employ the same approach as in case of OLM also for predictions obtained using MDA method. Confusion matrices for both in-sample and out-of-sample data can be again found in Figure B.13 and Figure B.15.

From the Table 6.4 we can clearly see that performance of MDA is significantly worse than the one of OLM - number of correctly assessed ratings dropped by 46 (11 %) to 146 observations and together with "by-one" misclassified now creates only 59 % of all observations. Number of ratings mis-estimated by more than 3 notches also increased to 67 and account for more 15 %. Next aspect which plays against MDA is wider range of errors - while in case of OLM the maximal misspecification was by 7 notches, it is by 12 for MDA. When analysing the confusion matrix we come to the very opposite findings than was drawn for OLM. MDA is much better able to handle outer groups with only few observations and on the contrary lag behind in case of large groups of average ratings. The only aspect where both methods are equal is the share of under/overestimated observations which is now 154/128.

Table 6.4: Prediction success rate - MDA

Distance	In-sample	In-sample (%)	Out-of-sample	Out-of-sample (%)
0	146	34.1 %	29	29 %
1	106	24.8 %	22	22 %
2	54	12.6 %	12	12 %
3	55	12.9 %	17	17 %
4	30	7 %	10	10 %
5	16	3.7 %	4	4 %
6	8	1.9 %	1	1 %
7	2	0.5 %	0	0 %
8	2	0.5 %	3	3 %
9	2	0.5 %	1	1 %
10	4	0.9 %	1	1 %
11	1	0.2 %	0	0 %
12	2	0.5 %	0	0 %
Total	428	100 %	100	100 %

Source: Author's computations.

Also in case of MDA the out-of-sample prediction produces slightly worse results than in-sample data and significantly worse results than OLM on the same dataset. The number of correctly assessed ratings is now only on 29 % of all observations and together with "by-one-notch" misclassified creates only tightly more than 50 %. Also the maximal mis-estimation is again higher than in case of OLM - 10 notches. Due to the low number of correctly assessed observations it is difficult to draw some reliable patterns from the confusion matrix and so we omit its discussion for now.

6.3.5 Summary

Generally our results obtained from MDA confirm the conclusions obtained during OLM analysis, though with several discrepancies. Also now the leading factors that help to distinguish between single rating classes are the bank specific accounting ratios, namely those representing *Asset_Quality*, *Liquidity* and *Capital_Adequacy* and again the importance of qualitative variables (especially *EBRD_index* and *Size*) was confirmed. The only principal difference is in perception of GDP and $Public\_Debt$ variable which is now included among the contributing ones.

Next difference can be also seen in successfulness of predicting out-of-sample ratings. It has dropped by more than 10 p.p. by both of two important groups, i.e. correctly assigned and "by-one" misclassified ratings. On the other side MDA was far more successful in border rating classes with only few observations. This confirms our previous statement that OLM should outperform MDA in case of sufficient number of observations, while MDA is more accurate in groups with low populations.

However as already mentioned the relevance of described determinants was confirmed also by this classification technique.

6.4 Areas for Further Research

We would like to mention especially two main areas for further research which could extend this thesis:

- **Qualitative variables:** The importance of qualitative variables during the credit rating assignment process was already proven however we believe that there are much more relevant factors which were not accounted for in this thesis. These are e.g. quality of (risk) management, organizational structure, business plan, competitive advantages and others.

- **Time perspective:** In our analysis we considered ratings which were assigned 3 - 6 months after the disclosure of corresponding financial statements which should be in our opinion sufficient time for manifesting of this information in the assessment. However there is possibility of some variables having impact on assigned rating even with longer delay, various lags of single determinants can therefore be investigated.

Chapter 7

Conclusion

This study attempts to reveal the main factors which determine quality of long-term credit ratings which CRAs assign to banks. In order to do so variables from three different areas are considered - these are Quantitative (accounting) measures, Macroeconomic indicators and finally Qualitative aspects of banks and banking sectors. We collected these data for more than 180 banks from all countries across CEE region in period between 2010 - 2012. The resulting dataset creates an unbalanced panel which comprises of more than 500 observations. Results obtained using such an extensive dataset should therefore provide us with reliable information with general validity.

In the beggining of the thesis we briefly introduce the general concepts of rating methodology and princpiles of the industry. After literature review which is mainly devoted to development of rating modelling frameworks and rating determinants we move to introduction of our two used classification methods - Ordered Logit Model and Multiple Discriminant Analysis. Apart from these we present, with respect to rather high number of chosen explanatory variables, also Factor analysis which retains most of the explanatory power of all variables while significantly decreasing its overall count.

Our results from both classification models coincides with the main finding of most of current research - the group of variables which is most contributing to the rating assignment explanation are the accounting ratios. It turned out that especially *Capital Adequacy*, *Asset Quality* and *Liquidity* are the key factors signalizing the financial health of the bank and hence determining probability of its eventual default. The remaining two areas - $Efficiency$ and $Profitability$ - although relevant as well, seem not to explain that much variation in assigned ratings as three previously mentioned ones.

Our findings regarding macroeconomic indicators already were partly ambiguous. While those directly related to money (*Inflation* and *Real Interest Rates*) and *Country Rating* proved to be important part of both our models, the significance of remaining ones (GDP, *Public Debt* and *Unemployment*) depends on used method and so we cannot provide clear judgement about their relevance. On the other hand we believe that similar information is already considered in *Country Rating* which may cause the insignificance of these variables in particular model. Based on this we may therefore conclude that our results do not support those of Poon *et al.* (1999) or Bissoondoyal-Bheenick & Treepongkaruna (2009) and state that indicators describing state of national economies determine quality of ratings of subjects (particularly banks) operating within them.

Results of the last group of qualitative variables do not have any comparison with current research however based on those obtained in this thesis we see that they indeed are an inseparable part of assessment process as stated by CRAs themselves. Apart from *Market Concentration* which appears to be irrelevant all other included variables are highly significant. Especially *Size* and *Institutional Environment* represented by EBRD *index* has substantial impact on final rating grade.

The overall results therefore suggest that variables from all three areas contribute to explanation of quality of assigned rating and should be therefore considered during the rating process. The most relevant turned out to be bank specific variables of both - qualitative and quantitative character. Macroeconomic indicators as well as common features of national banking sectors contribute moderately less.

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Appendix A

Nationally Recognized Statistical Rating Organizations

- Standard & Poor's
- Moody's Investros Service
- Fitch Ratings
- Kroll Bond Rating Agency
- Dominion Bond Rating Service, Ltd
- A.M. Best Company
- Japan Credit Rating Agency, Ltd
- Egan-Jones Rating Company
- Morningstar, Inc.
- HR Ratings

Appendix B

Regression and Statistical Output

Figure B.1: Factor Analysis (1)

```
Factor analysis/correlation                    Number of obs    =       531
    Method: principal-component factors        Retained factors =         7
    Rotation: (unrotated)                      Number of params =       112
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.79670	0.31475	0.1998	0.1998
Factor2	3.48196	1.73330	0.1833	0.3831
Factor3	1.74866	0.22980	0.0920	0.4751
Factor4	1.51886	0.21450	0.0799	0.5551
Factor5	1.30436	0.01228	0.0687	0.6237
Factor6	1.29207	0.23664	0.0680	0.6917
Factor7	1.05544	0.17450	0.0555	0.7473
Factor8	0.88094	0.04805	0.0464	0.7936
Factor9	0.83289	0.20467	0.0438	0.8375
Factor10	0.62822	0.07744	0.0331	0.8705
Factor11	0.55078	0.09151	0.0290	0.8995
Factor12	0.45927	0.02471	0.0242	0.9237
Factor13	0.43457	0.05568	0.0229	0.9466
Factor14	0.37888	0.11572	0.0199	0.9665
Factor15	0.26316	0.11709	0.0139	0.9804
Factor16	0.14607	0.02486	0.0077	0.9880
Factor17	0.12121	0.03587	0.0064	0.9944
Factor18	0.08534	0.06471	0.0045	0.9989
Factor19	0.02063	.	0.0011	1.0000

LR test: independent vs. saturated: chi2(171) = 6039.60 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Uniqueness
net_income	-0.0928	0.3723	0.0505	-0.3295	0.0281	0.3455	0.5549	0.3136
net_intere~n	0.3202	0.3479	0.2287	0.6215	-0.1393	0.0856	0.1629	0.2846
non_intere~v	0.2862	-0.5535	-0.0680	-0.2971	0.2978	0.0107	-0.0441	0.4281
roaa	0.4744	0.6531	0.1374	-0.0433	-0.1149	0.0378	-0.0061	0.3130
roae	0.3413	0.5931	-0.0376	-0.0999	-0.0284	-0.2300	0.0478	0.4643
cost_to_in~o	0.0264	-0.8006	-0.0729	-0.0444	-0.2416	0.3897	0.0144	0.1407
non_intere~e	0.0160	-0.4539	-0.0792	0.0038	-0.5470	0.5686	-0.0468	0.1627
impaired_l~s	-0.5226	-0.3672	0.0818	0.4764	0.2920	-0.1727	0.3178	0.1423
loan_loss_~s	-0.1917	-0.5000	0.4107	0.2976	0.0357	0.0373	0.4267	0.2712
net_loans_~s	-0.3018	0.3715	0.1973	0.3631	-0.4030	0.0037	-0.2453	0.3776
liquid_ass~r	0.5742	-0.2568	-0.0250	-0.1481	0.2961	0.0203	0.1858	0.4592
npacr	0.7005	0.1165	0.5388	-0.2026	-0.0486	0.2215	-0.0596	0.1094
equity___t~s	0.5077	0.0539	0.6782	0.1284	0.1552	0.1283	0.0428	0.2205
ltot_assets	-0.5462	0.5723	-0.0170	-0.2854	-0.0390	0.1945	0.2591	0.1860
market_share	-0.5262	0.3595	0.1514	-0.1569	0.3844	0.4288	-0.1220	0.1997
country_ra~s	0.6927	-0.3629	0.1663	-0.0592	0.0544	-0.1363	-0.1233	0.3205
growth_of~ts	0.5774	0.2108	-0.5756	0.3093	0.1348	0.2322	0.1507	0.1004
growth_of~ns	0.5753	0.2047	-0.5508	0.3228	0.1076	0.2273	0.0850	0.1491
herfindahl	-0.2500	0.1031	0.0808	0.2925	0.5280	0.4390	-0.4517	0.1592

Source: Author

Figure B.2: Factor Analysis (1) - rotation

```
Factor analysis/correlation                        Number of obs    =      531
    Method: principal-component factors            Retained factors =        7
    Rotation: orthogonal varimax (Kaiser off)      Number of params =      112
```

Factor	Variance	Difference	Proportion	Cumulative
Factor1	2.52392	0.25857	0.1328	0.1328
Factor2	2.26535	0.22384	0.1192	0.2521
Factor3	2.04151	0.03206	0.1074	0.3595
Factor4	2.00945	0.04334	0.1058	0.4653
Factor5	1.96611	0.06724	0.1035	0.5688
Factor6	1.89887	0.40602	0.0999	0.6687
Factor7	1.49285	.	0.0786	0.7473

LR test: independent vs. saturated: chi2(171) = 6039.60 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Uniqueness
net_income	0.1331	0.0777	-0.0238	-0.0787	0.8064	-0.0101	-0.0742	0.3136
net_intere~n	0.4301	0.4139	-0.1248	0.5467	-0.0348	0.2037	-0.0450	0.2846
non_intere~v	0.0883	-0.0149	0.1924	-0.6771	-0.2605	0.0205	-0.0062	0.4281
roaa	0.4576	0.2750	-0.3183	0.2594	0.1799	-0.4357	-0.1056	0.3130
roae	0.1872	0.2226	-0.4835	0.1356	0.1287	-0.3695	-0.2142	0.4643
cost_to_in~o	-0.0329	-0.0497	0.8405	-0.2782	-0.1858	0.1844	-0.0589	0.1407
non_intere~e	0.0087	0.0314	0.9047	0.1006	0.0000	-0.0632	-0.0612	0.1627
impaired_l~s	-0.2936	-0.1252	-0.0597	0.0286	-0.0607	0.8562	0.1212	0.1423
loan_loss_~s	0.1846	-0.2042	0.2476	-0.0222	0.0019	0.7636	-0.0896	0.2712
net_loans_~s	-0.0425	-0.1541	-0.0248	0.7618	-0.0065	-0.0636	0.1085	0.3776
liquid_ass~r	0.3470	0.2902	0.0047	-0.5462	-0.1298	0.0315	-0.1416	0.4592
npacr	0.8853	0.0270	0.0528	-0.0910	-0.0239	-0.3003	-0.0656	0.1094
equity___t~s	0.8626	0.0009	-0.0887	0.0111	-0.0896	0.1190	0.0724	0.2205
ltot_assets	-0.2401	-0.1788	-0.1800	0.2174	0.7851	-0.1185	0.1198	0.1860
market_share	-0.0764	-0.2157	-0.1122	0.0382	0.5099	-0.0346	0.6875	0.1997
country_ra~s	0.4818	0.1097	0.0774	-0.3553	-0.4976	-0.0899	-0.2178	0.3205
growth_of~ts	0.0261	0.9370	-0.0231	-0.0632	-0.0288	-0.1229	-0.0237	0.1004
growth_of~ns	0.0352	0.9058	-0.0089	-0.0278	-0.0767	-0.1496	-0.0038	0.1491
herfindahl	0.0077	0.0632	-0.0249	0.0673	-0.0596	0.0780	0.9066	0.1592

Factor rotation matrix

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
Factor1	0.6210	0.5261	-0.0204	-0.2409	-0.3232	-0.2948	-0.2963
Factor2	0.0909	0.2032	-0.5826	0.4686	0.4609	-0.4077	0.1134
Factor3	0.7390	-0.5896	-0.0721	0.1862	0.0247	0.2407	0.0891
Factor4	0.0089	0.4337	-0.0251	0.5816	-0.3728	0.5503	0.1766
Factor5	0.0495	0.1435	-0.4878	-0.5716	-0.0007	0.2823	0.5767
Factor6	0.2273	0.2741	0.6440	0.0175	0.4316	-0.0818	0.5150
Factor7	0.0767	0.2248	-0.0401	-0.1499	0.5978	0.5475	-0.5123

Source: Author

Figure B.3: Factor Analysis (1) - factor loadings

Scoring coefficients (method = regression; based on varimax rotated factors)

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
net_income	0.11612	0.09237	0.08218	-0.15126	0.56842	0.12324	-0.13560
net_intere~n	0.18337	0.20254	0.00893	0.32793	-0.00961	0.23998	-0.03624
non_intere~v	0.01188	-0.02891	-0.00556	-0.33772	-0.04724	-0.03351	0.07897
roaa	0.15431	0.03926	-0.05471	0.10758	0.06787	-0.14048	-0.04657
roae	0.01677	0.02433	-0.20372	0.01843	0.02369	-0.10411	-0.14826
cost_to_in~o	0.01280	0.02798	0.42159	-0.02509	0.04010	-0.00396	0.00457
non_intere~e	0.03316	0.05399	0.56884	0.18500	0.10020	-0.13631	-0.01210
impaired_l~s	-0.05388	0.07777	-0.15438	-0.00055	0.00226	0.50645	-0.00563
loan_loss_~s	0.16981	-0.00649	0.05185	0.02685	0.13702	0.46452	-0.12228
net_loans_~s	0.01336	-0.07878	0.08721	0.44066	-0.14893	-0.07606	0.03032
liquid_ass~r	0.10411	0.10717	-0.06428	-0.28622	0.06495	0.08753	-0.02283
npacr	0.37690	-0.10670	0.08870	-0.01621	0.05336	-0.12276	0.04874
equity___t~s	0.40337	-0.06509	-0.03760	0.02409	0.00895	0.14183	0.11057
ltot_assets	-0.03168	-0.02587	0.01425	-0.01649	0.40374	-0.01666	-0.03825
market_share	0.06755	-0.04046	0.01362	-0.10751	0.20697	-0.04443	0.44233
country_ra~s	0.14287	-0.04735	-0.03246	-0.10590	-0.20552	-0.05343	-0.03474
growth_of~ts	-0.08459	0.47089	0.03985	-0.02844	0.05752	0.05600	0.04746
growth_of~ns	-0.08119	0.44770	0.04983	-0.00018	0.01514	0.02552	0.06814
herfindahl	0.06210	0.08269	0.01438	-0.01096	-0.14519	-0.02332	0.68867

Source: Author

Figure B.4: Factor Analysis (2)

```
Factor analysis/correlation                        Number of obs    =      531
    Method: principal-component factors            Retained factors =        2
    Rotation: (unrotated)                          Number of params =        9
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.79409	1.59658	0.5588	0.5588
Factor2	1.19751	0.54219	0.2395	0.7983
Factor3	0.65532	0.36475	0.1311	0.9294
Factor4	0.29057	0.22804	0.0581	0.9875
Factor5	0.06252	.	0.0125	1.0000

LR test: independent vs. saturated: chi2(10) = 1703.37 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
gdp_real_g~e	-0.6491	-0.4013	0.4177
inflation_~e	-0.7303	0.6584	0.0331
public_debt	0.5934	0.6972	0.1618
unemployment	0.8182	0.1183	0.3166
real_inter~e	0.9044	-0.3207	0.0793

Source: Author

Figure B.5: Factor Analysis (2) - rotation

```
Factor analysis/correlation                        Number of obs    =      531
    Method: principal-component factors            Retained factors =        2
    Rotation: orthogonal varimax (Kaiser off)      Number of params =        9
```

Factor	Variance	Difference	Proportion	Cumulative
Factor1	2.15203	0.31246	0.4304	0.4304
Factor2	1.83957	.	0.3679	0.7983

LR test: independent vs. saturated: chi2(10) = 1703.37 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
gdp_real_g~e	-0.2474	-0.7219	0.4177
inflation_~e	-0.9823	0.0460	0.0331
public_debt	0.0167	0.9154	0.1618
unemployment	0.5576	0.6103	0.3166
real_inter~e	0.9027	0.3255	0.0793

Factor rotation matrix

	Factor1	Factor2
Factor1	0.7732	0.6341
Factor2	-0.6341	0.7732

Source: Author

Figure B.6: Factor Analysis (2) - factor loadings

Scoring coefficients (method = regression; based on varimax rotated factors)

Variable	Factor1	Factor2
gdp_real_g~e	0.03291	-0.40644
inflation_~e	-0.55079	0.25938
public_debt	-0.20498	0.58483
unemployment	0.16378	0.26206
real_inter~e	0.42012	-0.00185

Source: Author

Figure B.7: Correlation Matrix

	cap_adeq	growth	effic_~t	liquid	size	asset_~l	market~s	infl_i~r	gdp_debt	ebrd_i~x	control	countr~g
cap_adeq	1.0000											
growth	-0.0000	1.0000										
effic_profit	0.0000	0.0000	1.0000									
liquid	-0.0000	-0.0000	0.0000	1.0000								
size	0.0000	0.0000	0.0000	0.0000	1.0000							
asset_qual	0.0000	-0.0000	-0.0000	-0.0000	0.0000	1.0000						
market_pos	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	1.0000					
infl_inter	-0.0056	-0.3137	-0.0099	0.0277	0.0821	-0.0449	-0.1661	1.0000				
gdp_debt	-0.3478	-0.2843	0.0294	0.0796	0.1544	0.1107	0.2884	0.0000	1.0000			
ebrd_index	-0.2821	-0.3926	-0.0399	0.0692	0.1792	0.0481	0.2925	0.4499	0.7409	1.0000		
control	-0.0760	0.0321	0.0216	-0.0318	0.2184	0.0700	0.1440	-0.2674	0.0569	-0.1370	1.0000	
country_ra~g	-0.0833	0.1414	0.0794	0.0311	-0.0948	0.3341	0.0245	-0.4524	0.1465	-0.3027	0.0720	1.0000

Source: Author

Figure B.8: Test of Equality of Covariance Matrices

```
Test of equality of covariance matrices across 10 samples

      Modified LR chi2 =   14.5606
   Box F( 10 ,18364.8) =      1.35      Prob > F =  0.1950
         Box chi2( 10 ) =     13.55   Prob > chi2 =  0.1948
```

Source: Author

Figure B.9: Multivariate Normality Test

```
Test for multivariate normality

  Mardia mSkewness =  206.1672   chi2(364) =18364.814   Prob>chi2 =  0.0000
  Mardia mKurtosis =  505.4846     chi2(1) =44999.023   Prob>chi2 =  0.0000
  Henze-Zirkler    =  13.61072     chi2(1) = 3.24e+05   Prob>chi2 =  0.0000
  Doornik-Hansen                  chi2(24) =11657.683   Prob>chi2 =  0.0000
```

Source: Author

Figure B.10: Statistical Summary

Variable	Obs	Mean	Std. Dev.	Min	Max
gdp_debt	528	-.0035818	.9976895	-1.596762	3.115456
infl_inter	528	-.0043166	.999294	-6.091445	1.395539
market_pos	528	-.0229902	.8972534	-2.765909	6.873423
asset_qual	528	-.0097267	.9834069	-1.299631	5.814002
size	528	.0045917	.9890968	-2.012831	10.34805
liquid	528	.0201519	.9186165	-3.315623	3.847124
effic_profit	528	-.0051718	.6932362	-3.289404	5.76879
growth	528	.007195	.9975168	-1.888276	6.409175
cap_adeq	528	.0001595	1.001821	-4.911158	6.39515
ebrd_index	528	3.015909	.4927296	2.3	4
control	528	.1117424	.3153481	0	1
country_ra~g	528	9.285985	2.27761	3	16

Source: Author

Figure B.11: (Log)Normality tests - rating

Skewness/Kurtosis tests for Normality

				joint	
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
rating	528	0.0000	0.0629	43.24	0.0000

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rating	528	0.91505	30.017	8.197	0.00000

Shapiro-Wilk W test for 3-parameter lognormal data

Variable	Obs	W	V	z	Prob>z
rating	528	0.91505	30.017	2.931	0.00169

Source: Author

Figure B.12: Confusion matrix - OLM - in-sample

Count of year Predicted														
Assigned	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**Grand Total**
5	**1**	1		1										3
6		**3**	1	5	2									11
7		1	**6**	3	1	1								12
8				**3**	2	1	1	3	1		1			12
9	2	1	1		**11**	2	2	2	7	1	4			33
10		1			1	**9**	1	2	5	1	3			23
11					4	3	**4**	2	1	2	2	1	2	21
12					2	2	1	**6**	1	8	1			21
13							4	2	**6**	6	16	3		37
14							2	1	3	**16**	8	2		32
15				1	1	1	1		5	4	**49**	15	2	79
16									2		35	**70**	1	108
17						3			2		6	13	**8**	32
18								1				1	1	3
19												1		1
Grand Total	**3**	**7**	**8**	**13**	**24**	**22**	**16**	**19**	**33**	**38**	**125**	**106**	**14**	**428**

Source: Author

Figure B.13: Confusion matrix - MDA - in-sample

	Predicted															
Assigned	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**Grand Total**
5	**2**	1														3
6	1	**8**	2													11
7	2	1	**7**	1			1									12
8		1	3	**4**		2	1								1	12
9	1		2	2	**15**	2	2		3	2	1			1	2	33
10	1	1		2	1	**11**		1	1	2		1		2		23
11			2	3	2	8	**5**			1						21
12			1	1	3	4	1	**1**	4	3				2	1	21
13						6	1	1	**11**	8	1	1	2	4	2	37
14					1	3			6	**11**	2	3	1	4	1	32
15	2			1		5	2		6	11	**12**	16	7	11	6	79
16						2			9	6	12	**40**	20	2	17	108
17	2			1				1	2	1	1	2	**16**		6	32
18													1	**2**		3
19															**1**	1
Grand Total	**11**	**12**	**17**	**15**	**22**	**43**	**13**	**4**	**42**	**45**	**29**	**63**	**47**	**28**	**37**	**428**

Source: Author

Figure B.14: Confusion matrix - OLM - out-of-sample

Assigned	Predicted 7	8	9	10	11	12	13	14	15	16	17	19	Grand Total
5	**1**												1
7			1										1
8		**1**	4				1		1				7
9			**2**	1		1			2				6
10			1	**2**	1			2					6
11			1					1					2
12							3	1					4
13					1		**2**	1	4	2			10
14							1	**6**	4				11
15		1				1		3	**10**	2		1	18
16					1				8	**15**	1		25
17							1		3	2	**2**		8
18											1		1
Grand Total	**1**	**2**	**9**	**3**	**3**	**2**	**8**	**14**	**32**	**21**	**4**	**1**	**100**

Source: Author

Figure B.15: Confusion matrix - MDA - out-of-sample

Assigned	Predicted 5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Grand Total
5	**1**															1
7		1														1
8		1	3	**1**			1							1		7
9			1		**2**		1			1	1					6
10			1			**2**				1				2		6
11						1				1						2
12							1		2	1						4
13						2		1	**2**	1		1	2	1		10
14						2				**5**	2		1	1		11
15		1				2	2		3	3	**4**		1		2	18
16				1					3	1	3	**9**	1		7	25
17											2	2	**3**		1	8
18													1			1
Grand Total	**1**	**3**	**5**	**2**	**2**	**9**	**5**	**1**	**10**	**14**	**12**	**12**	**9**	**5**	**10**	**100**

Source: Author